THE PREVENTIVE MAINTENANCE PRACTICES AND PERFORMANCE AMONG MANUFACTURING ORGANIZATIONS IN MALAYSIA: THE MODERATING ROLE OF TECHNOLOGICAL CAPABILITIES

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ABSTRACT

The importance of maintenance has become the main focus in the manufacturing environment. New technologies and advancements in the manufacturing industry have driven many companies to implement reliable maintenance program in order to avoid stoppages and disruptions of equipment from occurring in their daily operations. The purpose of this study was to examine the preventive maintenance (PM) practices and performance among manufacturing organizations in Malaysia, and the technological capabilities (TC) used as a moderator in the relationship between preventive maintenance practices and performance among Malaysian manufacturing organizations. The correlations between three components of PM, namely time-based maintenance (TBM), condition-based maintenance (CBM) and predictive maintenance (PdM),:and manufacturing performance dimensions (cost; quality; flexibility and delivery) were evaluated and validated by employing Smart-PLS statistical tools. 600 questionnaires were circulated to various manufacturing organizations in all regions of Malaysia. However, only 155 questionnaires were returned and were usable for analysis. Correlation analysis was carried out and the results show that there is a positive relationship among PM practices. In general, PM practices, for instance predictive maintenance show positive and significant correlations among this sample of Malaysian manufacturing organizations. Meanwhile, the hypothesis result indicates that the performance of the manufacturing organizations is only influenced by PdM and the TBM and CBM practices, fail to positively influence manufacturing performance. In addition, the moderation analysis indicates that the TC not positively moderate TBM, CBM and PdM toward manufacturing performance. The overall results suggest that PdM practices can be identified as one of the best strategies to face stiff competitive environments in enhancing the effectiveness of quality improvement among Malaysian manufacturing organizations.

Keyword: Preventive maintenance, manufacturing performance, technological capabilities, time-based maintenance

ABSTRAK

Kepentingan penyelenggaraan telah menjadi fokus utama dalam persekitaran pembuatan. Teknologi terkini dan kemajuan dalam industri pembuatan memacu banyak syarikat untuk melaksanakan program penyelenggaraan yang boleh dipercayai demi mengelakkan terjadinya pemberhentian dan gangguan peralatan dalam operasi seharian. Tujuan kajian ini adalah untuk menyelidik amalan penyelenggaraan pencegahan (PM) dan prestasi perkilangan di Malaysia. Selain itu keupayaan teknologi (TC) digunakan sebagai penyederhana dalam hubungan antara amalan penyelenggaraan pencegahan dan prestasi dalam kalangan organisasi perkilangan Malaysia. Kajian ini akan meneliti hubungan antara tiga komponen PM iaitu, penyelenggaraan berasaskan masa (TBM), penyelenggaraan berasaskan keadaan (CBM), penyelenggaraan ramalan (PdM), dan untuk dimensi prestasi pembuatan (kos, kualiti, fleksibiliti dan penghantaran) yang dinilai dan disahkan dengan menggunakan alat statistik Smart-PLS. Sebanyak 600 borang soal selidik diedar kepada pelbagai organisasi pembuatan di seluruh Malaysia. Walau bagaimanapun, hanya 155 soal selidik yang dikembalikan boleh digunakan untuk analisis. Analisis korelasi dijalankan dan hasilnya menunjukkan bahawa terdapat hubungan positif di antara amalan PM. Secara umum, amalan PM, iaitu penyelenggaraan ramalan menunjukkan hubungan korelasi positif dan signifikan dalam kalangan sampel organisasi pembuatan di Malaysia. Sementara itu, hasil hipotesis menunjukkan bahawa prestasi organisasi perkilangan hanya dipengaruhi oleh faktor PdM dan bukannya faktor TBM dan CBM. Di samping itu, analisis penyederhanaan TC menunjukkan keputusan tiada perhubungan yang positif di antara TBM, CBM dan PdM terhadap prestasi organisasi perkilangan. Keputusan menyeluruh ini mencadangkan bahawa PdM merupakan antara strategi terbaik untuk menghadapi persekitaran kompetatif dalam meningkatkan keberkesanan penambahbaikan kualiti dalam kalangan organisasi perkilangan Malaysia.

Kata kunci: Penyelenggaraan pencegahan, prestasi perkilangan, keupayaan teknologi, penyelenggaraan berasaskan masa

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LIST OF ABBREVIATION

AMT	Advanced Manufacturing Technology
ANOVA	Analysis of Variance
AVE	Average Variance Extracted
BNM	Bank Negara Malaysia
BIMS	Bought in Materials and Services
Chi2	Chi-Square
CBM	Condition-based maintenance
C	Cost
CR	Composite Reliability
CFA	Confirmatory Factor Analysis
CB-SEM	Covariance-based Structural Equation Modelling
D	Delivery
DOM	Design-out maintenance
ETP	Economic Transformation Programme
EFA	Exploratory Factor Analysis
FDM	Failure-driven maintenance
FMM	Federation of Malaysian Manufacturers
F	Flexibility
GDP	Gross Domestic Product
IPMA	Importance-Performance Matrix Analysis
IMP	Industrial Master Plan
JIT	Just in Time

LPS	Lean Production System
MP	Malaysian Plan
MP	Manufacturing Performance
MIDA	Malaysian Investment Development Authority
MPC	Malaysia Productivity Corporation
MYR	Malaysian ringgit
NEP	New Economy Policy
NFI	Normal Fit Index
OEM	Original equipment manufacturers
OBM	Opportunity-Based Maintenance
PdM	Predictive maintenance
PM	Preventive maintenance
PLS	Partial least Square
Q	Quality
RMK	Rancangan Malaysia ke
RCM	Reliability Centred Maintenance
RBV	Resource-based view
ROI	Return on Investment
R&D	Research and Development
RMS	Root Mean Square
STML	School of Technology Management
SME	Small medium enterprise
SQC	Statistical Quality Control

SEM	Structural Equation Modelling
SRMR	Standardised Root Mean Residual
TC	Technological Capabilities
TBM	Time-based Maintenance
TPM	Total Productive Maintenance
TQM	Total Quality Management
UBM	Use-based Maintenance
VIF	Variance Inflation Factor

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

In general, maintenance is defined as the combination of all technical and administrative actions, that can reduce the consequences of failure and extend the life of a system which ensures continuous operation and growth of industrial processes (Liu, Wu, et al. 2017). In addition, maintaining a system is usually related to maintenance actions such as repairing, replacing, overhauling, inspecting, servicing, adjusting, testing, measuring and detecting faults in order to avoid any failure that would lead to interruptions in production operations (Lam & Banjevic, 2015). One of the cost influences in a manufacturing organization that can be experienced when production stops because of equipment breakdown or failures occurs (Gill, 2016). Basically, there are various maintenance approaches such as Preventive Maintenance, Corrective Maintenance, Reactive Maintenance, Breakdown Maintenance and Failure-Driven Maintenance (Chebel-Morello, Nicod, et al. 2017). Therefore, this study only focuses on three components of preventive maintenance (PM) practices that are time-based maintenance, condition-based maintenance, and predictive maintenance in order to examine the manufacturing performance. In this regard, preventive maintenance (PM) practices are considered as an integral part of the maintenance process, since optimal (PM) schedule facilitates the minimization of maintenance costs and ensures permanent production (Basri, Abdul Razak, et al., 2017). On the other hand, Bajestani and Beck (2015) recommended that preventive maintenance strategy is applicable for both maintenance and production decisions because it can independently decide for maintenance issues by analyzing the machines' state such as age and characteristics that result in static rules.

The Vision 2050 of the Malaysian government envisaged a plan of bringing the manufacturing sector in pace with the developed countries (Ahmad & Ahmad, 2015; Aun, 2017). Preventive maintenance that includes scheduled maintenance and condition-based maintenance is highly recommended to enhance the maintenance performance, as its concept is to prevent failure with optimal resources (Aghezzaf Khatab, et al., 2016). Therefore, the current study has taken a step further by investigating the impact of preventive maintenance practices on the performance of manufacturing organizations in Malaysia. Meanwhile, this study also intended to investigate the moderating role of technological capabilities in the relationship between preventive maintenance and the performance of Malaysian manufacturing organizations.

1.2 Contribution of Manufacturing Organization to Malaysian GDP

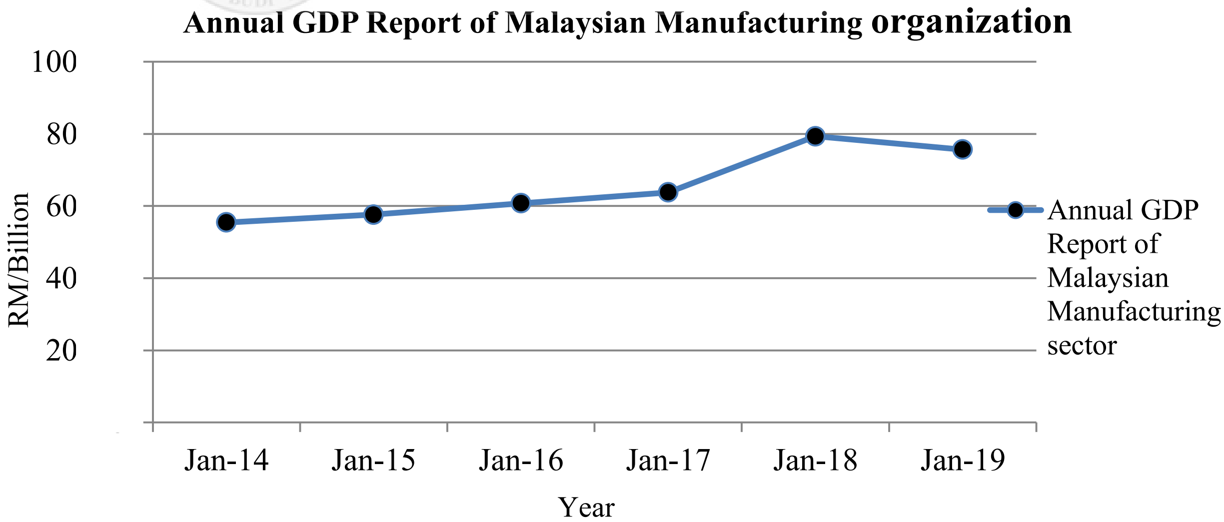

Figure 1.1
Annual GDP report for Malaysian Manufacturing in the Period 2014-2019
Source: Adapted from Department of Statistics Malaysia

It is evident from Figure 1.1 that the contribution of the Malaysian manufacturing sector in the gross domestic product has shown linear growth during the period of six years from 2014 to 2019. According to Figure 1.1 above, the contribution of the Malaysian manufacturing sector in the gross domestic product (GDP) has increased from RM 55 billion in 2014 to RM 80 billion in 2019 and the growth is linear with an average of RM 2.25 billion per annum. In another report, issued by Trading Economies, it is reported that in 2019 the growth in the Malaysian sector was 35 percent and it accounts for 70 percent of the total sale (Trading Economics, 2018). From the statistics presented in Figure 1.1, it is obvious that the Malaysian manufacturing sector is undoubtedly a key economic driver. However, the increasing issues of preventive maintenance and low-level technological capabilities of Malaysian manufacturing organizations affect the performance and are acting as bottlenecks for benchmark performance. The next section has shed a light on these issues and how they have to lead the manufacturing sector to the problems.

1.3 Problem Statement

Industries in the 21st century are faced with challenging needs to optimize their production system due to the continual evolving of world technologies, global competitiveness, environmental and safety requirement, and the perception towards total quality with different aspects threatening the company's profitability (Etemad & Dulude, 2018). In fact, the manufacturing sector has emerged as a leading sector of Malaysian economic development has led to the need to develop a deeper understanding of the sources of growth of this sector. In particular, there is increasing recognition of the necessity to assess the preventive maintenance practices and performance among manufacturing organizations in Malaysia. On the other hand, Maestas, Mullen, et al. (2016) emphasize that the conventional measures of performance among manufacturing organizations are labor and capital productivity as these measures offer insights on the contribution of input growth to output expansion. However, due to the limitations of these performance measures among manufacturing organizations, preventive maintenance (PM) has been utilized in an attempt to measure how Malaysian manufacturing organizations can enhance their competitiveness through preventive maintenance approaches. In addition, Radzi et al. (2017) and Chuah, Loayza, et al. (2019) imply that Malaysian manufacturing organizations have a lot of challenges such as low productivity improvement, low access to finance, lack of human capital and lack of technology adoption that become a hindrance for their development. In line with this argument, the objective of this study is to measure the preventive maintenance practices such as time-based maintenance (TBM); condition-based maintenance (CBM); predictive maintenance (PdM) among manufacturing organizations in Malaysia in order to understand its contribution to the growth of manufacturing organizations.

There are a large number of studies carried out to explain the determinants of manufacturing sector performance. However, many of them have offered contradictory results. Stuckler, Reeves, Karanikolos and McKee (2015) argued that stiffer competition is being faced by Malaysian organizations in the global market, and economic uncertainties cause the economic turmoil to become key challenges for the performance of Malaysian manufacturing sector. In addition, Epstein (2018) emphasized that it is important to acknowledge the best practices for costing and managing an effective environmental strategy that transforms the manufacturing organization into a leader in the market. It has been evident that the most important asset of any business is its resources (Barney, 1991). According to Singh and Ahuja (2017), stoppages and breakdowns can directly or indirectly affect manufacturing performance. Thus, the quality of products can be affected due to incorrect setting of machines, insufficient training of operators handling the machines, mechanical failures of machines, and so forth (Lazim, Taib, Lamsali, Saleh & Subramaniam, 2016). These issues of production operations certainly affect the delay in the production of products that must be delivered to customers. Many authors have determined that machine or equipment failure not only affects quality but also delivery and flexibility (Wickramasinghe & Perera, 2016; Troiano, Nolan, Parsons, Hoven & Zale, 2016; Helo, Gunasekaran & Rymaszewska, 2017; Lee, 2017). Hence, this study successfully justified that preventive maintenance practices are the best tools to enhance manufacturing performance. Though the majority of Malaysian organizations are adopting policies and strategies to improve their performance, still it seems that there is no consensus on a strategic roadmap towards vision 2050 (Stuckler, Reeves, Karanikolos & McKee, 2015). Many researchers have found that TBM, CBM, and PdM positively contribute towards manufacturing performance (Basri et al., 2017; Reid & File, 2017: Sheng et al., 2017; Shin & Jun, 2015; Cai & Yang, 2014).

Dodgson (2018) stated that small and medium-sized enterprises (SMEs) operate with scarce financial, human and tangible resources that characterize most new businesses. Such kinds of newly emerging firms have limited innovativeness, knowledge, and capabilities to achieve considerable market success in their early evolution stage. Similarly, Ren, Eisingerich, et al., (2015) mentioned that small and medium-sized companies are constrained with insufficient funds to purchase high technology equipment, which has led to limited R&D capabilities and innovations that eventually impede growth and success. In addition, Bouazza, Ardjouman, et al. (2015) found that most SMEs face numerous serious challenges that hinder their growth such as lack of access to external financing, low human resource capacities, lack of management skills and training, and low technological capabilities. This is supported by the report released by the World Economic Forum in 2018 that Malaysian SMEs‘ progress concerning innovative activities was ranked low (51st out of 144 countries in 2017–2018) in terms of technological readiness, which could significantly undermine Malaysia‘s efforts to become a knowledge-based economy by 2020 (World Economic Forum, 2018). These phenomena occur because, Malaysian SMEs are under constant pressure to seize competitive advantages and sustainability to address challenges arising from increasing costs of production, changes in input prices, globalization, and changes in customer preferences (Anuar & Yusuff, 2014). In another study, Ali and Perumal (2016) emphasized that the limitations faced by Malaysian SMEs because they lacked managerial and technical expertise and undertook limited technological adoption. Furthermore, the findings of Aziz and Samad (2016) and Yap and Lock (2017) exposed that Malaysian manufacturing SMEs possess limited skills and knowledge in manufacturing and strategy development. Additionally, Parvin Hosseini (2014) reported that there is very little knowledge about Malaysian SMEs‘ nature of innovation exists. Not only that, Mamun (2018) emphasized that beyond the significance of innovation highlighted in studies conducted in Malaysia and the government‘s efforts to provide an innovation ecosystem, very few opportunities remain for manufacturing SMEs to improve their practices. Nonetheless, Singla, Ahuja, et al. (2017) stated that in the current manufacturing scenario, all the industries are utilizing almost identical manufacturing operations, techniques, and innovation inbuilt regular manufacturing improvement with substantial output.

De Jonge (2017) mentioned that the changing role of TBM and PdM practices as a central factor in the manufacturing sector has enabled the identification of the main technical challenges that can potentially reduce equipment degradation and optimize maintenance activities scheduling based on a prediction of the systems‘ performance. On the other hand, Nguyen, Do, et al. (2015) asserted that TBM and CBM policies are popular for a maintenance decision-making process that relies on the diagnostic/prognostic of the system‘s condition over the period of time. By supporting this proposition, many researchers (i.e., Ahmad, 2018; Alaswad & Xiang, 2017; Shahrir, Adam et al., 2017) mentioned that many companies in Malaysia improved their competitiveness and profitability through maintenance performance by analyzing, planning, and optimizing the plant and equipment.

1.4 Research Question

i. What is the relationship between time-based maintenance and performance of Malaysian manufacturing organization?

ii. What is the relationship between condition-based maintenance and performance of Malaysian manufacturing organization?

iii. What is the relationship between predictive maintenance and performance of Malaysian manufacturing organizations?

iv. Do technological capabilities moderate the relationship between preventive maintenance practices and performance among Malaysian manufacturing organizations?

1.5 Research Objective

i. To examine the relationship between time-based maintenance and performance of Malaysian manufacturing organization.

ii. To examine the relationship between condition-based maintenance and performance of Malaysian manufacturing organization.

iii. To examine the relationship between predictive maintenance and performance of Malaysian manufacturing organizations.

iv. To examine the moderating effect of technological capabilities on the relationship between preventive maintenance practices and performance among Malaysian manufacturing organizations.

1.6 Definition of Key Terms

1.6.1 Maintenance

Maintenance is known as a process of preserving a condition or life cycle of the machine in order to remain the state of a machine with a combination of planned actions related to administrative, managerial and technical functions as required by the organizations (Campbell, Reyes-Picknell, et al., 2015).

1.6.2 Preventive Maintenance

Preventive Maintenance is known as maintenance activity that conducted at predetermined intervals or based on the prescribed criteria for the purpose to diminish the chances of breakdown or degradation of functioning of the item (Ben-Daya, Kumar, et al., 2016).

1.6.3 Time-based maintenance

Time-based maintenance involves routine activities conducted regularly based on a predetermined schedule by the companies to preserve the conditions or status of the operation of the building, tools and equipment, plant and systems (Kim, An, & Choi, 2017).

1.6.4 Condition-based maintenance

Condition-based maintenance is a strategy that monitors the actual condition of the asset to decide what maintenance needs to be done (Ben-Daya, Kumar & Murthy, 2016).

1.6.5 Predictive Maintenance

Predictive maintenance is a technique that developed to assist the determination of the condition of in-service equipment. This activity merely performed during order from management to predict when the maintenance should be performed (Lindström, Larsson, Jonsson & Lejon, 2017).

1.6.6 Manufacturing

Garetti and Taisch (2015) described manufacturing as the set of technical and organizational solutions contributing to the development and implementation of innovative methods, practices and technologies in the manufacturing field.

1.6.7 Technological Capabilities

Gonsen (2016) described the technological capability as the ability to design and build the products and processes through the guidelines offered by the miscellaneous technological fields of the depth dimensions and the activeness of the organizations.

1.7 Organization of the Thesis

This study is organized into five chapters.

Chapter One– This chapter discussed the introduction and research gap that deals with the view of preventive maintenance (PM) and technological capabilities in enhancing the performance of Malaysian manufacturing organizations. This chapter elaborated on the overview and current status of manufacturing organizations in Malaysia, the problem statement, research question, research objectives, significance of the study, the scope of the study, the definition of terms, and the organization of the thesis. All the information was provided thorough and compact views to the reader on the objective of this study.

Chapter Two–This chapter focused more on the literature review which consists of all past studies conducted by many authors regarding preventive maintenance and technological capabilities as well as the manufacturing performance. This chapter provided more information regarding issues and literature related to this study.

Chapter Three- Research methodology chapter described the methodology and the protocols that were used by the researcher in order to achieve the objectives of this study.

Chapter Four- This chapter explained the analysis of data and the outcomes obtained through statistical analysis. The researcher used SmartPLS 3 to analyze the data and results of the study.

Chapter Five- This chapter contained the literature about discussion, conclusion, and recommendation of this study. It also highlighted the implication from the outcomes, limitations, and recommendations for future research directions.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter thoroughly presents the related literature to provide a comprehensive picture of the topics of this study. The current study intends to clarify the practices of preventive maintenance and technological capabilities, and the influences of these aspects in enhancing the performance of Malaysian manufacturing organizationss.

2.2 Type of theory

2.2.1 Resource Based view (RBV)

The resource-based theory has been developed since the nineties of the 20th century. It was first introduced by Wernerfelt (1984) and later popularized by Barney (1991). More importance in this concept started to be attached to resources and competencies in the firm as the basis for formulation of the strategy. In the resource-based view, value-creating by the firm is affected by combination of the competitive strategy and the resource base (Grant, 1991). It is generally accepted that a key for achievement of competitive advantage is a business system used in the firm (the way the operations are carried out), which is comprised of a resource base, system of operation and range of products offered. Effective value-creation and achievement of competitive advantage result from harmonization of these three elements. Undoubtedly, the resource base (of tangible and intangible resources) is a factor which allows for production of any product and it is more and more frequently regarded as a source of survival and success of the firm. The principal assumption of the RBV view was Barney's statement (1991) that firm resources are _all assets, capabilities, organizational processes, firm attributes, information, knowledge, etc. controlled by a firm that enable the firm to conceive of and implement strategies that

improve its efficiency and effectiveness‘. Hence, the essence of the resource-based concept is a belief that it is resources and firm's competencies inherent in the firm (rather than in the environment) which determine its success. This approach to resources indicates its attributes. According to Barney (1991), the resources which determine competitive advantage have to meet VRIN criteria, i.e. they should be valuable, inimitable, rare and non-substitutable. Therefore, Barney, (1991) stated that the resources which are strategic to a firm should be:

- Important and represent a strategic value to the firm,
- Rare in terms of occurrence in current and potential competitors,
- Difficult to be copied by the competitors,
- Have limited mobility,
- Ensure permanent competitive advantage,
- Non-substitutable, which means that they area irreplaceable,
- Expensive when imitated.

According to Penrose, (1980); Wernerfelt, (1984); Barney, (1991); Grant, (1991); Peteraf, (1993) the RBV of the firm focuses specially on the inside of the firm, its resources and capabilities, to explain the profit and value of the organization. This theory is applied to explain differences in performance within an industry (Wójcik, 2015). The RBV of the firm states that differences in performance happen when well succeeded organizations possess valuable resources that others do not have, allowing them to obtain a rent in its quasi-monopolist form (Wernerfelt, 1984). The RBV of the firm is a suitable approach to understand competitive dynamics (Ruivo, Oliveira, et al. 2015). Since Barney's paper in the early 90's (Barney, 1991), several authors approached the firm and its strategy from a resource-based perspective. Barney presented in his paper a method of analysis to identify the characteristics of firm resources that are able to generate sustained competitive advantage (Hoskisson et al., 1999). More recently Barney (Barney, 2001) further developed his work, a decade after, contrasting the RBV of the firm to other theories, for many have been the developments and critics to his work since its publication in 1991 (Barney, 2001).

Barney (1991) considers that firm resources can be classified into three categories: physical capital resources, human capital resources and organizational capital resources. According to Barney (1991) there are certain conditions that resources must present to enable the firm to sustain its competitive advantage: rareness, value, imperfect imitability and non-substitutability. For Barney (1991) if all the firms were equal in terms of resources there would be no profitability differences among them because any strategy could be implemented by any firm in the same industry. The underlying logic holds that the sustainability of effects of a competitive position rests primarily on the cost of resources and capabilities utilized for implementing the strategy pursued. This cost can be analyzed with reference to strategic factor markets (Barney, 1986), that is markets where necessary resources are acquired. It is argued that strategic factor markets are imperfectly competitive, because of different expectations, information asymmetries and even luck, regarding the future value of a strategic resource.

2.2.2 Knowledge-Based View (KBV)

The knowledge-based view (KBV) of the firm is a recent extension of the (RBV) of the firm (Miller, 2019). The (KBV) of the firm considers knowledge as the most important strategic resource and, in that sense, this perspective is and extension of the RBV of the firm (Solesvik, 2018). The KBV of the firm is an extension of the RBV of the firm because it considers that organizations are heterogeneous entities loaded with knowledge (Alaneme and Kuye, 2018). The resource base of the organization increasingly consists of knowledge-based assets (Hörisch, Johnson, et al. 2015). The logic of the RBV of the firm suggests that unique characteristics of the intangible resources (especially knowledge) should determine the focus of research (Martínez-Costa, Jiménez-Jiménez, et al. 2019). Knowledge resources are particularly important to ensure that competitive advantages are sustainable, as these resources are difficult to imitate they are the foundation for sustainable differentiation (Popa, Soto-Acosta, et al. 2018). The KBV of the firm has attracted great interest as it reflects that academia recognizes the fundamental economic changes resulting from cumulatively and availability of knowledge in the past two decades. We are witnessing a structural change in the productive paradigm (Kirsimarja, and Aino 2015). The change from manufacture to services in the majority of developed economies is based on the manipulation of information and symbols and not on the use of physical products (Saglam and Hacklin 2015).

It is largely accepted that KBV of the firm is an extension of the RBV of the firm. Considering that the capabilities made that extension (Chen, Jiao, et al. 2016), we can make a logical deduction and admit that the influence of the capability development mechanism will affect KBV of the firm. Dynamic capabilities have the capacity to reconfigure, redirect, transform, shape and integrate central knowledge, external resources and strategic and complementary assets. They will allow the firmto respond to the challenges presented by the Schumpeterian competitive world, made of competition and imitation, changing so fast and pressured by temporal factors (Nair, Demirbag, et al. 2018). The KBV of the firm is the logical evolution of the RBV of the firm considering that it is a way to incorporate the temporal evolution of its resources and the capabilities that sustain the competitive advantage (Hitt, Carnes, et al. 2016)

The perspective of the KBV of the firm is consistent with the approach to organizations as cultures (Subramaniam and Chelliah, 2019). Considering that organizations are conceptualised as cultures, they are supposed to learn through activities that involve cultural artefacts. Organizational learning allows the firm to acquire, to change and to preserve its organizational capabilities (Jeon, Dant, et al. 2016). Culture is most repeatedly defined after Schein (Xiao, 2017), as a set of assumptions and beliefs held in common and shared by members of an organization, or as shared beliefs and knowledge after Nonaka and Takeuchi (Chen, Lee, et al. 2017). Organizational culture is, in each moment, the stock of knowledge, coded or not, integrated in patterns and recipes of action to be taken before certain situations. Time and routines often make knowledge become tacit, embedded, and a drive for action (Adnan, Nordin, et al. 2018).

Knowledge-based capabilities are considered to be the most strategically important ones to create and sustain competitive advantage (Freel, 2016). Superior talent is recognized to be the main creator of sustained competitive advantage in high performance firms (Hardy, Katsikea, et al. 2016). The capacity to learn faster than competitors could turn out to be the only sustained competitive advantage (Bals, Kelly, et al. 2017). This dynamic capability builds up over time a historical or path dependency creating causal ambiguity (creating barriers to imitability and making it very difficult for other firms to recreate the unique historical evolution each organization develops), and it establishes a basis for competitive advantage (Oltra, Vivas-Lopez, et al. 2018).

The firm absorbs internal and external knowledge, combines them with pre-acquired knowledge, and creates new one (Singh and Rao 2016). The organization may enlarge its knowledge base through the new application of pre-existing knowledge in the firm (Gonzalez and Melo 2019), as these new combinations of pre-existing knowledge generate new knowledge (Panda, 2017). Even external, explicit knowledge, involving high acquisition costs to the firm and available to competitors

simultaneously, combined with unique internal knowledge may result in new and exclusive knowledge (Singh, and Rao 2016). The sustainability of the knowledge-based competitive advantage depends on the following association: knowing better certain aspects than the competitors, along with the time limitations competitors have to acquire similar knowledge despite the amount of money they are willing to invest to achieve it (Alonso, Kok, et al. 2019).

According to Battagello, Cricelli, et al. (2019), regarding a knowledge-based strategic formulation the main intangible resource is people's capability. Human experience, in the large sense, might be the foundation of the KBV of the firm (Irwin Landay, et al. 2018). Organizational knowledge presents a tremendous wealth creating potential. Contrary to traditional and finite production factors, knowledge can generate increasing returns, through its systematic use (Mao, Liu, et al. 2016). Knowledge presents very special characteristics that differentiate it from physical resources and contribute to the creation and sustainability of competitive advantage. Knowledge can be used simultaneously in several applications and still it does not devaluate (Jali, Abas, et al. 2016). Organizational knowledge is such a marvellous substance, contrary to other resources, its utilization, under different forms, increases it, instead of decreasing it (Lentjušenkova, and Lapina 2016). The knowledge patrimony of the firm has a strategic potential (Xiao, 2017), as this asset becomes more valuable when is used, instead of depreciating (Burton, 2015). Another implication of the KBV of the firm is the necessity for knowledge integration in the production processes (Grant, 1997). The relationship between organizational knowledge and the firm's competitive advantage is influenced by its capacity to integrate and apply knowledge (Matusik and Hill, 1998). In this sense research has changed its focus from the institutions to the coordination mechanisms and their respective contexts (Grant, 2002). According to Drucker (1998), in future organizations coordination and control will depend on the availability of individuals to self-discipline.

2.2.3 Product Lifecycle Management (PLM)

Product Lifecycle Management (PLM) has emerged as a holistic approach to support and coordinate all the separate activities previously taking place in different parts of the organization and as viewed from different perspectives over the life of a product (Sonnemann and Margni 2015). PLM concept is a strategic business approach for the effective creation, management and use of corporate intellectual capital, from a product‘s initial conception to its retirement (Deuter, Otte, et al. 2019). According to Stark, (2018), PLM is a holistic business concept developed to manage a product and its lifecycle including items, documents and Bill of Materials (BOM). It supports the company from documentation like analysis results, test specifications, environmental component information, quality standards, engineering requirements, changing orders, manufacturing procedures, product performance information, component suppliers to system capabilities, including workflow, program management, and project control features that standardize, automate and speed up product management operations (Oh, Lee, et al. 2015). According to Stark, (2018)" PLM is the business activity of managing in the most effective way, a company's products all the way across their lifecycles; from the very first idea for a product all the way through until it's retired and disposed of" (Stark, 2018). The Product Lifecycle Management is derived from two areas: management of product information including management of product information during the product lifecycle, consisting initially of Computer Aided Design (CAD), Computer-Aided Manufacturing (CAM), and Product Data Management. Secondly, from enterprise management, it includes Material Resource Planning (MRP), Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), and Supply Chain Management (SCM). In the second case, as a tool for decision making (Lee et al., 2018). The main focus of the PLM is on the product, not the customer, supply chain, company's finances, human resources or information system, which are covered by ERP, CRM, SCM, etc. The focus is on maximizing the value of the current and future product (Stark, 2018).

Previous attempts to standardize different stages of a product's lifecycle focused mainly on a single aspect of part of the complete lifecycle. Therefore, different concepts emerged such as Bill of Materials (BOM), Computer-aided Design (CAD), Computer-aided Manufacturing (CAM), Computer-aided Engineering (CAE), Product Data Management (PDM), and others (Tao, Chen, et al. 2017). Each of these concepts addresses a specific problem of product development and is commonly supported by a specific information system. As a result, each of the product's development phases is managed by a different independent system, rather than a single integrated system. Based on below figure 2.1 show the simple product life cycle.

