EVALUATION OF THE IMPACT OF LEAN TOOLS ON SAFETY PERFORMANCE IN MALAYSIA'S MANUFACTURING FIRMS

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EVALUATION OF THE IMPACT OF LEAN TOOLS ON SAFETY PERFORMANCE IN MALAYSIA'S MANUFACTURING FIRMS

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A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Mechanical Engineering with Honours

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DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

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APPROVAL FOR SUBMISSION

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ABSTRACT

Occupational health and safety considerations are key aspects of manufacturing firms, along with profitability. Implementing lean tools is a comprehensive method for continuously improving industrial processes. The primary focus of the study is to evaluate how lean tools affect Malaysia's manufacturing firms' safety performance. The objective of this study is to develop the conceptual framework of lean tools and safety performance and to examine the hypotheses and the relationship between lean tools and safety performance. The variables to be examined in this study are continuous flow (CF), total preventive maintenance (TPM), employee involvement (EI), and safety performance (SP). Despite the increasing adoption of lean principles and practises to improve operational efficiency, there remains a significant knowledge gap regarding their influence on safety performance. Furthermore, manufacturing companies may lack awareness of the specific lean tools that should be prioritised to enhance safety performance. This lack of knowledge can lead to the inefficient allocation of time and resources, hindering their ability to effectively improve safety outcomes. A total of 134 responses of questionnaires were collected from all of the manufacturing companies listed on the Federation of Malaysian Manufacturers (FMM) and Wesley Malaysia websites. The data is analysed using the PLS-SEM analytical method with SmartPLS 4 software. The findings of this study indicate that continuous flow, total preventive maintenance, and employee involvement all significantly improve safety performance. Employee involvement has the greatest impact on safety performance, with a beta coefficient of 0.304. Followed by continuous flow and total preventive maintenance with beta coefficients of 0.274 and 0.232, respectively. Moreover, Importance-performance Map Analysis (IPMA) indicates that EI is the most pertinent construct for managerial action. In addition, it suggests Malaysia's manufacturing firms keep up their performance on CF. On the other hand, the industries may choose to maintain their existing performance on TPM or refocus on other constructs with high importance and performance. In conclusion, the findings of this study will contribute to filling the knowledge gap in the Malaysian context, providing evidence-based recommendations and guidance for Malaysia's manufacturing firms.

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LIST OF SYMBOLS / ABBREVIATIONS

Q^2	predictive relevance
$Q^2_{excluded}$	Q^2 value of at endogenous variable where the selected exogenous variable is excluded from the model
$Q^2_{included}$	Q^2 value of at endogenous variable where all the exogenous variables are included in the model
R^2	coefficient of determination
R^2_{new}	R^2 value obtained after removing a particular exogenous variable from the model
R^2_{old}	R^2 value obtained from the original model that includes the exogenous variable
f^2	effect size
q^2	effect size
$1-\beta$	power
α	significance level
λ	standardised factor loading
N	population size
e	acceptable sampling error
e	level of precision
i	number of items
k	number of exogenous latent variables
n	sample size
p	the population proportions
z	z-value at reliability level
AVE	Average Variance Extracted
BCa	Bias-correlated and Accelerated
BCC	Blind Carbon Copy
CB-SEM	Covariance based Structural Equation Modelling
CF	Certificate of fitness
CF	Continuous Flow

CR	Composite Reliability
CSV	Comma-separated Values
CVC	Cross-validated Communality
CVR	Cross-validated Redundancy
EI	Employee Involvement
FMM	Federation of Malaysian Manufacturers
GDP	Gross Domestic Product
GoF	Goodness-of-Fit
HTMT	Heterotrait-monotrait Ratio
IPMA	Importance-performance Map Analysis
JIT	Just-in-Time
MAE	Mean Absolute Error
OEE	Overall Equipment Effectiveness
OSHA	Occupational Safety and Health Administration
PLS-SEM	Partial Least Square based Structural Equation Modelling
PPE	Personal Protective Equipment
RMSE	Root Mean Squared Error
SEM	Structural Equation Modelling
SMEs	Small and Medium Enterprises
SOCSO	Social Security Organisation
SP	Safety Performance
TPM	Total Preventive Maintenance
TPS	Toyota Production System
VIF	Variance Inflation Factor
VSM	Value Stream Mapping
WID	Waste Identification Diagram
WIP	Work In Progress

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CHAPTER 1

INTRODUCTION

1.1 General Introduction

In the contemporary world, the competition rate in the manufacturing industry has increased in an exponential manner. This is due to the fact that globalisation affects manufacturing. Manufacturing and construction industries are classified as secondary sectors of the economy. In other words, the manufacturing industry plays a pivotal role in the economic growth and development of developing countries. In 2020, the contribution rate of Malaysia's manufacturing industry to the economy is 22.9 % (DOSM, 2021). The manufacturing industry has experienced remarkable development in the past few decades. It is continually developing with an increasing integration of automation, from mass production via the employment of an intense labour force in production lines to the use of robotics to boost efficiency. The Fourth Industrial Revolution, often known as Industry 4.0, is the next stage of development (Chellam, 2019).

Safety in manufacturing is very important to avoid or reduce the risk of injuries, diseases, and deaths in the workplace. Therefore, every manufacturer needs to establish a safe and protected working environment for its employees. In fact, no one wishes to get hurt at work, and no one wishes to be responsible for someone else being injured. Some common safety problems may occur in the manufacturing process that need to be taken care of, for instance, improper maintenance, tripping, slipping, and falling, electrical hazards, unrestricted access, etc (Peleg, 2021). The study showed that the number of occupational accidents in 2020 was 32674 (DOSM, 2021). A manufacturing industry requires to provide workers with health and safety training so as to improve productivity and speed up the sustainable development of the economy and society. In light of the fact that reducing the problem of injury may reduce the operating costs, strengthen the willingness and enthusiasm of the operator, and enrich the image of the industry.

Lean tools focus on diminishing waste (or "muda", which means waste in Japanese) in organisations and enhancing quality control, which is to say that lean tools are designed to abolish all worthless and unprofitable processes. The waste within an organisation includes defects, overproduction, transportation, waiting, inventory, motion, and over-processing (7 Wastes of Lean, n.d.). Other than improving processes and reducing waste, lean tools can also raise the level of safety in manufacturing industries. Some lean tools may be more suitable to be used in manufacturing. In spite of that, 5S, poka-yoke, kaizen, kanban, just-in-time (JIT), and value stream mapping (VSM) are among the most useful lean tools. Moreover, manufacturing industries should identify the problems and apply the correct and appropriate lean tools. Therefore, the properties, advantages and disadvantages, cost of implementation, and complexity of lean tools must be taken into account when selecting lean tools for the manufacturing process.

One of the most commonly used lean tools, namely 5S, which refers to Seiri, Seiton, Seiso, Seiketsu, and Shitsuke in Japanese. They are translated into English as sort, set in order, shine, standardize, and sustain. Recently, the concept of safety has been added to the traditional 5S, making the traditional 5S become 6S with the addition of an extra S. The potentially hazardous incident has been lowered with the use of 5S (Ulewicz and Lazar, 2019). Moreover, manufacturing industries claimed that the implementation of the 6S methodology was able to boost productivity, provide employees with a better working environment and workplace safety, and thus ameliorate performance (Sukdeo, 2017).

On top of that, in 1961, Shigeo Shingo, a Toyota Motor Corporation engineer, established the poka-yoke system (Dudek-Burlikowska and Szewieczek, 2009). The objective of this system is to identify and eradicate of aberrant circumstances that avert product failures. In other words, Poke-Yoke is a method for producing or assembling goods with few or no flaws by employing zero quality control. Additionally, poka-yoke allows for the elimination of numerous quality control inspections and the reduction of the time needed for staff training (Rewers, Trojanowska, and Chabowski, 2016). Some commonly implemented poka-yoke devices in manufacturing are sensors, vision systems, warning lights or buzzers, alarms, limit switches, etc (Poka-Yoke in Manufacturing, n.d.).

1.2 Importance of the Study

The primary focus of the study is to evaluate how lean tools affect manufacturing companies' safety performance. Worker safety is of utmost importance as it ensures the well-being and physical integrity of employees. Gaining insight into how lean tools impact safety performance may help to improve workplace safety procedures, reduce accidents, and safeguard workers (Demirkesen, 2019). Besides, workplace accidents and injuries can have a major economic impact. This study can shed light on how integrating lean concepts and practises can minimise accidents and costs by examining the influence of lean tools on safety performance. It could lead to better economic results by offering industrial companies evidence-based advice on how to improve safety performance while streamlining their processes.

In addition, the effectiveness and productivity of lean techniques and technology in industrial processes are well known. The study can aid in determining how safety measures can be easily incorporated into lean processes by looking at the link between lean tools and safety performance. Through this integration, safety considerations are maintained while productivity is increased, creating a win-win situation for both employees and companies. A common issue in industrial companies is that when productivity increases, the health and safety of workers are threatened. The study demonstrated that overall business performance might be improved by combining operational enhancement with safety considerations (Hamja, Maalouf and Hasle, 2019).

Apart from that, Malaysia's economy suffers losses as a result of workplace accidents. According to statistics from the 2012 annual report of the Malaysia Social Security Organisation (SOCSO), the direct cost of accidents was estimated to be RM2.02 billion, accounting for around 0.5 % of Malaysia's GDP. It is possible that indirect costs may be higher. Given the rise in compensation, it is clear that workplace safety has not considerable improved in Malaysia (Hong, Ramayah and Subramaniam, 2018). In 2020, a total of 68,710 accident cases were reported. Among these, 38,092 accidents were classified as industrial accidents. It is important to note that the actual number of accidents may be higher, as not all incidents are reported or documented. In general, there tends to be a positive correlation between the number of accident cases and the overall cost of accidents. When the number of accident cases increases, the potential for financial losses also rises. This is because a higher number of accidents typically leads to more injuries, damages, and costs (PERKESO, 2020).

Other than that, continuous improvement is emphasised in lean concepts. Research on the effect of lean technologies on safety performance might aid organisational development in manufacturing companies (Kumar et al., 2022). It can shed light on how well specific lean tools work to enhance safety outcomes and point out areas that still require improvement. As a result of this knowledge, companies may adjust and enhance their safety procedures over time. In short, it has the potential to guide manufacturing companies towards implementing effective safety measures while maintaining their commitment to lean principles, thereby promoting a safer and more effective working environment.

1.3 Problem Statement

Lean tools are a set of techniques and principles used in manufacturing operations to reduce waste and increase operational effectiveness. Many industrial companies in Malaysia have adopted lean tools to improve their production processes and reduce costs. However, even though lean tools are known to increase operational effectiveness, it is unclear how they will affect safety performance (Ulewicz & Lazar, 2019). The lack of study on the connection between lean tools and safety performance in Malaysia's manufacturing sectors is problematic since it creates uncertainty around the advantages of adopting lean tools. Manufacturing companies might not completely understand how lean tools might affect safety performance, which can result in missed opportunities to increase safety and save costs. Although there is research on safety and lean techniques, they might not explicitly address Malaysia’s context. The applicability of findings from studies conducted in other regions or countries might differ due to variations in regulatory frameworks and cultural factors.

Furthermore, manufacturing companies might not be aware of which specific lean tools to prioritise when attempting to enhance safety performance, that can result in the inefficient use of time and resources. The existing literature may not provide a comprehensive understanding of the specific lean tools that are most effective in improving safety performance. Moreover, when manufacturing companies adopt lean transformations, there will be serious safety issues, which need further research. An in-depth study is required to address these specific issues since the use of lean technologies could alter existing safety measures and generate new dangers. In addition, safety concerns have increased recently in Malaysia's manufacturing companies. As a matter of fact, Malaysia experienced over 2700 industrial accidents that resulted in fatalities and disabilities in 2018 (Yeow, Ng, Tai and Chow, 2020). Hence, it is essential to carry out this research to assess how the implementation of lean tools has affected Malaysia's manufacturing companies' safety performance.

1.4 Aim and Objectives

1.4.1 Aim

To evaluate the impact of lean tools on safety performance in Malaysia's manufacturing firms.

1.4.2 Objectives

(i) To develop the conceptual framework of lean tools and safety performance.

(ii) To examine the hypotheses and the relationship between lean tools and safety performance.

(iii) To identify how lean tools affecting safety.

1.5 Scope and Limitation of the Study

In spite of the fact that lean tools are extensively used worldwide, many Malaysia's organisations still have trouble implementing these tools due to factors such as limited funds, poor leadership skills, a lack of worker skills, and cultural differences. Factors that influence the adoption of lean tools are process, planning and controlling, interactions between client and vendor, human resource management, top management, and leadership. According to the research, the process was the primary determining factor since inefficient processes result in employees producing less work and squandering more resources (Chan et al., 2019). For successful lean tool adoption, these factors must be effectively managed to the greatest degree feasible.

On the other hand, due to several limitations or barriers, adopting lean tools in a third world nation like Malaysia is still seen as a significant challenge for manufacturing organisations. Adoption of lean tools is frequently hampered by a number of factors, including inadequate measurement systems, organisational cultures, a lack of practise and training, poor communication, and so on. However, a lack of understanding is the greatest barrier to effectively implementing lean tools in Malaysia since it necessitates new knowledge and cultural change throughout the transformation. To put it another way, a lack of skilled workers and a lack of knowledge are the biggest hindrances for Malaysian businesses implementing improvement projects. By way of illustration, due to a lack of sufficient guidance and rules from established companies and the government, certain sectors in Malaysia do not consider that a continuous programme can increase their productivity and cost control (Sahwan, Ab Rahman and Md Deros, 2012).