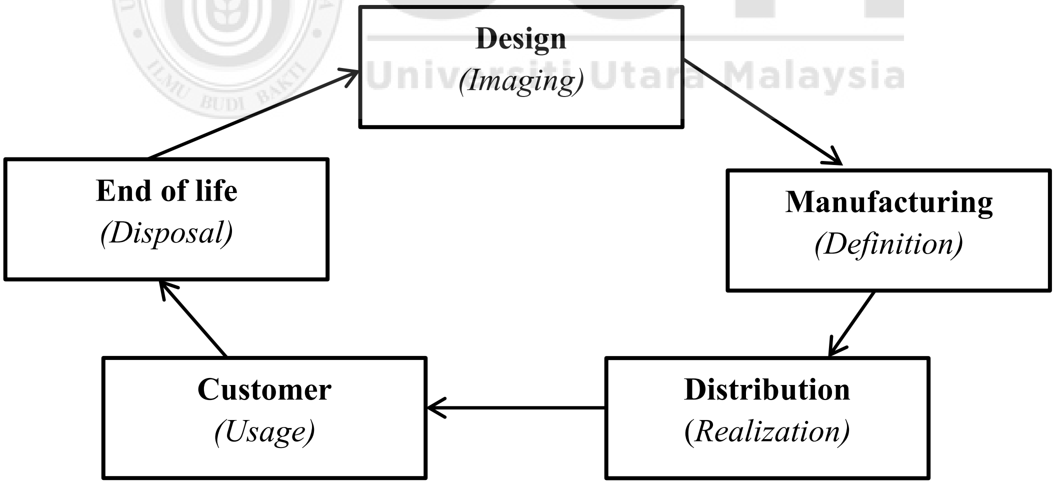

Figure 2.1
Simplified view of Product Life cycle
Source: Adapted from Stark, (2018)

According to Stark (Stark, 2018), the whole product lifecycle is divided into five stages/phases, starting with an imaging stage when the product is on the idea level. In the definition phase, a detailed description is performed. Realization phase turns it into final physical form used by the customer. Usage phase is on customer side and at the end is disposal when the product is no longer needed. The lack of a single integrated system to support the whole lifecycle through its phases (Figure 2.1) can result in a loss of control and cause a variety of different problems (such as delays in releases, failures, product recalls, exceeding the budget, and others). Any of those problems can cause consumer dissatisfaction, damage the company's image, and may result in a loss of revenues to other companies who bring new products faster and more efficiently (Stark, 2015). Currently, different specialized IT-systems are utilized during the product's lifecycle. Each of these systems is very efficient in its own area, for example, CAD systems are extensively used during the design phase. However, some of these specialized systems can cause bottlenecks to appear elsewhere in the data flow. The task of a PLM system is to interconnect these separate IT systems in order to permit a fluent data exchange across all of the different processes (Myung, 2018).

Table 2.1
PLM Categories
Source: Adapted from Stark, (2018) and Cheutet, Sekhari, et al. (2018)

Beginning of Life	**Middle of Life**	**End of Life**
Imagine	Support	Retire
Define	Maintain	Dispose
Realise	Use	

Cheutet, Sekhari, et al. (2018) has divided product lifecycle into three main phases (Refer Table 2.1) that are current issues: Beginning of life (BOL) including design and manufacturing, Middle-of-life (MOL) including distribution, use and support and End-of-life (EOL) where products are retired. PLM is ~~a~~ strategic business approach that applies a consistent set of business solutions in support of the collaborative creation, management, dissemination, and use of product definition information across the extended enterprise from concept to end of life integrating people, processes, business systems and information (Violante, Marcolin, et al. 2019). Accordingly (Soto-Acosta, Placer-Maruri, et al. 2016) Explained that - Product Lifecycle Management (PLM) is an information technology-based concept bringing several benefits to product development organizations. However, it has been reported that PLM implementations in industry render unsatisfactory results. (Pravin Patidar, 2017) - The luxury goods, outdoor gear and sporting goods industries, From large numbers of samples to extensive prototyping and exacting production requirements, material costs loom large for these companies. Obviously, this has a significant impact on a company‘s bottom line, many companies its advanced product lifecycle management software for apparel, footwear and consumer goods industries (PLM) designed to meet the specific needs of materials-driven product development (Campbell, Jardine, et al. 2016). Campbell continues that PLM has long been recognized for helping companies improve the design, development and production of on-trend products, optimizing lead times and managing sourcing. PLM replaces a chaotic system of multiple spreadsheets, scattered documents and an overwhelming amount of email. And it allows every person involved in a product‘s design and manufacture—from marketing and product designers to sourcing and international suppliers—to work collaboratively with one set of comprehensive, accurate and up-to-date information (McPherson and Pincus, 2017).

2.2.4 Technology Organization Environment Theory (TOE)

Technology-organization-environment (TOE) was introduced by Tornatzky and Fleischer (1990) that uses three elements that influence firms technological adoption; the environmental context, the organization context, and the technological context.

1. Environmental Context

The environmental context is the arena surrounding a firm, consisting of multiple stakeholders such as industry members, competitors, suppliers, customers, the government, the community, etc (Wang, Li, et al. 2016). They can influence how a firm interprets the need for innovation, its ability to acquire the resources for pursuing innovation, and its capability for actually deploying it. These stakeholders could either support or block technological innovation. Meanwhile Wolverton and Lanier (2019) stated that changing market and competitive conditions prod firms to use various forms of innovation. For example government regulation is also another powerful tool for constraining a firm‘s operational activities, increasing costs of production, and instigating an investigation of technologies that must meet specified criteria. Finally, dominant customer firms could exert their power to shift their suppliers‘ production activities to comply with its requirements.

2. Organizational Context

A range of descriptive measures characterize the ―organizational context”: firm size; the centralization, formalization, and complexity of its managerial structure; the quality of its human resources; the amount of slack resources available internally; formal and informal linkages within and outside the firm; decision making and internal communication methods; and boundary spanning mechanisms to communicate with the external environment (Egdair, Rajemi, et al. 2015). Frequent lateral communication, decentralization of leadership and control, and active networking both within and outside the firm are hallmarks of the ―organic” system (Widyasari, Nugroho, et al. 2018). Building inter organizational collaboration mechanisms is fundamental in meeting the needs of electronic coordination linkages enabling supply chain partnerships.

Top executives can energize major organizational changes by (Tushman and Nadler, 1986): (1) communicating a clear image of the firm's strategy, core values, and role of technology in meeting this strategy; (2) sending consistent signals within and outside the firm about the value of the innovation; and (3) creating a team responsible for crafting a vision relevant to the innovation.

3. Technological Context

The TOE framework suggests a method of implementing a technology innovation which will be referenced in the analysis of the deployment of the sustainability initiative. The following steps described below comprise the "systems design" perspective depicted by Tornatzky and Fleischer (1990), which incorporates the best aspects of the following methods used in implementing technology solutions : techno centric, socio centric, conflict/bargaining, systems life cycle, and socio-technical systems approaches. Different aspects of these approaches could be more prominent in the one or more steps discussed below.

The techno-centric approach: was derived primarily from industrial engineering and its key distinguishing feature is its exclusive focus on the hardware components and embedded knowledge domains to the exclusion of social, human end user needs and issues (Chen, Kang, et al. 2019).

The socio-centric approach: focuses on the organizational and social setting of the IT innovation, with its origins from organizational sociology; organizational behaviour and communications (Angeles, 2015). The socio centric approach espouses the following implementation activities: (1) measure the innovation‘s effectiveness in terms of the social system‘s social functioning; (2) consider the social and organizational issues when planning and pacing the implementation of the innovation; (3) allow for flexibility in the organizational design while keeping coordination and organizational purpose; and (4) support the innovation implementation with appropriate human resource development practices (Tornatzky & Fleischer, 1990).

The conflict/bargaining perspective: recognizes that decisions involving initiatives that include multiple parties will be challenged by their clashing interests (Elmore, 1978; Pressman and Wildavsky, 1973). Thus, the implementation initiative should embrace all affected stakeholders and promote practices and processes that encourage cooperation and collaboration to resolve their differences.

The socio-technical approach (STS): has its beginnings from both organization change practice (Trist and Bamforth, 1951) and social psychology (Katz and Kahn, 1978). It seeks the resolution of the main concerns of the social system (i.e., organizational design, reward systems, communication patterns) and the technical system (i.e., process, technology, tools, machines, and methods) in pursuing the implementation of an IT innovation in an organization (Tornatzky & Fleischer, 1990).

2.2.6 Transactional Cost Theory (TCT)

Transaction cost theory, as set by Coase (1937), states that ―the main reason why it is profitable to establish a firm would seem to be that there is a cost of using the price mechanism. This is the central idea of transaction cost economics, although there are some differences between the Coasian (1937) and the Williamsonian (1989) views of the transaction cost economies. Argyres, Mahoney, et al. (2019) claims that this economizing on transaction costs is the top priority for any company: ―Economy is the best strategy.” According to them, ―that is the central and unchanging message of the TCE perspective”. While Williamson (1989) does not completely trash the usefulness of strategy, he asserts that economizing is what counts, that most often strategizing is to be used to promote economic behavior and how to economize than how to strategize.

Transaction cost economics (TCE) then attempts to explain why firms exist and what are their boundaries: the existence is explained by those costs (firms exist in order to carry out their aims economically in terms of these transaction costs), and the boundaries of the firm are decided by what is efficient to do in-house and what is more efficiently done by the market (Cheung, 2016). Next, these (1) transaction costs; (2) Asset Specificity; (3) Uncertainty; (4) Frequency are explained.

1. Transaction Costs

There are two types of definitions for transaction costs. Dahlman (1979) divides the costs into three categories: discovery (sometimes labelled search and information), negotiation and conclusion (bargaining and decision), and other costs which later developed into contract policing costs. These latter types of costs were originally in essence the costs of re-negotiation; either re-contracting short contracts or changing longer-term contracts.

Table 2.2
Transaction costs

Ex-ante costs	Ex-post costs
Drafting	Maladaptation
Negotiating	Haggling
Safeguarding	Governance
	Bonding

Williamson (1979) provides a more structured format of the latter two types of costs. The costs are divided into two categories, ex-ante and ex-post costs.

Ex-ante costs: or those incurred before the entering an agreement, include drafting, negotiating and safeguarding an agreement (Benaroch, Lichtenstein, et al. 2016). Drafting and negotiating are self-explanatory, but safeguarding likely needs some articulation: safeguards are a priori mechanisms that aim to the fulfilment of the contract in a way that benefits both sides. For example, common ownership (of a specific asset) means that neither side will be able to hold the asset hostage in order to opportunistically negotiate a better deal (Kolstad, Johnson, et al. 2018).

The ex-post costs: incurred when the contract is in force, include maladaptation, haggling, governance, and bonding costs. Maladaptation costs are simply the costs of redefining the contract while it is still in force, but no longer meaningful for either or both of the parties; Williamson (1985) argues that maladaptation provides a situation in which strongly opportunistic behavior might arise.

Haggling costs are similar, but involve filling the blanks in an incomplete contract rather than changing the contents of a complete one. Governance costs consist of creating and maintaining a system to see that the contract is fulfilled. Finally, bonding costs refer to the boundaries of the provider, enabling secure, but not always effective fulfilment of the contract, i.e. the provider or its employee is not empowered to device a quick ad hoc action plan to effectively address an issue, but instead will have to stick to what is stipulated by the contract.

2. Asset Specificity

Specific assets, in general, mean assets that have less value everywhere else than in their current (or proposed) use (Ping Ho, Levitt, et al. 2015). On the opposite side, there are general or non-specific assets which are equally valuable everywhere. It should be stressed that asset specificity is the most important concept in the transaction cost paradigm (Williamson, 1981). Williamson (1981) recognizes four types of specific assets: site-specific, physically specific, and human-specific assets as well as dedicated assets. The meanings of the four are as follows:

Site-specific asset: is for example a warehouse situated near a factory (see figure 2.1 below). Ceteris paribus, the warehouse closer will be more valuable to the contractor and so the provider of the said warehouse can opportunistically ask for more than the fair price. This naturally implies that the firm would be better off acquiring the said warehouse.

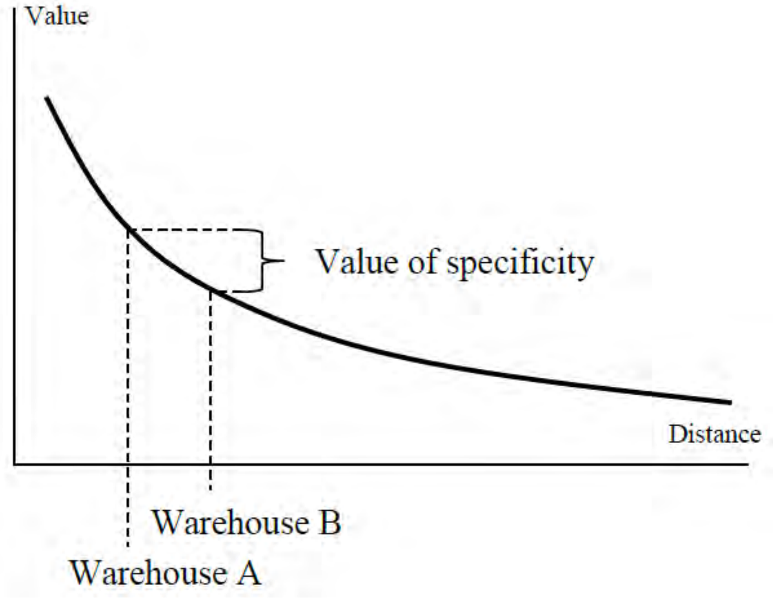

Figure 2.2
Asset specificity

In the Figure 2.2, it can be reasoned that warehouse A is preferred, obviously, by the contractor, and that it needs to protect its interests by acquiring rather than leasing the site (assuming that total cost of integration do not exceed the value difference) because the lessor might opportunistically charge higher prices.

A physically specific asset: is on that is used for a specific purpose. The way it is understood and thus used in this thesis is that it does not have to be physical as such; just something that is idiosyncratic. For example, a highly modified computer system makes the contractor dependent on the subcontractor, thus enabling opportunistic behavior from the latter.

Human-specific assets: are largely the same as firm-specific human capital in personnel economics, i.e. it is only valuable to the current firm. An often-used attribute of these assets is that of learning by doing. Although that is usually the way in which these assets are acquired, learning by doing is both unnecessary and insufficient as a descriptor. For instance, one may have a special set of skills which is more valuable to the current employer than for any other although the skills may have been acquired somewhere else – often this may be the case when employed by the government, i.e. the employer market for that particular set of skills is very thin.

Dedicated Assets: are such that might not be specific to a transaction per se, but have been acquired in order to fulfill a (prospective) contract. To continue with the warehouse example and assuming away the site specificity, i.e. the subcontractor may have acquired a warehouse which is of the general type of warehouses and in a generally preferred area. However, if it loses the contract it will have no use for the warehouse, resulting in large overcapacities (He, Lin, et al. 2016). Knowing this, the contractor can negotiate the price down opportunistically since it knows the supplier will either have to give discount or lose the investment.

3. Uncertainty

Uncertainty, in terms of transaction cost economics, is divided into behavioral and environmental uncertainties (Williamson, 1985). There are several different nominations for these two, but the terms are chosen for their simplicity. The former refers to controlling opportunism, while the latter refers to the expected variation. The difficulty of controlling opportunistic behavior means mostly that the contractor cannot confirm the behavior of the seller (Wacker, Yang, et al. 2016). In other words, it refers to the difficulty of measuring the labor done by the supplier. For instance, if a firm outsources recruitment, it cannot know for a certainty whether the supplier actually works toward the end of finding the best employees, or if it does the least possible work to produce somewhat adequate candidates (Stranieri, Orsi, et al. 2017).

According to Williamson (1985), low predictability should lead to higher transaction costs since the contracts need to be altered accordingly. In a time of high demand, the opportunity cost of (spot) contracting is even higher since the entrepreneur/manager should have even more than usual at hand. Since an internal employee (or perhaps another asset) can respond to these changes more quickly, a higher level of environmental uncertainty should lead to lower levels of outsourcing.

4. Frequency

Frequency, according to Williamson (1985) refers solely to the buyer‘s activity in the market, and higher frequency should lead to a lower level of outsourcing. As Williamson, we will assume away one-off dealings for a simple reason: they are not very common in this context. There are thus just two types of frequencies: occasional and recurrent. Occasional investments (this does not refer to just investment-type acquisitions; just something a firm puts its money into) are such where there is very rarely need for internal organization, but it increases as recurrence emerges.

The reason why outsourcing should decrease as frequency increases actually derives of increasing asset specificity. The logic is as follows: to achieve economies of scale, worker specialization must increase, and so do the idiosyncrasies as the organization‘s systemic complexity grows due to different interrelationships between workers and tasks. (Williamson,1985).

2.2.7 Relational View Theory (RVT)

Dyer and Singh (1998) have systematically examined inter organizational rent-generating processes. They identified four sources that generate relational rents: Investments in relation-specific assets, inter firm knowledge sharing routines, the combining of complementary resources and effective governance mechanisms. Firms can achieve supernormal profits by developing an idiosyncratic relationship with their alliances through these processes. The aim is to move away from arm‘s length market relationships, because competitors can easily duplicate this exchange relationship since there is nothing unique about the interactions between buyer and seller. What follows from the joint efforts of the partnering firms in forging a relationship beyond arm‘s length, is that rents are jointly generated and owned by partnering firms. Relational rents are then part of the network or dyad. A relational rent is defined by Dyer and Singh (1998) as: A supernormal profit jointly generated in an exchange relationship that cannot be generated by either firm in isolation and can only be created through the joint idiosyncratic contributions of the specific alliance partners (Dyer and Singh, 1998).

The relational view by Dyer and Singh (1998) has its roots primarily in the resource-based theory by Barney (1991) and Wernerfelt (1984) but it is also inspired by Cook‘s (1977) paper that underlines the advantages of exchange in networks of inter organizational relations. The resource-based view theory has substantially contributed to the field of competitive advantages on the firm level. According to the theory, firms that are able to accumulate resources and capabilities that are rare, valuable, non-substitutable and not easily imitable, will achieve a competitive advantage over competing firms. Firm heterogeneity is a critical condition in achieving differentiated firm performance (Barney, 1991; Wernerfelt, 1984; Rumelt, 1997).

Dyer and Singh (1998) point out that the relationship between firms is a unit of analysis that is suitable for understanding the competitive advantage that accrues from obtaining relational rents. Relationships with other firms, combined with own resources, bring greater rents than the individual result. In this approach, the authors identify four inter organizational resources (relational resources) that are sources of these relational rents: relation-specific assets, knowledge sharing routines, complementary resources, and relational governance. These resources are examined in detail and the authors identify isolated sub processes and mechanisms for preserving relational rents.

Asset-specificity comes from investments that are exclusively ear-marked for the partner in a relationship, with the expectation of obtaining mutual benefits and the development of competences that depend on the duration of the safeguards and the volume of transactions (Chernenko and Sunderam 2016). Knowledge sharing presupposes a constant and open flow of communication between partners, and is considered critical for interorganizational learning to succeed. Additional rents may be obtained by intensifying exchanges of knowledge about individual routines, which generates ideas and information that lead to higher levels of technological performance and innovation (Boguth and Simutin 2018).

By reducing transaction costs for the buyer and protecting the supplier‘s access to shared resources, resource complementarity enables partners to promote a synergistic combination of resources that have positive results on the relationship (Pinto, Henry, et al. 2015). Finally, the central idea of relational governance is to develop mechanisms that reduce transaction costs by restricting opportunism (Pike, 2015). The efficiency of governance measures in reducing costs and mitigating opportunistic behaviour increases the value created in a relationship and, under balanced power conditions, the parties also capture value.

2.2.8 Core Competencies Theory (CCT)

Prahalad and Hamel (1990) define Core Competences as the collective learning in the organization, leaning on how to coordinate production skills, integrate multiple streams of technologies in order to provide benefit to the customer. Chursin, and Tyulin (2018) stated that a Core Competence should fulfil three criteria to be distinguished from a competence: it has to contribute significantly to the customer‘s benefit from the product; it should be unique; and it should allow access to various markets. Three notions are commonly referred to as associated concepts of Core Competences – competences, capabilities and resources.

They are considered to convey information regarding the Core Competence concept by means of different influences they have on Core Competencies: competencies improve, capabilities support and resources utilize Core Competencies (Du, Deng, et al. 2017). By means of these influences, organizational change and rejuvenation can not only be comprehended, but also managed.

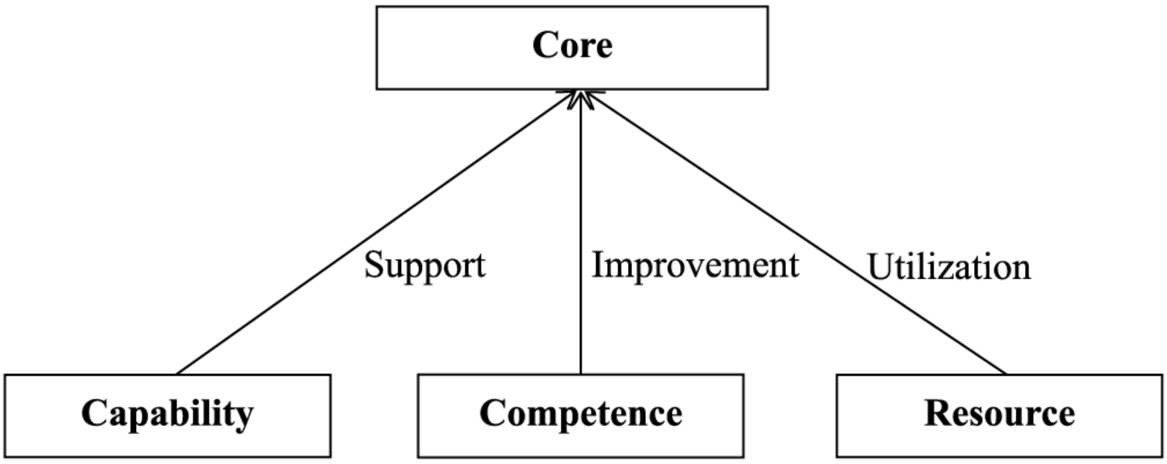

Figure 2.3
Outlined core competence model: associated concepts linked to the core competence concept.

Capabilities are defined either as the capacity for a team of resources to perform some task or activity (Daspit and D'Souza, 2017) or as consisting of different routines, tacit knowledge and organizational memory (Nelson and Winter, 1982). Capabilities are also separated into operational and dynamic, (Ivanova and Sceulovs 2017) where operational capabilities include all the routines generally involved when performing an activity, whereas dynamic capabilities build, integrate and reconfigure operational capabilities (Saul and Gebauer 2018). Here capabilities are viewed as tangible or intangible interaction of resources that are firm-specific and created over time (Acton, Morgan, Conboy, & Clohessy) 2016).This study defines a capability as a supporting system or routine. This type of system plays a critical role in many company undertakings, such as developing customer loyalties and core.

Competencies, routines that are crucial in providing supporting activities and processes (Reijonen, Komppula, et al. 2016). A competence has been defined by King, Thomson, et al. (2016) as ~~a~~ cross-functional integration and coordination of capabilities", and as a set of skills and know-how resident in strategic business units. Here we adhere to the view that a competence refers to an inherent quality of individuals or teams, a quality that develops and refines something to a commonly agreed goal. Hence, this study defines a competence as development made by individuals and teams. Core competencies are key contributors to organizational success and they must be developed at a high level as minor developments do would not have any impact on them.

Resources are commonly considered basics of an organizations, building blocks of competencies, and sources of sustainable competitive advantage if they are valuable, rare, inimitable and non-substitutable (Barney, 1991).They can be grouped in various ways, such as organizational (culture and reputation), physical (asset, equipment, location and plant) and human (manpower, management team, training and experience). In this study resources are defined along the lines of Grant, 1991 as inputs to the value process in an organization.

The core competency is the factor which determines the survival and development of the competitive advantage of a company (Brashers, Haizlip, et al. 2019). Theoretically, the company understands that it should focus on the core business such as strategic planning, quality of product, research and development activity of company. In core competencies theory, the company will concentrate on core tasks such as planning, development and production. There are three standards are further discussed in the core competencies theory, which are (Sumi, 2016).

i. Acknowledged by the market and it can offer opportunities to approach potential markets.

ii. Offer customers with increasing special benefits. Core competency of the firm has to produce value to the firm and increase customer‟s benefits through decreasing cost.

iii. Core competency must be difficult to duplicate as to support the competitive advantage on the basis of core competency.

Outsourcing is very closely related to core competencies theory because one of the actions to build up core competencies in a company is to divest non-core capabilities to release resources that can be used to develop core capabilities Gökkaya, and Özbağ (2015) Outsourcing is itself a relocation of the non-core activities to the third party so that the company can focus more on the in-house core activities and long-term planning (Halim et al., 2010). It is about transferring their non-core activities to the external so that the internal (in-house) can more have more time, resource and energy to plan long term goals and implement them.

The value chain of the primary activity shows that development of core competency and every value chain can also generate value. Core competency assists a company to achieve target quality as they focus on their core tasks. There are three tests to determine a core competencies, which are (Gebauer, Saul, et al. 2017).

a. Provides potential enter to a wide and diverse market

b. Makes a contribution and it bring the benefit of products to the customers.

c. A core competency is hard to be imitated by competitors.

A Core Competence can take various forms, including technical/subject matter know-how, a reliable process and/or close relationships with customers and suppliers (Kiel, Arnold, et al. 2017). It may also include product development or culture, such as employee dedication. According to Prahalad and Hamel core competencies lead to the development of core products. Core products are not directly sold to end-users but rather are used to build a larger number of end products (Fossas-Olalla, Minguela-Rata, et al. 2015). Although core competences do not necessarily result in physical core products, core competencies undoubtedly serve as sources of competitiveness (Kabue, and. Kilika 2016).

In a rapidly changing business environment, it is crucial to identify core competencies of an organization to outgrow in the market and outreach the potential part of the business segment. Prahalad and Hamel argue that Core Competences are some of the most important sources of uniqueness: These are the things that a company can do uniquely well, and that no-one else can copy quickly enough to affect competition. Essentially long-term sustainable and strategic competitive advantages derive from Core Competences (Saebi and Foss, 2015). Core Competencies are not fixed; they are subject to revision and change driven by the management in response to the changing company‘s environment (Mårtensson, and Westerberg, 2016). Long-term evolution of the company and its adaptation to the new competitive environment are achieved through Core Competence development to ensure the company is able to address latest (or future forecasted) needs, more value is added to company‘s products and services to enable further growth. On the contrary, inability of the management to timely drive the development of Core Competences sets company at high risk of failure and loss of competitive position. Polaroid, Xerox and recently Nokia good examples on this bad practice.

2.2.9 Organizational Learning Theory (OLT)

According to Shrivastava (1983), mainstream Organizational Learning Theory (OLT) historically had several conceptualizations of the phenomenon, including OLT as adaptation (Cyert and March, 1963; Cangelosi and Dill, 1965), OLT as assumption sharing (Argyris and Schon, 1978), OLT as developing knowledge of action-outcome relationships (Duncan and Weiss, 1978), and OLT as institutionalized experience (Boston Consulting Group, 1968) (OLT) is a key strategic management enabler that determines an organization's ability to evolve and meet the needs of the marketplace and take on new endeavors. This learning enables organizations to build an organizational understanding and interpretation of their environment and to begin to assess viable strategies (Daft and Weick, 1984). Organizational learning is described differently throughout the scholarly literature, but can be generally seen as the process of improving actions through better knowledge and understanding (Fiol and Lyles, 1985). OLT has also been described as the process of detecting and correcting errors, and requires that these actions are embedded in organizational memory for organizational learning to occur (Argyris and Schon, 1978). Duncan and Weiss (1978) described OLT as the process within the organization by which knowledge about action-outcome relationships and the effects of the environment on these relationships is developed. Argyris and Schon (1978) proposed that organizational learning occurs when members of the organization act as learning agents by detecting and correcting errors in organizational theory-in-use, and embedding the results of their inquiry in private images and shared maps of the organization.

Alvesson and Sveningsson (2015) explored organizational learning (OL) from a cultural perspective, suggesting that –cultural organizational learning would focus on the mutual creation of compatible and shared meaning. Cultural consideration is especially important in a university-community partnership as you bring together two distinct organizations with potentially different cultures. The congruence or disparity in culture between the organizations may affect the organizational learning proficiency. Popova-Nowak and Cseh (2015) recently described (OL) as –a social process of individuals participating in collective situated practices and discourses that reproduce and simultaneously expand organizational knowledge.

The reversal of the words into *learning organization* has a different meaning, defining more how skilled the organization is in creating, acquiring and transferring knowledge, and modifying its behavior to reflect this new knowledge (Gould, 2016). Learning organizations create supportive learning environments and reinforce learning. The creation of a learning culture, which includes communication, discourse and employee feedback is critical to enablement of this concept (Chia, 2019).

Baldwin, (2016) clarified that organizational learning and learning organization have two distinct meanings. Generally, –a learning organization is a form of organization, while organizational learning is activity or processes of learning in organizations. Ortenblad furthered the scholarship by challenging the notion of learning organizations, and suggested raising the bar as to what should be considered a learning organization. Baldwin suggested that organizations need to integrate four parts: learning at work, learning structure, learning climate and organizational learning to be considered a –full” learning organization (Baldwin, 2016). Learning organizations actively use knowledge management to develop processes that facilitate the firm‘s ability to create, transfer and retain knowledge (Serrat, 2017). These knowledge management systems incorporate technology into an organization‘s knowledge transfer process. These can be communication tools or repositories that help to tangibly enable employees to spread and reinforce knowledge (Shafritz, Ott, et al. 2015).

2.3 The importance of (RBV) Theory

Although all the theories mentioned above can explain competitive advantage in several contexts, one of their limitations is that they focus on the workplace, environment functionality, people, place, learning process and technology while ignoring that how production plant can avoid the machine failure which often depends on the resources, capabilities and performance of manufacturing organizations and interaction between cost; quality and flexibility; delivery. For this reason, this research draws upon the preventive maintenance (PM) practices to explain the Manufacturing Performance (MP) in the relationships in the technological capabilities (TC).

Building on the RBV, firms can gain superior performance and competitive advantages by developing and deploying unique and idiosyncratic organizational resources and capabilities (Wernerfelt, 1984; Barney, 1991). Some research suggests that preventive maintenance serves as a strategic resource within organizations (Mostafa, Dumrak, et al. 2015). Whereas Asid (2010) and Stuckler et al. (2015), pointed that Malaysian manufacturing industries have witnessed many challenges in the last four decades, involving drastic changes in innovative capability, corporate strategy, export orientation, transforming capabilities, customer satisfaction, and other related issues.

For example, Jean and Sinkovics (2010) drew on the RBV to propose that applied technological innovation as a resource enhances relationship manufacturing capability, which in turn influences supplier innovativeness and relationship performance in international supplier–customer relationships.

The KBV is an extension or sub-category of the RBV and recognizes that knowledge is a critical resource, which is usually both difficult to imitate and socially complex (Grant, 1996). Heterogeneous knowledge bases and capabilities among firms are the major determinants of sustained competitive advantage and superior corporate performance (Willis et al., 2016). Knowledge can be divided into two types: explicit and tacit. Explicit knowledge refers to knowledge that is transmittable in formal and systematic language (Nonaka and Toyama, 2015). Tacit knowledge has a personal quality, which makes it difficult to formalize and communicate (Nonaka, 1994). Technological capabilities (TC) are specifically associated to RBV theory, which highlights an organizations_s capability to reconfigure or upgrade its current resources or structure of assets that are key sources to achieve sustainable competitive advantage that leads to better performance (Penrose, 1959; Wernerfelt, 1984; Barney, 1991). Technological capabilities (TC), concern creating new ideas, know-how, and accumulated knowledge of technologies is the ability to find benefits and risks by integrating and utilizing not only explicit knowledge but also tacit knowledge (MÁ López-Cabarcos, et, al, 2019).

The core tenet of the Organizational Learning Theory (OLT) is that firms with greater learning capability can sustain a competitive advantage at least in the short and medium term (Hotho, Lyles, et al. 2015), and therefore, learning capability is a critical success factor (Peters, Wieder, et al. 2016). According to the (OLT), both explorative learning and exploitative learning are important and can help firms gain and sustain a competitive advantage (Belle, 2016). The RBV consists of a set of specific resources and capabilities as the basis for creating and protecting the organizations competitive advantage (Gellweiler, 2018). Hemmati, Feiz, et al. (2016) supported this notion by claiming that resources and capabilities empowering the organizations to improve its survival prospects.

Both the KBV and the OLT focus on opportunity creation and growth; Meanwhile the CCT is analytical thinking; the PLM lifecycle of a product; TCE focuses on cost minimization; RVT examined inter organizational rent-generating processes; TOE firms technological adoption. All above mentioned theories only focus on uni-dimension of resources and capabilities in organization. However in this study the MP was highlighting the multidimensional construct with cost, quality, flexibility, delivery in enhancing the performance of Malaysian manufacturing organization (Skinner, 1974). In addition Schönsleben (2016) assert that in order to compete for global demand every firm must improve their performance by decreasing production costs and increasing quality as well as delivery and performance.

2.4 Manufacturing Organization

The goal of any company is long time survival and the ability to produce useful outputs. In manufacturing organization the outputs are usually products offered to customers resulting in profits divided by its owners (Ortiz-Villajos and Sotoca 2018). Within the subject of Production Economics is one leg concerned with how manufacturing organization deploy their, potentially scarce, resources into the process of transforming inputs to useful outputs. In this, manufacturing organization offers a structured approach to decision making in facilitating an economic production (Vicente-Lorente, 2001). Lately, manufacturing organization has been augmented to also incorporate service operations and is hence often labelled operations strategy. Operations management is defined as “the planning, scheduling, and control of activities that transform inputs to finished goods and services” (Cardin, Trentesaux, et al. 2017) which clearly corresponds to the administrative role of production economics. Operations management is subordinated manufacturing organization, *i.e.* strategy precedes management. While manufacturing organization is concerned with providing long term guidelines, operations management is more concerned with the tactical actions taken to plan, schedule and control the value adding activities (Kerzner, 2017).

2.5 Manufacturing Performance

Since the first paper on manufacturing performance by Skinner in 1969 the field has established itself as a well-defined research area. Manufacturing performance has since received much attention, both within the academic communities but also from practitioners involved in the management of manufacturing performance. One of the main purposes of research on manufacturing performance is identification of the drivers of high performance, and more recently the sustainability of competitive advantage (Prajogo, Oke, et al. 2016). The link between practice and performance (actions and outcomes) has been the focus for much of the manufacturing performance research where the typical dependent variable has been some kind of measure of competitive performance, whether it is financial (*e.g.* ROI, market share) or operational (quality, delivery *etc.*) performance *vis-à-vis* competition. Practices studied range from very hands on (*e.g.* setup time reduction) to practices of a more conceptual nature (*e.g.* agile manufacturing). Godinho Filho, Ganga, et al. (2016) suggests using bundles of practices in order to better capture the inherent nature of wider, multidimensional manufacturing concepts such as *e.g.* lean manufacturing.

Hayes and Wheelwright (1984) suggest that a strategy planning process includes identifying ―ends and ways" (business objectives and strategy) and developing ―means" (resources and capabilities) by which the selected ends and ways can be realised. Similarly, Wamba, Gunasekaran, et al. (2017) note that manufacturing organization embodies the choices among the most needed set of manufacturing capabilities for a business unit and the investments required to build that set of capabilities. From a practical standpoint, it is central for managers to both understand the business and manufacturing objectives and to identify means to build and develop manufacturing capabilities that support these objectives (Huang and Li, 2017).

Over the years many concepts related to improving manufacturing capabilities have been advocated and put forward as *the* solution, as the key to improved performance and a sustainable competitive advantage (Hong Zhang, et al. 2018). However, similar to the idiosyncrasy of individuals, companies are not a homogeneous group that responds equally to certain actions (Croom, Svetina, et al. 2017). Hence, there are no action plans, improvement programs or manufacturing concepts that are universally applicable due to differences in *e.g.* industry structure (Burns and Stalker, 1961). The impact from any one concept may therefore vary significantly dependent upon the situation into which it is applied. Ang, Shimada, et al. (2015) find an important challenge in justifying and examining why and under which conditions certain actions have competitive value. In essence, fitting a manufacturing plant‘s practices and routines to its environmental, structural and strategic context is crucial to developing operations as a competitive advantage (Burns and Stalker, 1961).

The relationships among manufacturing capabilities have been the locus for much attention in operations management research. Typically, the research involve assessing the operational performance (Li Wu, et al. 2015), identifying the relationships among different operational performance dimensions (Nabass, and Abdallah 2019), or understanding the linkage between operational performance and business and manufacturing organization (Maletič, Maletič, et al. 2019). Underlying theories has been the well-known trade off theory initiated by Skinner (1969) and the more recent notion of cumulative capabilities (Gold Schodl, et al. 2017). Although the area has received much attention, there still exist differences in opinion within the academic community as to the relationships among and between different dimensions of manufacturing capabilities.

Hayes and Wheelwright (1984) describe manufacturing organization as a consistent pattern of decision making in the manufacturing function linked to the business strategy. Swamidass and Newell (1987) describe manufacturing organization as a tool for effective use of manufacturing strengths as a competitive weapon for achievement of business and corporate goals. A more comprehensive definition of manufacturing organization is provided by Espino-Rodríguez and Gil-Padilla (2015): ―*a pattern of decisions, both structural and infrastructural, which determine the capability of a manufacturing system and specify how it will operate, in order to meet a set of* *manufacturing objectives which are consistent with the overall business objectives."* *(*Espino-Rodríguez and Gil-Padilla, 2015*)*

The definition acknowledges two key properties of manufacturing organization content; decisions that determine the capabilities of the manufacturing system, and the existence of specific manufacturing objectives. Mirzaei,. Fredriksson, et al. (2016) summarises these into what has become the predominant model of manufacturing organization content (Figure 2.4). The model identifies two major constituents of manufacturing organization content, competitive priorities and decision categories (Mirzaei. 2016). These will be dealt with in the following sections.

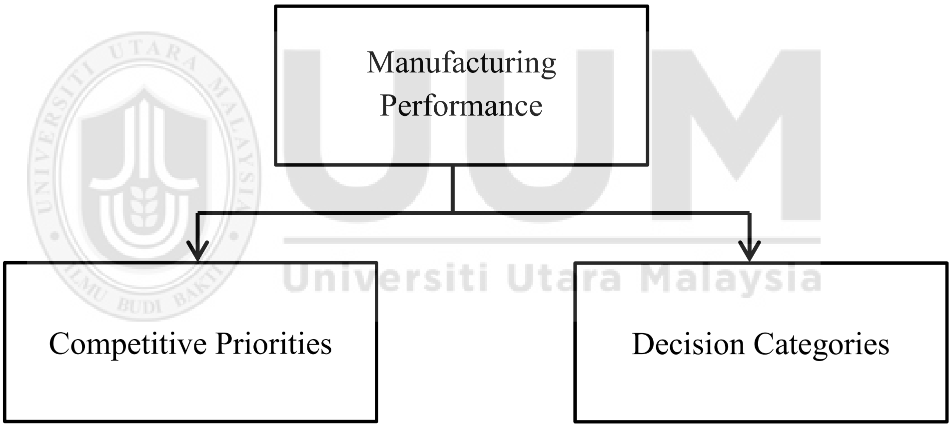

Figure 2.4
Manufacturing Performance content model
Source: Adapted from Mirzaei et al. (2016)

2.5.1 Competitive Priorities

Competitive priorities defines the set of manufacturing objectives and represents the link to market requirements (Sansone Hilletofth, et al. 2017). Dimensions commonly used are; cost, quality, flexibility, and delivery (Zhang, Guo, et al. 2019). The common set of competitive priorities with descriptions is presented in Table 2.4.

Most researchers consider the competitive priorities part of manufacturing organization as the link between market requirements and manufacturing (Sayem Feldmann, et al. 2018). Of particular interest is the relative weighting of different dimensions of competitive priorities. Among the competitive priorities there are often trade-offs inherent and to focus the attention to certain dimensions is the essence in the factory focus literature drawing on Skinner‘s (1974) work. However, limiting the scope brings another problem, which dimensions to focus on. Hill (1995)
presented the concept of order winners and qualifiers related to the importance of competitive priority dimensions. Qualifying criteria (dimensions) are those that a company must meet for the product to even be considered in the market place. Common criterions considered qualifiers are conformance quality and delivery reliability (Parvadavardini, Vivek, et al. 2016). Order winning criteria are those that differentiate the manufacturer from its competitors and ―win” the order.

Table 2.3
Competitive priorities with descriptions

Competitive priorities	Description
Quality	Manufacture of products with high quality and performance standards
Delivery	Reliable (on time) and fast (short delivery lead time) delivery of products
Cost	Production and distribution of the product at low cost
Flexibility	Ability to handle volume and product mix changes

Although the concept of order winners and qualifiers provides a categorisation and prioritisation of competitive dimensions it gives a rather rough account. The approach leads to a composite set of priorities where the dimensions are ranked according to importance to the competitive position of the company. Based on that it is possible to define the manufacturing task, *i.e.* the task the manufacturing function must perform well to support the overall market requirements. Related organizationsal perspectives are those of competitive strategies presented by *e.g.* Porter (1980), Treacy and Wiersema (1993) and Martinez and Bititci (2006).

2.5.2 Decision Categories

Decisions in manufacturing related issues are often grouped into categories, usually denoted decision categories. Since Hayes and Wheelwright (1984) first presented the concept numerous authors have contributed to the development and establishment of the set of decision categories, and associated policy areas, normally used. Table 2.3 lists some examples of decision categories and associated policy areas, based on Mirzaei, Fredriksson, et al. (2016). Similar descriptions can be found in *e.g.* Fine and Hax (1985), Platts *et al.* (1998).

Table 2.4
Examples of decision categories and associated policy areas
Source: Adopted from Mirzaei et al. (2016)

Decision categories	Policy areas
Structural	
Process choice	Process choice, technology, integration
Facilities	Size, location, focus
Capacity	Amount, timing, increments
Vertical integration	Direction, extent, balance
Infrastructural	
Manufacturing planning and control	System design, decision support
Performance measurement	Measurements, methods of measures
Organizations	Human resources, design
Quality	Definition, role, tools

As noted in the definition in section of the operationalisation of manufacturing organization comes through a pattern of decisions. This observation acknowledges the influence from management on the development and performance of the system, although seemingly trivial it is a very important observation also noted by Hayes and Pisano (1994). Decisions within the manufacturing functions determine which resources to use, what routines to use, *i.e.* what practices to employ and emphasise in order to achieve the manufacturing objectives. The set of practices, resources, routines used ultimately determine the operating characteristics of the manufacturing system, *i.e.* the manufacturing capabilities (Zarte, Pechmann, et al. 2019).

2.6 Manufacturing Internal and External Performance

Table 2.5
Examples of internal and external measures of operational performance
Source: Adopted from Porter, (1980)

Operational performance dimension	**Internal Performance Measures**	**External Performance Measures**
Quality	Rework cost, percentage of passed quality inspection, cost of quality control	Conformance to agreed upon specification, product performance
Delivery	Production lead time, accuracy of inventory status, dependability of internal lead times	Delivery lead time, on-time deliveries, stock availability
Cost	Unit cost of manufacturing, inventory turnover, capacity utilisation, yield	Product selling price, market price
Flexibility	Set up time/cost, length of fixed production schedule, amount of operating capacity	Product range, number of products offered, ability to handle volume and product mix changes

Examples of measures are provided in Table 2.5. All dimensions can be measured from both an internal as well as external perspective. The internal perspective represents measures that are useful for the internal monitoring and management of the manufacturing process while the external facing ones are measures apparent to and evaluated by the customers.

2.6.1 Quality Performance

Quality is a multifaceted term. According to Garvin (1987) quality can be viewed from up to eight different perspectives; performance, features, reliability, conformance, durability, serviceability, aesthetics and perceived quality. Within manufacturing operations the conformance dimension is most influential since it refers to the process' ability to produce products to their predefined specification reliably and consistently

(Jensen, Lidelöw, et al. 2015). High levels of conformance quality must be attained before trying to improve any other of the performance dimensions (Walker, Lee, et al. 2018). The logic being that scrap and rework is the outcome from poor conformance quality which in turn requires more buffers and the like. Higher total levels of inventory increases production lead times and thus negatively influence delivery performance. Internal measures of quality performance include percentage of products that pass final inspection, scrap rate among others. Customer satisfaction is often regarded as the prime measure of external quality performance (Belachew, Abera, et al. 2017).

2.6.2 Delivery Performance

The two main dimensions of delivery performance are delivery reliability and delivery speed (Jie, Subramanian, et al. 2015). Delivery reliability is sometimes referred to as dependability or on-time delivery and concerns the ability to deliver according to a promised schedule or plan. This sub dimension of operational performance is often regarded a prerequisite (Mokhtari, Slutsker, et al. 2016). Delivery speed is concerned with the length of the delivery cycle. Prajogo, (2016) argues that although the dimensions are separable, long run success requires that promises of speedy deliveries be kept with a high degree of reliability.

There is a caveat with the delivery dimension, companies in different environments relate differently to both delivery speed and reliability. Delivery speed is, from a market perspective, the elapsed time from the receipt of a customer order to final delivery (Tontini, Söilen, et al. 2017). This definition is quite straightforward for companies operating in a make-to-order environment. However, for companies operating under a make-to-stock strategy this definition is rather strange since the actual customer order enters the system more or less on the shelf leading to a delivery lead time that is zero (time of transport *etc.* not accounted for). Likewise, in make-to stock environments high delivery reliability is interpreted as the percentage of orders filled directly from inventory while in make-to-order environments delivery reliability is to honour the promises made to customers.

2.6.3 Flexibility Performance

Flexibility is also regarded to be a multidimensional concept (Choe, Tew, et al. 2015). Black, and Kohser (2017) define four dimensions of manufacturing flexibility; volume, variety, process and material handling flexibility. Further, they note that volume and variety are ―mainly externally driven" towards meeting the needs of the market. Similarly, Pérez Pérez, Serrano Bedia, et al. (2016) proposes volume, mix, new-product, and delivery-time flexibility as those types that directly influence the competitive position of the company. Within existing manufacturing operations the most influential types are the ability to adjust manufacturing volume and the ability to change between products (Kumar, Goyal, et al. (2017). A property that distinguishes flexibility from other dimensions of operational performance is that it is a measure of potential rather than actual performance. Also, the level of flexibility is not directly evaluated by the customer; it is more of an operational means to provide possibilities for more customised products and product deliveries (Slack, 1983). Flexibility can thus be referred to as an enabler, enabling the manufacturing system to offer shorter delivery lead times, wider product range *etc*. The externally visible properties of a highly flexible manufacturing system include a very broad product range, major opportunities to product customisation and highly flexible delivery times (Sáenz, Knoppen, et al. (2018).

2.6.4 Cost Performance

Cost is an absolute term and measures the amount of resources used to produce the product. Narazaki, Ruiz, et al. (2018) stress that all producers, even those whose primary source of competitiveness is different from product selling price, will be interested in keeping their costs low. Every dollar removed from the operation's overall cost is a dollar added to the bottom line profits. Therefore cost performance is the most important of the different operational performance dimensions (Wan Lei, et al. 2016), although cost often is ranked least important in empirical studies (Comăniță, Simion, et al. 2017). Important to note is that a reduction in the actual cost of manufacturing does not necessarily translate to an equally large decrease in the products selling price, *i.e.* there are managerial degrees of freedom in the distribution of cost reductions.

2.7 Maintenance

Maintenance: Ensuring that physical assets continue to do what their users want them to do Campbell, Reyes-Picknell, et al. 2015). Defining the mission of maintenance is a challenging task. There seems to be as many different answers as there are respondents (organizations). Denis, and Pontille (2017) emphasize quick reaction times in fixing breakdowns in order to service the customer more efficiently. On other hand Wijeratne, Perera, et al. (2019) pointed that some organizations intent on reducing the downtime and others focus on quality or cost control, while a few focus on safety or environmental security. All the above are right, which means that each company has its own type of interests. In addition Jianu, Jianu, et al. (2017) stated that maintenance is maintaining and preserving the productivity of fixed assets. According to the above statement the following matters belong to the maintenance concept:

- Preserving the operative condition of the equipment (not letting it to get worse or scatter)
- Complying the correct operational conditions.
- Recovering the original condition.
- Fixing the designing weaknesses
- Improving the operator and maintenance skills

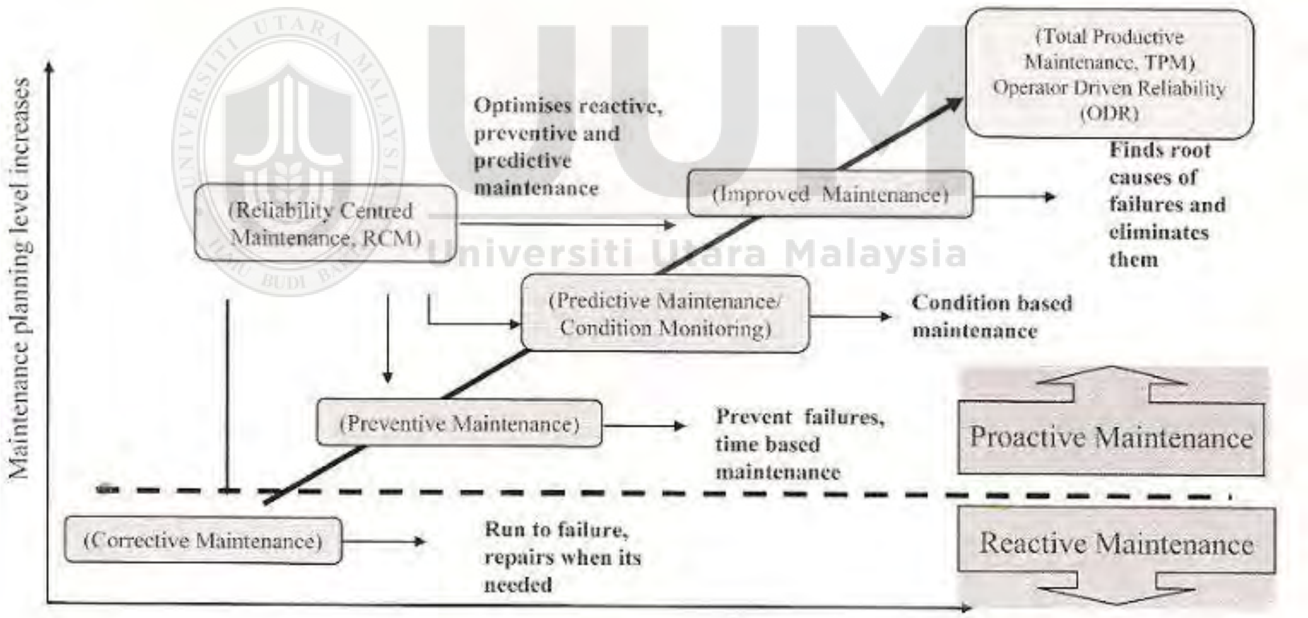

Figure 2.5.
Typical maintenance concepts
Soure:Adapted from *Pohjalainen,(2015):Gebus and Leiviskä (2009)*

Figure 2.4 presents different types of typical maintenance concepts. At the bottom of the picture it can be seen that there is only one concept, corrective maintenance that is purely reactive maintenance. The other concepts are above the run-to-failure dash line, which means that the others are trying to affect before something breaks down, meaning that the planning level increases; this is mostly known as proactive maintenance. Later there are more detailed discussions about different methods, which were somehow connected to this study. Maintenance is one of the biggest expenditure of the companies and it is estimated to be the 5% of the purchase cost each year (D'Onza, Greco, et al. 2016). In well-organized enterprises efforts have been made to master the maintenance and control the costs. The influence of the maintenance is indirect on the business result of an enterprise. It is truly important to understand the influence mechanism to be able to calculate the profits produced by the maintenance. (Bányai, Veres, et al. 2015).

2.7 Maintenance Types and Strategies

According to Tan, Hwang, et al. (2019) standards, maintenance practices approaches can be grouped into two major groups, namely Preventive Maintenance (PM) and Corrective Maintenance (CM) (Figure 2.5). Preventive approach can further be subdivided into condition-based maintenance and predetermined maintenance; this implies that PM can be time-based or condition-based (Chen, Cowling, et al. 2017). Corrective maintenance has been subdivided into two subgroups which are deferred and immediate; CM is an approach which is reactive in nature as compared to PM which is a proactive form of maintenance. Timing plays a major role in all these approaches (Alaswad, and Xiang, 2017).

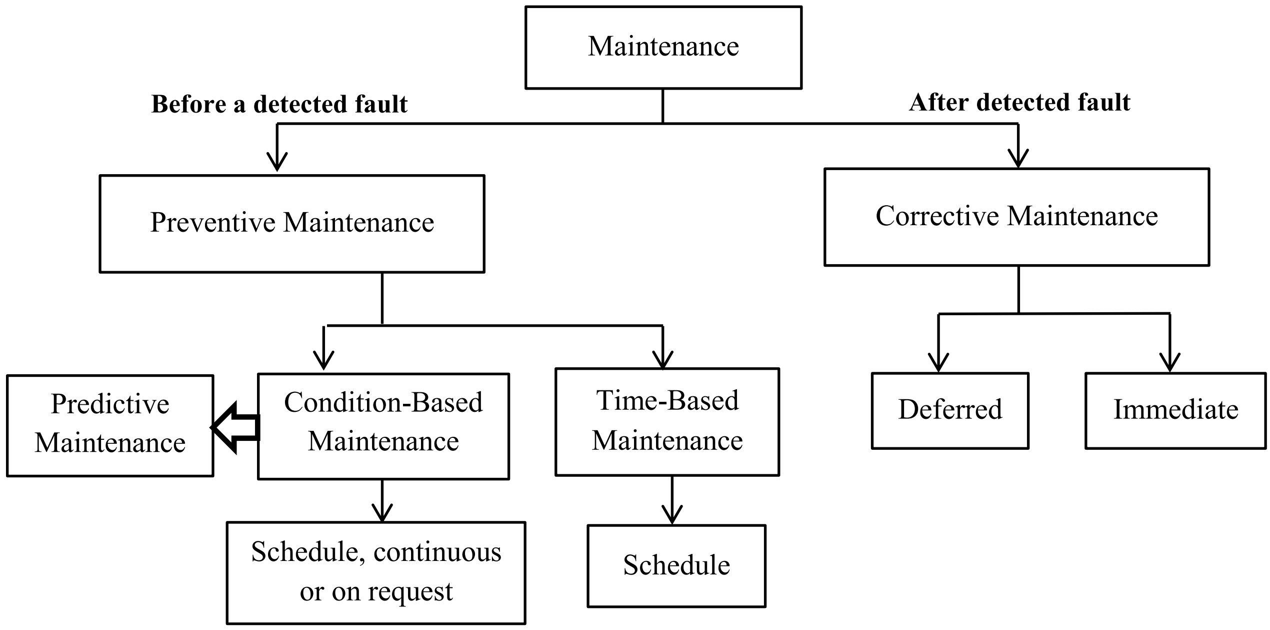

Figure 2.6
Maintenance overview chart
Source: Adapted From

2.7.1 Corrective Maintenance (CM)

CM is the maintenance carried out after fault recognition and intended to put an item into a state in which it can perform a required function (Stenström, Norrbin, et al. 2016). This is the most expensive form of maintenance especially if the maintenance is going to be done urgently because no planning or coordination can be made. Therefore the start-up cost and the cost of lost production can be large (Yepez, Alsayyed, et al. 2019). CM does not involve forecasting of failure when an item tends to fail. Depending on the necessity of the failed item(s) on the functioning of the system, maintenance can be done immediately or deferred. CM is the maintenance strategy applied most often when it is difficult to predict when an item will fail (Patil, Patil, et al. 2017).

2.7.2 Preventive Maintenance (PM)

PM is carried out at predetermined intervals or according to prescribed criteria and intend to reduce the probability of failure or the degradation of the functioning of an item (Lin, Pulido, et al. 2015), all preventive management programs are time driven. The item to be maintained can either be replaced or reconditioned depending on the condition of an item (Cha, Finkelstein, et al. 2017). The failure rate of the item is its probability to fail over a given period of time. PM can be divided into condition-based maintenance or time-based maintenance (Ben-Daya, Kumar, et al. 2016).

2.7.3 Condition-Based Maintenance (CBM)

According to Balakrishnan, Mani, et al. (2016) CBM of an item is PM based on performance and/or parameter monitoring and the subsequent actions. The standard needs to take note that performance and parameter monitoring may be scheduled, on request or continuous. Condition monitoring and inspection are the two main strategically approaches to CBM of an item (Lam and Banjevic, 2015). In condition monitoring, parameters are measured to ensure that maintenance is done before failure and is performed based on predetermined criteria. Inspection is done at regular intervals by a person involved in maintenance to ensure that maintenance is performed as soon as it is required (Chen, Ye, et al. 2015). Through regular inspections, measurements or tests, or continuous monitoring, one can determine when it is time for replacement, servicing or adjustments. These checks can be performed in three ways:

- Using the subjective senses (sight, hearing, touch, smell and taste)
- Intermittent or continuous use testing methods for detecting wear
- Running the equipment and notice that all functions work (Saeed, Shaikh, et al. 2018).

Brunner and Dowdell (2019) identified that CBM is normally suitable when failure rate is dependent on operating condition rather than time. A complete CBM program must include monitoring and diagnostic techniques. These techniques include vibration monitoring, acoustic analysis, motor analysis technique, motor operated valve testing, thermography, tribology, process parameter monitoring, visual inspections and other non-destructive testing techniques (Méndez, Sánchez, et al. 2017).

2.7.3.1 Vibration Monitoring

All mechanical equipments in motion generate a vibration profile, or signature that reflects its operating condition. This is true regardless of speed whether the mode of operation is rotation, reciprocation, or liner motion (Rastegari, Archenti, et al. 2017). Vibration analysis is applicable to all mechanical equipments; its profile analysis is a useful tool for predictive maintenance, diagnostics and many other uses.

2.7.3.2 Tribology

This is the general term that refers to design and operating dynamics of the bearing lubrication- rotor support structure of machinery (Mohanty and Paul 2018). Two primary techniques are being used for predictive maintenance; these techniques are lubricating oil analysis and wear particle analysis.

2.7.3.3 Lubricating oil analysis

Lubricating oil analysis is an analysis technique that determines the condition of lubricating oils used in mechanical and electrical equipment (Raposo, Farinha, et al. 2019).

2.7.3.4 Wear particle analysis

Wear particle analysis is related to oil analysis and the particles to be studied are collected by drawing a sample of lubricating oil (Peng, Wu, et al. 2017). Whereas lubricating analysis determines the actual condition of the oil sample, wear particle analysis provide direct information about the wearing condition of the machine-train.

2.7.3.5 Thermography

Thermography can be used to monitor the condition of the plant machinery, structures and systems. It uses instrumentation design to monitor the emission of infrared energy (i.e., surface temperatures) to determine operating conditions (Delgado-Prieto, Carino-Corrales, et al. 2018).

2.7.3.6 Ultrasonic

Ultrasonic like vibration analysis is a subset of noise analysis. The only difference in the two techniques is the frequency band they monitor. In the case of vibration analysis, the monitored range is between 1Hz and 30,000Hz, ultrasonic monitor noise frequencies which are above 30,000Hz (Angulo, Soua, et al. 2017).

2.7.4 Predictive Maintenance

The aim of predictive maintenance is to prevent two major drawbacks of time-based maintenance, namely unscheduled outages and needless repairs. Predictive maintenance is viewed as a principal method employed to optimise the operation of preventive maintenance (Behera and Sahoo, 2016). Compared to time-driven preventive maintenance procedures, predictive maintenance is condition-driven (Wilson, 2015). Conventionally, condition-based preventive maintenance is employed as a tool to manage maintenance to thwart unscheduled downtime and failures while predictive maintenance can be utilised as an efficient maintenance optimisation instrument (Daily and Peterson 2017). The goal of maintenance optimisation, through predictive maintenance, is to eliminate pointless maintenance tasks to prolong the lifecycle of a system and diminish costs (Yu, Dillon, et al. 2019).

Figure 2.7
Step in Predictive Maintenance
Source: Adopted from Chebel-Morello, Nicod, et al. (2017)

Based on Figure 2.7, an assumption can be made, that is the steps are used to prevent possible breakdowns in manufacturing organizationss by scheduling and executing stern time-based maintenance and conducting inspection of machines_ condition as part of preventive maintenance activities. These procedures are also known as predictive maintenance processes. The objectives of the steps are to track, estimate, and investigate the condition of machines, efficiency of operation, and additional indicators to determine the requirement for potential maintenance of machines. As mentioned earlier, the simplest type of predictive maintenance is visual inspection but there are additional intricate measures such as infrared imaging, vibration, and other non-persistent techniques (Chebel-Morello, Nicod, et al. (2017).

2.7.5 Time-Based Maintenance (TBM)

TBM is carried out in accordance with established intervals of time or number of units of use but without previous condition investigation (Kim, Ahn, et al. 2016). In order for TBM implementation to be successful, failure rate of an item needs to be increasing as the usage time of an item increases. Therefore the decision for the item maintenance interval should be based on machine hours, age, the frequency of use and the distance travelled (De Jonge, Dijkstra, et al. 2015). According to Camos, (2017) most groups of similar machines will display failure rates that can be predicted in some ways if averaged over a long period of time. The Bathtub curve (Figure 2.6) relates failure rate to operating time.

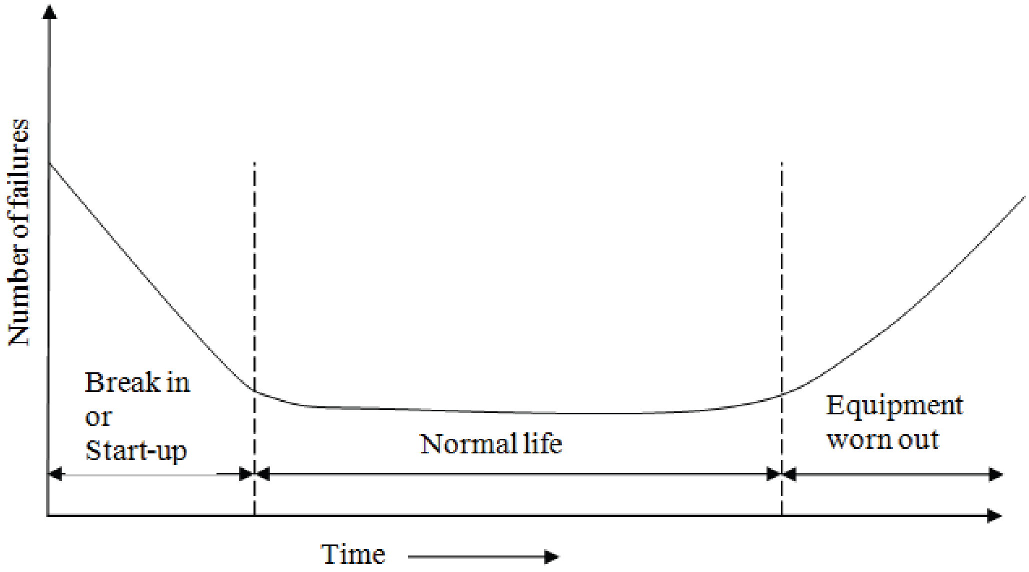

Figure 2.8
Typical bathtub curve
Source: Adopted from Mobley, (2002).

The mean-time to failure curve/Bathtub curve indicates that a new machine has a high probability of failure because of installation problems during the first few weeks of operation. After this initial period the probability of failure increases sharply with the elapsed time (Mobley, 2002).

2.8 Technological Capabilities

The definition of technological capability varies in perspective, depending on the aims of the researchers. Hancock, (2017) defines technological capability broadly as ―the entire complex of human skills (entrepreneurial, managerial and technical) needed to set up and operate industries efficiently over time". He defines TC in a narrow sense as the capability to execute all the technical functions entailed in operating, improving and modernizing the company's production facilities. Chatterji, (2016) define the term ‗technological capability' from the aspect of corporate development. Technological capability refers to the ability to make effective use of technological knowledge to assimilate, use, adapt, and change existing technologies. It also enables one to create new technologies and to develop new products and processes in response to a changing economic environment (Welford, 2016).

Technological capability can be categorized into two levels: the corporate level and the national level (Dodgson, 2018). This study concentrates on the corporate level of technological capability. At the corporate level, the technological capability development is the outcome of company-level efforts to build up new organizational and technical skills, its ability to generate and tap information, the development of an appropriate specialization vis-à-vis other companies, and the formation of linkages with suppliers, buyers and institutions (Vargas, 2018). Furthermore, the social benefits of corporate efforts to build and develop technological capabilities may far exceed the individual benefit of companies themselves because of technological diffusion – the widespread externalities of skills and technologies (Welford, 2016).

There are many different categorizations of technological capability depending on the research purpose (Eggers and Park 2018). Gonsen, (2016) distinguishes technological capability into three elements: production, investment, including duplication and expansion, and innovation. Azar and Ciabuschi (2017) categorizes technological capability into investment technological capability, production technological capability, and linkage technological capability according to the functions. Ca, (2019) pointes out that in emerging countries ‗technological capability‘ can be used interchangeably with ‗absorptive capacity‘ (Zawislak, Fracasso, et al. 2018): absorbing existing knowledge, assimilating it, and in turn generating new knowledge.

In this study, we use technological capability as the capability to make effective use of technical knowledge and skills, not only in an effort to improve and develop the manufacturing products and processes, but also to improve the existing technology and to generate new knowledge and skills in response to the manufacturing performance. In addition, the technological capabilities in this study cover production capability, investment capability, marketing capability and R&D capability.

2.9 Justification of Variables

i. Independent variables

This study employed three independent variables namely; Time-based, condition-based and predictive maintenance. According to Park, Moon, Do and Bae (2016) maintenance can be classified into three categories: corrective, preventive, predictive and condition-based maintenance. The reason why corrective was not include in this framework because; Park, Moon, Do and Bae (2016) stated that corrective maintenance may cause high risk in maintenance scheduling and performing because it does not consider adequate maintenance moment unlike preventive or predictive maintenance. This was supported by Arts, Basten, et al. (2019) were the weakness of corrective maintenance is it_s don_t have explicit decision on when to schedule next maintenance and this maintenance activity only carried out after machine failure and this strategy was basically ignoring the possibility of machine breakdowns. In meantime the preventive maintenance strategy can be applicable for both maintenance and production decisions these because it can decide the maintenance decisions independently based on analyzing the state of the machines such as age and characteristics of the equipment that will resulted static rules (Bajestani and Beck, 2015). Öhman, Finne, et al. (2015) stated that the preventive maintenance basically involve the condition-based and time-based action which was appropriate for all production plant were avoid the machine failure which sufficient to meet organization demand.