1.6 Contribution of the Study

There are several contributions that can be derived from this study. Firstly, this study makes a contribution by looking into how Malaysia's safety performance is affected by lean tools, which is an area that has not been extensively studied in the literature. This study aimed to fill the knowledge gap by investigating how safety performance is impacted by the use of lean tools in Malaysia. The findings may be used to create effective strategies that can help reduce accidents and injuries, and ultimately improve the bottom line for companies.

Furthermore, the contribution of this study lies in the development of a conceptual framework, which provides a theoretical basis for understanding the impact of lean tools on safety performance in Malaysia's manufacturing industries. The framework can serve as a roadmap for further study and a point of reference for other sectors and regions where lean tools are applied to enhance safety performance.

Additionally, the study makes a significant contribution by improving the public's perception of the manufacturing industry. This study can contribute to a rise in trust in the industrial sector's capability for responsible and safe operation by enhancing safety performance via the use of lean tools. This can have a positive impact on public opinion, attract investment, and create employment opportunities in this industry. A positive view of the manufacturing industry can also contribute to Malaysia's overall economic growth because it can help attract more enterprises to invest in the country and stimulate growth in related sectors.

1.7 Outline of the Report

The report consists of five main chapters. Chapter 1 provides an introduction to the research, including background information, a clear problem statement, and the objectives of the study, along with the scope and limitations, and contribution of the study. Chapter 2 is dedicated to a comprehensive literature review, presenting an overview of the research area, key concepts and theories, previous studies, and identified gaps in the existing literature. Chapter 3 focuses on the methodology and work plan. Chapter 4 presents the results of the research, including the findings and their analysis and interpretation, along with a discussion comparing them to previous studies and exploring their implications and significance. Finally, chapter 5 presents the conclusions and recommendations derived from the research, summarising the key findings, drawing conclusions, and suggesting future research directions.

CHAPTER 2

LITERATURE REVIEW

2.1 History of Lean Tools

The Toyota Production System (TPS), which was developed in the middle of the 20^{th} century, served as the foundation for the lean manufacturing and operations philosophy. Lean was first introduced by Henry Ford and Toyota in the 1900s; however, its origins may be found in Venice in the 1450s. In fact, a production technique known as “mass production,” which produces several standardised items in massive quantities, was first successfully implemented by Henry Ford. For the reason that there was a labour surplus and a substantial supply of goods to meet demand in the early stage of manufacturing development, manufacturers did not need to improve their efficiency. In spite of that, the manufacturing industry underwent a significant transformation in 1908 with the introduction of Henry Ford's Model T and the philosophy of mass production. As a consequence of the proposed mechanism, considerably lower production costs could be achieved, as well as reduced final product costs, which ultimately resulted in higher quality products. This technique drives a number of European businesses to adapt and produce things in mass quantities (Ribeiro et al., 2019).

The principle of Jidoka, developed in 1902 by Toyota founder Sakichi Toyoda, is the earliest element of the TPS. This principle relates to the idea of implementing quality into the production process and allowing the division of man and machine for effectively managing multiple processes. The Toyoda Spinning and Weaving Corporation, founded by Sakichi Toyoda, is where this idea first originated. A motor-driven loom with a unique mechanism designed to halt in the situation of the thread breaking off was created by Sakichi Toyoda, who was working in the textile industry at the time. Henceforth, the production capacity increased and the defection rate decreased. The mechanism served as the base for Jidoka, one of the two major pillars on which the Toyota Production System was formed. Later in 1924, Sakichi developed an automatic loom that allowed a single employee to control several different devices. Platt Brothers Ltd. in England eventually purchased the rights to produce the loom outside of

Japan. This funding was subsequently used in part to launch an automotive section that was subsequently spun off in 1937 as a distinct business and company under the leadership of Kiichiro Toyoda, Sakichi Toyoda's son.

Over and above that, in terms of the production system, the Just-in-Time pillar is the most well-known element of the TPS. Kiichiro Toyota invented the concept of “just-in-time” after the establishment of Toyota Motor Corporation in 1937. Due to its dire financial situation, the company was unable to afford to squander funds on extra machinery or supplies used during manufacturing. Everything was anticipated to arrive on time, not too early or too late. Takt time, standardised work, supermarket, and kanban were eventually added to the JIT framework in the 1950s. An historical practise in American supermarkets known as "pull-flow production" was introduced by Taiichi Ohno shortly after World War II. The pull-flow production enabled as many items to be manufactured as could be utilised in the subsequent phase. Consequently, it would make it easier to cut back on overproduction (Liker, n.d.). Figure 2.1 shows the house of Toyota Production System. In sum, countless other tools and methods, including the 5S, poke-yoke, value stream mapping, kaizen, and so forth, were created by Toyota.

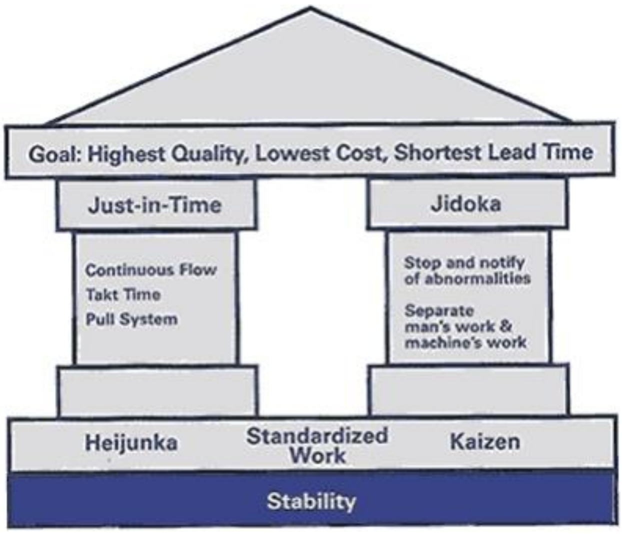

Figure 2.1: House of Toyota Production System (Liker, n.d.).

2.2 Safety Performance in Manufacturing Industry in Global and Malaysia

The manufacturing industry has typically been a major factor in the economic growth of developing countries. Owing the fact that the manufacturing sector is the primary driver of the country’s economic growth. According to economist Nicholas Kaldor, the growth of the country’s economic manufacturing industries was positively correlated with GDP growth (Libanio and Moro, 2007). Productivity in the manufacturing sectors was likewise favourably correlated with sector development. As an illustration, the manufacturing sector in the United States contributed an approximated 24 % of GDP in 2020, including direct and indirect value added (Thomas, 2020). However, due to the frequency of workplace accidents, the manufacturing sector is one of the highest risk sectors of the economy. In the United States, there were a total of 4,764 fatal workplace injuries in 2020. A total of 340 deaths, or 7.14 percent of all deaths during that time, were related to private manufacturing (A look at workplace deaths, injuries, and illnesses on Workers’ Memorial Day, 2022).

In this day and age, Malaysia’s industrial development has been supported by the small and medium enterprises (SMEs) sector. The manufacturing industry plays a significant role in Malaysia's phase transformation into high value-added activities. Since Malaysia started its path towards industrialization, the manufacturing industry has been the driving force behind the country's economic growth. This has been demonstrated by the manufacturing sector's contribution of 22.9 % to Malaysia's GDP in 2020. Despite that, SMEs seem to be a sector that has the highest prevalence of workplace accidents, up to 60 % to 70 % (Zulkifly et al., 2021).

The term “safety performance” often indicates the degree of safety as evaluated by industrial accidents, hospitalisations, and deaths (Mullen, Kelloway and Teed, 2017). In addition, it may be used to refer to two different concepts. Occasionally, the term "safety performance" may be used to describe an organisational statistic for safety outcomes, such as the annual number of injuries. On the other hand, a metric measuring a worker's safety-related behaviour may be referred to as safety performance (Christian, Bradley, Wallace and Burke, 2009).

Regarding safety performance, there are two generally held points of view: the old viewpoint and the new viewpoint. The old viewpoint holds that workplace accidents are caused by human error. In response to this viewpoint, accidents and injuries were frequently directly attributed to people. Based on this, the old viewpoint's primary indicators for evaluating safety performance were the numbers of accidents and injuries. The root causes of human behaviour are not addressed by human error. As a result, it is still unknown what causes accidents and injuries. This viewpoint has been proven to be ineffective at present. In contrast, the new viewpoint evaluates deeper underlying causes such as organisational issues, task characteristics, and working environments and treats human error as a symptom rather than a direct cause of accidents. At present, the holistic view offers a compelling justification for determining and controlling the causes of accidents, while the existing method fails to identify the primary variables that affect workplace accidents and injuries. Organisations might avoid frequent accidents with the use of this methodology. The new viewpoint has led to the development of several instruments and methodologies for measuring safety performance. A leading indicator is a commonly used indicator for analysing safety performance, whereas a lagging indicator is used to assess safety program effectiveness. These indications address the fundamental elements that have been hidden beneath human error (Mousavi, 2018).

An accident is described as a sudden, unexpected incident that causes disaster. According to the study, an industrial injury can be non-fatal or fatal. A non-fatal industrial injury is one that requires at least four days away from work but does not result in death. On the contrary, a fatal industrial injury is one that results in death. In order to reduce the frequency of workplace accidents in the industrial sector that result in death, permanent disability, or non-permanent disability, more knowledge on safety behaviour and precaution should be evaluated. Furthermore, workplace accidents cause loss of productivity and additional medical expenses, thus increasing the social cost.

Workplace accidents are influenced by several factors. Research showed that environment, employee behaviour, employee selection practice, job satisfaction, and stress are the factors most frequently linked to work-related accidents. A related research indicates five key factors, including psychology, environment, ergonomics, physical activity, and stress, as probable causes of accidents. Besides, according to safety experts in the manufacturing field, behavioural issues may be the cause of approximately 90 % of all workplace accidents. Understanding how behaviour affects safety performance is fundamental, and this cannot be overstated. The two primary causes of occupational accidents have usually been identified as internal cause variables and external cause variables, which also refer to worker dispositional characteristics and workplace characteristics, respectively (Gyekye, 2010).

Unexpected hazards and unfortunate circumstances have killed the majority of qualified workers at several manufacturing companies in Nigeria that failed to adopt safety and health practices. Four independent parameters, including safety training, management commitment, safety awareness, and hazard exposure, are used as indicators of industrial safety and health. These parameters all have an impact on and affect employee performance in manufacturing industries in river state. The analysis's findings showed that safety practices significantly affect workers' productivity. To put it differently, low job satisfaction, which has also impacted organisational performance, is caused by a lack of or ineffective adoption of safety and health procedures. The research suggested some ways to overcome this problem. One way to decrease workplace accidents is to provide various types of personal protective equipment (PPE) to all employees. Moreover, the manufacturing company must ensure that all employees, including top, middle, and low-level employees, attend safety and health training. Additionally, a good production layout and the storage of potentially hazardous substances can also help to prevent workplace accidents (Nwachukwu, Akpuh, Samuel and Udeme, 2020).

Furthermore, the rate of workplace accidents involving SMEs in Malaysia has risen in recent years. This study was conducted in the Malaysian manufacturing company in Klang, Malaysia. A strong relationship between safety management practices and safety behaviour has been reported in the literature. In order to reduce the frequency of workplace accidents in the manufacturing industries that result in death, permanent disability, or non-permanent disability, more research on safety behaviours and precautions should be evaluated. The organisation may raise the degree of safety management practices in the manufacturing industry by conducting a number of actions, including providing suitable personal protective equipment (PPE) for every employee, offering intensive training on all workplace health and safety-related topics to every employee, and enforcing the idea that everyone should value safety as highly as they value productivity. Hence, the optimum safety practices that are adopted by management and staff are effective practical steps against workplace accidents and injuries (Saraih, Maniam, Norsyafawaty and Valquis, 2021). In short, safety performance increases with the decrease in the incidence of accidents and injuries in the manufacturing industries.

More than 3000 significant injuries and nine fatalities happen every year within the manufacturing industry, making it one of the riskiest industries to work in statistically. As a matter of fact, every seven seconds, an employee being injured in the United States. As a case in point, a 53-year-old labourer had his arm broken while running a brick crushing machine. As a result of the inability of a Pennsylvania, the United States, manufacturer to install a guard on a brick-crushing machine. Further analysis showed that in the process of loading bricks into the machine, the injured labourer's left hand and arm were trapped in and drawn into the whirling drums. Also, in accordance with the Occupational Safety and Health Administration's (OSHA) finding, the organisation failed to set up guards to ensure that no worker's body accidentally entered the danger zone while it was in use. A lack of warning signs and labels on machinery is another factor leading to accidents (Fluxman, 2022).

In addition, in February 2022, a 25-year-old Ohio, the United States industrial worker needed medical attention after suffering severe arm burns. The investigation demonstrated that the employee was not given spark-resistant hand tools and proper personal protective equipment (PPE) by the organisation (Fluxman, 2022). Another industrial catastrophe that happened in Whyalla, South America, in the year 2020 involved a 20-year-old teen whose shirt got trapped in the machinery, dragging her arm into the roller. This industrial catastrophe occurred because no emergency stop button had been placed on the conveyor. Besides, there was no complete protection on the return roller conveyor (Cosic, 2022).

Apart from that, there are also quite a significant number of workplace accidents happening in Malaysia from time to time. One of the examples is a victim who slipped and fell from an unprotected platform from a height of 15 metres onto the factory floor in a glove factory in Klang, Malaysia. Upon further examination, it was discovered that no proper personal protective equipment (PPE) was given to the victim (Renovation work ceased at glove factory after fatal accident, 2021). In addition, in the year 2022, a foreign general labourer was killed in Johor after being trapped between an iron plate and a gantry crane pole. According to the findings of the inquiry, the employer neglected to examine the equipment, which had a valid certificate of fitness, and the "single girder cantilever gantry crane" remote control was stored without any supervision from the employer. Other than that, an employee was killed after being crushed between two hoisting devices in Perak in the year 2020. According to the result of the investigation, the employer failed to set up a control system from the manufacture of wet bricks to the Drying Kiln section (DOSH, 2022).