Moreover in recent study that did by He, Gu, Chen and Han, (2017) they stated that integrating predictive maintenance strategy achieves approximately 26.02 and 20.54% cost improvement over time-based maintenance and condition-based maintenance. Moreover Shin and Jun, (2015) stated that the predictive maintenance become an attractive technique to the industry that operated using sophisticated and efficient assets. Thus this study was decided to use these three variables namely; Time-based maintenance; Condition-based maintenance and predictive maintenance in order to examine the manufacturing performance.

ii. Dependent Variables

This study is using manufacturing performance as dependent variables in order to conduct this study. In other words, this study intended to identify manufacturing performance in the dimension of cost, quality, flexibility and delivery. These dimensions are employed because Skinner (1974) categorized manufacturing performance into four dimensions, namely, quality, cost, delivery, and flexibility. Therefore, in this study, the cost, quality, delivery, and flexibility are referred to as the manufacturing performance dimensions. On the other hand, Jin, Siegel, Weiss, Gamel, Wang, Lee, and Ni (2016) stated that machine or equipment failure not only affects quality but also delivery and flexibility. Thus, Boon-Itt and Wong (2016); Chavez, Yu, Jacobs, and Feng (2017) and Schönsleben (2016) assert that in order to compete for global demand every firm must improve their performance by decreasing production costs and increasing quality as well as delivery and performance.

According to Jardine and Tsang (2013) manufacturing cost will be increased by inadequate maintenance jobs that lead to breakdowns and equipment failures. Due to this problem, the product being produced by a manufacturing plant may be off-centered due to the poor quality of machine performance (Kumar, Lad, Manjrekar, & Singh, 2016). The defective products must be reworked in order to rectify the quality deficiency. Hence, due to re-inspection, the machine in the manufacturing plant the product cannot be delivered on time which leads to a delay in production lines (Xiao, Song, Chen & Coit, 2016). The delay of equipment settings to accommodate any re-inspection process also causes the flexibility of the operators and equipment to be affected (Phogat, Phogat, Gupta & Gupta, 2017; Petroni, Zammori & Marolla, 2017; Khatami & Zegordi, 2017). The above arguments show that manufacturing performance dimensions such as cost, quality, delivery, and flexibility have a crucial relation to equipment maintenance. Moreover, the findings from extensive reviews of past literature on manufacturing performance have suggested that empirical research on Malaysian manufacturing performance is still at an immature stage. For example, Azadeh, et al., (2015); Azizi and Kiumars Fathi (2014); Portioli et al., (2012) claim that the empirical manufacturing performance is still at the early stage. Furthermore, Sojka, (2017); Ajagbe and Ismail (2014); Sakikawa, Chaudhuri, and Arif, (2017); Tan and Wong, (2017) also affirm that the study of manufacturing performance has not fully explored, especially in the context of Malaysian manufacturing industry.

iii. Moderating Variables

As stated this study employ technological capabilities as moderating variables in order to test moderating relationship between preventive maintenance practices and performance of Malaysian manufacturing organizations. Technological capabilities are known as the ability of a firm to actually create impactful innovations (Prajogo, 2016). This study intended to measure technological capabilities of Malaysian manufacturing organizations because recently the uncertain in a global business environment that gives new challenges and opportunities to Malaysian manufacturing organization. Despite the arguments of Radzi, Shamsuddin and Wahab (2017) and Hasnan et al.,(2014) studies that the existence of most manufacturing organizations in Malaysia due to the support from various ministries and agencies. These phenomena have urged the Malaysian manufacturing organizations to use technological capabilities to improve their existing resources (Radzi et al., 2017). Moroever, Reichert and Zawislak (2014) highlight the past few years technological capabilities has becme the focus of interest in developing countries.

However, Reichert and Zawislak (2014) found that medium-low-tech companies are showing less interest in investing in their own technological capability. This can be found study did by Radzi et al. (2017) and Hasna et al. (2014), implying that Malaysian manufacturing organizations have a lot of challenges such as low productivity improvement, low access to finance, lack of human capital and lack of technology adoption that become a hindrance for their development. Due to this issue, this study intends to examine on how Malaysian manufacturing organization can enhance its competitiveness through technological capability approaches. Thus, the technological capability is used as a moderating variable to test between preventive maintenance practices and manufacturing organization performance.

2.10 Hypothesis Development

In this study, PM Practices is categorised into three dimensions namely: TBM, CBM and PdM. Many researches have empirically investigated the relationship between of PM Practices and manufacturing performance. For example, Bourne Pavlov, et al. (2017) have found in their studies a positive relationship between PM Practices and manufacturing performance. The results of the study of Hooi and Leong (2017) show that PM implementation initiatives gradually enable engagement, proper planning, right execution and continuous improvement, ultimately improving the manufacturing performance indicators significantly. There is also evidence that the PM Practices improve their business performance and gain competitive advantage (Wickramasinghe and Perera 2016; Jin, Weiss, et al. 2016; Kamath and Rodrigues 2016). Numerous studies also have demonstrated that the PM Practices has a positive and significant effect Optimizing production and product quality (Aghezzaf, Khatab, et al. 2016). In addition Jayaram, Das, et al. (2010) points out that the preventive maintenance leads to better quality in terms of cost, quality, cycle time and delivery speed. Furthermore, the results of the study of Ortiz, and Park (2018) demonstrate that the product quality and business performance of SMEs are improved after acquiring preventive maintenance. Nallusamy, (2016) present empirical evidence of the positive effect of Preventive Maintenance on operational performance. Many quality studies demonstrate that companies that effectively implement PM Practices improve their quality and also have a positive and significant effect on operational performance (Bouslah, Gharbi, et al. 2016; Fujishima, Mori, et al. 2017; Modgil and Sharma, 2016).

Many authors support the view that high product quality is positively related to market share. Cooper, (2017) reports that quality improvement makes companies increase their market share, product value and price and consequently the financial benefits. As an evident Lazim, Sasitharan, et al. (2019) state that preventive maintenance practices has a positive impact on the cost and quality that increase in sales and profits among manufacturing organizations. On other hand Rastegari and Mobin (2016) also pointed that when appropriate maintenance decision is implemented it significantly reduced, machine breakdowns, downtime, and cost of repairing which consequently increases firm profitability. Meanwhile Vogl, Weiss, et al. (2019) stated that the TBM and CBM is the optimal maintenance strategy that allowing an reduce time and costs for maintenance of products or processes through efficient and that lead to asset readiness, that improved product quality which is lead to sales and profit margin increase. Taking into consideration the previous research referred to above, the following research hypothesis is formulated:

H1: Time-based maintenance is positively related to performance of Malaysian manufacturing organization.

H2: Condition-based maintenance is positively related to performance of Malaysian manufacturing organization.

H3: Predictive maintenance is positively related to performance of Malaysian manufacturing organizations.

According to the findings of the empirical research studies of Baranová, Landryová, et al. (2016) TBM is positively influenced by the improvement of process management practices. Similarly, Mahamood and Akinlabi (2016) noted that unlike in traditional manufacturing process the implementation technologies in manufacturing lead to mass production that a reduction in product wastage, coupled with improvement in productivity result in increased product quality and company profits. Furthermore, the results of the studies of Abdallah, Phan, et al. (2016) found that technological innovations have a strong and direct effect on ocustomer satisfaction as well as the indirect effects through operational performance and quality improvement. Meanwhile Ruffoni, D'Andrea, et al. (2018) note that the innovation capabilities improved manufacturing business performance of a company is result of improved operational performance. Moreover Szalavetz, (2018) stated that technological capabilities enhances the organizationsal decomposition of innovation, which facilitates manufacturing organization in improving manufacturing operational performance. In addition, the findings from the study of Benitez, Chen, et al. (2018); Hartley (2017); Ross (2017) show that the improved technology has a positive effect on operational competence that decreases over time and manufactuirng performance results in fewer defective products, decreased quality cost, increased productivity, on time product delivery and finally in increased manufactuirng performance. Taking into account the above studies, we reach the following hypothesis:

H4: The technological capabilities positively moderate the relationship between TBM practices and performance among Malaysian manufacturing organizations.

H5: The technological capabilities positively moderate the relationship between CBM practices and performance among Malaysian manufacturing organizations.

H6: The technological capabilities positively moderate the relationship between PdM practices and performance among Malaysian manufacturing organizations.

2.11 Conclusion

This chapter reviewed information in the existing body of knowledge, whereby readers of this thesis can evaluate the appropriate arguments and support from previous studies. The next chapter will provide information on the methodology of this study.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

In this chapter, the methodology and other related procedures utilised to collect data are thoroughly explained. This study aimed to investigate the practice of preventive maintenance and performance of manufacturing organizationss in Malaysia by considering the influence of technological capabilities at the organizations level instead of the individual level. Besides that, this study intended to clarify whether technological capabilities moderate the relationship between preventive maintenance practices and the performance of manufacturing organizationss.

The Federation of Malaysian Manufacturers (FMM) directory 2017 was referred to obtain the list of manufacturing organizationss in the country. A questionnaire was used to identify whether preventive maintenance practices influence the performance of Malaysian manufacturing organizationss. Data was collected via a self-addressed and stamped envelope that was provided to encourage respondents to return the completed questionnaire from prospective companies listed in the FMM Directory. However, the questionnaire was accompanied by a covering letter that explained the main study objectives and its contribution to the Malaysian manufacturing sector. Moreover, to analyse the hypotheses raised in this study, Structural Equation Modelling (SEM) or Partial Least Squares (PLS) v. 3 (PLS 3) was employed during the analysis of inputs collected from the respondents.

3.2 Research Framework

This study's research framework was proposed based on the precise overview formed through the review of relevant literature, which highlighted the issues, problems, and research gaps. According to Borgatti and Everett (2006), the development of a research framework in most studies could assist researchers to recognise the actual phenomena that occur in measuring the subjects of the investigation. Furthermore, the measures could be used as determinants to identify the presence of definite relationships between independent and dependent variables through statistical and mathematical concepts. Thus, the research framework can be referred to as the conceptual model that researchers apply to make logical conclusions by evaluating the relationships among various elements identified as significant factors of vital problems (Sekaran & Rani, 2010).

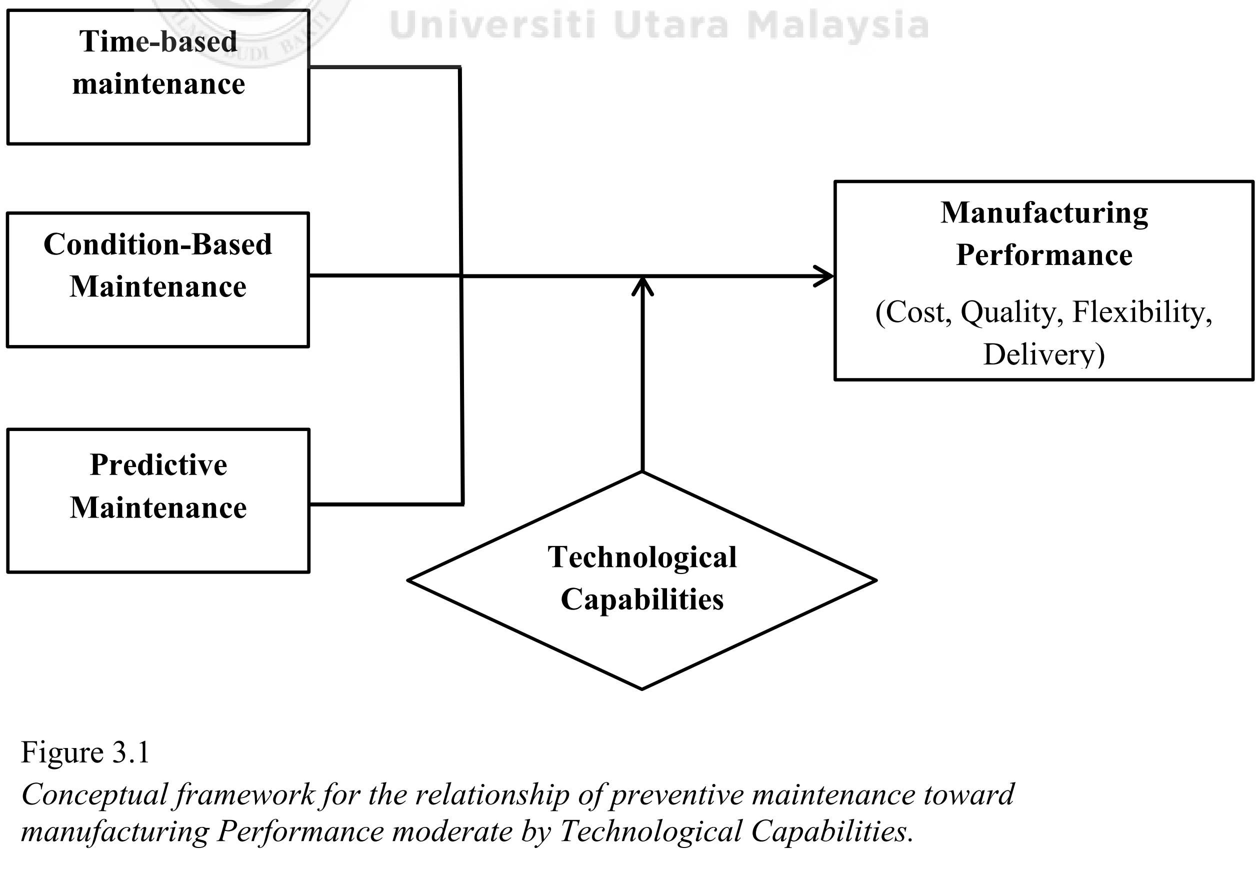

Figure 3.1
Conceptual framework for the relationship of preventive maintenance toward manufacturing Performance moderate by Technological Capabilities.

Based on Figure 3.1, an independent variable (preventive maintenance practices) and a dependent variable (performance of manufacturing organizations) were evaluated by the hypotheses raised in this study. These two variables were measured with technological capabilities as the moderator. Based on the proposed framework, it is noticeable that the chosen methodology can reveal the definite performance of manufacturing organizations based on the perspective of preventive maintenance practices. Four factors were used to measure the performance of manufacturing organizationss, namely, cost, quality, flexibility, and delivery. On the other hand, this study examined technological capabilities as the moderating variable.

3.3 Research Hypotheses

This study's research hypotheses were developed by considering the research framework. Generally, hypotheses are developed to provide insight to readers as tentative suppositions or assumptions put forth by the researcher concerning the specific states of relationships commonly investigated. This is done by referring to past empirical studies and statistical concepts to affirm the presence of definite relationships between the proposed attributes instead of simply assuming the existence of the elements or the probability of its existence (Hair et al., 2010). The following six hypotheses were constructed to investigate whether relationship are present among the proposed variables.

H1: Time-based maintenance is positively related to performance of Malaysian manufacturing organization.

H2: Condition-based maintenance is positively related to performance of Malaysian manufacturing organization.

H3: Predictive maintenance is positively related to performance of Malaysian manufacturing organizations.

H4: The technological capabilities positively moderate the relationship between TBM practices and performance among Malaysian manufacturing organizations.

H5: The technological capabilities positively moderate the relationship between CBM practices and performance among Malaysian manufacturing organizations.

H6: The technological capabilities positively moderate the relationship between PdM practices and performance among Malaysian manufacturing organizations.

3.4 Research Design

According to Creswell (2013), the research design is a thorough elaboration to describe the flow of the research to significantly mirror the exploratory nature of the study to the readers. Meanwhile, Hair et al. (2017) explained that research design discloses the suitable methods chosen by researchers to examine the ambiguity or the research objectives to comprehend and expose the limited literature on the research topic. Next, Cooper and Schindler (2001) stated that the research design clarifies the direction and plan of the study to gather data and the methods used to obtain answers to the research questions. In addition, Muaz (2013) listed six well-known categories of research design, namely, correlation, review, descriptive, meta-analytic, experimental, and semi-experimental.

The main objective of this study was to identify whether preventive maintenance practices could improve the performance of manufacturing organizationss in Malaysia. This study correlated nature of issues faced by manufacturing industries as the major concerns to discover the attributes that might influence the performance of manufacturers exposed to practices of preventive maintenance. Correlation analyses were used to identify the causal relationship between variables (Zikmund et al., 2010). This study also intended to identify the moderation effect of technological capabilities on the relationship between preventive maintenance and the performance of manufacturing organizationss in Malaysia. The collected data were cross-sectional, whereby all the variables were measured simultaneously. To fulfill the research objectives, this study used the questionnaire approach to collect data from the respondents of manufacturing organizationss in Malaysia.

3.5 Source of Data

The respondents were employees in manufacturing organizationss located in Malaysia. They were managers and engineers who directly participated in the operation of the manufacturing plant. Similarly, Jasti and Kodali (2016) conducted data collection at the organizational level and their respondents were maintenance managers, logistics managers, production managers, and quality managers from various manufacturing industries. The decision to choose them as the organizations‘s representative was based on the arguments posed by Philips (1981), which emphasised that the information gathered from high ranking personnel was more reliable than those accumulated from lower-ranking employees. From the perspective of this study, the chosen personnel were full-time technical employees with high skills and have been employed at the company for more than six months and were familiar with manufacturing tasks such as quality checking, operation in the production line or maintenance of machines. Furthermore, these personnel were selected because: 1) they are considered key employees in the manufacturing process and are familiar with core elements of the plant; 2) their tasks are critical to the performance of any manufacturing plant (Wong et al., 2010); and 3) previous studies on manufacturing industry used them as respondents to collect more reliable and accurate data since they directly participated in forming and implementing the manufacturing practices within the organizations (Nordin et al., 2010; Wong et al., 2009). The reason to select personnel who have worked for more than six months was due to the period being adequate for organizationsal socialisation and thus they can provide a stable and concrete evaluation about their organizations (Lashley &West, 2002).

3.6 Data Collection Procedure / Ethical Consideration

This study intended to collect data from manufacturing organizationss using the questionnaire approach. Before commencing data collection, the research instrument (i.e., the questionnaire) must be validated by experts in the research field. Hence, the questionnaire was submitted to two professors who are experts in the field of manufacturing and maintenance. After their inspection, several changes were made to the questionnaire according to the criteria provided by both experts.

Next, the questionnaire was sent to the supervisor for a final inspection. After receiving approval from the supervisor, a permission letter to conduct data collection was applied from the School of Technology Management (STML). The researcher was completed the data collection in 3 months. Once the permission letter was given by

STML, data collection was performed at selected companies listed on FMM's directory 2017.

Research access was not easy to obtain. Means (2017) stresses the difficulties in obtaining access to private companies, particularly when analysing organizationsal and internal issues, as this could undermine _the interests of the powerful'. However, in this study, the questionnaire was accompanied by a covering letter that explained the main study objectives and its contribution to the Malaysian manufacturing sector. For instance, in the course of this research, the data was collected from 600 Malaysian manufacturing organizationss via sending a self-addressed and stamped envelope to encourage the respondents to return the completed questionnaire to prospective companies listed in the FMM Directory. The following section will explain the detailed information on how the mail survey was conducted in this study:

Step 1: Put together lists of email and postal address all 600 Malaysian manufacturing organizationss who should get a survey.

Step 2: Write a cover letter explaining the survey form that the responses given are strictly confidential. (refer to Appendix A)

Step 3: Put together the mailing stamp and address each envelope, and put the following inside:

- Cover letter signed by the lecturer;
- Blank survey; and Self-addressed stamped envelope to return the completed survey to the researcher.

Step 4: Mail out the surveys.

Step 5: After about 5 days, the researcher sends a reminder/thank you message through email by saying:

> ―Greetings, we recently sent you a survey entitled ―*The Preventive Maintenance Practices and Performance among Manufacturing Organizations in Malaysia; the Moderating Role of Technological Capabilities*. If you have already sent the survey back to us, thank you. If you have not sent the survey back, please take a moment to fill it out. If you have any questions, please call …”

Step 6: As surveys are returned, store them in a safe place. Keep the records.

Step 7: Enter survey data into the *excel Spreadsheet* (recommended). You may want to do this as the surveys come in to save time later and avoid misplacing data.

Step 8: When it comes time to report your performance measure survey results, the summary page of the *excel spreadsheet* automatically calculates the numbers of respondents who were surveyed and who met the outcome targets.

3.7 Population and Sample Selection

The population of this study consisted of Malaysian manufacturers located throughout Peninsular Malaysia. According to the Malaysian Industry Development Authority (MIDA), there are two main types of manufacturing investment, namely resource-based and non-resource-based (EPU, 2006). This study utilised the FMM directory to select suitable companies to distribute the questionnaire. Based on the directory, until January 2017 there were a total of 3,752 manufacturing companies (FMM, 2017). However, in order to ensure an equal distribution of types of manufacturing industries in the manufacturing sector for this study, proportionately stratified random sampling was used and is illustrated as follows:

There are two types of sampling approaches namely probability and non-probability (Bryman and Bell, 2007). For this investigation, probability sampling technique was selected to gather data from respondents. This technique was chosen because the chance for any manufacturing organizations to participate or be selected was equal. In addition, this method enabled random selection of respondents without selection biases. Moreover, Sekaran (2010) stated that the sampling technique allowed a broad view to be made from the results. Through the data collection process and better response rate, the results can be extrapolated to the entire population. In an empirical-based study, it is essential to determine the proper size of sample. According to Roscoe (1975), the conditions to determine the appropriate sample size are as follows:

i. A sample size of more than 30 and below 500 is appropriate.
ii. In multivariate research (including multiple regression analyses), the sample size should be several times (preferably 10 times or more) as large as the number of variables in the study.

Furthermore, Krejcie and Morgan (1970) asserted that there are several requirements in identifying the appropriate sample size to ensure the sample size correctly mirrors the population size. For instance, Krejcie and Morgan (1970) exemplified that if the population size (N) is 4,000, then, the sample size should be 351. However, according to Jusoh (2007) and Wong et al. (2010), the response rate of Malaysian manufacturers is 12%, which is the typical minimum percentage followed by many researchers. Moreover, Ahmed et al. (2004) also reported a very low response rate (only 9.1% or

63 completed questionnaires were returned from 695 delivered) for the study on TBM implementation in Malaysian SMIs. On the other hand, Yusuff (2004) reported that only 31 completed questionnaires were received from 350 questionnaires distributed to electric and electronic organizationss in Malaysia (about 8.8% response rate). Nevertheless, to make sure an equal distribution of respondents, this study employed proportionately stratified random sampling based on the suggestion of Gay and Diehl (1992). According to them, proportionate stratified random sampling consists of the five following steps:

3.8 Sample Selection Process

i. Define the Population

Based on FMM's 2017 directory, 3,752 manufacturing organizationss were the population for this investigation.

ii. Determine the Desired Sample Size

As suggested by Krejcie and Morgan (1970), the sample size for this study was 351, based on the total population of 3,752 manufacturing organizationss. Furthermore, Krejcie and Morgan (1970) provided a table of values that permits easy determination of the size of sample needed to represent a given population. Therefore, the sample selection for this study was based on Krejcie and Morgan's (1970) guidelines.

iii. Identify the Variable and Desired Subgroup (Strata)

The variable and desired subgroup were based on FMM's definition of the manufacturing sector that includes dozens of industries such as printing and publishing, chemical and petroleum, electrical and electronics, fabricated metal, machinery, plastic, transport, basic metal, paper, non-metallic mineral, precision and optical instruments and textile, rubber, medical, food, beverage and tobacco, wearing apparel and leather, manufacture of furniture wood and wood products, and recycling (FMM, 2017).

iv. Classify the Population Elements into Subgroups

Throughout the total of 3752 manufacturing organization, the 15 subcategory of the firms illustrated in Table 3.1.

Table 3.1
Sample Selection

Type of Industries	Population	%	Selected sample
Chemical and Petroleum	510	13.6%	46
Food, Beverage and Tobacco	495	13.2%	48
Electrical and Electronics sector	427	11.4%	49
Fabricated Metal	412	11%	40
Rubber-based and plastic	375	10	36
Machinery and Equipment	337	9%	33
Paper, Printing and Publishing	225	6%	19
Transport	150	4%	16
Basic metal products	150	4%	14
Other Non-Metallic Mineral	150	4%	15
Wood-based product	75	2%	6
Furniture and fixtures	75	2%	7
Textile and apparel	75	2%	9
Tobacco and Beverages	37	1%	5
Others	296	6.8%	26
TOTAL	3752	100	351

v. Sample that selected randomly based on the population size

As proposed by Krejcie and Morgan (1970), the 351 organizationss were selected using the simple random selection approach. Microsoft Office Excel 2016 application was utilised to randomly select the sample. First, all the organizationss in the FMM 2017 directory were numbered, then companies from each sector were randomly chosen. For instance, there were 427 electrical and electronic organizationss. From that figure, about 49 organizationss were selected using the RANDBETWEEN command in Microsoft Office Excel 2016, i.e. if the setting was RANDBETWEEN

(1,427), therefore, the random number picked by Microsoft Office Excel 2016 was 33. The same formula or command was used to randomly select organizationss from other manufacturing sectors.

However, there are many studies has reported that the respond rate from manufacturing sector are low due to uncertainty about the number of questionnaires to be returned by respondents. As an evidence Tye, Halim, et al. (2011) reported that from total of 300 questionnaires were distributed only 64 questionnaires were returned (21.3% response rate). Moreover Abu Bakar, and Ahmed (2015) has sent total 1,700 questionnaires to Malaysian manufacturing companies and only 116 usable questionnaires received (7% response rate) and Garza-Reyes and Chaikittisilp (2018) distributed 618 questionnaires and only 250 responses. For instance Garza-Reyes and Chaikittisilp (2018); Rasamanie and Kanapathy (2011); Wong, Coates, et al. (2016); suggest that to increase the response rate it was advisable to send additional questionnaire that help to increase the response rate. After taking consideration to the low responses from respondents based on previous studies as mention above, the researcher added additional (75%) or 249 questionnaires to increase the response rate. Thus there are total 600 questionnaire (351 sample size + 249 additional questionnaire) was send to the respective industries.

3.9 Data Collection Method

Sekaran (2002) stated that the data collection approach is an integral part of an study design. It is the process of accumulating the views of respondents regarding specific topics (Zikmund, 2003). The survey is one of the instruments for data collection in quantitative studies administered through random sampling to generalise the population as a whole (Robson, 2016). The sample of this study was 351 Malaysian manufacturers and data was collected using self-administered questionnaires.

3.10 Operational Definition

The measurement of variables in the theoretical framework is an important aspect of research design (Sekaran, 2003). As such, the operational definition of variables used in research is essential to ensure that subjective measurements are done in a manner that can be clearly understood. This study consisted of three main concepts, namely, preventive maintenance, technological capabilities, and the performance of the organizations. All these concepts need to be encapsulated to measure the study‘s variables (Sekaran, 2003).

3.10.1 Preventive Maintenance

i. Preventive maintenance is a maintenance activity that is either time or condition-based, conducted by manufacturing organizationss to prevent machine breakdown and preserve machines' lifespan.

3.10.2 Manufacturing Organization

ii. Malaysian manufacturing organizationss are operated in small, medium and large scales, and are responsible for producing consumer or industrial products using appropriate raw materials.

3.10.3 Technological Capabilities

iii. Technological capabilities are present in small, medium and large industrial sectors which include manufacturing organizationss. These capabilities allow the development and design of products by determining the rates and patterns of growth and industrialisation by referring to diverse types of technological fields.

3.11 Research Instrument

This section will illustrate the measurement instruments applied in this study. Many scholars employed questionnaires as the research instrument to answer their research questions. According to Sekaran (2003), in quantitative studies, the survey method has the lowest cost compared to other quantitative data collection methods. A questionnaire was used in this study to collect data from the respondents. The unit of analysis for this study was the organizationsal level whereby Malaysian manufacturing organizationss were the respondents. Thus, this study employed the quantitative approach to gather data from respondents to achieve the research objectives. This study used a five-point Likert scale to measure the respondents' perceptions gathered using the research instrument. To measures perceptions, Sekaran (2000) divided the group of scales into two (i.e., rating and ranking). The rating scale contained 10 additional scaling items. One of the prominent measurement instruments is the seven-point Likert scale introduced by Rensis Likert (Likert, 1932). The Likert scale which has widely used, was neither used in the five nor seven-point scale in several investigations related to the topic of this study (Venkatesh et al., 2003; Venkatesh & Bala, 2008). Nonetheless, previous studies on manufacturing performance revealed that most researchers used a five-point Likert scale as their measurement scale to collect data from the respondents. Examples are studies by Yusoff, Imran, Qureshi and Kazi (2016), Sakikawa, Chaudhuri and Arif, (2017), Adebanjo et al. (2017), and Wickramasinghe et al. (2017). Hence, this study used the five-point Likert scale to gather data from manufacturing organizationss. Coding activity was conducted to ease the identification process prior to the insertion of data into PLS 3. The detailed description of the research instrument is described in Table 3.1.

Table 3.1
Summary of Research Instrument

Section	Factor	Code	Total Items	Source
1	Demographic Details	--	6	Gaur, Bathula and Singh (2015) Law, 2012) Tolbert, (2015)
2	Time-based maintenance	TBM	4	Ghazi, (2016)
	Condition-based maintenance	CBM	7	Maletič, Maletič, et al. (2014)
	Predictive Maintenance	PdM	8	Grosbois, 2011
3	Cost	C	5	Li, Ragu-Nathan, Ragu-Nathan and Rao, (2006)
	Quality	Q	5	Hallgren and Olhager, (2009) Al Khattab, (2013)
	Flexibility	F	8	Kioko (2015)
	Delivery	D	5	
4	Technological Capability	TC	9	Zahra, Neubaum and Larrañeta, (2007)

Based on Table 3.1, the research instrument comprised four main sections. In the first section, respondents' demographic details were collected. Next, the second section consisted of 19 questions related to the independent variables (IVs) (TBM, CBM, and PdM). The source of research items was adapted to fit accordingly with this research's objectives. The third section represented the dependent variables of this study and contained five factors (FM, Q, C, F and D). Finally, the fourth section represented the moderating variables (TC) (refer to Appendix A). The total number of items of this research instrument was 57 (for all items/factors).

3.12 Moderating Impact

According to Baron and Kenny (1986), a moderator is the variable that influences the path and/or the strengths of the relationship between an independent or predictor variable and the dependent criterion variable. Throughout this study, the moderating variables were expected to represent a significant impact on other proposed variables (refer to Figure 3.1). It is essential to take note that all analysed moderator variables were based on exploratory approaches. In other words, the influences of technological effects were investigated by employing the correlation method. According to this method, the paths are recognised, ascertained and correlated with definite predictors (Sekaran, 2000).

3.13 Data Analysis Process

To evaluate the theoretical model, this study employed Sequential Equational Modelling (SEM), which is also known as path analysis with latent variables (Bagozzi, 1984; Bagozzi & Yi, 1988). SEM is a set of statistical approaches that encourage concurrent development or evaluation of the association between constructs (Tabachnick & Fidell, 2007). SEM statistical techniques can be divided into two types, namely covariance-based modelling (e.g., LISREL and AMOS) and variance- or component-based modelling (e.g., PLS) (Gefen, Straub & Boudreau, 2000). In this research, a component-based SEM approach-PLS was principally embraced to investigate the paths in the structural model.

Application of the PLS-SEM approach provided several benefits for the investigation process. First, PLS-SEM technique facilitates the assessment of the measurement model within the theoretical context. Thus, constructs obtained definition from the items employed to compute them in the context of theoretical elements embedded in this technique. Next, the model of errors is computed in PLS explicitly. Third, SEM facilitates the analysis of multiple dependent and independent variables in the same model. Furthermore, PLS-SEM application has certain advantages over other SEM software which do not use PLS. PLS-SEM enabled researchers to directly include and compute the influences of moderators in the model. This is useful if the structural model has numerous moderating effects.

3.14 The Structural Model

The structural model is interchangeably employed as an inner model or path model that stipulates the set of dependent associations connecting the constructs of hypothesised models. A construct can be defined as a latent or unobservable concept that can be conceptualised (in abstract terms) but cannot be directly measured (Malhotra, 2010). Such constructs can either be endogenous or exogenous depending on whether its value is determined internally or externally of the model. One benefit of SEM is that endogenous constructs may predict other endogenous constructs in what Durbach (2010) termed as a chain of models. Such an analysis of higher-order models is not facilitated by other multivariate techniques (Durbach, 2010).

Table 3.2

Summary Indices for Measurement Model Analysis using PLS-SEM (Source: Ramayah et al., 2018)

Summary of Reflective Model Assessment

No	Required Analysis	Purpose	Name of Index	Reference	Required value
1.	Internal Consistency	Cronbach alpha used to estimate the reliability based interior-correlation of observed indicator	Composite Reliability (CR)	Hair et al., 2016; Henseler et al., 2016; Sijtsma 2009	Loading Value equal to 0.5 or Greater than 0.5-0.9
2.	Factor Loadings/ Outer Loadings	To evaluate which indicator is consistent.	Indicator Loading/ indicator Reliability	Hair et al., 2016; Henseler et al., 2016	> 0.5-0.90
3.	Convergent Validity	To identify which individual indicator reflect a construct converging in comparison to indicator measuring other construct.	Average Variance Extracted (AVE)	Urbach and Ahlemann, 2010; Hair et al., 2014; Hair et al., 2017	> 0.5-0.90
4.	Discriminant Validity	Which indicator differentiates across construct measures distinct concept by examining the correlation between the measures of potentially overlapping.	Cross Loading	Loading of each indicator are highest for the designated construct. The difference between loading and across latent variables must not be less than 0.1.	
			Fornel and Larker's Criterion	The square root of AVE of construct should be larger than correlation between the construct and other construct model.	
			(HTMT) Criterion	Kline,2011; Henseler 2015	< 0.85- 0.90

3.15 The Measurement Model

The second component of a PLS-SEM encompasses the measurement model or outer model that graphically presents the unidirectional predictive association among every latent construct and its correlated cues (Hair, Ringle, & Sarstedt, 2011). In continuation of a preceding discussion on the abstract, the unobservable and therefore not measurable nature of latent variables and the indicators (manifest variables) serve collectively as surrogates and are assumed to represent the constructs that they are associated with. The individual indicators can be further understood as observed scores obtained through self-report, interview, observation, or some other means (Edwards & Bagozzi, 2000).