2.3 Types of Waste and Their Impact of Safety

Waste is one of the primary impacts on profitability in any firm. Time, material, and labour are examples of lean waste. Nonetheless, it could also be connected to a lack of preparation and the misuse of certain skill sets. In this manner, the elimination of unnecessary waste within an industry is a key tenet of the lean technique. In view of the fact that any expenditure or effort that is made in lean manufacturing that does not result in the manufacture of a product that customers are willing to compensate for is considered waste. These seven different waste categories might compromise safety.

First and foremost, defect is one of the wastes of lean manufacturing. The definition of a defect is the failure to satisfy customer expectations or comply with requirements. Simply explained, defects happen when a product is unfit for its intended use. As an illustration, it is considered wasteful to rework or scrap a product since these actions raise operating expenses while providing no benefit to the customer. It is frequently brought on by imperfect manufacturing systems, unsatisfactory parts, or inaccurate process mapping documentation. The additional wasted time and effort required to fix or replace a defective product may put employees' safety at risk.

Besides, overproduction happens when parts are manufactured before they are demanded by the subsequent downstream process. In other terms, generating more, more quickly, or earlier than necessary are considered as overproduction. A manufacturer would incur a significant cost for overproduction because it interferes with the flow of resources, lowers product quality, and reduces overall productivity. Inaccurate demand and forecast information, as well as unreliable production schedules, are common causes of overproduction. Overexertion, additional handling, and unneeded machine contact are all risks associated with excessive material handling.

In addition, transport waste comprises the unnecessary and unproductive movement of people, materials, stocks, equipment, or goods. Excessive material movement might result in faults and product damage. Furthermore, a lot of movement of people and products might result in extra effort, higher wear and tear, and tiredness. The movement and handling of goods during transit may not necessarily increase their worth, and too much movement and handling might harm the product. The product's quality can be damaged as a result of this. Lack of delivery route planning and poor plant design might result in transportation waste. Thus, whenever a product is transported, there is an increased chance of personnel danger.

Moreover, waiting is another type of waste that occurs when a product or work-in-process item is not being moved or processed. This may refer to periods when employees are not working, when machinery is not being used, or to just unproductive time that costs money. It results in supply chain interruptions and delays, both of which constitute unneeded waste. Additionally, a significant portion of a product's life cycle is wasted waiting in batch-and-queue production. This often happens when there is an inadequate flow of materials, an excessively long production cycle duration, and an excessively long distance between workstations. Waiting also happens when accidents take place.

Next, the storing of excessive amounts of stock, raw materials, or equipment leads to inventory waste. In fact, one of the major expenses faced by industrial sites is the cost of keeping goods in inventory. Also, too much inventory can lengthen lead times, take up productive workspace, and prevent the problem from being identified instantly. It restricts the flow of funds for the company and possibly increases risk for the business. Inventory waste may result from excessive procurement or inadequate forecasting and planning. In this way, injury risk increases with the continuous handling of stock.

Apart from that, unnecessary or excess motion is another kind of waste in a manufacturing firm. For example, additional actions or steps performed by workers that result in laborious and unproductive operations. Any unneeded movement of people, objects, or machines is considered as waste in motion. Excessive physical movement or action, including bending, lifting, and stretching, is a waste of time and drives up prices. These motions induce further production delays, yet they could also put the workers' health and safety at risk. In sum, laborious and unproductive operations are often dangerous for the workers in manufacturing industries.

Last but not least, over-processing waste is the process of performing more effort than is required and includes repetitive work that does not enrich the outcome, such as repeated inspection, counting, or superfluous paperwork. This may result in processing that seems to be excessive or unnecessary, wasting manpower and equipment resources. On the other hand, this may also refer to employing costly manufacturing equipment when less costly tools will perform just as well. Some typical over-processing reasons are poor communications, human error, and poor project management. As workers will be required to complete additional processes and tasks, over-processing might potentially jeopardise their safety (Pestana and Gambatese, 2016).

2.4 Implementation of Lean Tools

The idea of minimising waste in the manufacturing process is the foundation of the lean manufacturing concept, which is a thorough method of continuous industrial improvement. The connection between lean tool implementation and other management techniques has emerged as a major subject of lean studies over the past few years. Additionally, lean is a multifaceted methodology that incorporates comprises a huge spectrum of operational and supervisory practices, such as just-in-time (JIT), continuous flow, total productive maintenance (TPM), employee involvement, etc (Fadly Habidin and Mohd Yusof, 2013).

By effectively implementing lean principles, it is possible to achieve the production system's optimal outcome (Sundar, Balaji and Kumar, 2014).

Lean is a formidable tool for process improvement, waste reduction, and even enhancing safety in the manufacturing industries (James, Ikuma, Nahmens and Aghazadeh, 2013). In order to obtain a higher level of quality and adaptability at lower costs, the application of lean manufacturing principles and practices has become ubiquitous, even in the current background of rising labour demand (Tortorella, Fettermann, Piñeres and Gaiardelli, 2018). Numerous studies have emphasised the application of tools and techniques for the establishment of strategies to prevent and minimise the risk factors of work-related injuries, resulting in a massive effect on occupational health and safety management systems. In this manner, the effective application of an occupational risk management system in manufacturing industries contributes to reduce work-related disorders and catastrophes. Therefore, this signifies that organisations must keep in touch with employees, enrolling them in training that will further prevent work-related incidents (Tortorella et al., 2020).

The ability to maintain better housekeeping appears to be an essential capability for accomplishing assigned work, which can reduce workplace hazards, provide visual order, support employees, and improve quality and productivity (Becker, 2001). Another study showed that the key advantages of applying lean are the ability to better understand the processes and the ability to reduce lead times, stock levels, costs, and rework (Melton, 2005). Today, a number of graphical techniques exist that assist users in understanding the process flow and identifying wastes, such as value stream mapping (VSM) and the waste identification diagram (WID). For instance, the results of the study indicate that the reduction in stock levels, lead times, occupied space, and flow time in the electronics industry (Detty and Yingling, 2000). The development of a continuous flux in a manufacturing facility for metallic structures that reduced unnecessary movement, delays, transportation time, faults, and lead times (Carvalho, Lopes and Alves, 2011).

SMEs’ adoption of lean has been extensively studied by scholars. A study found it challenging to deploy productivity enhancement methods, especially those related to lean manufacturing (April, Powell and Bart, 2010). In addition, SMEs encounter resource shortages compared to larger organisations, which achieve more since they have greater access to resources. Yet, by concentrating on production efficiency, SMEs might use soft technologies like lean to achieve significant reductions in cost, quality, and time (Kumar et al., 2006). Another study has noted that the most important concerns for implementing lean manufacturing in the setting of SMEs tend to involve leadership, management, finance, organisational culture, skills, and knowledge (Achanga, Shehab, Roy and Nelder, 2006). In order to determine and get rid of waste while improving flexibility, lean manufacturing incorporates a set of tools and methodologies as continuous improvement tools (Mathur, Mittal and Dangayach, 2012). Among these tools and methodologies are value stream mapping (VSM), kanban, just-in-time (JIT), total preventive maintenance (TPM), 5S practices, kaizen, etc.

2.4.1 Barrier to the Implementation of Lean Tools

Similar to any other attempt aimed at boosting productivity, the implementation of lean principles is anticipated to pose significant challenges (Denton and Hodgson, 1997). It is difficult for SMEs to adapt to the transition of lean manufacturing from conventional manufacturing methods of production due to both internal and external issues (Godinho Filho, Ganga and Gunasekaran, 2016). As reported by Shah and Ward (2002), the adoption of lean approaches is directly impacted by factors like the system's maturity. Another study by Bamber and Dale (2000) believed that the human aspect is essential for success. As mentioned in the literature review, examples of main barriers and challenges in developing a lean culture in SMEs include a lack of ability to evaluate benefits, worker behaviour, a lack of resources, a lack of commitment from senior management, a lack of training, internal opposition, the risk of operational disruption, and so on (Sahoo and Yadav, 2018).

As mentioned in subsection 2.3, a fundamental principle of the lean technique is the removal of unnecessary waste within an industry. In other words, eliminating everything that does not improve the value of goods or services is one of the major objectives of executing lean techniques. On top of that, it has been demonstrated that not all lean manufacturing strategies can be applied by SMEs owing to the high cost of the technology investment (Mohd Yusof and Aspinwall, 2000). This can be seen from the fact that SMEs are more likely to experience financial, technical, and time restrictions. These challenges are exacerbated by a number of factors, including a lack of management and technical knowledge and inadequate human resources (Achanga, Shehab, Roy and Nelder, 2006). SMEs occasionally believe that implementing lean may jeopardise their existing level of production and cause them to incur losses.

2.4.2 Continuous Flow

Traditional batch production has a number of drawbacks, including a high volume of work-in-progress (WIP), lengthy cycle times, and a high liability for faults. Contrary to batch production, continuous flow requires manufacturers to operate continuously and produce goods at a constant rate (Venkat Jayanth et al., 2020). Therefore, switching from batch production to small lot production is advised for businesses. Also, companies are encouraged to shorten cycle times, transportation, and work-in-progress (Breyfogle, 2007). The benefits of applying continuous flow strategy are to reduce or eliminate waste, reduce the work-in-progress, shorten cycle times, and improve the quality of the product.

Rahani and al-Ashraf (2012) pointed out that a continuous flow strategy can effectively lower or get rid of WIP and keep the product of high quality. In view of the fact that every machine in a machining process has a standard or maximum WIP at the transfer line. As a result, at the end of the day, if the WIP exceeds the maximum allowable level, the production line will not be able to continue running in accordance with the organisation’s schedule and plan. In this manner, waste is produced through waiting and overproduction. As a matter of fact, waiting frequently results from inadequate process design.

Other than that, the product may be damaged by improper positioning and rejected as being of low quality. In essence, this might be caused by the different groups of products mixing together. Furthermore, incorrect product positioning might make workplace accidents more likely. Consequently, it is necessary to classify items into groups with similar processing and routing by implementing the continuous flow methodology. It is important to have a good and ergonomic design with adjustment features to reduce operator backache while running operations (Rahani and al-Ashraf, 2012). In addition, product classification and ergonomic design of equipment can also greatly reduce the worker’s motions, such as bending and stretching.

Apart from that, continuous flow provides a good layout and factory design that can alleviate common health and safety threats. In particular, U-shaped production lines were designed as a way to reduce waste and make the best use of workers' abilities in lean manufacturing environments (Gil-Vilda et al., 2017). Additionally, a well-designed factory structure can greatly enhance the efficiency of the manufacturing line and minimise worker motion. On top of that, workplace safety can also be greatly affected by clutter. Shutoffs and other key controls will be easier to access if clutter is minimised. Also, employees will have sufficient space to work effectively if work areas and emergency exits are kept clear of obstructions. Therefore, a good structure of factory layout can ensure the employee is working in a safe environment.

One machine's cycle time is determined by both man and machine time. Rahani and al-Ashraf’s (2012) study found that the operator's movement during the part-unloading process is what causes the lengthy man time. These actions waste the operator's time and extend the handling time beyond what is necessary. To put it another way, a good continuous flow of production lines can lower the possibility of workplace accidents involving manual and long-term material handling.

2.4.3 Total Preventive Maintenance (TPM)

The importance of maintenance in contemporary manufacturing systems is increasing due to organisations accepting maintenance as a revenue-generating business element. The pillars of TPM are usually regarded as the fundamental procedures for implementing TPM. Figure 2.2 shows the TPM idea is supported by eight pillars.

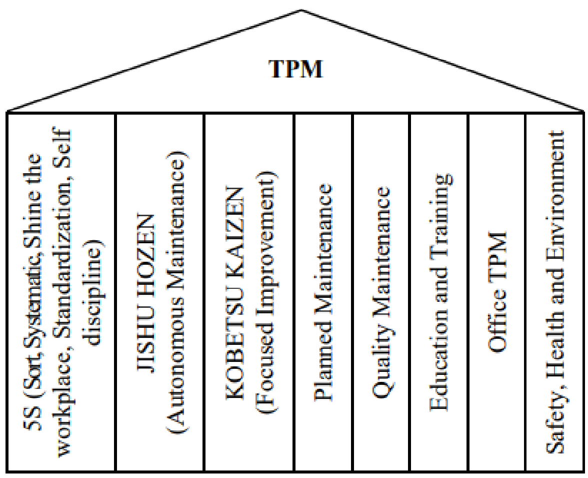

Figure 2.2: Eight Pillars of TPM (Masud et al., 2008).

The involvement of all employees is the most fundamental TPM requirement in order to increase or strengthen equipment effectiveness, availability, performance, quality rate, overall equipment effectiveness (OEE), reliability, and safety. Besides, improved teamwork and communication are required to support autonomous maintenance teams (Chan et al., 2005). In this manner, employees tend to conduct preventive maintenance activities without the ask from the top management, according to the equipment maintenance records. Therefore, it is believed that publishing equipment maintenance records at the workplace will increase worker safety as well as maintain the quality of the products.

According to Eti, Ogaji and Probert (2004), TPM is a method to maximise equipment efficiency, enhance quality, promote safety, minimise costs, and more importantly, boost team morale. In order to prevent machine failure or malfunctioning throughout production, TPM includes the approaches of operator ownership and preventive maintenance operations (Chand and Shirvani, 2000). Fostering an ownership culture and encouraging operator participation will help TPM achieve its main objectives, such as zero breakdowns, zero faults, and improved outputs. The application of TPM fosters a sense of employee responsibility for equipment and emphasises the significance of maintaining fundamental equipment conditions. According to Mad Lazim and Ramayah’s (2010) investigation, TPM is a resource-based method where all employees are accountable for preventing equipment wear and tear, breakdowns, failures, and stoppages.