3.16 Reliability

The PLS model analysis consists of two essential tasks, i.e. reliability and validity evaluation of the measurement model and appraisal of the structural model. The consistency of the measurement model was evaluated by analysing the loading factors. Assessment of Cronbach‗s α and internal consistency (ρη) measurement developed by Fornell and Larcker (1981) were also used to assess convergent validity. Meanwhile, to measure the square of each outer loading, it was essential to identify the reliability of the indicators and Cronbach's value of 0.70 or higher was acceptable. Nonetheless, if the research was conducted based on exploratory approaches, a Cronbach value as low as 0.4 is preferred (Hulland, 1999). Composite and Internal Consistency Reliabilities should be at a minimum Cronbach value of 0.7. In the same principle, if the study was executed based on the exploratory investigation, a minimum Cronbach value of 0.6 is acceptable (Bagozzi & Yi, 1988).

Finally, all the measurement items were loaded into individual latent attributes and then the loading values were evaluated. If an item failed to achieve the cut-off condition of at least 0.707, the element was considered unacceptable. Thus, to measure internal consistency, composite reliability (ρη) analysis was applied in this study (Fornell & Larcker, 1981). The composite reliability level defined the Cronbach's alpha for each construct, and it was screened to ensure the condition was achieved at a value greater than 0.7. The screening revealed that the condition was met for all the constructs. Traditionally, the Cronbach's α coefficient is used to determine the internal consistency reliability in the social sciences domain but later it offered conventional measurement for PLS-SEM. Past empirical studies suggested the use of the term composite reliability as a lexical substitution for Cronbach's alpha coefficient (Bagozzi & Yi, 1988; Hair et al., 2012).

Reliability is defined as the degree to which the scales yielded consistent outcomes if the procedures are repeated (Malhotra, 2010). Moreover, reliability is a researcher's first point of investigation regarding the measurement model as an unreliable measurement cannot be valid (Malhotra, 2010). Concerning measurement models, reliability was assessed by examining alpha coefficient ($a < 0.7$) and if it is not assumed to be equivalent, composite reliability ($a < 0.6$). Formative indicators are not necessarily expected the covariance and thus such an internal consistency reliability analysis is inappropriate (Diamantopouls et al., 2001). As noted by Coltman et al. (2008), there are no globally accepted conditions to assess the consistency of formative indicators. Therefore, to achieve these criteria, the data went through several stages of elimination and the measurement scales were modified. First, loaded items with a value below 0.6 were discarded and new loading values were calculated. The same procedure was repeated several times until only the items with a loading rate of more than 0.707 were kept in the pool. The cut-off point of 0.707 showed that the construct kept the variance at a minimum value of 50% on each item.

3.17 Validity

Data analysis was conducted based on two steps. First, the SmartPLS measurement model was constructed by employing two first-order latent variables as the independent (preventive maintenance) and dependent (manufacturing performance) variables. To evaluate convergent validity, the Average Variance Extracted (AVE) that illustrates the variance distributed between a construct and its measures, was used. The AVE for each construct should be at least 0.5 for convergent validity to be met. A screening of AVE values by SmartPLS software revealed whether the condition was met or not. To evaluate the discriminant validity, two types of tests were primarily applied. Firstly, the association between constructs was used to check whether the value was below the square root of each construct‘s AVE (Chin, 1998). If every item loaded greater on its own construct than other constructs, additional support for discriminant and convergent validity was established (Gefen, Straub & Bourdreau, 2000). Convergent validity value must be lower than 0.5 (Bagozzi & Yi, 1988). Fornell and Larcker (1981) opined that the square root of AVE for every latent attribute must be higher than the correlation values among latent attributes to achieve the standard discriminant validity value.

Hair (2013) described that validity as the extent to which a set of indicators measures based on what it asserted to measure and there is no significant measurement of errors. Thus, validity is known as the degree of divergence in the scores of observed scales that mirror the definite differences among the respondents based on the features being measured (Malhotra, 2010). The validity of a set of reflective indicators is assessed by demonstrating convergent and discriminant validity. Convergent validity can be defined as the degree of scales positively correlate with other events in the same construct (Durbach, 2010). This validity is assessed via two ways: 1) factor loadings (the simple correlation between indicator and construct) should be statistically significant at >0.7, and 2) AVE must be >0.5 which indicates that the latent factor explains, on average, more than 50% of the variance in individual indicators. Convergent validity for formative indicators is not relevant as such indicators are not assumed to covary (Freeze & Raschke, 2007). In contrast, discriminant validity attempts to establish that each construct is truly distinct from other constructs in the model and hence makes a unique contribution (Malhotra, 2010). Cross-loadings would be indicative of problematic discriminant validity (Malhotra, 2010). Discriminant validity is assessed by examining the Fornell and Larker (1981) conditions in which discriminant validity is demonstrated if AVE for a construct is more than the square of the construct's correlation with all other factors. In short, a construct should explain more variation in its own indicators than of any other constructs in the model. Discriminant validity for formative indicators can be demonstrated in a similar manner (MacKenzie, Podsakoff & Jarvis, 2005). If the measurement model is shown to be sufficiently reliable and valid, the focus of the analysis should proceed to structural model evaluation.

3.19 Structural Model Evaluation and Hypothesis Testing

Evaluation of the SEM structural model primarily included the assessment of absolute fit measures, incremental fit measures, and parsimony fit indices. However, there are no globally accepted goodness-of-fit measures for PLS-SEM (Hair et al., 2012). Instead, evaluation of the inner model is commonly accomplished through interpretation of the coefficient of determination (R^2) for endogenous latent variables and assessment of magnitude and significance of estimated path coefficients (Hair, Ringle & Sarstedt, 2011). The coefficient of determination is an index of the relative fraction of variation in a latent variable constructed or accounted for by its antecedents (Churchill & Iacobucci, 2010).

The general research objective is to achieve a high R^2 for the study‘s key constructs; what threshold level may be regarded as high _differs according to the domain of each study. An R^2 of 0.2 is perhaps considered as a better coefficient in certain domains while an R^2 of 0.75 could be the minimum accepted coefficient value in areas such as marketing (Hair, Ringle & Sarstedt, 2011). The level and significance to compute the path coefficients are further assessments in the structural model. These path coefficients are estimated via the resampling procedure known as bootstrapping that facilitates the hypothesis testing process (Hair et al., 2012). The structural model is considered valid only to the extent that the proposed hypotheses are supported (Malhotra, 2010).

3.20 Coefficient of Determination, R^2

This was the first criterion for the assessment of PLS-SEM, in which each endogenous latent variable‘s coefficient was measured by examining the coefficient of determination. According to Breiman and Friedman (1985), the criterion R^2 is critical in evaluating a structural model, as it measures the amount of variation of each endogenous construct accounted by the exogenous construct. Chin (1998) considers values of around 0.670 as substantial, 0.333 as average, and 0.190 and lower as weak.

3.21 Effect Size, f^2

Effect size measures if an independent variable has a substantial impact on dependent variables (Cohen, 1988). It is calculated as the increases in R^2 of the independent variable to which the path is connected, relative to the dependent variable‘s proportion of unexplained variance. Values between 0.020 and 0.150, 0.150 and 0.350, and exceeding 0.350 indicate whether a predictor (independent variable) has a small, medium or large effect on a dependent variable, respectively. As such, the effect size was calculated using Cohen‘s f^2 formula (Cohen, 1988).

3.22 Predictive Relevance, Q^2

According to Chin (2010), Q^2 statistics is a measure of the predictive relevance of a block of manifest variables. The structural model‘s predictive relevance can be assessed using the nonparametric Stone-Geisser test (Stone, 1974; Geisser, 1975). Q^2 values indicate how well-observed values are reconstructed by the model and its parameter estimates. Positive Q^2 values confirm the model‘s predictive relevance in respect of the particular construct. On the other hand, a less than zero Q^2 value implies that the model lacks predictive relevance. Therefore, the proposed threshold value is $Q^2 > 0$ (Fornel & Cha, 1994). Table 3.4 lists the rule of thumb for structural model analysis that was employed in this study.

Table 3.4
Rule of thumb for structural model analysis
Source Adopted from Ramayah et al., (2017)

No	Assessment	Name of Index	Level of Acceptance	Literature Support
1	Lateral Collinearity	Variance Inflator Factor (VIF)	VIF <3.3 VIF <5.0	Diamantopoulos and Sigouw (2006)
2	Path Coefficient	Path Coefficient	$p < 0.01$ $t > 2.58$ (2-tailed) $t > 2.33$ (1-tailed)	Hair et al., (2017)
			$p < 0.05$ $t > 1.96$ (2-tailed) $t > 1.645$ (1-tailed)	
			$p < 0.10$ $t > 1.645$ (2-tailed) $t > 1.28$ (1-tailed)	
3	R^2	Coefficient of determination	0.26-Substantial 0.13-Moderate 0.02-Weak	Cohen (1986)
			0.67-Substantial 0.33-Moderate 0.19-Weak	Chin (1998)
			0.75-Substantial 0.50-Moderate 0.25-Weak	Hair et al., (2017)
4	f^2	Effect size to f^2	0.35-Substantial effect 0.15-medium effect size 0.02-Small effect size	Cohen (1988)
5	Q^2	Stone-Geisser Q^2 Predictive relevance	Value larger than 0 indicates that exogenous constructs have predictive relevance for endogenous constructs	Hair et al., (2017); Stone (1974)
6	q^2	Effect Size of q^2 (Optional)	0.35-Substantial 0.15-Moderate 0.02- Weak	Hair et al., (2017)

3.23 Assessing Moderation in PLS-SEM

Potency and/or path of relationship dependency between two latent variables may change or be contingent upon the presence of a third variable. In such cases, the third variable is termed a moderating variable (Little, Bovaird & Card, 2007). In this study, technological capabilities were the moderator for the relationship between preventive maintenance and the performance of manufacturing organizationss. Finding statistical support for such interactive effects can be troublesome with much of the difficulty attributed to measurement error resulting from the use of surveys and other observational methods. Indeed, only 21% of moderators tested in the field of manufacturing organization were found to be significant (Chin et al., 2003). Furthermore, even if such moderators were detected, they generally made negligible contributions to theory development as measured by their slight increase in variance (R^2) (Chin et al., 2003).

The lack of empirical support for hypothesized moderator variables suggested by Chin et al. (2003) to be a by-product of the analytic method used to oppose theoretical development flaw. They also concluded that the perpetual null results may be a moderating effect and are not only detected by analytical methods. Typically, researchers relied on ANOVA and/or multiple-linear regression analysis to assess moderating effects. Nonetheless, the technical assumption of infallible measures resulted in measurement error being a primary issue in the approaches (Chin et al., 2003). However, in this study, SEM represented the essential moderating effect as it directly addressed the existence of measurement errors in the statistical model (Little et al., 2007).

Most approaches related to modelling interactive effects within SEM models followed Kenny and Judd‗s (1984) product-indicators technique that is heavy with complex constraints (Little et al., 2007). Generally, the approaches were used to create novel variables as the product of variable being moderated (say X) and variable that is moderating (say W). This latent interaction term (the multiplicative XW) is then included in the model and its significance and effect size are assessed along with every other latent variable in the model. If the interactive terms are shown to be significant, it can be concluded that a statistically significant relationship is presented between X and Y. Although it is a proactive solution, Chin et al. (2003) noted that this approach is technically demanding and hence developed another approach that can overcome the problems of the traditional analytical technique.

As an alternative, Chin et al. (2003) conceptualised using the product indicator approach within the easy-to-use PLS context. This one-step product indicator technique has less restrictive assumptions and has been shown to produce more accurate estimations allowing researchers to better detect moderating effects. Akter et al. (2011) noted that this approach can improve researchers‘ ability to validate their theoretical models. In this study, the hypothesised moderating effect was assessed in accordance with the guidelines charted by Chin et al. (2003). This multiplicative indicator was standardised to prevent computational errors by lowering the collinearity (Smith & Sasaki, 1979). The resultant interactive term was then subjected to the PLS algorithm along with the other hypothesised relationships in the final conceptual model.

3.24 PLS-SEM Model Assessment

One of the challenges in survey-based research is the selection of an appropriate statistical model for analysis. PLS-SEM and Covariance-based Structural Equation Modelling (CB-SEM) are two well-known multivariate data analysis methods (Bagozzi & Yi, 1988; Götz, Liehr-Gobbers & Krafft, 2010; Lowry & Gaskin, 2014).

CB-SEM is based on the concept of factor analysis, which is suitable for theory testing. It uses maximum likelihood estimation, whereas PLS-SEM is based on the principal component concept (which is suitable for theory building) and uses the PLS estimator (Hair, Ringle & Sarsted, 2011; Lowry & Gaskin, 2014; Vinzi, Chin, Henseler & Wang, 2010). PLS variance-based SEM is widely applied in business management research, including operations management (Carter, Sander & Dong, 2008; Peng & Lai, 2012; Shah & Goldstein, 2006), information systems management (Urbach & Ahlemann, 2010), marketing management (Hair, Sarstedt, Ringle & Mena, 2012), and organizationsal behaviour and human resource management (Anderson & Gerbing, 1988). PLS-SEM was chosen for this study because it is: 1) suitable for theory building studies (Vinzi et al., 2010; Sarsted, 2008); 2) considered appropriate for examining complex cause-effect-relationship models (Henseler, Ringle & Sinkovics, 2009; Lowry & Gaskin, 2014); and 3) a non-parametric approach and poses fewer restrictions, especially on data distribution and sample size (Vinzi et al., 2010). To test the hypothesis, SmartPLS 3 software was used (Ringle et al., 2014). PLS-SEM approach was employed to assess the measurement model (also referred to as the outer model) and structural model (also referred to as the inner model). Figure 3.2 provides more details of the chosen approach.

3.25 Construct Development

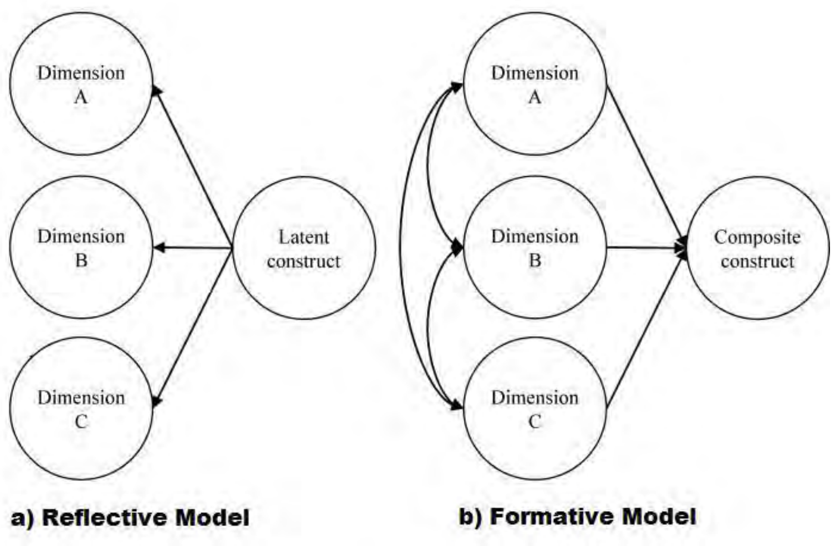

Figure 3.2
Specifying reflective and formative measurement models Source (Petter et al., (2007)

Figure 3.2 illustrates the formative and reflective measurement models. According to Diamantopoulos et al. (2008), reflective models are characterised in two ways, namely: 1) a change in the latent variable causes variation in all measures simultaneously, and 2) all indicators in a reflective measurement model must be positively intercorrelated. On the other hand, Petter et al. (2007) stated that the formative model is not used to account for observed variances in the outer model, but rather to minimise residuals in the structural relationship. In fact, formative indicators determine the latent variable that receives its meaning from the former (Diamantopoulos et al., 2008).

Other than that, Diamantopoulos and Winklhofer (2001) pointed out four distinct characteristics of a formative model. These include: 1) formative indicators characterise a set of distinct causes, which are not interchangeable, as each indicator captures a specific aspect of the construct‘s domain; 2) there are no specific expectations about patterns or magnitude of inter-correlations between indicators; 3) formative indicators have no individual measurement error terms (i.e., they are assumed to be error-free in a conventional sense; and 4) while reflective measurement models with more than two indicators are identified and can be estimated, a formative measurement model in isolation is under-identified and cannot be estimated. Haenlein and Kaplan (2004) and Petter, Straub and Rai (2007) stated that if the indicators cause the latent variable and are not interchangeable among themselves, they are formative. However, Haenlein and Kaplan (2004) and Hair et al. (2013) postulated that if the indicators are highly correlated and interchangeable, they are reflective, and their reliability and validity have to be carefully inspected. Since all indicators in this study were reflective, the reflective analysis was applied.

3.26 Multidimensional Approach

This study had three independent variables, one moderator, and one dependent variable. Nevertheless, the dependent variable had four separate dimensions, i.e. cost, quality, flexibility, and delivery. Thus, this study used a multi-dimensional approach for analysis. Multidimensional constructs are characterised as having more than one dimension (Edwards, 2001; Jarvis et al., 2003; Law and Wong, 1999; Petter et al., 2007; Polites, Roberts, and Thatcher, 2011; Wetzels, Odekerken-Schröder, and Van Oppen, 2009). In contrast, unidimensional constructs have a single underlying dimension (Netemeyer et al., 2003; Polites et al., 2011; Wetzels et al., 2009).

Edwards (2001) refers multidimensional constructs as ‗several distinct but related dimensions treated as a single theoretical concept‘ and each ‗dimension represents a unique content domain of the broader construct‘ (Polites et al., 2011). That is, while both multidimensional and unidimensional constructs represent a single theoretical concept, they differ in that the latter lacks distinct dimensions (Edwards, 2001; Polites et al., 2011). The use of multidimensional constructs is based on several empirical and theoretical bases (Edwards, 2001; Polites et al., 2011; Wetzels et al., 2009) and has generated considerable debate in the literature. Edwards (2001) stated that this debate has been ongoing for decades and shows little sign of abating. Furthermore, Edwards (2001) recapitulated the views of multidimensional constructs‘ advocates by stating that multidimensional constructs are useful in that they provide holistic representations of complex phenomena, allow researchers to match broad predictors with broad outcomes, and increase explained variance. Additionally, multidimensional constructs allow for more theoretical parsimony (Edwards, 2001; Law et al., 1998; MacKenzie et al., 2005; Wetzels et al., 2009) and allow matching the level of abstraction for predictor and criterion variables (Edwards, 2001; Wetzels et al., 2009). Polites et al. (2011) noted that multidimensional constructs provide an opportunity to advance IS research by enabling the capture of complex concepts in comparatively simple abstractions. Due to their potential in advance theory, multidimensional constructs have appeared with more frequency in top IS journals in recent years. As mentioned previously, constructs are described as multidimensional constructs when their indicators are themselves latent constructs (Edwards, 2001; Jarvis et al., 2003; Law and Wong, 1999; Petter et al., 2007; Polites et al., 2011). These indicators are referred to as dimensions. As such, the basic distinction between the types of multidimensional constructs is the direction of the relationship between a construct and its dimensions (e.g., Edwards, 2001; Law and Wong, 1999; Petter et al., 2007; Polites et al., 2011).

On the other hand, if the relationships point from the construct to its dimensions, the construct is referred to as *superordinate* because ‗it represents a general concept that is manifested by its dimensions‘ (Edwards, 2001), and each dimension ‗represents a different manifestation or realisation of the underlying construct‘ (Polites et al., 2011). In contrast, if the relationships point from the dimensions to the construct, the construct is referred to as *aggregate* because ‗it combines or aggregates specific dimensions into a general concept‘ (Edwards, 2001).

3.27 Measurement Model Analysis

There were five latent constructs examined in this research, namely, time-based maintenance, condition-based maintenance, predictive maintenance (independent variables), technological capabilities (moderator), and manufacturing performance (dependent variable). These constructs were measured in reflective mode whereby constructs were assumed to cause indicators to vary. Time-based maintenance (TBM) had six indicators, whereas condition-based maintenance (CBM) and predictive maintenance (PdM) were measured by seven indicators each. Next, technological capabilities were measured by nine indicators. Manufacturing performance construct had four latent dimensions i.e. cost, quality, flexibility, and delivery, and these had a total of 23 indicators. Furthermore, these latent dimensions were also specified as reflective indicators of their second-order construct, manufacturing performance. PLS requires manifest variables for all latent (or in other words, unmeasured) constructs in a model. Therefore, higher-order constructs cannot be directly included in the model. In this study, higher-order constructs in PLS were modelled using a two-stage approach.

3.28 Two-Stage Approach

The idea of two-stage approach was initially suggested by Chin et al. (2003) and later elaborated by Henseler and Fassott (2010). These authors recognised that if an exogenous variable or moderator variable is formative, the pairwise multiplication of indicators is not feasible. This is because ‗since formative indicators are not assumed to reflect the same underlying construct (i.e., can be independent of one another and measuring different factors), the product indicators between two sets of reflective indicators will not necessarily tap into the same underlying interaction effect' (Chin et al., 2003). Instead of using the product indicator approach, Henseler and Fassott (2010) similarly proposed the two-stage PLS approach for estimating moderating effects, especially when formative constructs are involved. This two-stage approach makes use of PLS path modelling advantage of explicitly estimating latent variables‘ scores. The two stages are as follows:

Stage 1: In the first-order, the main effect PLS path model is run to obtain estimates for the latent variable scores. The latent variable scores are then calculated and saved for further analysis.

Stage 2: In the second-order, the interaction term is built as the element-wise product of the latent variable scores of the exogenous and moderator variables.

This interaction term and the latent variable scores were used as independent variables in a multiple linear regression on the latent variable scores of the endogenous variable. The two-stage approach implemented in this research. Even though the latent variable scores are standardised, the interaction term is not and should not be. If the interaction term was standardised, it is difficult to quantify an interaction effect, because an interpretation as illustrated at the basis of Equation 2 would not be feasible anymore. Although the latent variable scores are estimated in the first-order, they are used in the second stage to determine coefficients of the regression function in the form of Equation 1.

The second stage can be realised by multiple linear regression or be implemented within PLS path modelling by means of single-indicator measurement models. Although Chin et al. (2003) and Henseler and Fassott (2010) limited use of the two-stage approach to cases when exogenous or moderator variable or both are formative, this limitation is not mandatory. It can also be applied to reflective measurement models with interaction effects among latent variables. The fact that the two-stage approach is a limited-information approach was a key reason for Chin et al. (2003) to prefer product indicator approach.

3.24 Repeated Indicators Approach

In repeated indicators approach, first-order dimensions of a construct are measured by their manifest indicators and then, these first-order dimension indicators are applied as indicators of the second-order construct (Chin, Marcolin, and Newsted, 2003). Thus, indicators of first-order dimensions are used twice in the model. This approach works well when the number of indicators is equal for all the first-order dimensions (Chin, Marcolin, and Newsted, 2003). In this two-stage approach, measurements happen in two stages. In the first-order, the model is run with only first-order constructs with their manifest indicators. In this study, it was the four latent constructs (TBM, CBM, PdM, and TC) and their manifest indicators (cost, quality, flexibility, and deliver) (refer to Figure 4.2).

In the second stage, second-order constructs are introduced in the model with the latent variable scores computed for first-order dimensions as their manifest variables. In this study, the four latent variables (TBM, CBM, PdM, and TC) were constructed to the dependent variable, manufacturing performance. A disadvantage of this method is that the second-order construct appears only in the second stage and is not included in the first-order when the latent variable scores are computed for the latent dimensions (Ciavolino and Nitti, 2013).‖

This study used the two-stage approach for modelling manufacturing performance. Since the number of indicators for the first-order dimensions was not equal, the two-stage approach was preferred. Furthermore, two-stage approach has been used for reflective higher-order constructs (Agarwal and Karahanna, 2000). In the present study, manufacturing performance construct was modelled as a second-order construct consisting of four first-order latent dimensions namely cost, quality, flexibility, and delivery. This model was specified as reflective at both first and second order-levels. Such a model with reflective measurement at both first and second-order levels is called a Type-I model (Jarvis, Mackenzie, and Podsakoff, 2003) and a total disaggregation second-order factor model (Baggozi and Hearthertons, 1994).

3.25 Conclusion

This chapter had thoroughly elaborated this study‘s methodology. Information regarding research techniques, procedures employed to identify the population, sampling procedures, and rationale for using the proposed approaches were highlighted. Furthermore, information on measuring instruments, data gathering procedures, and data analysis techniques to verify the proposed hypotheses were elaborated. The following chapter will demonstrate the results obtained from the implementation of the proposed methodology.

CHAPTER FOUR

DATA ANALYSIS

4.1 Introduction

This chapter presents the outcomes of data analysis. SmartPLS v. 3.2.7 was employed to extract and analyse the responses from the respondents. The goal of this study was to examine the moderating role of technological capabilities in the relationship between preventive maintenance practices and the performance of manufacturing organizationss in Malaysia. The following sections comprehensively discuss all relevant information regarding the procedures and data analysis results.

4.2 Response Rate

Data collection started on 1st November 2017 and ended in March 2018 (5 months). Letters were mailed to 600 selected organizationss across Malaysia. Each letter contained an introductory cover letter, the survey questionnaire, and a postage-paid self-addressed envelope. The postal addresses were gathered from FMM's 2017 directory. Dillman (2000) mentioned mail and internet surveys practices improve the response rate of any empirical survey. This study adopted similar practices to encourage respondents to respond. First, the respondents were assured regarding the secrecy of their response and were offered a summary of the results if they replied. Second, a self-addressed and stamped envelope was provided to encourage the respondents to return the completed questionnaire. Third, the questionnaire was accompanied by an introductory cover letter that explained the main study objectives and its contribution to the Malaysian manufacturing sector.

4.3 Adequacy of Sample Size

This study employed G-power tool to determine the adequate sample size. According to Button, Ioannidis et al. (2013), G-power is the probability of detecting a true effect when it exists. In this study, F-test-linear multiple regression fixed model R^2 deviation from zero statistical test was applied to identify the sample size. Brown and Benedetti (1977) stated that effect size (f^2) refers to the magnitude of the result as it occurs, or would be found, in nature, or in a population. When researchers estimate effect sizes by observing representative samples, they generate an effect size estimate. This estimate is usually expressed in the form of an effect size index. Meanwhile, alpha (α) represents the probability of making a Type I error while beta (β) the probability of making a Type II error (Lyles, Lin & Williamson, 2007). On the other hand, Erdfelder, Faul and Buchner (2005) explained that the critical level of alpha to determine either a result can be judged statistically significant or vice versa is conventionally set at 0.05. When this standard is adopted, the likelihood of making a Type I error, or concluding there is an effect when there is none, cannot exceed 5%. Statistical power is inversely associated with beta or probability of making a Type II error. Simply put, power = $1 - \beta$ (Armitage, Berry & Matthews, 2002).

The power of any statistical significance test is the probability of it to reject the false null hypothesis. If the statistical power is high, then the probability of making a Type II error, or concluding there is no effect, if in fact there is one, goes down (Benton & Krishnamoorthy, 2003). Statistical power is primarily affected by the size of the effect and the size of the sample used to detect it. Huge changes are easier to detect than smaller ones, while large samples offer better test sensitivity compared to smaller ones (Muller, LaVange, Landesman-Ramey & Ramey, 1992). After calculating the corresponding sample size using G-power, the required sample size was identified as

103. As such, the sample size of 155 was deemed adequate as it was more than the one suggested by G-power software.

4.4 Respondent Descriptive Details

Table 4.1
Summary of Total Company Implementing Preventive Maintenance

	Frequency	Percent
YES	155	100%
Total	155	

Table 4.1 presents the demographic analysis results for the question ‗does your company implement preventive maintenance'. All 155 manufacturing organizationss agreed that they implemented preventive maintenance (refer to Appendix B).

Table 4.2
Summary of Respondents Position in Their Company

	Frequency	**Percent**
Chief Executive Officer	12	7.7
Operations manager	78	50.3
Quality manager	33	21.3
Maintenance Manager	21	13.5
Low level Managerial Post	11	7.2
Total	155	100%

Table 4.2 shows that the majority of respondents were operation managers (78 respondents; 50.3%). Meanwhile, there were 33 and 21 quality managers and maintenance managers, respectively. Next was Chief Executive Officer with 12 respondents. Finally, low-level managerial posts (maintenance officers, maintenance engineers, and production supervisors) had the lowest number of respondents with 11.

Table 4.3
Summary Type of Company

	Frequency	Percent
Joint venture	22	14.2
Multi National Corporation (MNC)	80	51.6
Private Limited (Sdn Bhd)	53	34.2
Total	155	100%

Three types of organizationss were listed in the questionnaire to classify respondents' background. Results indicated that 80 organizationss were Multi-National Corporation (MNC), followed by Private Limited (Sdn Bhd) with 53 organizationss and joint venture with 22.

Table 4.4
Summary of Companies Annual Sales Turnover

	Frequency	Percent
Less than RM300,000	33	21.3
RM 300,000 - RM 15 million	98	63.2
More than RM 15 million	24	15.5
Total	155	100%

From the information gathers on the gains the companies made yearly, most companies sales are around RM300 thousand to RM15 million. It is about 63.2% or 98 out of 155 companies. Moreover, 33 companies or 21.43% gain profit less than RM300 thousand and 24 companies have more than RM15 million sales turnover annually.

Table 4.5
Summary of Total Employees in Company

	Frequency	Percent
5 to 75	40	25.8
76 – 200	72	46.5
More than 200	43	27.7
Total	155	100%

Table 4.5 indicates the number of employees in a company. The result shows that 72 companies hired around 76 – 200 employees. While (43 companies or 27.7%) have more than 200 employees. In fact, there is a small portion of 40 companies with a small number of employees between 5 and 75 employees.

Table 4.6
Summary Companies Production Category

	Frequency	Percent
Foods products	24	15.5
Rubber-based/plastic	43	27.7
Electrical/electronic	33	21.3
Petroleum/Petrochemical/chemical	34	21.9
Machinery/equipment Basic metal product	21	13.5
Total	155	100%

Table 4.6 shows the production categories of organizationss surveyed in this study. It was discovered that the rubber-based/plastic category registered the highest response rate with 43 organizationss. Meanwhile, the second-largest respondents were from the petroleum/petrochemical/chemical product (34 companies) followed by electrical/electronic category (33 companies). Finally, foods products category represented 15.5% of the total response rate while 21 organizationss belonged to the machinery/ equipment/ basic metal product category. In summary, rubber-based/ plastic and electrical/ electronic categories formed the largest respondents in this study.

4.5 Model Estimation

SmartPLS software used for PLS path model analysis. The result of PLS algorithm calculation is shown in Figure 4.1 with independent variables, dependent variable, the relationship among variables, and all indicators of variables. Outer Loadings values for indicators of reflective and formative construct outer weights of indicators constructs are also shown.

4.5.1 Evaluation of Measurement Model

The measurement model is the part of the model that examines the relationship between the latent variables and their measures. To test the measurement model, this study was examined the Composite reliability (CR), Outer loadings and Average variance extracted (AVE) by allowing all the latents to correlate. Evaluation of measurement Model is carried out by assessment of Reflective measurement models.

4.5.2 Assessment of Reflective Measurement Models

It includes assessments of

i. Composite reliability to evaluate internal consistency,
ii. Outer loadings of indicators for individual indicator‘s reliability
iii. Average variance extracted (AVE) to evaluate convergent validity.
iv. Fornell-Larcker criterion and cross loadings to assess discriminant validity.