Employee training, employee involvement, teamwork, and preventive maintenance are cited as the four core TPM elements (Swanson, 2001). The main objective of preventive maintenance is to make sure that machinery is always in good condition for production. In this way, preventive maintenance can effectively lengthen the equipment’s lifespan, lower the risk of breakdown, boost customer satisfaction, and promote the health and safety of employees. In other words, injuries in the workplace can be reduced by routine maintenance. Also, an effective preventive maintenance program can help to improve the uptime of machines.

In addition, TPM enhances various aspects of an organisation's performance, such as safety and cleanliness (Brah and Chong, 2004). In order to achieve the goal of implementing TPM, for example, having zero accidents, zero health damage, and zero fires, a workplace safety training is essential to provide employees with the necessary knowledge and skills. For instance, proper PPE should be worn all the time in the workplace. A worker must learn how to use, maintain, and dispose of their PPE properly in order for it to perform as intended. Thereby, productivity and time can be improved, while safeguarding the health and safety of the employees.

2.4.4 Employee Involvement in Lean

In manufacturing companies, an effective employee involvement practice could lead to more attainable job satisfaction, quality enhancement, and productivity improvement. Employee involvement refers to the process by which employees participate in or hold the decision-making rights of an organisation. The productivity, accuracy, and job satisfaction of employees in the manufacturing processes are stated to be improved through employee involvment. Employee interaction and information exchange can raise standards of the outcomes and lower the possibility of work-related accidents. For instance, brainstorming sessions that encourage idea sharing among employees result in problem-solving (Pun, Chin and Gill, 2001).

Coffey (2000) demonstrated that the more committed an employee is, the more they will contribute to discovering and eliminating waste as goals. Effective participation implies that workers operate professionally at work and within their authority. Additionally, it offers practical solutions to work-related issues and problem-solving advice (Tseo and Ramos, 1995). The organisation can create a better and safer working environment with the assistance of problem-solving guidance and suggestions from employees. A high level of employee involvement can also result in product and process improvement. One of the interesting findings from Lawler, Mohrman and Ledford (1995) was that employee safety and health had improved for 60 % of the organisations employing employee involvement procedures.

Cross-functional training is another essential element of employee involvement. A cross-functional training that results in multiskilling may raise employee awareness of production and machinery issues. As a result, the high awareness of employees can prevent or reduce the risk of injury, illness, and death. Moreover, multiskilled workers can effectively reduce waste in terms of waiting, thereby improving production efficiency.

2.5 Summary

Lean tools are implemented due to their positive impact on safety performance in manufacturing firms. The type of lean tools that can be implemented to improve safety performance in Malaysia's manufacturing firms, such as continuous flow, total preventive maintenance, and employee involvement.

CHAPTER 3

METHODOLOGY AND WORK PLAN

3.1 Introduction

In this chapter of the report, the methodology section is divided into a few subsections, namely conceptual framework, hypothesis, research design, questionnaire development, flowchart, sampling design, method of data analysis, pre-test, data collection, data analysis, and pilot studies.

3.2 Conceptual Framework

Based on the proposed conceptual framework resulting from the previous literature review and in order to understand the relationship between lean tools and safety performance. The framework developed in this research is composed of several lean tools and safety performance. The components of lean tools include continuous flow, total preventive maintenance, and employee involvement. In this instance, the lean tools serve as the independent variable, while the safety performance serves as the dependent variable. The relationship between lean tools and safety performance was highlighted by conducting a thorough literature review. Despite that, the literature of early research reveals that there is a lack of evidence to show the connection between lean tools and safety performance in manufacturing firms, notably in Malaysia. Theoretically, based on the literature evaluation, the current research will deepen the understanding by evaluating how lean tools affect safety performance. Practically, this research is one of the first to analyse this connection among Malaysia's manufacturing firms. Figure 3.1 shows the conceptual framework.

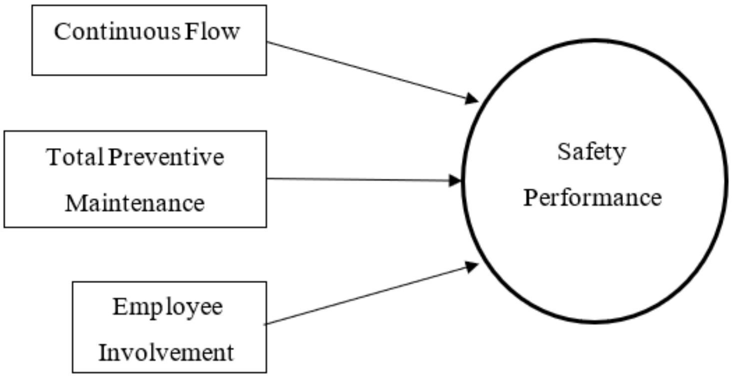

Figure 3.1: Conceptual Framework.

The following hypotheses have been formulated based on conceptual framework:

(i) Hypothesis 1 (H1): Continuous flow and safety performance are significantly correlated.

(ii) Hypothesis 2 (H2): Total preventive maintenance and safety performance are significantly correlated.

(iii) Hypothesis 3 (H3): Employee involvement and safety performance are significantly correlated.

3.3 Research Design

The main objective of conducting quantitative research is to determine the relationship between variables within a population, particularly independent and dependent variables. With the aid of the SmartPLS software programme, data can be computed and processed by a computer, saving a significant amount of energy and resources. Experimental and survey-based methods are among the methods used in quantitative research (Apuke, 2017).

There are multiple common techniques for carrying out quantitative research. Descriptive research seeks to identify a phenomenon and its properties. In other words, this study is more interested in what occurred than in how or why it occurred. Hence, a descriptive research design with survey tools was carried out in this research.

3.4 Questionnaire Development

The questionnaire was adopted and adapted from two journals: *Defining and developing measures of lean production* and *The relationships between OHS prevention costs, safety performance, employee satisfaction and accident costs.*

The first part of the questionnaire is Section A, which includes company details and demographic data. The company details include the company location, company businesses size and type of businesses. On the other hand, the demographic data include gender, age, educational level, and working experience in the industry.

In comparison to their male colleagues, female employees reported more positive and constructive opinions of workplace safety, exhibited higher levels of compliance with safety procedures, and had a lower incidence of accidents (Gyekye and Salminen, 2011). According to Siu, Phillips and Leung (2003), some older workers do in fact have more positive views about safety than younger workers. Therefore, this means that the worker's age and gender have an impact on their performance in terms of safety.

In the study of Gyekye and Salminen (2009), a positive correlation was found between education and safety perception. Higher educated employees had better perceptions of safety, higher levels of job satisfaction, greater compliance with safety protocols, and lower accident involvement rates. The high accident involvement rate among workers with less education, especially those with only a basic education, indicates the necessity for special safety programmes created just for them. Furthermore, Ayim Gyekye and Salminen (2010) demonstrated that the more experienced workers had a more positive view of safety. In other words, the working experience may affect the safety performance. In short, a worker's educational level and working experience have a positive effect on safety performance.

The questionnaire's goal is to evaluate the impact of lean tools on safety performance in Malaysia's manufacturing firms. The questionnaire consisted of 2 sections: lean tools and safety performance. The section on lean tools consisted of 12 statements, while the section on safety performance consisted of 5 statements. The lean tools section was separated into 3 different types of lean tools: continuous flow, total preventive maintenance, and employee involvement. A 5-points Likert scale is utilised in this questionnaire.

This is due to the fact that the Likert scale is easy to create and is expected to generate a highly reliable scale. 5-point Likert scale anchored with 1= “No implementation”, 2 = “Little implementation”, 3 = “Some implementation”, 4 = “Extensive implementation” and 5 = “Complete implementation” for independent variables. On the other hand, a 5-point Likert scale anchored with 1= “Strongly disagree”, 2 = “Disagree”, 3 = “Neither agree nor disagree”, 4 = “Agree” and 5 = “Strongly agree” for the dependent variable. This scale ranges from 1 to 5. The questionnaire was conducted through Google Forms. Appendix A shows the questionnaire.

3.5 Flowchart of Methodology

Figure 3.2 shows the flowchart of methodology.

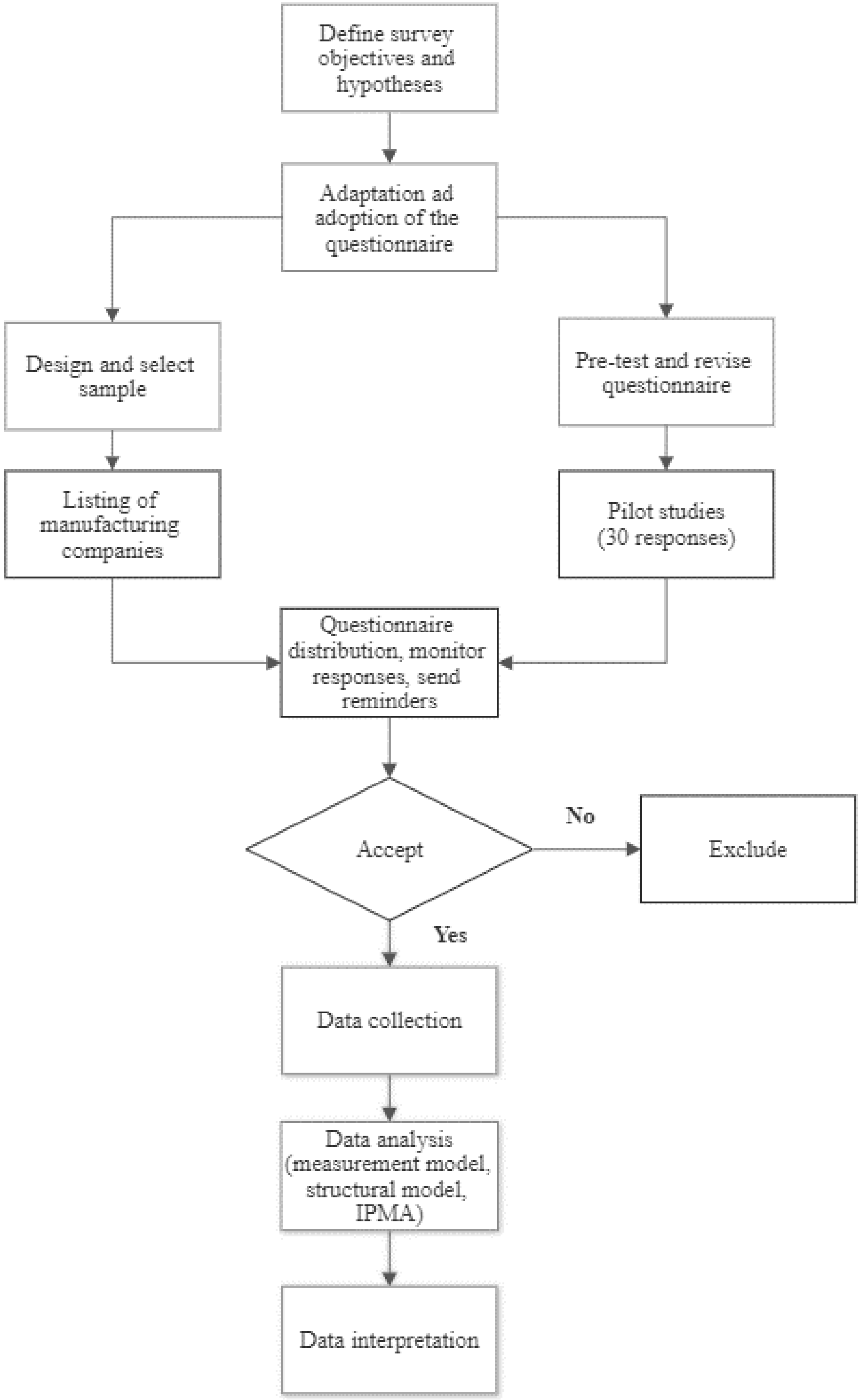

Figure 3.2: Flowchart of Methodology.

3.6 Sampling Design

3.6.1 Sample Size

Sampling is the process of choosing a sample from an individual or from a large population for a certain type of research purpose. Since it is not always feasible to get data from every unit of the population, sampling techniques are frequently required. Therefore, choosing a suitable sample size is essential to making reliable inferences from research findings. Generally, there are two main categories of sampling methods: random sampling and non-random sampling. Every item in the population has an equal chance of being included in the sample because it is done via random sampling, while case study research design and qualitative research are frequently linked with non-random sampling. In this study, simple random sampling and G*Power analysis were used to calculate the sample size.

3.6.2 Simple Random Sampling

In this method, every member of the population seems to have an equal chance of being chosen. According to the Federation of Malaysian Manufacturers (2022), there are a total of 3429 manufacturing companies, which indicate as the population in this study. Formulas below are adopted from Cochran (1977) and Yamane (1973).

Cochran Formula:

$$n = \frac{p\,(1-p)}{\frac{e^2}{z^2} + \frac{p\,(1-p)}{N}} \tag{3.1}$$

where

n = sample size

N = population size

e = acceptable sampling error

p = the population proportions

z = significance level

By using the Cochran formula with a reliability level of 95 %, a significance level of 1.96, an acceptable sampling error of 0.05, a population size of 3513, and a population proportion of 0.5, the number of sample size obtained is equal to 346.

Taro Yamane Formula:

$$n = \frac{N}{1 + Ne^2} \tag{3.2}$$

where
n = sample size
N = population size
e = level of precision

By using the Taro Yamane formula with a population size of 3513 and a level of precision of 0.05, the number of sample sizes obtained is equal to 359. In sum, the sample size determination in Yamane is suitable for survey research. On the other hand, the Cochran formula is depending on the size or number of inputs, statistical values, acceptable error, and population size. However, the results of the sample size are still high for both.

3.6.3 Power Analysis

A recent study suggests that power analysis should be used to decide sample size. The portion of a model with the greatest number of predictors is taken into consideration during power analysis to calculate the minimal sample size. To determine the minimal sample size required, power, effect size, and significance level information are required. In social science studies, a power value of 80 % or more is considered appropriate. The magnitude of the effect that each independent variable truly has on the dependent variable is measured by the term "effect size." Cohen (1988) recommended that the values of 0.02, 0.15, and 0.35 be viewed as small, medium, and large effects, respectively. The percentage of rejecting the null hypothesis is related to the significance level (α). The significance level is typically considered at 0.05 (5 %). It is possible to perform power analysis using a variety of statistical programmes. Although any of these programmes can be used to estimate sample size, researchers frequently start with G*Power (Memon et al., 2020).

A type 1 error is also called false-positive, which will occur if the null hypothesis that is actually true in the population is rejected. On the other hand, a type 2 error is also called false-negative, which will occur if the null hypothesis that is actually wrong in the population is accepted. As a matter of fact, the type 1 error is also known as alpha, α, whereas the type 2 error is known as beta, β (Banerjee et al., 2009).

3.6.4 G*Power

In this report, G*Power was used to measure the sample size. When conducting a power analysis, an a priori analysis is applied since it offers a method for controlling type 1 and type 2 errors in order to prove the hypothesis (Kang, 2021). For linear multiple regression analysis, the medium effect size (f^2) of 0.15 is used. In fact, the smaller the effect size, the harder it is to determine the degree of deviation from the null hypothesis in the quantitative unit of response. The significance level (α) used is 0.05, and the power ($1 - \beta$) is 0.8. Figure 3.3 shows the G*Power analysis with a total sample size of 77.

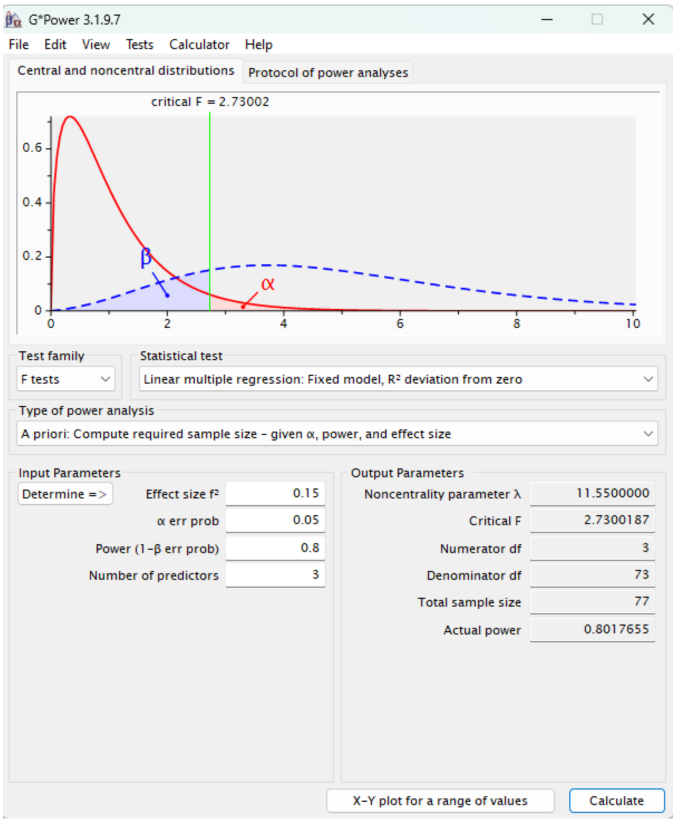

Figure 3.3: G*Power Analysis.

3.7 Method of Data Analysis

Structural Equation Modelling (SEM) is an approach for illustrating, calculating, and analysing a network of relationships between variables. SEM is a thorough statistical method for analysing relationships among latent and observable variables. To put it differently, SEM is a strong multivariate tool for testing and assessing multivariate causal connections. The fact that SEM examines the direct and indirect impacts on presumed causal connections sets it apart from other modelling techniques (Fan et al., 2016). Additionally, SEM makes a significant contribution by examining the direct, indirect, and moderating effects of many variables in complicated models (Shaheen et al., 2017).

In general, there are two popular approaches for structural equation modelling (SEM), namely partial least square based SEM (PLS-SEM) and covariance based SEM (CB-SEM). CB-SEM is the proper approach if the purpose of the study is to test and verify theories. On the contrary, PLS-SEM is the proper approach if the purpose of the study is to develop predictions and theories. In other words, in particular where there is little prior understanding of causal relationships, PLS-SEM is the effective method when the study object lacks a strong theoretical base. Essentially, PLS-SEM's main goal is to increase the explained variance in the dependent constructs as well as assess the quality of the data based on the properties of the measurement model (Dash and Paul, 2021).

Moreover, PLS-SEM uses an iterative series of ordinary least squares regressions to estimate partial model associations in order to maximise the endogenous latent variables' explained variance, whereas CB-SEM estimates model parameters to minimise the difference between the estimated and sample covariance matrices. Additionally, Dash and Paul (2021) stated that PLS-SEM typically has greater item loadings than CB-SEM. In short, PLM-SEM will be utilised in this study to examine the relationship between lean tools and safety performance.

The most popular tool for conducting PLS-SEM analysis is SmartPLS. In other words, SmartPLS is a useful tool for computing, developing, and validating models. The relationship between variables and indicators may be explained using the path model offered by SmartPLS. The purpose of the path models is to describe how several hypotheses affect one another. This path modelling technique has the advantage of a smaller sample size and the absence of distributional assumptions. The formulation of theories and exploratory research have both utilised SmartPLS. This implies that SmartPLS can be used for scientific work with a wide range of objectives. The ability to foresee and interpret non-standard data is what SmartPLS contributes most to (Sander and Teh, 2014). In this study, the measurement model includes continuous flow, total preventive maintenance, and employee involvement, whereas the structural model is safety performance.

3.8 Pre-test

A pre-test is very important for evaluating the research designs, data collection instruments, and experimental manipulations. Its primary objective is to discover and address potential issues, including errors or flaws in the design or instrument. For example, conducting a pre-test on a questionnaire can assist in detecting issues related to the phrasing, style, format, and organisation of the questionnaire. Furthermore, a pre-test ensures the clarity and accuracy of research questions or hypotheses, prevents harm to respondents, estimates sample sizes, and validates the data collection instrument or manipulation. Besides, pre-testing is essential for improving the validity and reliability of the study's results. During the pre-test phase, the questionnaire was distributed to a group of experts in the field in order to get their feedback and evaluation on various aspects of the questionnaire, including its language, tone, structure, design, and overall suitability for the research. After the pre-test phase, the questionnaire underwent modifications that were informed by the feedback and evaluation provided by a group of experts who had been given the questionnaire. Table 3.1 shows the summary of pre-test.

Table 3.1: Summary of Pre-test.

Suggestion	Changes	Modification
Section A: Demographic Profile		
7. Setting a period of working experience in the sector to every five years is advised.	Yes	Accept suggestion.
Section B: Measurement of Dependent and Independent Variable		
Continuous Flow		
2. Naming conventions are conflicting. Groups are classified into station / stage.	No	Since it was adopted, no changes have been made.
Total Preventive Maintenance		
3. Add calibration date and record replacement date. We record and schedule all the equipment maintenance activities daily.	No	Since it was adopted, no changes have been made.

Table 3.2 (Continued)

4. Less match. Need emendation. Employee would not see the records because it is for ISO auditor references.	No	Since it was adopted, no changes have been made.
Employee Involvement		
1. Replace with production engineer employees are the key to problem solving team.	No	Since it was adopted, no changes have been made.
2. Replace with industry engineer employees drive suggestion programs.	No	Since it was adopted, no changes have been made.
Safety Performance		
1. Use reduced instead of improved.	Yes	Accept suggestion.
2. Use reduced instead of improved.	Yes	Accept suggestion.
5. Use reduced instead of improved.	Yes	Accept suggestion.

3.9 Data Collection

The English-language questionnaire was prepared in a Google Form and distributed to Malaysia's manufacturing companies. The Federation of Malaysian Manufacturers (FMM) website, which has a total of 3429 manufacturing businesses listed on it, is where the manufacturing companies were discovered. In addition, around 250 Japanese companies operating in Malaysia were found on the Wesleynet Malaysia website. The companies' details, such as company name, email address, contact, and office address, were provided on the FMM and Wesleynet Malaysia websites. Therefore, a Google Form link was included in an email that was sent in blind carbon copy (BCC) to every company listed on the FMM and Wesleynet Malaysia websites. BCC is frequently used to send emails to a large group of recipients without revealing their email addresses to each other.

3.10 Data Analysis

The G*Power analysis showed that a minimum sample size of 77 was required. However, the questionnaire survey received a total of 134 responses, above the minimum requirement. Based on the collected data, it was revealed that a majority of the responses were located in Selangor, which comprises 34.3 % of the total responses. Following Selangor, the next highest concentration of responses was found in Johor and Penang, comprising 20.9 % and 17.2 % of the total, respectively. Out of the 134 responses, only two were collected from Kuala Lumpur, making it the location with the least number of responses. Furthermore, the statistics also showed that 42.5 % of the respondents belonged to large-scale manufacturing companies, while 29.1 % and 28.4 % of the respondents were from medium-sized and small enterprises, respectively.

Next, it was found that a large number of the manufacturing companies were from the metal industry, with a percentage of 16.4 %, followed by the food industry and chemical industry, which had percentages of 11.2 % and 10.4 %, respectively. In addition, in terms of gender, it was observed that the majority of the respondents were male, accounting for 66.4 % of the total. Moreover, it was shown that respondents aged 50 and older contributed the most responses, comprising 38.8 % of the total. This was followed by the age group between 41 and 50 years old, which accounted for 35.1 % of the responses. The age group with the least number of responses was between 21 and 30 years old.

In terms of educational level, the data showed that 46.3 % of the respondents held a bachelor’s degree, 29.9 % held a master’s degree, 19.4 % held a diploma, and 4.5 % held a secondary education. Apart from that, it was found that more than half of the respondents, comprising 50.7 % of the total, had 20 or more years of experience in the industry. The remaining respondents had varying years of working experience in the industry, with 15.7 % having 1 to 5 years of experience, 13.4 % having 11 to 15 years of experience, 11.2 % having 16 to 20 years of experience, and 7.5 % having 6 to 10 years of experience. According to the research, these demographic factors could have a potential impact on safety performance. Table 3.2 shows the email addresses of the responses. The confidentiality of personal information, including email addresses, in survey data must be ensured. Disclosure of email addresses can compromise privacy and breach data protection laws.

Table 3.3: Email Addresses of the Responses.

@enersys.com.my	@newedgecorp.com	@gmail.com	@ctmind.com	@cclind.com
@dynapackasia.com	@gmail.com	@yahoo.com	@gmail.com	@gmail.com
@gmail.com	@entegris.com	@hirata.com.my	@dosb.com.my	@klsmartin.com
@gmail.com	@yara.com	@wellcall.com.my	@chuanluck.com	@wmisb.com.my
@dankaffe.com	@gmail.com	@yahoo.com	@transpak.com	@unisyncmy.com
@ngai-cheong.com	@smctech.com.my	@escatec.com	@jinkosolar.com	@gmail.com
@gmail.com	@everbest.my	@gmail.com	@live.com	@yahoo.com
@riverstone.com.my	@venture.com.sg	@innoglass.com.my	@gmail.com	@nippo.com.my
@essexfurukawa.com	@taisin.com.my	@fibertexpersonalcare.com	@dhl.com	@mail.nabel.co.jp
@hoya.com	@triplus.com.my	@bunge.com	@hzgreenpulp.com	@fmca.com.my
@vsptech.com.my	@fnbnutrition.com.my	@gmail.com	@fci.com	@hotayi.com
@mpm.com.my	@kimhin.com.my	@vsptech.com.my	@nationgate.com.my	@newbillion.com
@trendtechnologies.com.sg	@gasmalaysia.com	@chinherr.com	@gmail.com	@gmail.com
@kosel-group.com.my	@ageng.com.my	@pacs.com.my	@soonsoongroup.com	@gmail.com
@seiko-mfg.sg	@sissonspaints.com.my	@gmail.com	@ohtaprecision.com	@ngeam.com.my
@steris.com	@gmail.com	@watertec.biz	@gmail.com	@gmail.com
@yahoo.com	@scrubbermembrane.com	@yahoo.cpm	@mpisb.com	@gbmarinegroup.com
@mnametal.com.my	@vacuumschmelze.com	@gmail.com	@gmail.com	@hotayi.com
@kookapaper.com	@yahoo.com	@gmail.com	@uisb.com	@k-one.com
@toray-basf-pbt.com.my	@tigercasting.com	@morimatsu-dialog.com	@chaoyuanind.com	@qsrbrands.com.my
@gmail.com	@qsrbrands.com.my	@m-mmotor.com	@kzhgroup.com	@tecomet.com
@spiritaero.com	@sekoplas.com.my	@gmail.com	@gmail.com	@zeito.com.my
@gmail.com	@waterotec.com	@toyopacksp.com	@gmail.com	@gmail.com
@harristonchocolate.com	@gcpat.com	@chemstationasia.com	@msmmgroup.com	@hotmail.com
@gmail.com	@vishay.com	@ghee-hiang.com	@gmail.com	@neujkf.asia

Table 3.4 (Continued)

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3.11 Pilot Studies

In a research study, a pilot study is one of the fundamental stages. Pilot research is described as "small-scale research to test research methodologies, data collection tools, sample collection approaches, and other research methodologies in preparation for a broader study." A practitioner-based pilot study was conducted to verify the validity of the data. In addition, it is also one of the crucial phases of a research project, which is performed to discover any possible issues and errors in the research tools and methodology before they are applied in the larger study (Hassan et al., 2006). 30 responses were used to conduct pilot studies via SmartPLS 4 software. These 30 responses were converted into comma-separated values (CSV) format, and the data file was imported into the SmartPLS 4 software. The CSV format is required since SmartPLS software can only recognise files in this format. After investigating and analysing the results of the pilot studies, the questionnaire was distributed for the larger study with minor modifications. The values of Cronbach's alpha and composite reliability during the pilot studies were more than 0.9 for continuous flow, total preventive maintenance, employee involvement, and safety performance. In the pilot studies, it was found that the average variance extracted (AVE) values for the measured constructs were greater than 0.5. Apart from that, the factor loading of the pilot studies was remarkably high, exceeding the threshold of 0.7 and indicating a significant correlation between the variables being measured. Figure 3.4 shows the values of Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE).