4.6 First Order Measurement Process

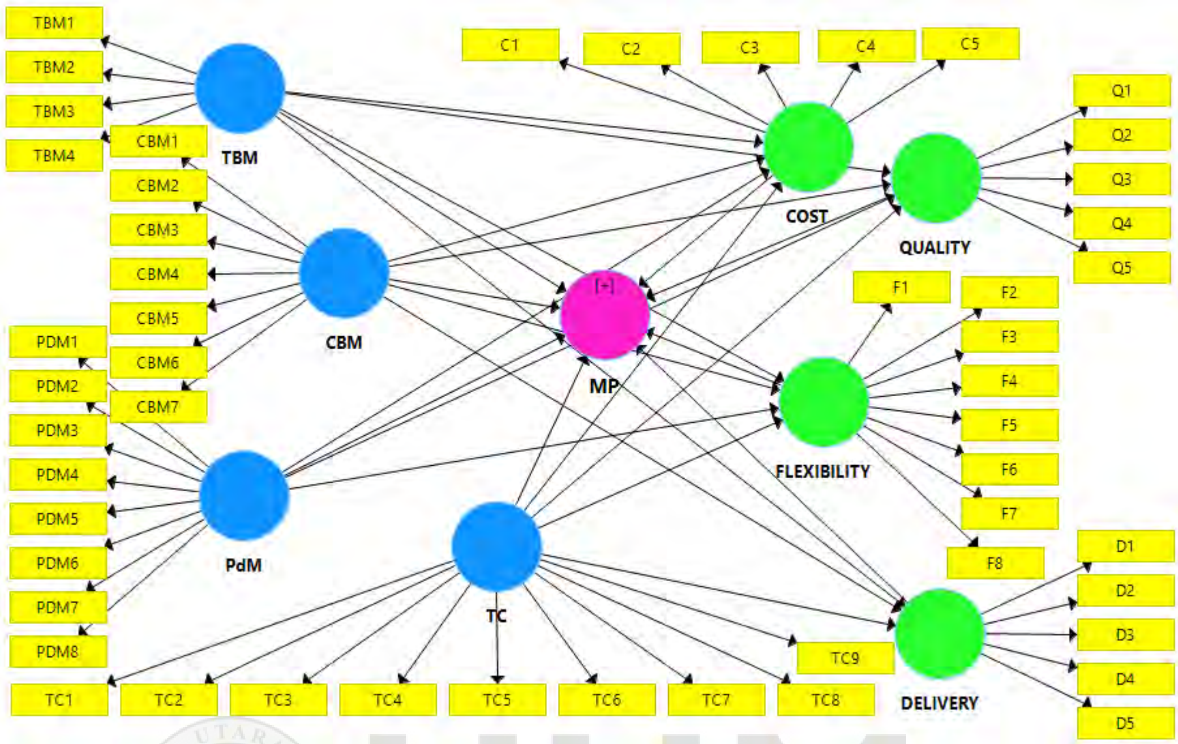

Figure 4.1
1st stage Measurement Model

Figure 4.1 show the first stage measurement model of this study. All four variables, time-based maintenance (TBM), condition-based maintenance (CBM), predictive maintenance (PdM) (independent variables), and technological capabilities (TC) (moderator), were connected manufacturing performance (MP) (dependent variables) which has four dimensions of (cost, quality, flexibility and delivery). There are total 51 items in this model; TBM (4 items); CBM (7 items); PdM (8 items); TC (9 items); Cost (5 items); Quality (5items); Flexibility (8 items); Delivery (5 items). Before proceeding to the second stage, it was ensured that the first stage fulfilled the minimum required values for loading, composite reliability, and AVE, as shown in Table 4.7.

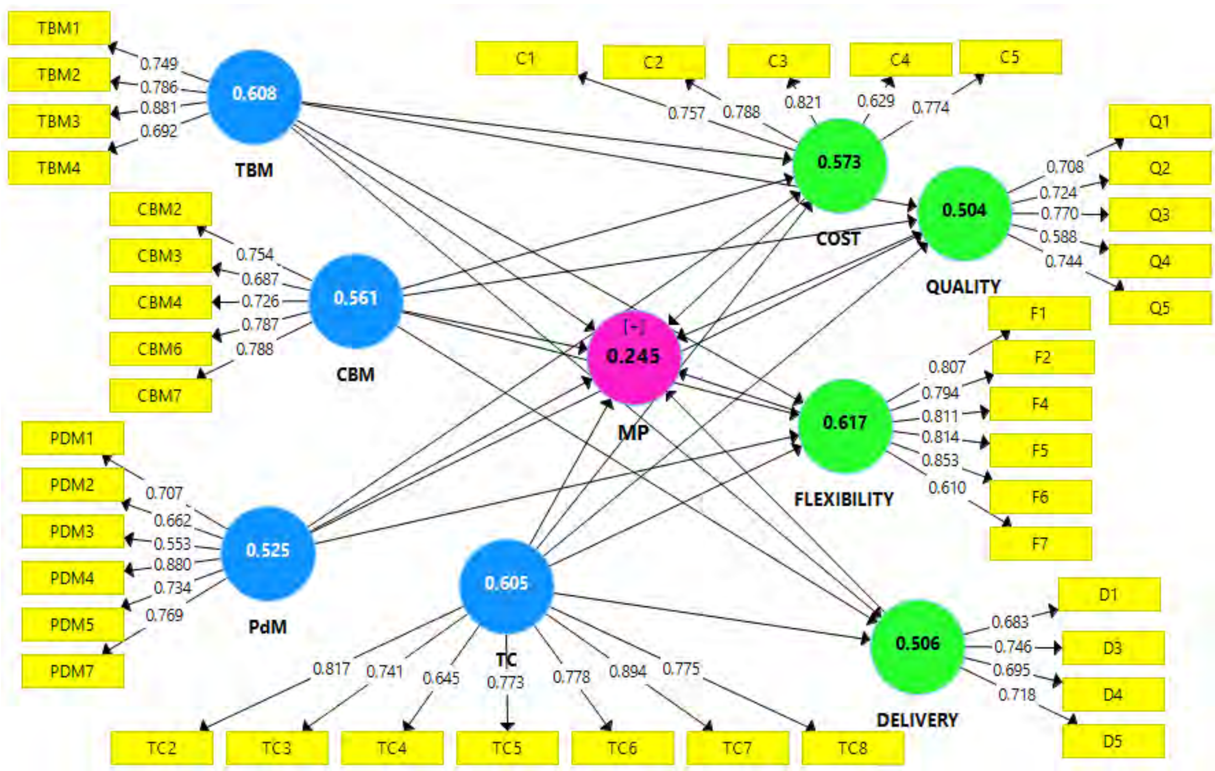

Figure 4.2
PLS Path Model after PLS Algorithm calculation.

Figure 4.2 illustrates the summary of the path model of this study for the first stage measurement model. The entire construct met the minimum composite reliability (CR) and AVE values of above 0.5. This equals to the minimal threshold point highlighted by Hair, Babin, and Krey (2017). If a construct does not meet adequate AVE and CR values (above 0.5), thus, the lowest loading, i.e. below 0.4, should be deleted until the satisfactory value of AVE is achieved. Nevertheless, Hair, Babin, and Krey (2017) mentioned that it is important not to delete more than 20% of total items in the measurement model. However in this study from total 51 items only 15% or (9 items) was deleted due to lower loading values it was (CBM 1 &5; PdM 2&8; TC 1&9; F 3&8; D2). Finally 42 indicators were retained for further analysis. According to Hair, Babin, and Krey (2017) and Hair et al. (2010), if measurement model delete more than 20% of total items, the whole research moves into adopting Exploratory Factor Analysis (EFA) rather than Confirmatory Factor Analysis (CFA). However in this study only 15% of total items were deleted. Thus this study use Confirmatory Factor Analysis (CFA) to conduct further analysis.

4.7 Validity and Reliability Result

Table 4.7
Summary of Construct Validity of First stage

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Measurement Model			
Time-based maintenance (TBM)	0.786	0.860	0.608
Condition-based maintenance (CBM)	0.805	0.865	0.563
Predictive Maintenance (PdM)	0.805	0.852	0.500
Technological Capabilities (TC)	0.891	0.914	0.606
Latent Dimensions			
Cost	0.811	0.868	0.569
Quality	0.750	0.833	0.500
Flexibility	0.874	0.904	0.614
Delivery	0.674	0.803	0.505

Table 4.7 shows summary of the validity and Reliability Result for first stage. As reported in several studies (Djikstra and Henseler, 2015; Byrne, 2016; Hair et al., 2016, 2017), validity and reliability of a measurement can be assessed by checking whether the item total correlations exceed 0.50. Based on the results presented in Table 4.7, all item-to-total correlations exceeded 0.50. Moreover, in Table 4.7, Cronbach‘s alpha and CR values of all reflective constructs are reported and Cronbach‘s alpha values ranged from 0.674–0.891, which were acceptable for exploratory research. Moreover the Loading, CR, and AVE values were above 0.5 the minimum criteria suggested by Hair et al. (2017). Thus, it can be assumed that the assessment of validity and reliability of the scores of all latent variables and four dimensions met the adequate level.

Table 4.8
Summary of Effect size R^2 result for First Order

	R Square (R^2)	Effect Size
Cost	0.102	Small
Delivery	0.030	Small
Flexibility	0.041	Small
Quality	0.118	Small

Table 4.8 lists the R^2 results for the four latent dimensions (cost, quality, flexibility, and delivery). Henseler et al. (2009) defined effect size as ‗the increase in R^2 relative to the proportion of variance of the endogenous latent variable that remains unexplained'. Cohen (1988), Henseler et al. (2009), and Kura and Kura (2016) suggested effect size values of 0.02 (small), 0.15 (medium), and 0.35 (large). Hence, the four latent variables, namely cost, quality, flexibility, and delivery , had a small effect size, in which R^2 value was in range between 0.030-0.118 Overall, the results indicate that this measurement model was applicable for further analysis (second-order).

Table 4.9
Indicators Factor Loading Value Result for First Stage

Measurement Model	**Indicators Code**	**Factor Loading**
Time-based maintenance (TBM)	TBM1	0.744
	TBM2	0.784
	TBM3	0.885
	TBM4	0.693
Condition-based maintenance (CBM)	CBM2	0.770
	CBM3	0.710
	CBM4	0.691
	CBM6	0.779
	CBM7	0.796
Predictive Maintenance (PdM)	PDM1	0.785
	PDM3	0.629
	PDM4	0.701
	PDM5	0.662
	PDM6	0.676
	PDM7	0.741
Technological Capabilities (TC)	TC2	0.824
	TC3	0.753
	TC4	0.650
	TC5	0.768
	TC6	0.769
	TC7	0.892

	TC8	0.771
Cost	C1	0.705
	C2	0.797
	C3	0.826
	C4	0.681
	C5	0.752
Quality	Q1	0.717
	Q2	0.701
	Q3	0.784
	Q4	0.611
	Q5	0.716
Flexibility	F1	0.801
	F2	0.773
	F4	0.824
	F5	0.804
	F6	0.865
	F7	0.607
Delivery	D1	0.645
	D3	0.757
	D4	0.687
	D5	0.749

Based on Table 4.9, the loading value results for all indicators were at an appropriate level, i.e. above 0.5 as proposed by Hair et al. (2017). Indicator reliability was assessed using the outer loadings as shown in Table 4.10. This represents how much of the variation in an item is explained by a variable (Hair et al., 2013). A higher outer loading on a variable indicates that the associated measure has much in common, that is measured by the variable (Hair et al., 2013). Hair, Hult, Ringle, and Sarstedt (2013) suggested that items having a loading of >0.70 should be retained, items having an outer loading value >0.5 As such, the cross-loading output confirmed that the second assessment of the measurement model's discriminant validity is satisfied. therefore This study, concludes that the measurement model had established its discriminant validity.

Table 4.10
Summary of Fornell- Larker Criterion (Discriminant Validity)

	CBM	COST	DELIVERY	FLEXIBILITY	PdM	QUALITY	TBM	TC
CBM	0.750							
COST	0.119	0.757						
DELIVERY	-0.019	0.368	0.711					
FLEXIBILITY	-0.067	-0.072	-0.070	0.783				
PdM	0.004	0.238	0.196	0.108	0.724			
QUALITY	0.094	0.717	0.482	-0.134	0.293	0.710		
TBM	-0.144	0.148	0.159	-0.111	0.147	0.186	0.780	
TC	0.058	-0.191	-0.069	-0.214	-0.115	-0.162	-0.066	0.778

In this study, the measurement model's discriminant validity was assessed using two measures namely Fornell and Larcker's (1981) criterion and cross-loading. Table 4.10 shows that the square root of AVE for all latent variables was higher than the inter-construct correlations (Fornell & Larcker, 1981) and therefore, the required discriminant validity according to Fornell-Larcker was achieved. Moreover, all indicators' individual loadings were found to be higher than their respective cross-loadings (Hair et al., 2013). This provided additional evidence for discriminant validity.

Table 4.11
Summary of Heterotrait-Monotrait Ratio (HTMT) (Descrimiant Validity)

	CBM	COST	DELIVERY	FLEXIBILITY	PdM	QUALITY	TBM	TC
CBM								
COST	0.176							
DELIVERY	0.163	0.502						
FLEXIBILITY	0.139	0.109	0.159					
PdM	0.118	0.237	0.252	0.148				
QUALITY	0.158	0.622	0.674	0.169	0.332			
TBM	0.218	0.180	0.252	0.138	0.190	0.236		
TC	0.121	0.221	0.141	0.227	0.178	0.206	0.121	

Table 4.11 provides a summary of the Heterotrait-Monotrait (HTMT) ratio for first-order. Henseler et al. (2015) performed simulation studies to demonstrate that a lack of discriminant validity is better detected by the HTMT ratio. In essence, as recommended by Nunnally (1978) and Netemeyer et al. (2003), the HTMT approach is an estimate of the correlation between constructs. According to Kline (2011), technically, HTMT provides two advantages over the disattenuated construct score correlation. According to Garson (2016), in a well-fitting model, heterotrait correlations should be smaller than monotrait correlations, meaning HTMT ratio should be below 1.0, which indicates a lack of discriminant validity. Hence, the constructs in the study satisfied the discriminant validity assessment based on HTMT.

4.8 Review of Measurement Model (First Order)

Each construct in the first-order was assessed through its observed variables (measurement items). In the first-order of model validation, latent variables were assessed in terms of their reliability and validity using three main properties i.e. individual item reliability, convergent validity, and discriminant validity. Individual item reliability was evaluated using factor loading. As shown in Table 4.9, loading value of the measurement item exceeded the recommended value of 0.50, indicating the acceptable level of individual item reliability. On the other hand, convergent validity was assessed using Cronbach‘s alpha, CR, and AVE. In Table 4.7, all the values were above the recommended levels needed for this study, which were 0.60 for Cronbach‘s alpha, 0.70 for CR, and 0.50 for AVE. With satisfactory results for reliability and validity, the stage two was conduct to analyse the structural model to determine the explanatory power of the research model and to test the research hypotheses.

4.9 The Second Order Measurement Model

The second-order constructs, time-based maintenance (TBM), condition-based maintenance (CBM), predictive maintenance (PdM), and technological capabilities (TC), were modelled as measured by their first-order latent dimensions (manufacturing performance) as the reflective indicators. Latent variable scores obtained in the first-order were used as observed values for first-order dimensions. To evaluate the second stage measurement model, PLS-SEM measurement model analysis proposed by Ramayah et al. (2018) was followed, namely: 1) internal consistency; 2) factor loadings/outer loadings; 3) convergent validity; and 4) discriminant validity.

Measurement process of the second-order consisted of analysing, validity and reliability analyses, effect size, measuring loading value, cross-loading analysis, discriminant validity analysis, goodness of fit, and confidence interval result. This ensured all measurement model (MP, TBM, CBM, PdM, and TC) and latent dimensions (cost, quality, delivery, and flexibility) fulfilled the minimum threshold value.

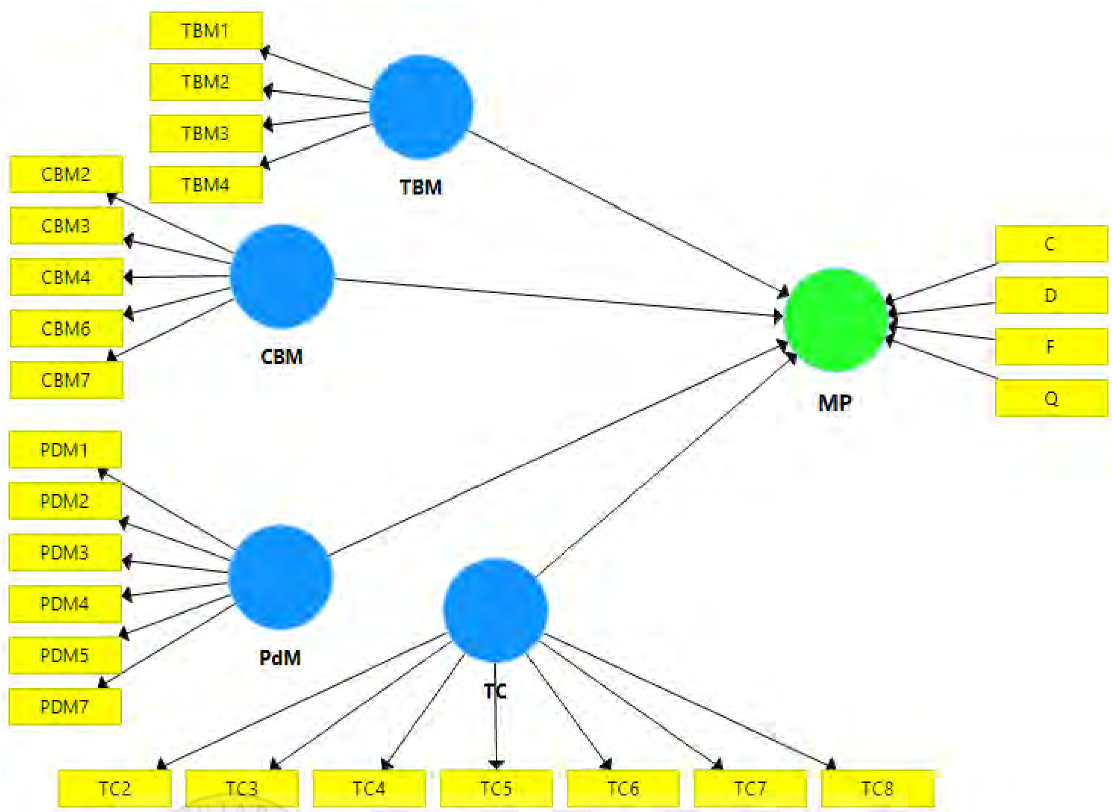

Figure 4.3
Measurement model for2nd Order

Based on figure 4.3, show the measurement model for 2nd order. After the measurement model was conducted independent variables, i.e. TBM, CBM, PdM, and TC, had 22 items TBM (4 items); CBM (5 items); PdM (6 items); TC (7 items) and for manufacturing performance (MP) (dependent variable) has four latent dimensions it was (cost); (quality); (flexibility); (delivery).

4.11 Validity and Reliability Result for Second Order

Table 4.12
Summary of Construct Validity of Second Order

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Measurement Model			
Time-based maintenance (TBM)	0.786	0.800	0.515
Condition-based maintenance (CBM)	0.805	0.803	0.508
Predictive Maintenance (PdM)	0.827	0.866	0.523
Technological Capabilities (TC)	0.891	0.914	0.606

As tabulated in Table 4.12, correlations value was in the range of 0.508– 0.891. Other than that, Cronbach‘s alpha and CR of all reflective constructs showed a higher than minimum range that was suggested by Hair et al. (2017), which is acceptable for exploratory research. Thus, it can be assumed that assessment of validity and reliability of the scores of all latent variables and five measurement items met the adequate level.

Table 4.13
Summary of Effect size f^2 result for Second Order

	R Square (R^2)	Effect Size
Time-based maintenance (TBM)	0.010	Small
Condition-based maintenance (CBM)	0.034	Small
Predictive Maintenance (PdM)	0.072	Small
Technological Capabilities (TC)	0.082	Small

Effect size (f^2) results for the measurement of five variables (TBM, CBM, PdM, TC and MP) are listed in Table 4.13. Henseler et al. (2009) defined effect size as ‗the increase in f^2 relative to the proportion of variance of the endogenous latent variable that remains unexplained‘. Cohen (1988), Henseler et al. (2009), and Kura and Kura (2016) suggested effect size values of 0.02 (small), 0.15 (medium), and 0.35 (large). Therefore, as shown in Table 4.13, TBM, CBM, PdM and TC had a small effect size.

Table 4.14

Summary of Fornell- Larker Criterion for Second Order (Discriminant Validity)

	CBM	PdM	TBM	TC
CBM	0.684			
PdM	0.027	0.723		
TBM	-0.027	0.119	0.718	
TC	0.032	-0.151	-0.056	0.778

Refer table 4.14 the discriminant validity is assessed by using Fornell and Larcker's (1981) criterion. It can be found that all the latent variables was higher than the inter-construct correlations (Fornell and Larcker, 1981) and therefore the required discriminant validity by Fornell-locker has been achieved. Further, all indicators' individual loadings were found to be higher than their respective cross-loadings (Hair et al., 2013).

Table 4.15

Summary of Heterotrait-Monotrait Ratio(HTMT) for Second Order (Descrimiant Validity)

	[CBM]	**[PdM]**	**[TBM]**	**[TC]**
Condition-based maintenance [CBM]				
Predictive maintenance [PdM]	0.108			
Time-based maintenance [TBM]	0.218	0.140		
Technological capabilities [TC]	0.212	0.188	0.121	

Table 4.15 presents the summary of HTMT ratio for second-order. Henseler et al. (2015) conducted simulation studies to demonstrate that lack of discriminant validity is better detected by HTMT ratio. HTMT correlations (Table 4.19) showed that all values were below 1.0, which indicated a lack of discriminant validity among measured variables. Thus, it can be declared that the constructs in this study satisfied the discriminant validity assessment based on HTMT.

4.12 Assessment of Structural Model

Structural model reflects the relationships between the latent variables. The purpose is assessing the structural model whether the data support the proposed conceptualisation. The issues of interest are: (i) whether the directions of the relationships between the constructs are as hypothesised, which can be examined looking at the signs of the respective parameters; (ii) the strength of the hypothesised links, reflected by the estimated parameters, which should be at least significant, i.e., their respective *t*-values should be greater than 1.96; and (iii) the amount of variance in the endogenous variables explained by the respective proposed determinants, which can be evaluated looking at the squared multiple correlations (R^2) for the structural equations.

i. Collinearity issues of structural model

ii. Relevance and Significance of Path Co-efficient

iii. Confidence Interval Bias Corrected

iv. Overall Structural Model result (Q^2, R^2, F^2)

v. Importance performance matrix

4.13 Collinearity issues of structural model

Table 4.16
Summary of Collinearity issue of structural model

	Inner (VIF) Value
Time-based maintenance [TBM]	1.017
Condition-based maintenance [CBM]	1.003
Predictive maintenance [PdM]	1.038
Technological capabilities [TC]	1.026

Table 4.16 lists the inner variance inflation factor (VIF) values for dependent variables. VIF measures the degree of multicollinearity among latent variables that are hypothesised to affect other latent variables (Diamantopoulos & Sigouw, 2006). The collinearity issue of the constructs was assessed by validating VIF values which should be less than 5.00. The VIF is assessed for reflective constructs, whereby in this study, it was the manufacturing performance construct. As shown in Table 4.20, VIF values of CBM, PdM, TBM, and TC were significantly less than 5.00, as suggested by Diamantopoulos and Sigouw (2006) (refer Table 4.20). Thus, these inner VIF results indicated that collinearity was not a concern (Hair et al., 2017). Overall, the reliability results for reflective indicators of CBM, PdM, TBM, and TC implied that the VIF values were less than 5, which meant there was no multicollinearity in the reflective constructs.

Table 4.17
Summary of Relevance and Significance of Path Co-efficient

	(Path Coefficient) **Original Sample (O)**	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P Values**
TBM -> MP	0.089	0.108	0.17	0.522	0.301
CBM -> MP	0.166	0.118	0.184	0.905	0.183
PdM -> MP	0.246	0.269	0.073	3.358	0.000

Table 4.17 presents the path coefficient results for the direct relationship between manufacturing performance and the four constructs (TBM, CBM, PdM, and TC). Nonparametric bootstrapping routine advocated by Vinzi et al. (2010) was used on 155 data points and 500 samples. The main purpose of bootstrapping is to calculate the standard error of coefficient estimates to examine the coefficient's statistical significance (Vinzi et al., 2010). Path coefficients indicate whether the hypothesised relationships among the constructs exist or not and if they do, are they in the predicted directions. According to Lohmoller (1989) (as quoted in Chin (1998)), the path should be above 0.1 and 0.2 to be meaningful and theoretically interesting, respectively. As shown in Table 4.17, all paths (CBM, TBM, and TC) were not significance toward MP were p-value more than 0.1. Nonetheless, PdM path coefficient shows significant relationships toward MP because the p value was 0.000 (i.e., a p-value less than 0.05).

Table 4.18
Summary of Confidence Interval Bias Corrected

Relationship	Original Sample (O)	Sample Mean (M)	Bias	5.00%	95.00%
TBM -> MP	0.089	0.108	-0.226	0.335	0.089
CBM -> MP	0.166	0.118	-0.24	0.339	0.166
PdM -> MP	0.246	0.269	0.145	0.381	0.246

The bootstrap (500 samples) confidence interval values should be significantly different from the value of 1. Columns labelled 5% and 95% show the lower and upper boundaries of the 95% bias-corrected confidence interval. As shown in Table 4.18, neither the lower or upper boundary confidence intervals were included in the value of 1 (Hair, Hult, Ringle & Sarstedt, 2017; Henseler, Ringle & Sarstedt, 2015).

Table 4.19
Summary of importance performance matrix

CONSTRUCT	IMPORTANCE (Total Effect)	PERFORMANCE (Index Value)
Time-based maintenance **[TBM]**	0.147	71.159
Condition-based maintenance **[CBM]**	0.111	62.949
Predictive maintenance **[PdM]**	0.271	70.040
Technological capabilities **[TC]**	-0.175	60.497

Importance performance matrix analysis (IPMA) is useful in extending findings of the basic PLS-SEM using latent variables‘ scores (Fornell et al., 1996; Hock et al., 2010; Gronholdt et al., 2000). To avoid an ambiguous explanation of IPMA results, the findings are compiled in Table 4.19. It was revealed that the most important variable was PdM (0.271) followed by TBM (0.147) and CBM (0.111). On the other hand, less important were TC (-0.175). Thus, it can be concluded that PdM and TBM were the better importance and performance variables for this research.

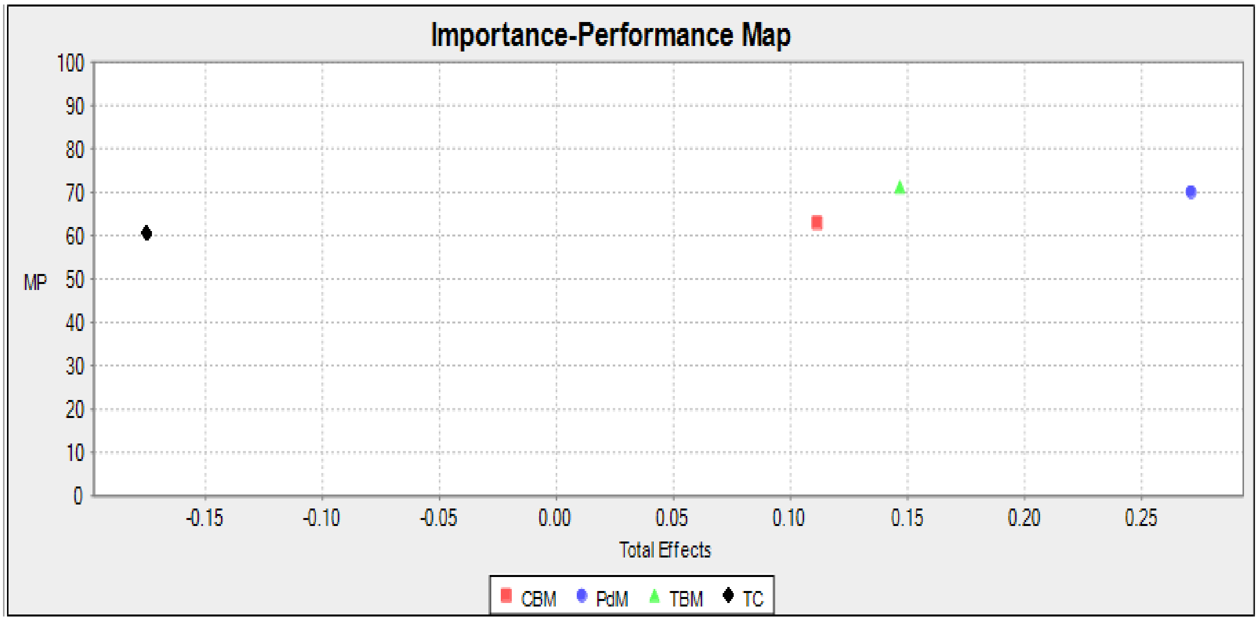

Figure 4.4
IPMA Summary for TBM, CBM, PdM and TC

Figure 4.4 illustrates the IPMA results of TBM, CBM, PdM, and TC. Overall, PdM and TBM had primary importance and performance on manufacturing performance. In contrast, TC had little relevance because of its low importance, even though it had a relatively high performance compared to CBM. Consequently, to improve MP, organizationss should focus on PdM and TBM. As such, TC and CBM constructs can be used in future research to enhance manufacturing performance.

4.10 Moderating Analysis

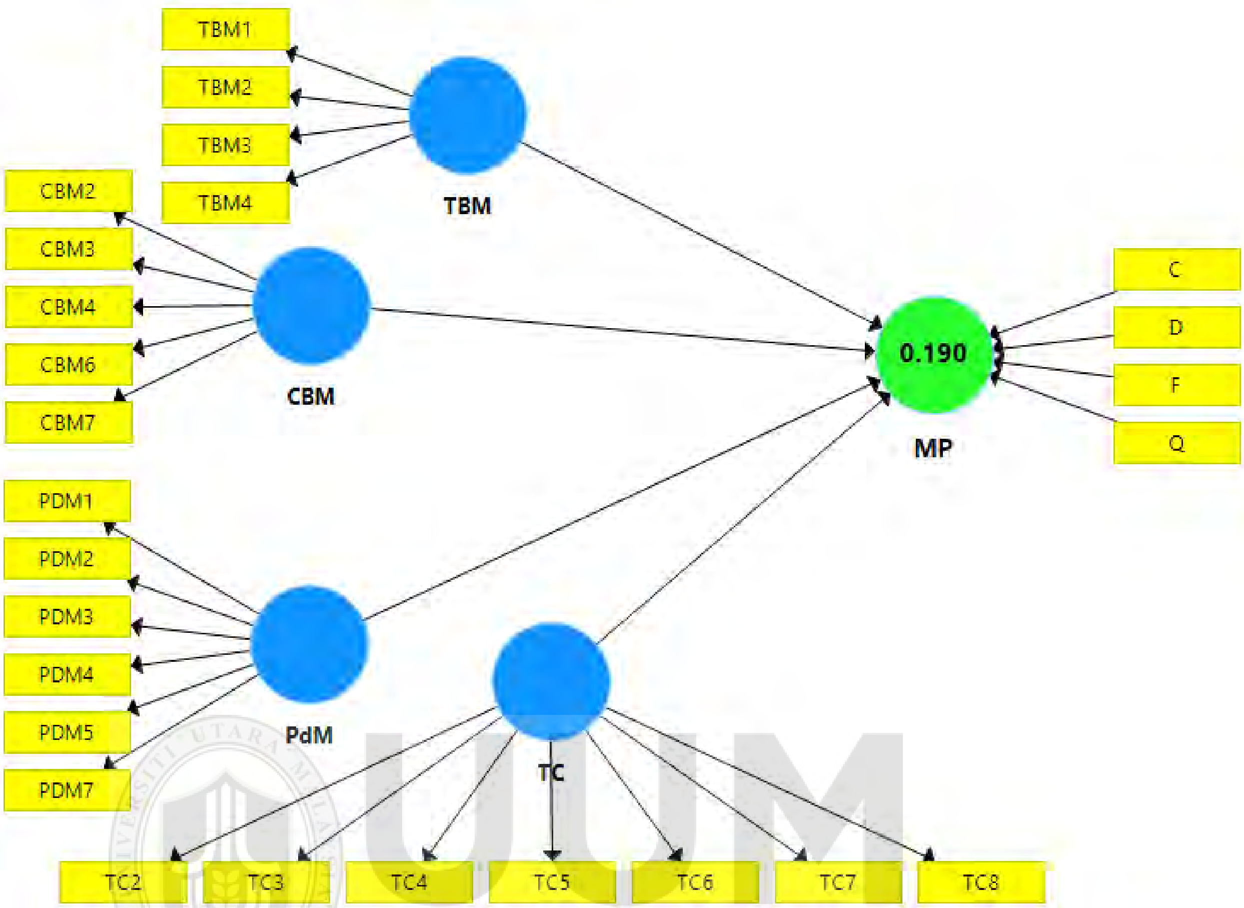

Figure 4.5
R square value of manufacturing performance

In moderation analysis, R^2 is an important issue. Based on figure 4.5 above the R^2 value of (MP) was 0.190. The R^2 indicates that (TBM, CBM, PdM) and moderator variabels TC explain 19.0% of the variance of Manufacturing performance (MP). In this study, the TC is known as moderator and the researcher look at the R^2 changes from the main effect model (Figure 4.5) and new R^2 value (refer figure 4.6) after TC interact with TBM, CBM and PdM.