Construct reliability and validity - Overview   Zoom (150%)   Copy to Excel   Copy to R

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
CF	0.926	0.943	0.947	0.818
EI	0.920	0.922	0.944	0.808
SP	0.980	0.981	0.984	0.926
TPM	0.925	0.926	0.947	0.817

Figure 3.4: The Values of Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE).

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

In this chapter of report, the result section is divided into 4 main sections: measurement model, structural model, importance-performance map analysis, and discussion. The measurement model section includes internal consistency, convergent validity, and discriminant validity. The structural model section includes collinearity issues, path coefficient, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), effect size (q^2), and Goodness-of-Fit (GoF).

4.2 Measurement Model

The functionality of SmartPLS 4 software was utilised to access both the measurement model, structural model, and importance-performance map analysis in the interim. The measurement model is a critical component of PLS path modelling in SmartPLS, as it contributes to establish the validity and reliability of the latent constructs being studied. The measurement model assessment includes internal consistency, convergent validity, and discriminant validity.

4.2.1 Internal Consistency

The reliability of a scale or instrument is frequently assessed using Cronbach’s alpha and composite reliability (CR), two measures of internal consistency reliability. Composite reliability yields higher values than Cronbach’s alpha. Cronbach's alpha and composite reliability values vary from 0 to 1, with higher values suggesting more internal consistency reliability. For preliminary research, values between 0.6 and 0.7 could be deemed adequate, whereas for further studies, values ranging from 0.7 to 0.9 might be viewed as acceptable (Kamis et al., 2020). In general, a value of 0.7 or above is seen to be suitable for research purposes. According to the rules of thumb, a Cronbach’s alpha value above 0.9 denotes excellent internal consistency of the scale’s item (Gliem and Gliem, 2003). Figure 4.1 shows the findings of internal consistency reliability. The values of Cronbach's alpha computed through SmartPLS 4 were 0.945 for continuous flow (CF), 0.909 for total preventive maintenance (TPM), 0.922 for employee involvement (EI), and 0.960 for safety performance (SP). Moreover, the composite reliability result values were 0.960 for CF, 0.936 for TPM, 0.945 for EI, and 0.969 for SP. The values of the exogenous and endogenous constructs were substantially over the threshold of 0.70, indicating excellent degrees of internal consistency and reliability for all the constructs. These imply that the constructs are highly reliable and that the indicators employed to evaluate the underlying constructs are consistent.

Construct reliability and validity - Overview Zoom (150%) Copy to Excel Copy to R

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
CF	0.945	0.954	0.960	0.858
EI	0.922	0.930	0.945	0.812
SP	0.960	0.963	0.969	0.863
TPM	0.909	0.910	0.936	0.787

Figure 4.1: Findings of Internal Consistency Reliablity.

4.2.2 Convergent Validity

Convergent validity measures how well a construct converges to account for the variation in its elements. Ordinarily, the convergent validity of a measurement is evaluated by analysing the factor loading of the indicator, composite reliability, and average variance extracted (AVE). The PLS-SEM analysis was performed to evaluate the framework's outer model. The term "outer loading" describes the relationship between a latent variable and its corresponding indicator variables. Outer loading is also referred to as factor loading. The factor loading values vary from 0 to 1. A high factor loading number is often defined as 0.7 and above, while a low factor loading value is defined as less than 0.7. If an indicator variable has a high factor loading value, it is a reliable measure of the construct it is supposed to represent. On the other hand, if an indicator variable has a low factor loading value, it might not accurately reflect the underlying construct. In some circumstances, indicator variables with low factor loading values might need to be discarded from the model (Ab Hamid et al., 2017).

Figure 4.2 shows the outer loadings of the constructs. All constructs' outer loadings were significantly higher than the threshold value of 0.7, proving that the indicators have a strong relationship with the latent construct. The indicator EI4 has the lowest outer loading value (0.824), while the indicator SP2 has the highest outer loading value (0.953). Therefore, based on their outer loading values, the indicator EI4 has the lowest reliability with a value of 0.679 (0.824^2), while the indicator SP2 has the highest reliability with a value of 0.908 (0.953^2). The variance extracted from an item is expressed as the square of the corresponding outer loading of a standardised indicator, which signifies the amount of variation in an item that is explained by the underlying construct. In general, a recommended threshold for the variance extracted from an item is 0.5 or higher (Hair et al., 2017).

Outer loadings - Matrix

	CF	EI	SP	TPM
CF1	0.896			
CF2	0.950			
CF3	0.945			
CF4	0.912			
EI1		0.910		
EI2		0.936		
EI3		0.930		
EI4		0.824		
SP1			0.944	
SP2			0.953	
SP3			0.895	
SP4			0.946	
SP5			0.905	
TPM1				0.895
TPM2				0.895
TPM3				0.918
TPM4				0.838

Figure 4.2: Outer Loadings of the Constructs.

The average variance extracted (AVE) can be described as the grand mean value of the squared loadings of the indicators linked to the construct. In other words, the total of the squared loadings divided by the quantity of indicators. Thus, the AVE is identical to the communal variance of a construct. The range of AVE values is 0 to 1. A desirable AVE value is 0.5 or greater, which implies that the underlying construct accounts for at least 50 % of the variance of its constituent items (Hair et al., 2019). This indicates that the constructs being studied were able to account for more than 50 % of the variance observed in their constituent items. The following formula may also be used to get the value of AVE (Sudbury-Riley et al., 2017).

$$AVE = \frac{\sum_{i=1}^{n} \lambda_i^2}{n} \tag{4.1}$$

where
λ = standardised factor loading
i = number of items

Figure 4.1 provides the experimental data on AVE. The AVE values of CF (0.858), TPM (0.787), EI (0.812), and SP (0.863) surpassed the minimum required threshold value of 0.5. Hence, it indicates that the constructs have a good level of convergent validity.

4.2.3 Discriminant Validity

Discriminant validity is a form of validity that evaluates how distinct a construct is from other constructs in a research model. Furthermore, it also measures the level of discrepancy between the intersecting constructs. There are several ways to evaluate the discriminant validity in SmartPLS. For instance, discriminant validity can be evaluated by using cross loadings, the Fornell-Larcker criterion, and the Heterotrait-monotrait ratio (HTMT). These techniques were developed particularly to assess the reflective constructs' discriminant validity; as a result, they are unsuitable for evaluating formative constructs. As a matter of fact, discriminant validity is a crucial component of construct validity in SEM, and failing to appropriately disclose discriminant validity issues can result in biased structural parameter estimations and inaccurate interpretations about the connections between constructs.

In a reflective measurement model, it is essential to examine the cross loading of the indicators to ensure that the indicators are accurately allocated to their intended construct. In particular, the factor loading of each indicator on its intended construct should be larger than its loading on all other constructs, provided that the factor loading surpasses the cutoff value of 0.7 (Ab Hamid et al., 2017). When an indicator's loading value on other constructs is greater than its loading value on the intended construct, it implies that a possible problem with discriminant validity may exist (Kamis et al., 2020). Figure 4.3 shows the cross loadings of discriminant validity. It can be seen from the data in Figure

4.3 that the intended construct showed the highest cross loading value compared to all the other constructs. As a result, discriminant validity is established.

Discriminant validity - Cross loadings

Zoom

	CF	EI	SP	TPM
CF1	0.896	0.582	0.512	0.623
CF2	0.950	0.639	0.580	0.709
CF3	0.945	0.685	0.662	0.709
CF4	0.912	0.698	0.669	0.704
EI1	0.632	0.910	0.650	0.718
EI2	0.701	0.936	0.621	0.780
EI3	0.652	0.930	0.647	0.678
EI4	0.561	0.824	0.524	0.676
SP1	0.672	0.666	0.944	0.640
SP2	0.614	0.615	0.953	0.603
SP3	0.583	0.558	0.895	0.557
SP4	0.631	0.679	0.946	0.683
SP5	0.564	0.632	0.905	0.645
TPM1	0.719	0.735	0.605	0.895
TPM2	0.679	0.663	0.584	0.895
TPM3	0.629	0.696	0.609	0.918
TPM4	0.611	0.708	0.596	0.838

Figure 4.3: Cross Loadings of Discriminant Validity.

The Fornell-Larcker criterion is another way of evaluating the discriminant validity of a measurement model. This approach involves comparing the correlation coefficients between latent constructs with the square root of the AVE for each construct. In light of this, the Fornell-Larcker criterion recommends that the square root of the AVE of each construct should be greater than the correlations with other latent constructs. The diagonal elements represent the square root of the AVE of each construct, while the off-diagonal elements represent the correlations between the latent variables. The correlation matrix's diagonal elements should be larger than its off-diagonal elements to establish discriminant validity (Hair et al., 2017). Figure 4.4 presents the Fornell-Larcker criterion of discriminant validity. Based on the data in Figure 4.4, it is apparent that the correlation between the latent variables was smaller than the square root of the AVE for each construct. Moreover, the diagonal elements in the EI, SP, and TPM constructs were compared with all the correlations in the respective rows and columns. In short, it indicates that discriminant validity has been recognised.

Discriminant validity - Fornell-Larcker criterion

	CF	EI	SP	TPM
CF	0.926			
EI	0.708	0.901		
SP	0.661	0.680	0.929	
TPM	0.744	0.790	0.675	0.887

Figure 4.4: Fornell-Larcker Criterion of Discriminant Validity.

Nevertheless, simulation research found that the Fornell-Larcker criterion and cross loading evaluations are insufficient and have a limited ability to identify discriminant validity issues in variance-based SEM. Additionally, the research discovered that the sensitivity of these methods is unacceptably low, and the evaluation of cross loadings entirely fails to recognise problems with discriminant validity. In short, these methods are typically unable to spot the absence of discriminant validity, except in the case of heterogeneous loading patterns and large sample sizes (Henseler et al., 2015).

An alternate method for evaluating discriminant validity in SEM called the Heterotrait-monotrait ratio (HTMT) was proposed. Henseler et al. (2015) carried out a Monte Carlo simulation to evaluate the performance of three different methods in assessing discriminant validity in SEM: cross loadings, the Fornell-Larcker criterion, and the Heterotrait-monotrait ratio (HTMT). The results demonstrated that, in comparison to the cross loadings (0.00 %) and the Fornell-Larcker criterion (20.82 %), the HTMT method had superior sensitivity and specificity rates (97 % to 99 %). Therefore, this indicates that HTMT is a more efficient method for evaluating discriminant validity in SEM. Moreover, if the HTMT value is higher than the cutoff, discriminant validity may be comprised. The initial study of Henseler et al. (2015) did not provide a specific threshold for the HTMT ratio. On the contrary, they have recommended that a value less than 0.9 would be indicative of acceptable discriminant validity. The threshold of 0.9 was proposed by Gold et al. (2001), and this threshold has been widely adopted by researchers using SmartPLS software to evaluate discriminant validity. However, some of the researchers have recommended 0.85 as a threshold value if the constructs are conceptually more distinct (Henseler et al., 2015).

Figure 4.5 shows the HTMT ratio of discriminant validity. Every HTMT measurement fell within the 0.85 criterion, except for the relationship between TPM and EI, which has a value of 0.865. Although this value exceeds the threshold of 0.85, it is still within the acceptable cutoff of 0.9, which is a good indicator of discriminant validity. Therefore, it can be concluded that the data supports the establishment of discriminant validity.

Discriminant validity - Heterotrait-monotrait ratio (HTMT)

	CF	EI	SP	TPM
CF				
EI	0.752			
SP	0.685	0.718		
TPM	0.800	0.865	0.721	

Figure 4.5: HTMT Ratio of Discriminant Validity.

4.3 Structural Model

The structural model is a statistical model that aims to describe the relationships between variables in a system. The structural model assessment includes collinearity issues, path coefficient, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), effect size (q^2), and goodness of fit (GoF).

4.3.1 Collinearity Issues

In a structural model, the coefficients are estimated through a series of regression equations, but collinearity issues might make these estimates biased. The coefficients in these equations indicate the strength and direction of the relationships. Collinearity can result in biased coefficient estimates, and it tends to be challenging to correctly evaluate how the variables relate to one another. In each regression of the structural model, the construct scores of the predictor constructs are used to determine the variance inflation factor (VIF) values. Collinearity can exist at lower VIF values of 3 to 5, however, it is more likely to exist at VIF value over 5, which indicate problems with predictor constructs. In other words, the higher the VIF values, the higher the degree of collinearity between the predictor variables (Becker et al., 2014). Hair et al. (2017) suggested ways to deal with collinearity problems, such as the removal of constructs, merging predictors into a single construct, or developing higher-order constructs.

Figure 4.6 illustrates the collinearity statistics of the inner model. All of the VIF values were shown to be below 3, except for TPM, which has a VIF value of 3.257. Despite the fact that the VIF value for TPM was slightly higher than the threshold of 3, it can still be considered acceptable since values below 5 are generally acceptable for most studies. Thus, the structural model does not have a critical problem with collinearity among the predictor constructs.

Collinearity statistics (VIF) - Inner model

Zoom

	CF	EI	SP	TPM
CF			2.448	
EI			2.914	
SP				
TPM			3.257	

Figure 4.6: Collinearity Statistics of the Inner Model.

4.3.2 Path Coefficient

Since PLS-SEM is a non-parametric method, it makes no assumption about the data's normality. Therefore, when the data is not normally distributed, parametric significance tests such as those used in regression analysis cannot be applied to test the significance of the outer weights, outer loadings, and path coefficients in PLS-SEM. In contrast, non-parametric bootstrap resampling methods are frequently applied in PLS-SEM to estimate the standard errors, t-values, and p-values of the model coefficients.

First, bootstrapping setup involved using subsamples with a size of 5000 by following the general guidelines for PLS-SEM bootstrapping. Second, bias-correlated and accelerated (BCa) bootstrap was selected as the confidence interval method. In comparison to other bootstrap methods, the BCa method was specially constructed to overcome problems with bias and skewness in the bootstrap distribution and to provide more accurate and precise confidence intervals. Third, the two-tailed test was selected as the test type, and the significance level was 0.05. For instance, the bootstrapping procedure may be used to obtain t-values for the indicator weights and other model parameters. In order to establish if the coefficients are statistically significant, these t-values may be contrasted with the critical values of the standard normal distribution. The critical values for significance levels of 1 % (α = 0.01), 5 % (α = 0.05), and 10 % (α = 0.10) probability of error for a two-tailed test are 2.576, 1.96, and 1.645, respectively. In other words, a t-value above 1.96 for a two-tailed test with a significance level of 5 % indicates the statistical significance of the path coefficient (Hair et al., 2021). Figure 4.7 shows the bootstrapping setup.

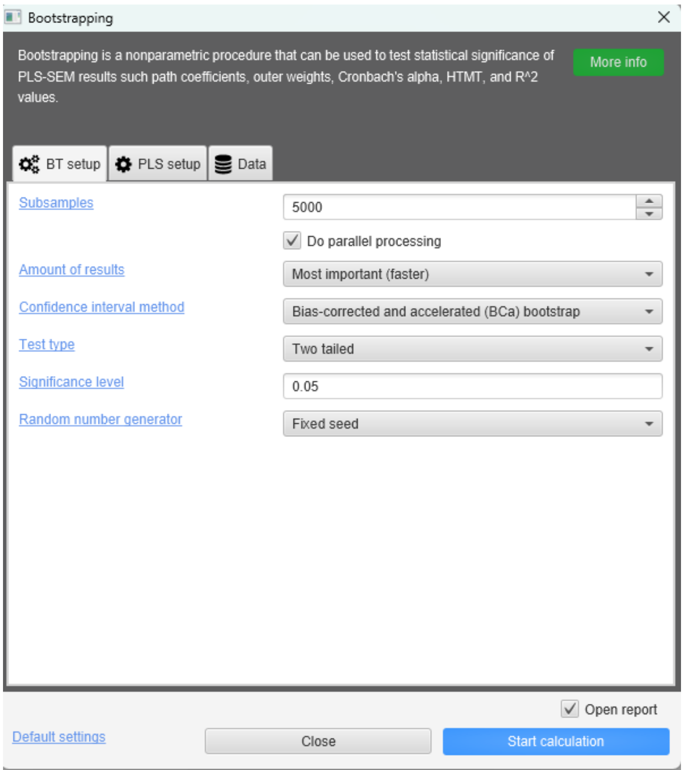

Figure 4.7: Bootstrapping Setup.

Path coefficients generally vary between -1 and +1, with readings closer to -1 denoting strong negative relationships and readings closer to +1 denoting strong positive relationships. Due to extremely high levels of collinearity, it is conceivable to have a path coefficient outside of this range;

however, values greater than +1 or lower than -1 are unacceptable, and multicollinearity reduction techniques have to be applied to resolve this issue. Other than that, path coefficients in PLS-SEM are based on standardised data and depict the changes in an endogenous construct's values that are correlated to one standard deviation unit change in a predictor construct while maintaining the remainder of the predictor constructs unchanged.

Figure 4.8 displays the path coefficient of the structural model, and Figure 4.9 shows the graphical output of the framework. The findings of the bootstrapping validate the substantial correlations between the independent and dependent variables, where all t-values were over 1.96 and all p-values were below 0.05. The statistical significance suggests that the relationships are unlikely to occur by chance. Figure 4.8 demonstrates that there is an inverse correlation between the t-value and the p-values. Specifically, the p-values fall as the values of the t-statistics rise. Furthermore, the beta coefficients for the relationships between CF and SP, TPM and SP, and EI and SP were 0.274, 0.232, and 0.304, respectively, as shown in Figure 4.9. The presence of positive beta coefficients indicates that the variables have positive relationships that are statistically significant. In addition, the higher the beta coefficient of a construct, the greater the impact on the dependent variable. In this instance, employee involvement has the greatest impact on safety performance, with a beta coefficient of 0.304. Followed by continuous flow and total preventive maintenance with beta coefficients of 0.274 and 0.232, respectively.

Path coefficients - Mean, STDEV, T values, p values   Zoom (150%)   Copy to Excel   Copy to R

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
CF -> SP	0.274	0.274	0.130	2.113	0.035
EI -> SP	0.304	0.299	0.120	2.524	0.012
TPM -> SP	0.232	0.238	0.103	2.251	0.024

Figure 4.8: Path Coefficient of Structural Model.

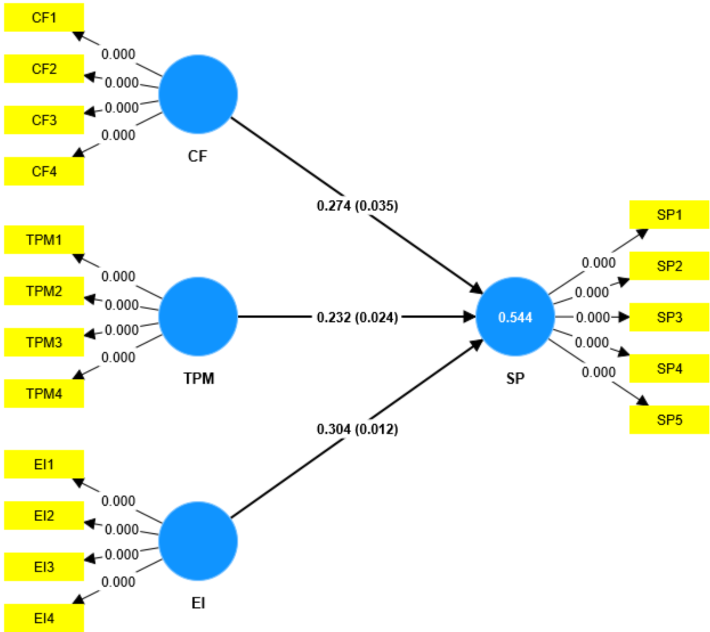

Figure 4.9: Graphical Output of the Framework.

4.3.3 Coefficient of Determination, R^2

The coefficient of determination (R^2) represents the amount of variance explained in each of the endogenous (dependent) constructs. In essence, it provides an evaluation of the model's explanatory power in relation to endogenous constructs (Shmueli and Koppius, 2011). Besides, R^2 is often known as in-sample predictive power (McIntosh et al., 2014). The R^2 has a range of 0 to 1. A R^2 value of 0 demonstrates that the model does not explain any of the variance in the dependent variable, while a R^2 value of 1 demonstrates that the model explains all of the variance in the dependent variable. Consequently, a higher R^2 value implies that the model fits the data more accurately and has a greater level of explanatory power.

As a rule of thumb, R^2 values of 0.75, 0.50, or 0.25 for endogenous latent variables in the structural model can be described as substantial, moderate, or weak, respectively (Hair et al., 2011). On the contrary, Falk and Miller (1992) suggested that a R^2 value of 0.10 or higher should be considered to satisfactorily explain the variance in a given endogenous construct. However, an acceptable R^2 value depends on several factors, including the model's complexity, the quantity of independent variables, the size and quality of the dataset, and the research field or discipline.

R^2 value is a frequently used metric for assessing how well a model fits. Nonetheless, it has certain limitations when comparing models with varying model specifications, such as those with different exogenous (independent) constructs that predict the same endogenous (dependent) constructs. Adding constructs that are not statistically significant but have little correlation with the endogenous latent variable to a structural model can increase the R^2 value. Despite that, this can be deceptive, especially when the sample size is similar to the number of exogenous latent variables predicting the endogenous latent variable being studied. Relying solely on the R^2 value to evaluate a model's predictive power can create a tendency to favour models that have numerous exogenous constructs, even those with only weak relationships to the endogenous constructs. As a result, it is possible to have bias in the selection of models. In general, parsimonious models that effectively describe the data while utilising fewer exogenous elements are preferred by researchers (Hair et al., 2017).

The adjusted R^2 value may be employed as a parameter to prevent bias towards complicated models, which is equivalent to multiple regression. Particularly, this parameter is adjusted in accordance with the sample size to exogenous construct ratio. The formula below can be used to determine the adjusted R^2 value (Hair et al., 2017).

$$\text{Adjusted } R^2 = 1 - (1 - R^2)\frac{(n-1)}{(n-k-1)} \qquad (4.2)$$

where
n = sample size
k = number of exogenous latent variables

The range of the adjusted R^2 value is 0 to 1, with higher values signifying that the model has a higher degree of fit with the data. As the number of predictors (exogenous constructs) increases, the adjusted R^2 value will decrease unless the additional predictors considerably enhance the model's fit. The reason is that the adjusted R^2 value takes into account the number of predictors in the model and reduces the value of models containing irrelevant or redundant predictors. By considering the quantity of exogenous constructs and the sample size used in the model, the adjusted R^2 value will adjust the R^2 value and generate a more conservative estimate of the prediction ability of the model. This is accomplished by lowering the R^2 value as the number of exogenous constructs rises. Figure 4.10 illustrates the R^2 value of the structural model. The R^2 value obtained was 0.544, which denotes that the independent variables in the model can account for 54.4 % of the variation in the dependent variable. According to the rules of thumb, the R^2 value of SP can be considered moderate. On the other hand, the adjusted R^2 value obtained was 0.533, which accounts for the quantity of predictors in the model and gives a more precise measurement of the model's goodness-of-fit.

R-square - Overview

Zoom (15

	R-square	R-square adjusted
SP	0.544	0.533

Figure 4.10: R^2 Value of the Structural Model.

4.3.4 Effect Size, f^2

The effect size (f^2) is a metric used to evaluate how an exogenous variable affects an endogenous variable in regression analysis. It precisely assesses the variation in the R^2 value that occurs when a particular exogenous variable is omitted from the model. The use of effect size (f^2) is becoming more prevalent among journal editors and reviewers since it offers a more in-depth understanding of how exogenous variables affect endogenous variables in a regression model. The formula below may be used to compute the effect size (f^2) value (Hair et al., 2017).

$$f^2 = \frac{R_{new}^2 - R_{old}^2}{1 - R_{new}^2} \tag{4.3}$$

where

R_{new}^2 = R^2 value obtained after removing a particular exogenous variable from the model

R_{old}^2 = R^2 value obtained from the original model that includes the exogenous variable

Both the path coefficient and effect size (f^2) provide information about the consequences of independent constructs in defining the dependent construct in a structural model. However, they offer different perspectives. The path coefficient shows the degree to which independent and dependent constructs are correlated. On the other hand, the effect size (f^2) measures the proportion of the dependent construct's discrepancy that can be attributed to a specific independent construct.

If the path coefficient and the effect size (f^2) are in the same rank order in explaining a related construct, then the effect size (f^2) may not provide any additional information beyond that already conveyed by the path coefficient. However, when the rank order between the path coefficient and effect size (f^2) is different, the effect size (f^2) can help identify which predictor construct is relatively more important in explaining the related construct (Hair et al., 2019). As a general guideline for interpreting effect size (f^2), values greater than 0.02, 0.15, and 0.35 are indicative of small, medium, and large effects, respectively (Cohen, 1988). Figure 4.11 shows the effect size (f^2) of the structural model. The effect size (f^2) of the CF was 0.067, TPM was 0.036, and EI was 0.069. These indicate that CF and EI have a considerably greater effect on the endogenous construct compared to TPM. In spite of that, all the exogenous constructs have relatively small effects on the endogenous construct. Despite the effect size being relatively small, all exogenous variables exhibit a statistically significant effect on the endogenous variable.

f-square - Matrix

	CF	EI	SP	TPM
CF			0.067	
EI			0.069	
SP				
TPM			0.036	

Figure 4.11: Effect Size (f^2) of the Structural Model.

4.3.5 Predictive Model Assessment

In addition to R^2 value, Q^2 value is also used to assess the PLS path model's predictive accuracy (Geisser, 1974; Stone, 1974). The Q^2 metric is widely applied as a measure of the predictive relevance of the model or out-of-sample predictive power. As a matter of fact, the Q^2 metric incorporates aspects of both in-sample explanatory power and out-of-sample predictive power (Shmueli et al., 2016). The term "in-sample explanatory power" describes how well a model can explain the data used for parameter estimation, while "out-of-sample predictive power" describes the capability of the model to accurately predict new and unseen data. According to Hair et al. (2017), a Q^2 value above 0 denotes that the model is predictively relevant for a particular dependent construct. Q^2 values greater than 0, 0.25, and 0.5 are generally regarded as indicating small, medium, and large predictive relevance of the PLS-SEM model, respectively. In other words, the model's out-of-sample predictive power or predictive relevance increases as the Q^2 value increases.