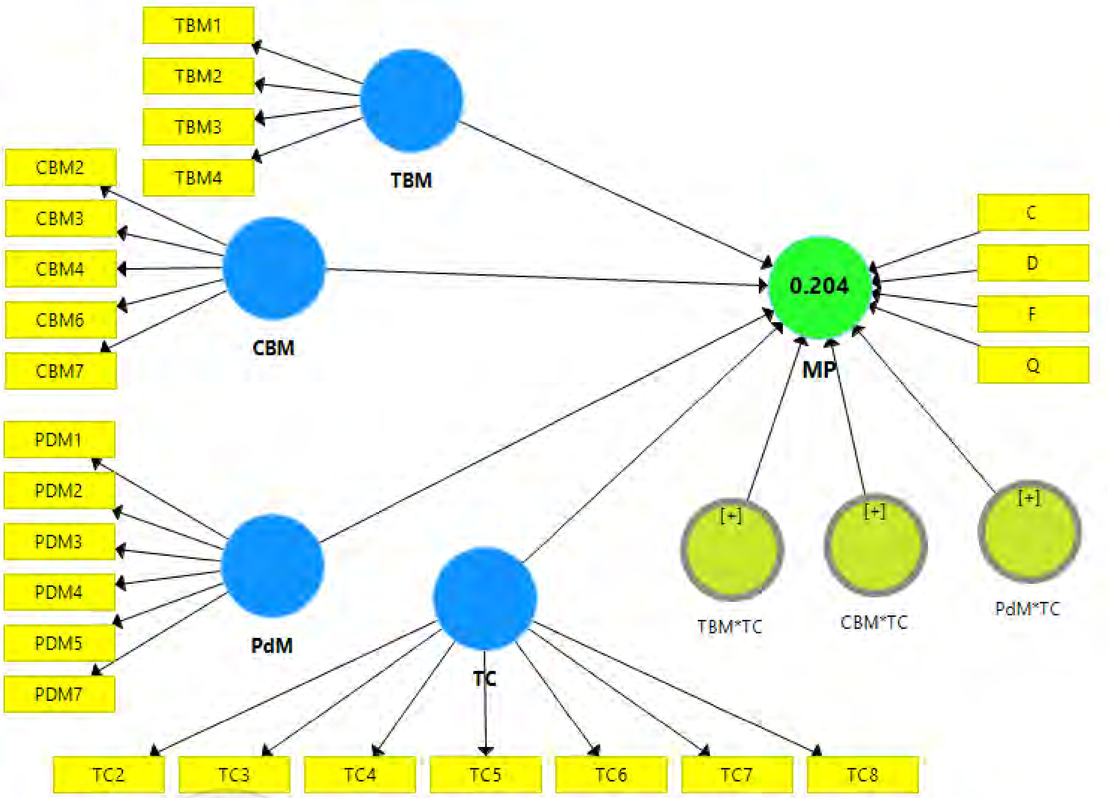

Figure 4.6
Moderating effect of MP

Referring to Figure 4.6, the R^2 values of MP was 0.204. After moderating analysis was conducted, the R^2 value for MP increased to 0.204 from the original value of 0.190 (refer to Figure 4.5), i.e., an increase of 0.014 (0.204 - 0.190), which indicated the moderating variable explained 1.4 % of the variance. As such, interpretation of the moderation analysis results through the slope plots was performed. Therefore, the following section explains the outcome of the path coefficient analysis.

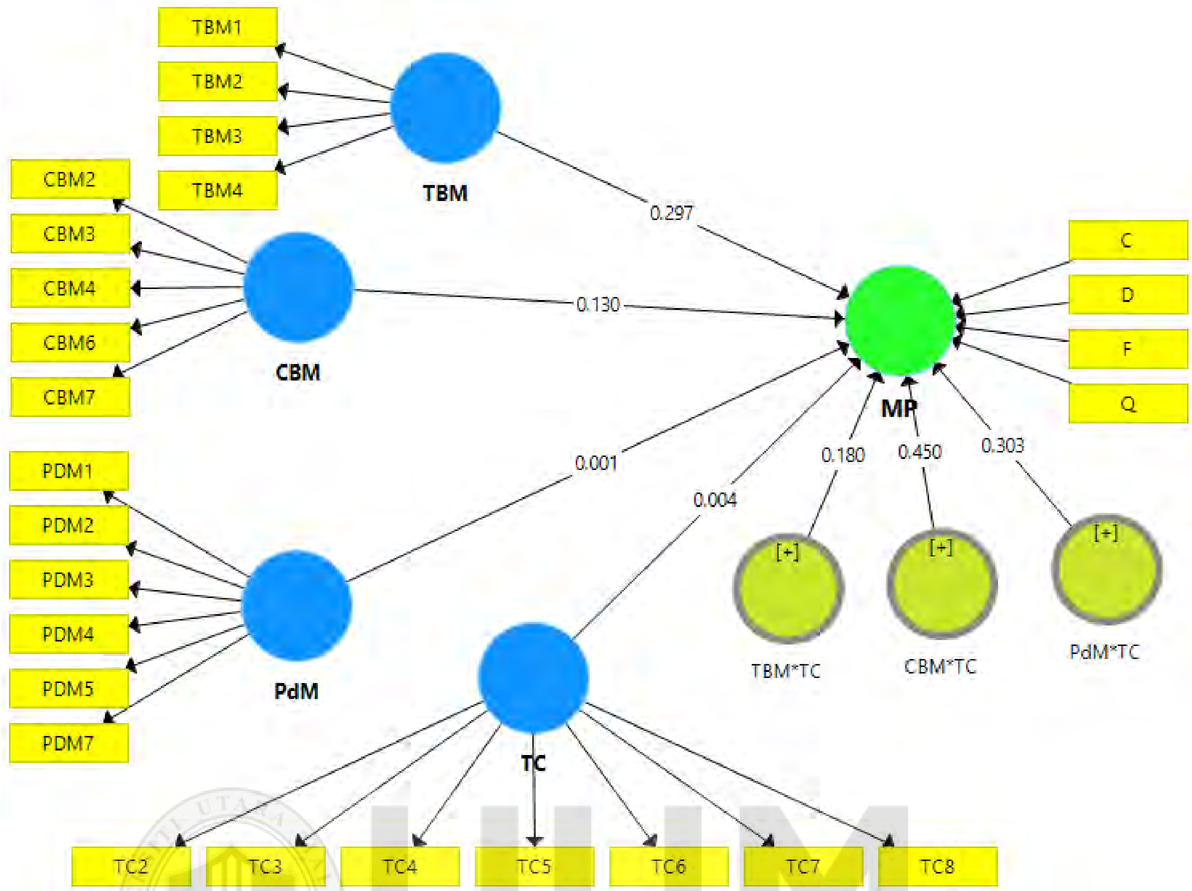

Figure 4.7
Path coefficient Value for MP

Figure 4.7 reveals the P value for the inner model. Hair et al. (2017) mentioned that in order to conduct a hypothesis test, P value must be at the significance level of 0.000, 0.05 or 0.10. Two-tailed P value associated with the path coefficient was calculated. For the moderating effect, all P values were above 0.10. As shown in figure 4.5, the P values were: TBM*TC->MP: 0.180; CBM*TC -> MP; 0.450; and PdM*TC -> MP: 0.303 (refer table 4.20).

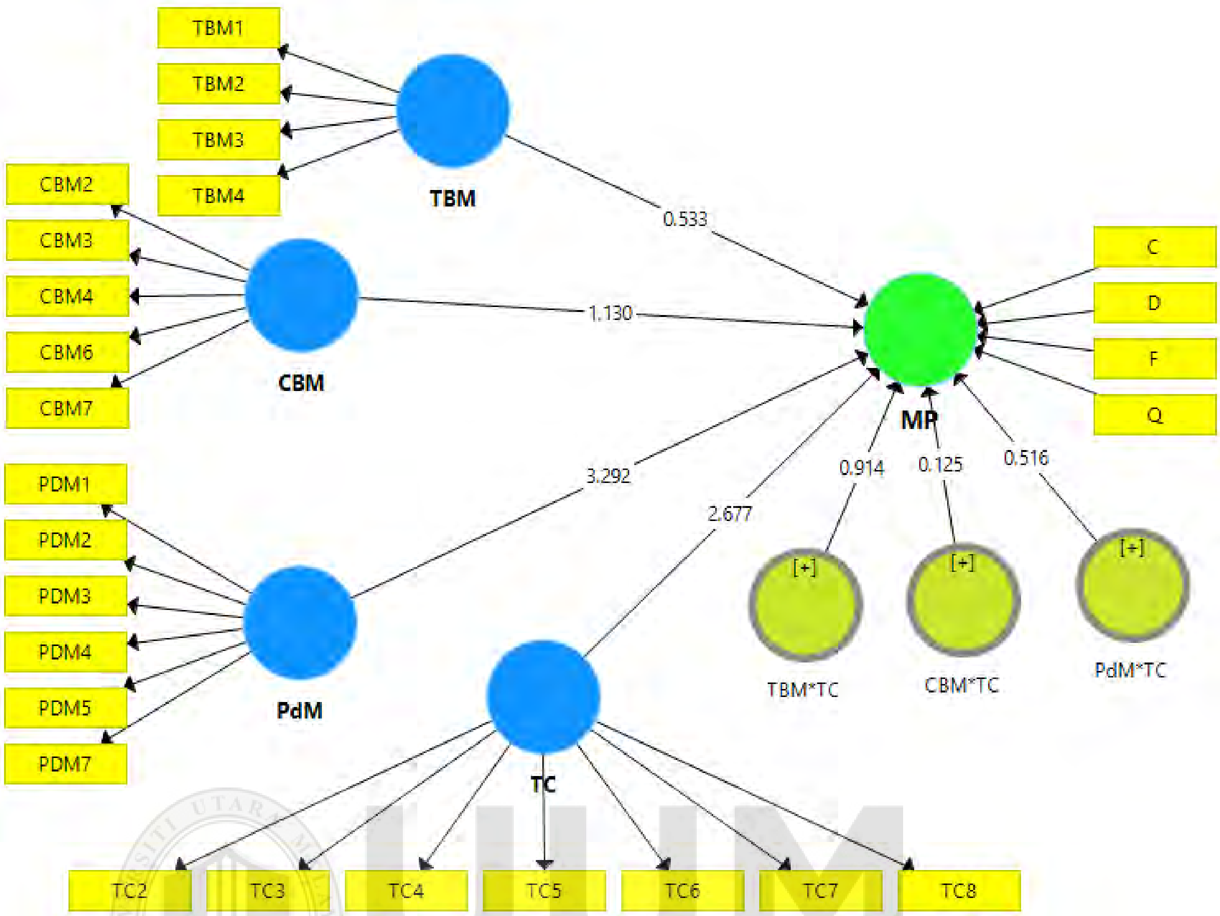

Figure 4.8
T- value for MP

Figure 4.8 shown, the path coefficient and t value for MP. Hair et al., (2017) stated that the t ratio test is a variation of this test, in which the t ratio (also termed t value and t statistic) is used instead of the corresponding P value for comparison against a threshold such as 1.64 or 1.96. To conduct the t-test using a 95% confidence interval, lower and upper limits of the confidence interval were calculated. However, the moderation analysis implied that there was a non-significant effect between TC and TBM, CBM, and PdM towards MP. This because the t value of (TBM*TC->MP= 0.914), (CBM*TC->MP = 0.125) and (PdM*TC->MP =0.516) towards MP was less than 1.64 (refer table 4.20).

Table 4.20
Path coefficient value

	Hypothesis	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T-value (|O/STDEV|)	P Values	BCI LL	Bias	f^2	VIF
Direct relationship										
H1	TBM -> MP	0.083	0.077	0.156	0.533	0.297	0.271	-0.007	0.008	1.047
H2	CBM -> MP	0.183	0.148	0.162	1.130	0.130	0.342	-0.035	0.041	1.025
H3	PdM -> MP	0.233	0.253	0.071	3.292	0.001	0.367	0.020	0.065	1.052
Moderation relationship										
H4	TBM*TC -> MP	0.093	0.051	0.101	0.914	0.180	0.206	-0.042	0.014	1.054
H5	CBM*TC -> MP	-0.014	0.021	0.113	0.125	0.450	0.195	0.035	0.000	1.048
H6	PdM*TC -> MP	0.048	0.047	0.093	0.516	0.303	0.209	-0.001	0.003	1.045

Table 4.20 provides the results for moderation analysis of TC and TBM, CBM, and PdM towards MP. According to Hair et al. (2017), the acceptance level must be $p<0.01$, $p<0.05$, or $p<0.10$. Thus, based on table 4.20 above the p value indicates that there is no moderation relationship among measured variable (TBM*TC -> MP 0.180) (CBM*TC -> MP 0.450) and (PdM*TC -> MP 0.303) this because the p-values are more than 0.10. On the other hand, referring to the direct relationship of TC and TBM, CBM, and PdM towards MP, only PdM had a significant relationship with MP. This was shown by the P values, i.e. PdM -> MP: 0.001. Meanwhile, TBM and CBM did not show a significant relationship with MP. The p-value was: TBM -> MP: 0.297 and CBM -> MP: 0.130, which were more than $p>0.10$.

Table 4.21
Summary of Hypotheses Testing

Hypothesis	Relationship	Decision	P value
H1	Time-based maintenance is positively related to performance of Malaysian manufacturing organization.	Not Support	0.297
H2	Condition-based maintenance is positively related to performance of Malaysian manufacturing organization.	Not Support	0.130
H3	Predictive maintenance is positively related to performance of Malaysian manufacturing organizations.	Support	0.001
H4	The technological capabilities positively moderate the relationship between TBM practices and performance among Malaysian manufacturing organizations.	Not Support	0.180
H5	The technological capabilities positively moderate the relationship between CBM practices and performance among Malaysian manufacturing organizations.	Not Support	0.450
H6	The technological capabilities positively moderate the relationship between PdM practices and performance among Malaysian manufacturing organizations.	No Support	0.303

Based on table 4.21 the summary of hypotheses was found that there are only one hypotheses were supported it was H3: Predictive maintenance is positively related to performance of Malaysian manufacturing organizations. However, five hypotheses were not supported such as H1, H2, H4, H5 and H6. These decisions were made based on the summary of the path coefficient value (Refer Table 4.20).

The findings indicated that only PdM presented a significant relationship with MP (PdM -> MP= 0.009). Therefore, hypothesis H3 is supported while H1, H2, H4, H5 and H6 are rejected due to p-value more than 0.1. Moreover, there was no moderation relationship between TC with TBM, CBM and PdM toward MP.

CHAPTER FIVE

DISCUSSION AND CONCLUSION

5.1 Introduction

This chapter discusses the findings from data analysis as reported in the previous chapter and provides a conclusion. Furthermore, the limitations of this current study and recommendations for future research are also presented.

5.2 Recapitulation of the Study Findings

This study was conducted to explore the relationship between preventive maintenance practices and manufacturing organizationss performance (MP) moderated by technological capabilities (TC). The independent variable was preventive maintenance with three dimensions, namely, time-based maintenance (TBM), condition-based maintenance (CBM) and predictive maintenance (PdM). This research employed TC as a moderating variable to test the relationship between preventive maintenance practices and the performance of Malaysian manufacturing organizationss. Questionnaires were sent to 600 Malaysian manufacturing organizationss but only 155 questionnaires were returned by the respondents. Due to the low response rate, this study used G-power software to determine the adequate sample size. After calculating the sample size using G-power, the required sample size was identified as 103. This meant a total of 103 respondents were required to test the seven predictors (15 respondents for each predictor). Thus, the sample size of 155 was adequate as this figure was higher than the one suggested by G-power software. Overall, the results of this study indicated that only PdM had significant relationships with manufacturing performance. This was proven when all 155 participating companies agreed that PdM have an important role in improving manufacturing performance.

From the six hypotheses put forth, after data analysis only one hypotheses were supported, H3. Whereas the hypotheses H1, H2, H4, H5 and H6 were rejected due to p-value more than 0.1 (refer to table 4.21).

5.2.1 Justification of Hypothesis

There were only one hypotheses were supported in this study, are as follow H3 (Predictive maintenance is positively related to performance of Malaysian manufacturing organizations). However, five hypotheses were rejected in this study, are as follow: H1 (Time-based maintenance is positively related to performance of Malaysian manufacturing organization); H2 (Condition-based maintenance is positively related to performance of Malaysian manufacturing organization); H4 (The technological capabilities positively moderate the relationship between TBM practices and performance among Malaysian manufacturing organizations); H5 (The technological capabilities positively moderate the relationship between CBM practices and performance among Malaysian manufacturing organizations); H6 (The technological capabilities positively moderate the relationship between PdM practices and performance among Malaysian manufacturing organizations) were rejected (refer table 4.23). The following section discussed the reasons behind the H3 were supported, and why H1; H2; H4; H5 and H6 were rejected via empirical support.

This study used three maintenance strategy namely, TBM, CBM, and PdM in order to identify whether PM practices improve the performance of Malaysian manufacturing organization (H1, H2, H3). Furthermore, this study also examines whether technological capabilities moderate the relationship between TBM, CBM, and PdM TBM practices and performance among Malaysian manufacturing organizations (H4, H5, H6). The overall analysis for the hypotheses reveals that only PdM shows a significant relationship in improving the performance of Malaysian manufacturing organizations. It can be found that only H3 were supported; H3 (Predictive maintenance is positively related to performance of Malaysian manufacturing organizations). These indicate PdM has a strong relationship with manufacturing organizations.

Selcuk (2017) stated predictive maintenance (PdM) primarily involves foreseeing breakdown of the system to be maintained by detecting early signs of failure in order to make maintenance work more proactive. He added that the aim of acting before failure, PdM also aims to attend to any fault, even if there is no immediate danger of failure, to ensure smooth operation and reduce energy consumption. Moreover, Thaduri, Galar, et al. (2015) and Zornio and Boudreaux (2019) stated that PdM programme basically consists of three main steps: data acquisition, data processing and maintenance decision-making conditions of the system and mostly the data gathers by sensors to identify the conditions of the system. Due to this aspect, the predictive maintenance has been widely adopted by various sectors in manufacturing industries in order to improve reliability, safety, availability, efficiency and quality as well as to protect the environment (Liu, Dong, et al., 2018). Meanwhile, Wang (2016) also pointed that predictive maintenance techniques are closely associated with sensor technologies but efficient predictive maintenance is mainly based on the current situation of the system, rather than predicting the future by using statistical data applications, a comprehensive approach. On the other hand, Selcuk (2017) summarized that PdM advantages as; improved worker and environmental safety; higher reliability and availability; improved product quality; less costs for parts and labour; less waste in terms of raw materials and consumables, such as lubricants and energy savings. Thus, this study concludes that PdM is undeniable practices that widely accepted by the Malaysian manufacturing sector.

This study, in contrast, found four hypotheses (H1; H2; H4; H5; H6) were rejected. The core variable of those four hypotheses was TBM and CBM. Whereas the hypotheses result for (H1and H2) show that TBM and CBM practices did not improve the performance of Malaysian manufacturing organizations and the (H4 and H5) show that technological capabilities did not have a moderate relationship between TBM and CBM practices and performance among Malaysian manufacturing organizations. This study found the reason behind the rejection of TBM and CBM practices is due to the type of organizations that participated in this study. Referring to the summary of descriptive analysis for companies ‗annual turnover', it was found that the majority of the respondents were from small-sized manufacturing organizationss. it was a total of 98 companies or (63.2%) from the total number of responses (refer to Table 4.4). Meanwhile, the second-largest group was micro-level manufacturing organizationss (33 companies or 21.3%) followed by medium-sized manufacturing organizationss (24 respondents or 15.5%). These details signified that small and micro-level organizationss were the major participants of this study (98 + 33 = 131 companies).

Dodgson (2018) stated that small and medium-sized enterprises (SMEs) operate with scarce financial, human and tangible resources that characterise most new businesses. Such early emerging firms have limited innovativeness, knowledge, and capabilities to achieve considerable market success early in their evolution. Similarly, Ren, Eisingerich, et al. (2015) mentioned that small and medium-sized companies are facing insufficiency in funds to purchase high technology equipment, which has led to limited R&D capabilities and innovations that limit success. In addition, Bouazza, Ardjouman, et al. (2015) found that most SMEs face numerous serious challenges that hinder their growth such as lack of access to external financing, low human resource capacities, lack of management skills and training, and low technological capabilities.

Hence, TBM and CBM practices were rejected because small and micro-level manufacturing organizationss in Malaysia give less important to these manufacturing practices in their manufacturing process due to limitations in finance, knowledge, and resources. This is supported by the report released by the World Economic Forum that Malaysian SMEs‘ progress concerning innovative activities was ranked low (51st out of 144 countries in 2012–2013) in terms of technological readiness, which could significantly undermine Malaysia‘s efforts to become a knowledge-based economy by 2020. Furthermore, Anuar and Yusuff (2011) stated that Malaysian SMEs are under constant pressure to seize competitive advantages and sustainability to address challenges arising from increasing costs of production, changes in input prices, globalisation, and changes in customer preferences. In their study, they examined 270 Malaysian manufacturing SMEs, reported that technology and product innovation scored the lowest among eight indicators used to measure manufacturing practices. In another study, Ali and Perumal (2016) emphasized the limitations faced by Malaysian SMEs because they lacked managerial and technical expertise and undertook limited technological adoption. Next, the findings of Aziz and Samad (2016) and Yap and Lock (2017) exposed that Malaysian manufacturing SMEs possess limited skills and knowledge in manufacturing and strategy development. Additionally, Parvin Hosseini (2014) reported that very little knowledge about Malaysian SMEs‘ nature of innovation exists. Not only that, Mamun (2018) emphasised that beyond the significance of innovation highlighted in studies conducted in Malaysia and the government's efforts to provide an innovation ecosystem, very few opportunities remain for manufacturing SMEs to improve their practices. These are clearly linked to the reasons behind the rejection of (H1; H2; H4; H5), whereby TBM and CBM were not supported. Thus, this study assumes that the reason behind TBM and CBM was not supported because the majority of participants of this study were from small and micro-level manufacturing organizations and may not use TBM and CBM in their manufacturing process.

5.3 Hypotheses Discussion

H1: Time-based maintenance is positively related to performance of Malaysian manufacturing organization.

There is a reason why (H4) was not supported in this study because Predictive maintenance turns out to be preferred over condition-based and time-based maintenance. The p-value for TBM was 0.148 were more than $p<0.10$ (Refer table 4.24). Kim, Ahn, et al. (2016) and Alaswad and Xiang (2017) compare the optimal condition-based maintenance policy with the optimal time-based maintenance policy. Finally, they found that the performance of condition-based maintenance turns out to be much better than time-based maintenance. Meanwhile, Keizer, Teunter, et al. (2016) examine the deterioration level at which failure occurs, and the result shows that there is potential cost saving through implementing a condition-based maintenance policy as opposed to time-based maintenance.

More sophisticated research is conducted by Zou, Banisoleiman, et al. (2019) by combining TBM and CBM maintenance actions to measure optimal maintenance of marine structures and the final analysis indicates that the CBM achieve higher reliability with fewer maintenance costs than the TBM which considerably outperform that lead to increased maintenance budgets. They concluded that failures are not self-announcing but should be identified by inspections; a cost is introduced for system inactivity. Overall the above empirical finding indicates that the use of TBM systems in the manufacturing sector has been reported to be one way of increasing maintenance budgets. It can increase costs by performing within the predefined performance. The influence of the values of the cost parameters is studied in more detail and the relative benefit of the condition-based strategy turns out to increase in the preventive replacement cost (Nazemi & Shahanaghi, 2015).

TBM is one of the strategies that can be applied to reduce the machine breakdown problems due to unplanned maintenance. However, Lazemi, and Dehkordi (2016) state that the application of TBM in term of when is the best time to carry out the PM is an important issue. The answer to this question should be based on an adequate maintenance analysis. Moreover Alaswad & Xiang, (2017) and He, Gu, Chen, & Han, (2017) demonstrated that CBM is more cost-effective than TBM in preventing unexpected failures and reducing economic losses. This because TBM is not based on an adequate maintenance analysis, where there are not considered the external factor (covariate) and without understanding the failure mechanism (physical failure). However, Zheng, and Makis (2020) mention that it is challenging to solve the optimization problem considering the TBM policy. First, the continuous-state covariate process in the PH model makes it difficult to evaluate the conditional reliability between two successive inspection intervals. To handle this problem, a matrix-based method that discretizes the joint process of age and deterioration is employed to achieve a precise estimation of conditional reliability function. Moreover, the structure of the maintenance strategy becomes more complex when multiple maintenance actions are considered.

Zheng, R. and V. Makis (2020) and Zheng, Su, & Zheng, (2019) classify the machine failure into soft and hard failure. The soft failure involving many deteriorating systems also experience random failure caused by hidden manufacturing defects, excessive loads, external shocks, etc. Meanwhile the hard failure mode is referred as the engines break down or shield damage due to the wear deterioration and thermal cracking (Sun, Song, et al. 2018 and Mezger et al., 2017). Compared with soft failure, hard failure usually has more serious consequences since it can interrupt the continuity of a manufacturing process abruptly and result in considerable downtime loss. Thus necessary to take both soft and hard failures into account when making TBM decisions. As mentioned before, most of the machines are designed in serial configuration and in many cases of the machine breakdown (failure) are due to unplanned maintenance. Most of the unplanned maintenance is due to component failures. According to Liu, Liu, et al. (2019), failure of the machine component is influenced by internal and external factors. Internal factor refers to the age (time usage) of a component and it is normal causes of component failure. In many cases, increasing in the component aging will be followed by reducing in the component performance due to failure and it occurs for all types of components (mechanical, electrical and electronic) (Hazreek, Nizam, et al. 2018; Kovalenko, Leshukov, et al. 2016). In other words, this situation is nature process in a component lifetime. In addition Liu, Yang, et al. (2020) stated any component that operates in a machine (as a system), this factor also results on reliability reduction, means that the failure rate of the component is increased by machine age (time usage). The main issue in TBM application is in determining the optimal time to carry out the PM's task (replacement or inspection) (Giancarli, Ahn, et al. 2018). If the task is made too early, the components may not have been utilised to full capacity. If the interval is too long, it reflects too high machine down time due to unplanned maintenance (restoration due to sudden failure). Moreover, Hu, Shen, et al. (2020) highlighted that most manufacturers recommend that TBM intervals must be followed to preserve warranty rights. The determination of these intervals by the manufacturer may not reach to maximum benefits of TBM strategy (Bahrami et ai, 2000).

Duan,. Makis, et al. (2019) stated that failure rate of a component (that operating in a machine) can exist in three states; there are decreasing failure rate (early state), constant failure rate (useful state) and increasing failure rate (deteriorating state). External Factors The environmental causes such as overheated (temperature), high humidity level, extreme dust condition and over dosed radiation may influence to the component failure (Taveau, Hochgreb, et al. 2018). For instance, Yamauchi, Akamatsu, et al. (2016) discussed the effects of high temperature and humidity on electronic component. He states that when the working temperature and humidity drastically change (increase or decrease), it affects to the performance of the component due to failure. Human error is another cause of external factor that may influence on the component failure. Human error is defined as the failure to perform a specified task that result in damage to property and equipment (Reason and Hobbs 2017). According to Wang and Hwang (2004), human errors can be divided by two types: first is the critical human error which will cause system breakdown (unplanned breakdown) and second is latent human error which does not lead to immediate system breakdown. Unskilled technicians or maintenance crews may lead to the component failure as well as machine breakdown through maintenance activities. For example, Stringer, Thompson, et al. (2019) stated that component failure may occur due to maintenance error by carrying out incorrect repair or preventive action. For examples, incorrect calibration of component and application of the wrong grease at appropriate points of the component. In addition, Reason, and Hobbs (2017) presented the most common maintenance errors related to industry; there are incorrect installation of components, fitting of the wrong parts, electrical wiring discrepancies (including cross connection), loose objects (tools) and inadequate lubricant. Even the human error is unavoidable, but the percentage of error of unskilled operators and technicians can be reduced by intensive training program or improving the maintenance management system (McDonnell, Balfe, et al. 2018).

H2: Condition-based maintenance is positively related to performance of Malaysian manufacturing organization.

The p-value of (H5) is (0.286) which shows insignificant level was more than p>0.10, thus (H5) not supported in this study (Refer table 4.24). De Jong et al. (2019) stated that the relative benefit of CBM strongly depends on the behaviour of the deterioration process and the severity of failures. Furthermore, CBM is affected by failure-based and age-based, that are often presented in practice, required planning time, imperfect condition monitoring, and variation in the deterioration level at which failure occurs (De Jonge, Teunter, et al., 2017). Therefore, they suggested that CBM should only be applied if this relative benefit outweighs the efforts and costs during the entire life cycle that are required to apply CBM. According to De Jonge, Teunter, et al. (2017) and Chen, Cowling, et al. (2017), CBM strongly depends on the behaviour of the deterioration process and it basically requires a dynamic scheduling of maintenance activities and prediction accuracy without which organizationss might not have the capability for such flexible planning. This statement was agreed by Shin and Jun (2015) who mentioned that CBM is only attractive to industries operating high-valued assets. Moreover, Shin and Jun added that it would be difficult to achieve effectiveness in maintenance operations using CBM because there is no information visibility during the product usage period. This was supported by Shin and Jun (2015), Baglee and Jantunen (2014), and Hashemian and Bean (2011). Nearly 30% of industrial equipment does not benefit from CBM and the investment cost for CBM is usually high.

Apart from that, the technologies and technical methods for the CBM approach are still in their infancy (Azadeh, Asadzadeh, et al., 2015). This means that there are some limitations in ensuring the accuracy of diagnostics and prognostics. This might be the reason all the respondents in this study did not agree that CBM can be used as a competitive strategy in boosting manufacturing organizationss performance. Meanwhile, Mortensen (2017) pointed out that companies that are interested in implementing condition-based maintenance must also consider the risks related to the lack of experience. Furthermore, they should realize that CBM requires dynamic scheduling of maintenance activities, whereas they might not have the capability for such flexible planning. Condition-based and time-based maintenance, as well as studies that consider the above practical factor in a CBM model. In addition, De

Jonge, Teunter, et al. (2017) highlighted that although both CBM and TBM have received ample attention in the scientific literature, however, few studies compare them. Moreover, existing comparative studies confine themselves to a few examples. Insights on how the various characteristics influence the performance of condition-based and time-based maintenance are lacking.

Albrice and Branch (2015) consider the integration of condition-based maintenance with traditional periodic preventive maintenance. The available condition information is limited to a signal of a potential failure that might be received before the actual failure. The probability that this signal is received depends on the prediction accuracy, and the time between the signal and the failure depends on the prediction precision. Therefore, this study concluded that the performance of the condition-based maintenance strategy depends on prediction accuracy and precision. In some situations, periodic preventive maintenance or a combination of condition-based and periodic preventive maintenance is preferred.

According to Deshpande, Nandi, et al. (2017) most of the maintenance analysis is performed without understanding the root causes of the machine failure. Therefore, it may result in the wrong information and data for reliability analysis and affected to the determination of CBM. Furthermore, many of the researches and articles in the CBM maintenance analysis assumed that the failure of the component or machine depends only on actual and operating condition of an asset (Fumagalli, Cattaneo, et al. 2019). However, in reality most of the component or machine failures are influenced not only by the internal factor (age-time usage) but also by the external factor (Keowsiri and Leeprechanon 2019). The external factor would be the effects of environmental (dust, humidity and heat), human skills, product types and maintenance activities. In fact, when the external factor is not considered in the maintenance analysis, it may give rise to errors in the identification of machine characteristics (failure rate and failure distribution) (Majchrzycka, Okrasa, et al. 2017 and Sabatino, Frangopol, et al. 2016). Consequently, there are some scholars detecting limitations on CBM which is not accurate enough and it reduces the cost saving, high failure rate and reduction lost (Hong-Jiang Tang Tan et al 2014; Zhu HJ, Shao LH, Huang Zhuang 2015). The emphasis of this research is to develop a CBM for Malaysian manufacturing organizations by considering not only the internal factor but also the external factor. However the finding of this study indicates that CBM are not popular among Malaysian manufacturing organizations that expressed that CBM not used to detect the root of internal and external failure in manufacturing plant.

H3: Predictive maintenance is positively related to performance of Malaysian manufacturing organizations.

Based on the p-values of PdM is significantly contributed to the performance of Malaysian manufacturing organization (Refer Table 4.23). Goyal, Saini, et al. (2016) and Carnero, López-Escobar et al. (2015) highlighted that PdM is viewed as a contemporary and well-known maintenance technique because PdM helps determine the condition of in-service equipment to predict when and what repairs need to be employed accordingly. This study‘s results are consistent with other Malaysian studies conducted to explore the relationship between PdM practices and manufacturing performance (MP) which is quality. For example, Ghani, Lazim, et al. (2017) explored the potential relationships between PdM practices and manufacturing performance moderated by organizationsal capability with a focus on Malaysian Highway maintenance management. They found that predictive maintenance practices played a vital role in the effectiveness of the highway maintenance management system in Malaysia by ensuring no equipment breakdowns occurred during plant operation. On the other hand, Ahmad (2018) examined different maintenance decisions for punching toolsets in a pulp manufacturing process. Ahmad discovered that the failure rate of punching toolsets reduced due to the implementation of the PdM policy. Similarly, Shahrir, Adam, et al. (2017) stated that PdM gives the lowest impact in a wafer manufacturing industry_s production loss without sacrificing equipment quality and safety.

Besides that, Hooi and Leong (2017) stated that PdM is a great practice to reduce cost, improve productivity, and increase profitability for manufacturing organizationss. This was supported by Ahmad (2018), Alaswad and Xiang (2017), and Shahrir, Adam et al. (2017). They mentioned that many companies in Malaysia improved their competitiveness and profitability through maintenance performance by analysing, planning, and optimising the plant and equipment. This was done by establishing optimum repair and maintenance periods to ensure service reliability and maximum utilisation of assets. Additionally, Singh and Ahuja (2017) reported that industries today are trying to increase their manufacturing efficiency by focusing on new inventions, consistent improvements, and trying newly discovered tools and processes. Nevertheless, scholars emphasised that PdM is a prominent competitive strategy in the manufacturing sector (Shahrir, Adam, et al., 2017; Taib, Lazim, et al., 2017; Basri, Abdul Razak, et al., 2017; Susto, Schirru, et al., 2015). This is because PdM has emerged as an efficient method to achieve industry effectiveness by concentrating on enhancing machine efficiency, reducing production flaws, and improving work rate (Nakajima, 1988). This standardised assessment resulted in substantial growth in manufacturing efficiency by extending equipment uptime and lifespan. Basically, the PdM decision is based on the age of system and knowledge of statistical information concerning the system‘s lifespan (Nguyen Do et al., 2015). On the other hand, Wang Zhang et al. (2017) stated that PdM involves fault diagnosis and retaining service life prediction and maintenance plans by providing scientific and technological information for decision making. Through a literature review, this study discovered that PdM has been extensively researched in the context of manufacturing performance. This is possible by combining the detection and interpretation of different parameters, i.e., environmental, operational and performance parameters, necessary for assessing the health state of the system and for predicting the remaining useful life. The rapid development of PdM techniques and methods, and their applications, is leading to the perception of PdM as engineering discipline (Sun et al. 2012), based on the use of in-situ monitoring and advanced methods for assessing degradation trends of a system of PdM strategies and the various performances of manufacturing organizationss. For example, Jin, Siegel, et al. (2016), Muchiri, Pintelon, et al. (2014), and Lee Siegel et al. (2013) determined the positive impact of PdM on manufacturing performance, specifically cost reduction and enhanced production quality. Furthermore, De Jonge (2017) mentioned that the changing of the role of PdM as a central factor in the manufacturing sector has enabled the identification of the main technical challenges that can potentially reduce equipment degradation and optimise maintenance activities scheduling based on a prediction of the systems‘ performance. On the other hand, Nguyen, Do, et al. (2015) asserted that

PdM policies are popular for a maintenance decision-making process that relies on the diagnostic/prognostic of the system's condition over time. This has been recently introduced and has become an interesting approach for maintenance optimisation among most organizations. Besides that, PdM utilizes the operating condition of equipment to predict a failure event. The goal of this policy is to prevent any unplanned downtime and to minimise maintenance cost by avoiding unnecessary preventive actions (Moubray, 1997). All these statements undoubtedly reflect that PdM significantly impacted manufacturing performance.

The findings of this study revealed that PdM can lower manufacturing time and cost by continuously monitoring machine health and predicting or detecting faults and malfunctions that affect product quality efficiency. This is because PdM can detect and diagnose run-up failures of machines at a crucial time before any severe problem or unscheduled downtime occurs (Goyal & Pabla, 2015). With the help of PdM, Malaysian manufacturing organizationss can achieve multiple capabilities simultaneously because the concurrent pursuit of capabilities can lead to superior overall performance improvements. .

H4: The technological capabilities positively moderate the relationship between TBM practices and performance among Malaysian manufacturing organizations.

The p-value of (H4) is (0.587) which shows an insignificant p-value was more than p>0.10, thus (H4) not supported (Refer table 4.23). In recent decades, traditional maintenance models that combine CBM and time-based maintenance (TBM), are transforming to more proactive types in most industrial sectors by optimizing the amount of time spent on maintenance tasks (Guillén López, Crespo Márquez, et al., 2019). In this evolution, TC is considered one of the key factors to achieve system-level efficient maintenance and reduce life cycle costs (Kim, Song, et al., 2015). The prognosis research field is, in fact, promising new capabilities to improve the reliability of systems, leveraging both on design and maintenance along with useful lives (Sun et al 2012). Besides, TC provides capabilities to achieve more proactivity in maintenance: in this regard, it is worth remarking that, as expectation for the future, the equipment data will be transformed by TC solutions into valuable information to help not only maintenance managers but also plant managers for optimizing planning, saving cost, and minimizing equipment downtimes (Lee et al., 2014).

Along this vision, manufacturing will be strongly affected by sustainability issues and, what is relevant for the discussion in this study, ~~–~~technological capabilities, on which the manufacturing is largely based, is asked to give the tools and options for building new solutions towards a sustainable manufacturing performance" (Guillén, Crespo, et al. 2016). This study found that TC plays its role, as it is fundamental in the current evolution of maintenance function towards advanced maintenance systems. However, the analysis shows that TC did not moderate with other maintenance systems like TBM and CBM that did not serve as conceptual support to general use and applications in maintenance appear as the key factors in achieving higher performance among Malaysian manufacturing organizations.

In this regard, this study believes that there are currently two relevant challenges for the ineffective design, implementation, and use of TBM solutions in advanced maintenance systems. First of all, the technical profiles, with new skills and capabilities, are far from those that can be found in traditional maintenance engineers or technicians. This is deeply discussed by Karpus, Ivanov, et al. (2018) who examine the basis of design and technological features is a multidisciplinary domain that is undergoing rapid evolution especially in the type of demanded skills and capabilities. The industry will then require highly qualified professionals, combining an initial training in technological techniques and methods with specific expertise in this field; in regard to the work organization, the necessity of simultaneous use of different skills and capabilities with high-level knowledge and expertise will also have to be integrated into maintenance work-teams. Existing studies on this problem typically consider strategies that minimize the expected costs based on current information and update the strategies when more data becomes available. Time-based maintenance can be performed before the failure of the unit. These maintenance practices make the unit as-good-as-new, maintaining and replacing the unit are thus interchangeable notions. However, the analysis of this study shows that this time-based maintenance is assumed to be more expensive among the Malaysian manufacturing sector because failures occur and are likely to have severe consequences.

Tan and Nasurdin (2010) stated that to remain competitive, Malaysian manufacturing organizations need to continuously increase the effectiveness and efficiency of their production processes. Further, the introduction of lean manufacturing increases concerns regarding equipment availability. As a result, the demand for effective maintenance has significantly increased (Taib and Bakri 2018). In adding Mohamed, Rahim, et al. (2016) and Radej, Drnovšek, et al. (2017) stated that the importance of the maintenance function has increased due to its role in sustaining and improving availability, product quality, safety requirements, and plant cost-effectiveness levels. Maintenance costs constitute an important part of the operating budget of manufacturing organizations. According to Cao, Samet, et al. (2019), in most production units, inappropriate maintenance can have serious consequences for product quality, equipment availability, environment, and firm competitiveness.

Majumdar, (2017) noted that proper maintenance practices can contribute to overall business performance through their impact on the quality, efficiency and effectiveness of a company's operations. This can improve the company's competitiveness, including productivity advantages, value advantages and long-term profitability (Alsyouf, 2004). Consequently, proper maintenance can have positive effects for shareholders, customers, and society. Jantunen et al. (2014) state that maintenance is a relatively neglected subject in many companies. To change incorrect attitudes on this issue, several actions are necessary on a political, social, and technical level. Despite the importance of developing strategic maintenance, a large part of the manufacturing industry currently lacks clear maintenance strategies (Corazza, Di Mascio, et al. 2016). It is therefore difficult to develop maintenance work in accordance with the strategic goals of manufacturing companies. Al-Najjar and Alsyouf (2004) and Al-Najjar

(2009) promote the idea that CBM can convert maintenance into a profit centre. Sundin et al. (2007) document a number of cases of savings afforded by the use of CBM. A study by Rosmaini and Kamaruddin (2012) suggest that the application of CBM is more beneficial than that of time-based maintenance (TBM) from a practical perspective. However, the practical implementation of advanced maintenance technologies, such as CBM, in the manufacturing industry is relatively limited (Bengtsson, 2007). According to Rastegari, (2015), who consider a number of industrial sectors, 60% of companies have basic skilled staff and follow a primarily reactive strategy, whereas only 10% use advanced maintenance techniques such as CBM. Walker (2005) identifies some of the more common reasons that CBM technologies are unsuccessful with respect to effective maintenance activities, including discrepancies in training, management direction, technology selection, user commitment and user competence. According to Zare, Bruland, et al. (2016), it is important that TBM be applied to appropriate problems in a plant rather than as an overall policy; it would not be cost effective option to use expensive techniques everywhere. Li, Jing, et al. (2019) also emphasizes that an important aspect of or precondition for a successful TBM implementation shall pursue comprehensive optimization of multiple objectives such as safety, high efficiency and cost effectiveness is to implement the correct approach at the correct location in the correct manner.

Given the ever-increasing global competitive pressures, it is essential that companies gain a better understanding of maintenance management programmes in an effort to optimize both overall equipment effectiveness and productivity (Fraser et al., 2015). These pressures have given firms worldwide the motivation to explore and embrace proactive maintenance strategies (Albano, Ferreira, et al. 2018). Over the last few decades, maintenance functions have significantly evolved with the growth of technology (Rosmaini and Kamaruddin, 2012). Conventional maintenance strategies such as corrective maintenance are no longer sufficient to satisfy the industrial need to reduce failures and degradations of manufacturing systems to the greatest possible extent (Rastegari, 2017). Jantunen et al. (2014) hold that the concept of maintenance has evolved over the last few decades from a corrective attitude (maintenance intervention after a failure) to a predictive attitude (maintenance intervention to prevent the fault). This assumption lead to technological capabilities fails to moderate the relationship between TBM practices and performance among Malaysian manufacturing organizations in this study.

H5: The technological capabilities positively moderate the relationship between CBM practices and performance among Malaysian manufacturing organizations.

The p-value of (H5) is (0.997) which shows an insignificant p-value was more than p>0.10, thus (H5) not supported (Refer table 4.23). The proposed hypothesis indicates that Malaysian manufacturing organizations are facing pressure that difficult to compete with foreign companies. The remaining competitiveness, especially in high tech sectors, requires continuous incorporation of new advances with higher requirements, among others, of reliability while optimizing operation and maintenance. This was supported by Abdullah, Zailani, et al. (2016) pointed out that technological effort is vital to Malaysia, even though it is clear that it is not innovating at the frontier. Thus far, Malaysia has only learned to use imported new technology and equipment from more advanced countries (Chandran, Rasiah, et al., 2009).

Moreover, Rasiah, Lin, et al. (2015) highlighted that Malaysia is unable to attract a significant number of experts because currently, it is facing increased competition from Singapore, Vietnam, Taiwan, and China, which has made the country lag in adopting and promoting innovation. Indeed, reliability and maintenance have an increasingly important role in modern engineering systems and manufacturing processes (Diallo, Venkatadri, et al. 2017), which are becoming increasingly complex and are operating in a highly dynamic environment (Lee et al., 2011). Waeyenbergh and Pintelon (2002) claim that, in the case of leading-edge systems, characterized by a large number of technical items with great interaction level between them, maintenance is now more important than ever for business goals, not only in terms of cost reduction but regarding decisive contribution to the company performance and efficiency as part of an increasingly integrated business concept. Considering the maintenance department, Macchi and Fumagalli (2013) remark the importance of maintenance for the competitiveness of manufacturing companies and, in this regard, assess the maturity of its processes in terms of managerial, organizational and technological capabilities; especially looking at the technological capability, the maintenance objective is to adopt new technologies and tools in the company‘s practice to effectively contribute to competitiveness. In short, Jasiulewicz-Kaczmarek and Saniuk (2017) claim the importance of more efficient maintenance as a key for the sustainability and competitiveness of enterprises and production systems, associating the decision-making process with the so-called ―eco-efficiency” of the production systems. This is an even more comprehensive view of the maintenance role since eco-efficiency encompasses both the impact on business and on the environment. Under this perspective, emphasis on the life cycle of manufacturing assets has caused a redefinition of the role of maintenance as ―a prime method for life cycle management whose objective is to provide society with the required functions while minimizing material and energy consumption.

On the whole, the changes undergoing for the maintenance function are aligned with the transformation of the current manufacturing models based on the old paradigm of ―unlimited resources and unlimited world‘s capacity for regeneration” towards sustainable manufacturing (Garetti & Taisch, 2012). Lin, Wu, et al. (2019) stated that preventive maintenance actions allow for both immediate and postponed upon the identification of a defect at an inspection. This results both in better utilization of the useful life and in a reduced maintenance cost. They find that if the cost difference between a planned maintenance action and an immediate maintenance action is sufficiently large, maintenance actions should always be planned in advance. According to Gittler, Gontarz, et al. (2019), condition-based maintenance information may contain noise due to errors of measurement and interpretation, and due to the limited accuracy of the measurement's instruments. Typical condition monitoring techniques like vibration and oil debris monitoring, which are widely applied in industry, generally result in such inaccuracies. These techniques can, therefore, be considered as imperfect. Also, when considering the crack growth of a mechanical component subject to fatigue degradation, observations of the crack depth at inspections are just estimations of the true values (Mourtzis & Vlachou, 2018).

The analysis of this study indicates that even small levels of measurement errors can render condition-based maintenance no better or even worse than time-based maintenance. The study of Badía, Berrade, et al. (2018) indicates that for large measurement errors the performance of condition-based maintenance gets worse if the number of inspections increases. However, they model all measurement errors by independent normal distributions and perform preventive maintenance when a single observed deterioration level exceeds a safety threshold. However, if the number of inspections is large, it becomes likely that one of the observed deterioration levels exceeds the safety threshold while the real deterioration level is still low. This can be avoided by using a decision rule for initiating preventive maintenance that does not only take the most recent condition measurement into account. Furthermore, such a continuous-time process may also be appropriate for modelling measurement errors when conditions are monitored continuously. The most simple models that include imperfect condition monitoring contain two or three deterioration states, and inspections reveal the true system state with specifically given probabilities (Liu, Liang, et al., 2019). These basic models are extended with inspections that might induce failures, a distinction between minor and major inspections, and a periodic inspection (Yahyatabar & Najafi 2019).

H6: The technological capabilities positively moderate the relationship between PdM practices and performance among Malaysian manufacturing organizations.

The path coefficient results showed that PdM played a insignificant role in improving manufacturing performance. This was clearly shown by the technological capabilities fail to moderate the relationship between PdM practices and performance among Malaysian manufacturing organizations, thus (H6) was not supported. Indeed Spiegel, Mueller, et al. (2018) stated that PdM efforts, such as the installation of sensors, extraction of information, preparation and maintenance of models and maintenance activities, generate costs for companies, in which PdM methods are introduced. These costs may vary according to multiple factors, e.g. the type and complexity of assets and corresponding sensors, cost of consulting, installation and knowledge extraction according to whether the necessary skills can be sourced from in-house or external people. A method to evaluate, whether a PdM introduction may be of benefit, is the educated creation of a projected Return on Investment (ROI) (Diamond and Marfatia, 2013). The projection of the ROI has to consider the value of PdM results, the amortization time and the described costs. The financial reasoning of PdM usage and applicability is further dependent on the size and type of company, in which it is introduced (Xiaoning Jin et al., 2016). While small and medium-sized company are generally more limited in their technological apparatus, larger companies may also be less endangered by the financial risks of the PdM investment. Technology providers usually adapt to the choice of their customers and the market need. Nonetheless, Singla, Ahuja, et al. (2017) stated that in the current manufacturing scenario, all industries utilise almost identical manufacturing operations, techniques, and innovation inbuilt regular manufacturing improvement with substantial output. Undoubtedly, these situations clearly indicate that worldwide technological challenges encouraging perfection in manufacturing arise as an essential objective of the industry (Albrecht, Laleman, et al., 2015; Chryssolouris, Mavrikios & Mourtzis, 2013). Hence, Jun and Ji (2016) urged that all organizationss must clearly know and must be able to precisely justify what technologies they require. Another source of cost may arise through an extended effort of extracting insights from PdM data. While continuous monitoring with current information on asset conditions is available, the produced information and visualizations are difficult to understand with current PdM solutions (Efthymiou et al., 2012). Directly accessing the model output is complex and as stated by Efthymiou et al, (2012) the created visualizations are held too simple and miss an insightful as well as a user-friendly view. Bokrantz et al, (2017) propose that aPdM system should be easily understandable and automated in the future, particularly considering that the complexities of models increase further with big data.

As insights may be difficult to extract, knowledge management is one factor to make the gathered knowledge available to an extended group of people and retain this knowledge. Especially the area of fault detection demands a high amount of prior technical and domain knowledge as well as specific training (Efthymiou et al., 2012). A way to distribute fault detection capabilities is the introduction of fault detection automation. In practice, it is stated that failure information from the past is difficult to isolate. Failure detection clarity regularly decreases with the amount of time dated back. Taking rule-based approaches in fault detection, the number of combinations exponentially grows with the count of characteristics and may be too large to process. In the research of Xiaoning Jin et al, (2016) technology providers reported that missing failure occasions in the given data present an obstacle in the creation of PdM models. This may lead to incorrect alarms in the derived model, as conditions during a failure status may be unclear.

Knowledge Management does not only constitute a technological possibility, but also an organizational method of collaboration. The organization, in which prognostic measures are introduced has been recognized as an important factor for the benefits, which are achieved with the use of PdM methods (Xiaoning Jin et al, 2016 and Katrin Jonsson, 2010). The employees in Small and medium-sized enterprises (SMEs) saw the extension of available information to an employee on the production floor more critical than larger companies in a survey by Xiaoning Jin et al, (2016). Katrin Johnsson et al (2010) found organizational issues to surpass human factors in their relevance to PdM and defined recommendations on organizational and human factor related PdM preconditions and PdM execution. Among other points, they recommended employees in high positions to favor PdM openly to raise acceptance and awareness. Another focus was especially set on training and knowledge of employees, especially with regards to information technology and the factors and inferences that influence a PdM system. Thus based above reason that lead to the insignificant moderator relationship between TC toward PdM practices and performance among Malaysian manufacturing organization.

5.4 Contribution of Study

The findings of this study revealed that preventive maintenance practices optimised the operating performance of manufacturing organizationss. This study‘s contributions are divided into two dimensions, namely, theoretical and practical.

5.4.1 Theoretical Contributions

According to Barney (1991), Resource-based View (RBV) is divided into human capital resources and organizationsal resources. The focus of this study was how PM practices improve manufacturing organizations. Barney (1991) stated that RBV examines the link between an organizations‘s internal characteristics and its performance. The analytical framework showed that preventive maintenance role is to retain or restore machine life that is directly linked with technological capabilities, which leads to manufacturing performance. This is supported by Umar Al-Turki et al.

(2014) who mentioned that preventive maintenance practices played an essential role in the development of manufacturing industries. This is due to the maintenance task being a major activity in manufacturing industries that greatly influence the quality and quantity of production, which ultimately affects production cost and customer satisfaction.

On the other hand, Barney (1997) explained that through RBV, any contemporary views of an organizations should focus on other related organizational attributes like the overall structure of the firm, control system, and policies related to compensation to ensure that resources are completely exploited. By theorising the moderating role of technological capabilities in the manufacturing performance relationship, this study provided a more rigorous test of RBV. As a result, this study contributed significant findings to the existing body of knowledge. Technological capabilities have a direct influence on the continuous growth of an organizations that will determine its leading position among competitors and helps improve its performance (Lee & Lee, 2016). RBV typically contains various aspects that must be noted by the organizations and its employees to improve performance, enhance capabilities, and sustain the long-term growth of resources owned by the organizations (Freiling & Baron, 2016). Crook et al. (2008) applied meta-analysis to examine 125 RBV related empirical studies and discovered that the RBV technique offered extensive support to the claim that firm performance enhanced organization with a golden opportunity to develop competitive advantages. This has added value to the existing body of knowledge via the all-inclusive framework.

5.4.2 Practical Contribution

The findings of this study revealed that the implementation of preventive maintenance practices improved the performance of Malaysian manufacturing organizationss. PdM practices minimise machine stoppages and breakdown in manufacturing plants and this significantly increases manufacturing performance in terms of product quality retainment. Thus, maintenance officers in manufacturing plants must understand the importance of TBM, CBM, and PdM practices to not only extend the machine lifespan but also for delivery and flexibility of products. Through the findings of this study, it is believed that academicians and practitioners will gain new knowledge, whereby PM practices can be a good influencer in enhancing the performance of Malaysian manufacturing organizationss. This argument is supported by various researchers such as Wickramasinghe and Perera, (2016); Troiano, Nolan, Parsons, Hoven, and Zale, (2016); Helo, Gunasekaran, and Rymaszewska, (2017); Willis and Schrieber, 2016; Lee, (2017) in which preventive maintenance practices are widely accepted by manufacturing plants to decrease machine failures, stoppages, and breakdowns that directly affect manufacturing performance. This study concludes that a lack of PM practices can potentially affect manufacturing performance. The findings of this study are most suitable for plant or manufacturing managers who face uncertainties concerning quality of production due to imperfect processes and machine deteriorations and breakdowns that directly or indirectly affect manufacturing performance.

5.5 Limitations and Suggestions for Future Research

This study has several limitations. First, preventive maintenance (PM) practices and technological capabilities (TC) were employed to examine manufacturing performance, which may have potentially increased the bias in this study. Thus, scholars are recommended to extend this research by adding various variables such as human resource practices; leadership practices, competitive priorities; lean manufacturing practices; strategic fit manufacturing practices to deepen the understanding of manufacturing performance. Besides, the total number of participants was only 155 organizations. Hence, in the future, this number should be increased. In terms of directions for future research, researchers are advised to focus on small manufacturing sectors to provide valuable information and contribute to the RBV theory. In short, the limitations of this research may be examined by future investigators.

5.6 Recommendation to Malaysian Organizations

Malaysian Department of Statistic 2017 report claimed that the country‘s manufacturing sector is a major contributor to the growth of Malaysian GDP and the creation of new job opportunities. Nevertheless, Ibrahim, Mohamad, et al. (2018) stated that currently, Malaysia is facing increased competition from countries such as Vietnam, Taiwan, and China, which are attracting low-cost companies. This situation created a serious challenge to Malaysian manufacturing organizations to find a way to remain competitive not only in the country but also internationally. In addition, MIDA also emphasised that Malaysian manufacturing organizations s need to move ahead by embracing the incentive of technological knowledge to make the production process efficient that indirectly leads to good management decision-making (MIDA, 2016). Thus, Malaysian manufacturing organizations can use the findings of this study to evaluate their PM and manufacturing performance. Moreover, this study revealed that TBM, CBM, and PdM practices contributed to manufacturing performance. Jin, Siegel et al. (2016), Muchiri, Pintelon, et al. (2014), and Lee Siegel et al. (2013) determined the positive impacts of TBM, CBM, and PdM practices on manufacturing performance, specifically enhanced production quality. Therefore, Malaysian manufacturing organizationss must ensure that these practices are continuously implemented. Strong support from top management will ensure proper implementation of PM practices in Malaysian manufacturing organizationss. This study can assist Malaysian manufacturing organizationss wanting to improve their performance by increasing quality.

5.7 Conclusion

In this research, the role of preventive maintenance practices in achieving sustainable manufacturing performance was examined. This study explained that Malaysian manufacturing organizationss can enhance competitiveness by implementing preventive maintenance and the technological capabilities approach. Empirical evidence revealed that TBM, CBM, and PdM practices are the key to improve manufacturing performance by increasing quality. This study emphasised that technological capabilities are important for manufacturing organizationss to increase productivity and accelerate innovation. This is because when the implementation of technological capabilities was explored, it was found to create impactful innovations. Nevertheless, the moderating analysis showed that technological capabilities do not have an impact on manufacturing performance. It was identified that technological capabilities do not provide opportunities for Malaysian manufacturing organizationss to improve their existing resources.

Recognising the importance of boosting the performance of Malaysian manufacturing organizationss, this study had successfully provided evidence of preventive maintenance practices greatly upgrading manufacturing performance. This study empirically proved that the implementation of PdM improved manufacturing performance by increase product quality to ensure manufacturing plants operate smoothly. Data analysis exposed that PM practices were significantly and positively related to manufacturing performance. Meanwhile, technological capabilities failed to show a moderating effect on the relationship between TBM, CBM and PdM among Malaysian manufacturing organizationss. This was because moderation analysis showed negative path coefficient values for quality. The present study also investigated the extent of PM practices in Malaysian manufacturing organizationss. Generally, all the participating manufacturing organizationss agreed that PM practices (TBM, CBM, and PdM) are important. IPMA analysis determined that the implementation of PM practices was led by TC followed by PdM, TBM, and CBM. This study declared that the PM strategy is a successful practice in Malaysian manufacturing organizationss. This indicates that participating manufacturing organizationss are concerned that PdM practices increase the profit margin of manufacturing organizations. Meanwhile, PdM were the most implemented PM practices in Malaysian manufacturing organizationss. Hence, operators involved in the daily operation of equipment were able to detect any abnormalities by utilising these maintenance practices. PdM activities help determine the condition of in-service equipment to predict when maintenance should be performed. This approach promises product quality over routine or time-based preventive maintenance because tasks are performed only when warranted. Overall, the analysis showed that participating organizationss agreed that PdM play a vital role in creating a dynamic production plant. Perhaps a longitudinal study and case study approaches may be suitable to investigate PM implementation with the inclusion of more variables. On the other hand, the results of this study were interpreted with caution as the response rate was quite low. Since the research was designed to consider different types of industries in Malaysian manufacturing organizationss, the conclusions can be generalised to all manufacturing organizationss where PM practices can still be improved.

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APPENDICES

Appendix A: Questionnaire

Pusat Pengajian Pengurusan Teknologi dan Logistik
SCHOOL OF TECHNOLOGY MANAGEMENT AND LOGISTICS
Universiti Utara Malaysia

Dear Sir / Madam,

I am a PhD student of UUM, conducting research entitled “**The Preventive Maintenance Practices and Performance among Manufacturing Organizations in Malaysia; the Moderating Role of Technological Capabilities**”. Your participation in this research will be appreciated by responding to the attached questionnaire which has been designed to capture data on strategies for improving Malaysia Manufacturing Organizations performance by utilizing preventive maintenance practices. The questionnaire should take no more than 30 minutes of your time. I ensure that all responses given are **STRICTLY CONFIDENTIAL** and for the purpose of the research only. Neither you nor your organization will be identified. If you have any questions, please contact me through email at semtharan@gmail.com Thank you in advance for your participation and cooperation to submit the questionnaire by **20th November 2017**.

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Section 1: Respondent Demographic Details

Please kindly respond to the following questions by ticking (√) the appropriate box for each item

1. **Does Your Company Implement Preventive Maintenance?**

   Yes ☐ No ☐

2. **Position in Organization** (tick one box only)

   ☐ Chief Executive Officer ☐ Operations manager ☐ Quality manager

   ☐ Maintenance Manager **Others** (Please Specify) _________________

3. **Ownership**

   ☐ Joint venture ☐ Multi National Corporation (MNC)

   ☐ Private Limited (Sdn Bhd)

4. **Annual Sales Turnover**

   ☐ Less than RM300,000 ☐ RM 300,000 < RM 15 millions

   ☐ More than RM 15 millions

5. **Number of Employees in organization**

   ☐ 5 to 75 ☐ 76 – 200 ☐ More than 200

6. **This company is in the following category:** (please tick only one)

☐ Foods products ☐ Rubber-based/plastic ☐ Electrical/electronic

☐ Petroleum/Petrochemical/chemical ☐ Machinery/equipment Basic metal product

Others (please specify) __________________________

Section 2: Preventive Maintenance Practices

Kindly please tick (√) only one box to indicate in your opinion/experience.

1: **Strongly Disagree** 2: **Disagree** 3: **Neither Disagree nor** 4: **Agree** **5. Strongly Agree**

Code	Time-Based Maintenance (TBM)	1	2	3	4	5
TBM 1	Carrying out daily maintenance activities with repetitive nature, such as taking meter readings, start-up/shut-down chillers, etc (Routine maintenance approach)					
TBM 2	Carrying out the scheduled or unscheduled activities after a failure has occurred to restore to normal functions (Corrective/failure-driven maintenance approach)					
TBM 3	Carrying out regular/scheduled activities at predetermined intervals of time (Preventive/time-based maintenance approach)					
TBM 4	Carrying out immediate maintenance actions of unexpected defects to avoid further damage or adverse consequences. (Emergency maintenance approach)					

1: **Strongly Disagree** 2: **Disagree** 3: **Neither Disagree nor Agree** 4: **Agree** 5: **Strongly Agree**

Code	Condition-Based Maintenance (CBM)	1	2	3	4	5
CBM 1	Decreasing the repair time					
CBM 2	Helping improve the production process					
CBM 3	Performing periodic planned replacement					
CBM 4	Recording process quality rate					
CBM 5	Performing the maintenance tasks based on statistical modelling of failure data					
CBM 6	Analysing equipment failure causes and effects					
CBM 7	Monitoring the production equipment status					

1: **Strongly Disagree** 2: **Disagree** 3: **Neither Disagree nor** 4: **Agree** **5. Strongly Agree**

Code	Predictive Maintenance (PdM)	1	2	3	4	5
PDM 1	Operational decision support systems (e.g. change machine oil)					
PDM 2	Regularly updated (i.e. "living") probabilistic risk models of equipment reliability for maintenance and outage planning					
PDM 3	Real-time probabilistic risk models for operator evaluation and awareness of plant safety (i.e. "a safety monitor").					
PDM 4	System health monitors (e.g. predictive maintenance tools such as vibration, acoustic, thermal, or other monitors).					
PDM 5	Advanced model-based monitoring and diagnostics (e.g. physics, chemistry, boiler, feed water and thermal hydraulics models).					
PDM 6	Advanced information exchange (e.g. hand-held computers, plant-wide equipment status monitoring, wireless communications).					
PDM 7	Electronic (i.e. graphical) road-maps of business and decision processes or work-flows (e.g. operational flow-sheets) with links to supporting procedures, related resources or documents					
PDM 8	Automated field data collection (i.e., smart instruments, fieldbus, radio frequency identification (RFID) tagging, data logging, equipment monitors).					

Section 3: Manufacturing Performance

Kindly please tick (√) only one box to indicate in your opinion/experience.

1: **Strongly Disagree 2**: **Disagree 3**: **Neither Disagree nor Agree 4**: **Agree 5**: **Strongly Agree**

Code	Organization Performance	1	2	3	4	5
	Cost					
C 1	Organization can gain labor productivity cost by implementing Preventive Maintenance practices.					
C 2	Preventive maintenance has an ability to reduce product cost.					
C 3	Preventive maintenance practices have an ability to reduce inventory cost.					
C 4	By the Implementing Preventive Maintenance Practices Organization can achieve low manufacturing cost per unit.					
C 5	Organization is capable of competing against major competitors based on low price.					
	Quality					
Q 1	Organization is capable of offering product quality that creates higher value for customers.					
Q 2	Organization are able to compete based on quality.					
Q 3	Organization can offer highly reliable products.					
Q 4	Organization can offer durable products.					
Q 5	Organization offer high quality products to customer.					
	Flexibility					
F 1	Ability to add or substitute easily new part.					
F 2	Ability of a firm to produce different combinations of products economically and effectively.					
F 3	Ability of a machine to perform different types of operation without requiring a prohibitive effort in switching from one to another.					
F 4	Ability of the workforce to perform a broad range of manufacturing tasks economically and effectively.					
F 5	Ability to adapt to a changing market environment easily.					
F6	Ability of a manufacturing system to process a given set of components with different processes, operations sequence and materials.					
F7	Ability of a manufacturing system to introduce and manufacture new Products.					
F8	Ability to increase capacity and capability easily when needed.					
	Delivery					
D 1	Organization is capable of deliver product on time.					
D 2	Organization can deliver right quantity at the right time.					
D 3	By practicing preventive maintenance organization can deliver on time to meet vendors request.					
D 4	Preventive maintenance enables organization to provide reliable delivery.					
D 5	Preventive maintenance enhancing the Organization to deliver according to customer demand.					

Section 4: Technological Capabilities

Kindly please tick (√) only one box to indicate in your opinion/experience.

Please tick only one box to indicate in your opinion/experience.

1: Much Worse 2: Worse 3: About the Same 4: Better 5: Much Better

Code	Technological Capabilities	1	2	3	4	5
TC 1	Skills in conducting applied R&D.					
TC 2	Ability to transform R&D results to product.					
TC3	Skills to develop new products.					
TC 4	Ability to upgrade existing products.					
TC 5	Efficiency in manufacturing the products.					
TC 6	Skill in Manufacturing.					
TC 7	Overall Technological skills.					
TC 8	Speed of new product development.					
TC 9	Efficiency in manufacturing the product.					

< THANK YOU >