The blindfolding method is used in PLS-SEM to determine the Q^2 metric for a given omission distance (d). The sample reuse method known as "blindfolding" involves omitting all dth data points from the indicators of the endogenous construct and estimating the model parameters from the remainder of the data points. The missing values are addressed appropriately by the PLS-SEM method and are regarded as missing data points. Chin (1988) recommended using an omission distance between 5 and 10. Furthermore, it is recommended that the number of observations used in the model estimation divided by the omission distance (d) is not an integer. This is done to avoid the possibility of biased results and assure the model's validity. The default omission distance setting of 7 was utilised while setting up blindfolding in SmartPLS. Figure 4.12 shows the blindfolding setup.

Figure 4.12: Blindfolding Setup.

Cross-validated communality (CVC) and cross-validated redundancy (CVR) are two different forms of Q^2 value that are produced by the blindfolding process in PLS-SEM. Yet, the research model opted to use cross-validated redundancy (CVR), which is in line with the recommendation offered by Hair et al. (2017). The rationale is that the CVR value comprises the essential component of the path model, which is the structural model, in forecasting the omitted data points. Figure 4.13 reveals the Q^2 value of the structural model. The Q^2 value for the endogenous construct was over 0, therefore, predictive relevance is established. The Q^2 value of SP obtained was 0.459, indicating that the PLS-SEM model has medium predictive relevance.

Construct cross-validated redundancy - Total Zoom (150%)

	SSO	SSE	Q^2 (=1-SSE/SSO)
CF	536.000	536.000	0.000
EI	536.000	536.000	0.000
SP	670.000	362.473	0.459
TPM	536.000	536.000	0.000

Figure 4.13: Q^2 Value of the Structural Model.

The effect size (q^2) enables evaluating the contribution of an exogenous construct to the Q^2 value of an endogenous construct. In other words, the degree of connection between the exogenous and endogenous constructs is assessed using the predictive relevance's effect size. According to Cohen (1998), effect size (q^2) values of 0.02, 0.15, and 0.35 indicate small, medium, and large predictive relevance of an exogenous construct on an endogenous construct, respectively. The formula below may be used to compute the effect size (q^2) value (Hair et al., 2017).

$$q^2 = \frac{Q^2_{included} - Q^2_{excluded}}{1 - Q^2_{included}} \tag{4.4}$$

where

$Q^2_{included}$ = Q^2 value of at endogenous variable where all the exogenous variables are included in the model

$Q^2_{excluded}$ = Q^2 value of at endogenous variable where the selected exogenous variable is excluded from the model

Table 4.1 shows the effect size of predictive relevance (q^2). The calculated effect size (q^2) for CF, TPM, and EI were 0.044, 0.026, and 0.052, respectively. According to Cohen (1998), the endogenous construct is only marginally predicted by each of the exogenous constructs. Nevertheless, all exogenous variables show a statistically significant effect on the endogenous variable.

Table 4.1: Effect Size of Predictive Relevance (q^2).

	Omitted Exogenous Construct	$Q^2_{included}$	$Q^2_{excluded}$	q^2	**Predictive Relevance**
1	Continuous Flow	0.459	0.435	0.044	Small predictive effect
2	Total Preventive Maintenance	0.459	0.445	0.026	Small predictive effect
3	Employee Involvement	0.459	0.431	0.052	Small predictive effect

Other than that, recent studies have suggested $PLS_{predict}$ as a predictive model assessment in PLS-SEM. $PLS_{predict}$ was created by Shmueli et al. (2016) to assess the predictive power of a PLS-SEM using a holdout-sample-based procedure. In particular, the holdout-sample-based procedure divides the dataset into a training sample and a holdout sample. The training sample is exploited to estimate the model, whereas the holdout sample is exploited to evaluate the predictive performance. The default fold number and repetition number of 10 were applied in the $PLS_{predict}$ setup, which is recommended by Shmueli et al. (2019). Figure 4.14 shows the $PLS_{predict}$ setup.

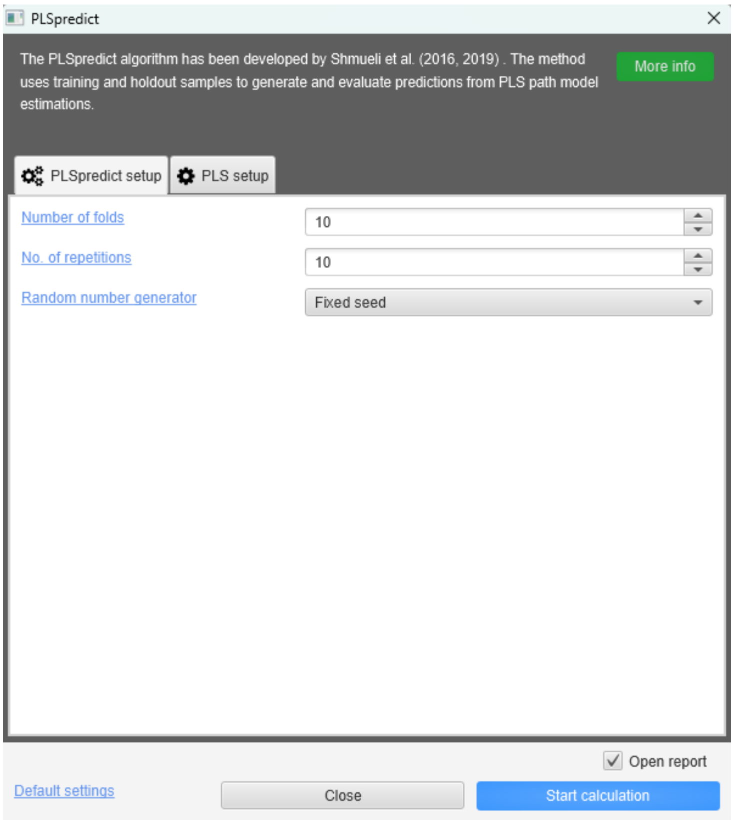

Figure 4.14: $PLS_{predict}$ Setup.

Two prediction statistics were used to measure the predictive power of the model, such as root mean squared error (RMSE) and mean absolute error (MAE). The RMSE is the square root of the average of the squared discrepancies between the anticipated values and the actual observations. RMSE is very beneficial when big mistakes are not desired, for the reason that it gives greater weight to larger errors by squaring them before averaging. In contrast to the RMSE, the MAE is a statistic used to calculate the average amount of mistakes in a series of predictions, regardless of their direction. Additionally, the MAE assigns equal weight to all the individual variations between the predicted and actual values. Nevertheless, the RMSE is commonly recommended as the primary choice for evaluating the predictive power of the model, while the MAE may be appropriate if the distribution of the prediction error is significantly non-symmetric. In this case, a lengthy left or right tail in the prediction error distribution may be an indicator of a highly non-symmetric distribution.

Figure 4.15 shows the MV prediction summary. Since all indicators of $Q^2_{predict}$ were larger than 0 and the prediction errors were highly symmetrically distributed, the values of the RMSE of the PLS-SEM analysis and naïve LM benchmark were compared. Each indicator of the dependent construct is linearly regressed against each indicator of the exogenous constructs in the PLS path model to obtain the LM benchmark values (Danks & Ray, 2018). According to the general guidelines, all metrics in the PLS-SEM analysis have lower RMSE values than naïve LM benchmark, indicating that the model has a high degree of predictive power (Shmueli et al., 2019).

MV prediction summary - Overview

	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
SP1	0.494	0.611	0.483	0.619	0.477
SP2	0.407	0.663	0.497	0.692	0.515
SP3	0.342	0.727	0.524	0.758	0.529
SP4	0.497	0.598	0.460	0.631	0.471
SP5	0.423	0.673	0.519	0.688	0.540

Figure 4.15: MV Prediction Summary.

4.3.6 Goodness-of-Fit (GoF)

A structural equation model's overall performance is evaluated using the Goodness-of-Fit (GoF) metric. For endogenous constructs, it is derived as the geometric mean of the average variance extracted (AVE) and the average coefficient of determination (R^2) (Tenenhaus et al., 2005). Moreover, the GoF index can serve as a benchmark for globally evaluating complex PLS-based models. The GoF index has a value between 0 and 1, with a value nearer to 1 demonstrating greater data and model fit (Akter et al., 2011). The GoF index may be divided into three categories according to its small, medium, and large validating powers, with values of 0.1, 0.25, and 0.36, respectively. The formula below can be applied to determine the Goodness-of-Fit (GoF) (Wetzels et al., 2009).

$$GoF = \sqrt{\overline{AVE} \times \overline{R^2}} \tag{4.5}$$

where

GoF = Goodness-of-Fit

AVE = Average variance extracted

R^2 = Coefficient of determination

Table 4.2 shows the calculation of Goodness-of-Fit (GoF). The GoF metric of this research model was calculated to be 0.672. When compared to the baseline values, the calculated values clearly demonstrate that the empirical data has strong predictability and fits the model satisfactorily.

Table 4.2: Calculation of Goodness-of-Fit (GoF).

Constructs	**AVE**	$\boldsymbol{R^2}$
Continuous Flow	0.858	0.544
Total Preventive Maintenance	0.787	
Employee Involvement	0.812	
Safety Performance	0.863	
Average	**0.830**	**0.544**
Square Root	**0.911**	**0.738**
GoF	**0.672**	

4.4 Importance-performance Map Analysis (IPMA)

The importance-performance map analysis (IPMA) is a valuable PLS-SEM approach that provides an extension to the standard reporting of path coefficient estimates. It adds a new dimension to the analysis by taking into account the average values of the latent variable scores. This analysis is often referred to as a priority map analysis, impact-performance analysis, or importance-performance matrix analysis (Ringle and Sarstedt, 2016). More specifically, the average latent variable scores of the predecessor constructs (exogenous constructs) are compared to the total effects of the predecessor constructs on a target construct (endogenous construct). This makes it possible to evaluate the importance and performance of each predecessor construct in influencing the target construct. The total effects of IPMA describe the significance of predecessor constructs in forming the target construct, while the average latent variable scores of the predecessor constructs show their performance. The main objective of IPMA is to determine the predecessor constructs that are significantly important in forming the target construct but, at the same time, have low performance (Hair et al., 2017).

Other than that, there are two conditions that must be satisfied for the application of the IPMA. One of the conditions for applying the IPMA is that all indicator codings must have the same direction, with a low value signifying an unfavourable result and a high value signifying a favourable result. On the contrary, the interpretation of the IPMA results may be inaccurate if the indicator coding is inconsistent. In these circumstances, it is necessary to modify the indicator coding so that all indicators are in the same direction and the higher values always denote better performance. Secondly, it is necessary to make sure that the outer weights in the measurement model, whether formative or reflective, are not negative. The performance values will be scaled between 0 and 100 when the outer weights are positive. In contrast, if the outer weights are negative, the performance values will not fall within this particular range but may vary, for instance, between -10 and 90. Indicator collinearity may result in negative weights. In this case, it may be appropriate to consider eliminating the problematic indicator. During the setup of IPMA, the “target construct” selected was safety performance, and “all predecessors of the selected target construct” were selected as the IPMA result.

Figure 4.16 shows the IMPA setup, and Figure 4.17 shows the IPMA model. According to Figure 4.17, the performance values for CF, TPM, EI, and SP were 78.292, 71.224, 75.532, and 79.911, respectively. Therefore, in comparison to total preventive maintenance, predecessor constructs such as continuous flow and employee involvement exhibit comparatively good performance. Besides, Table 4.3 displays the importance and performance of predecessor constructs. The mean values of importance and performance were calculated to be 0.27 and 75.016, respectively.

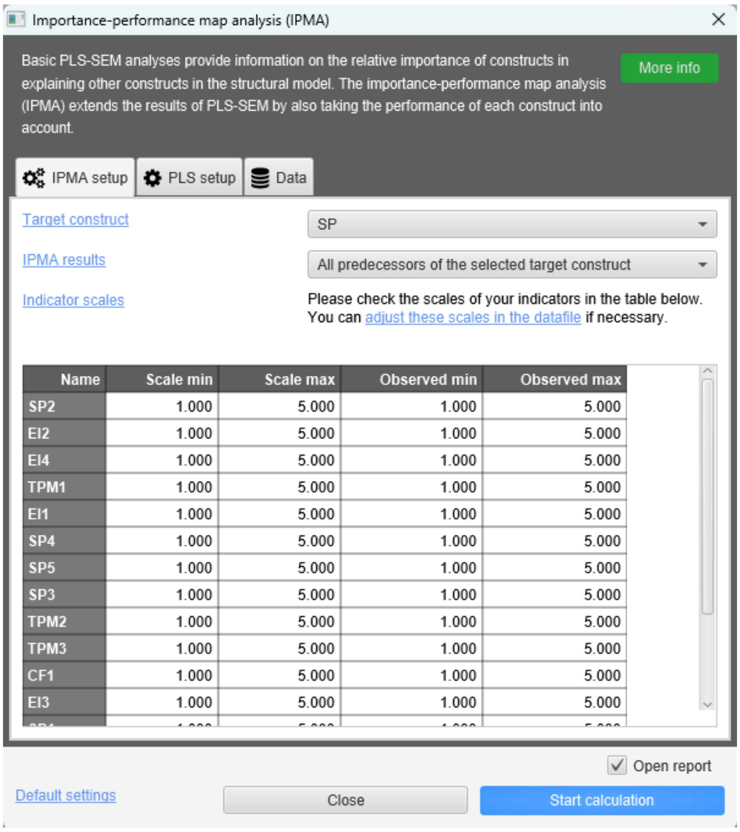

Figure 4.16: IPMA Setup.

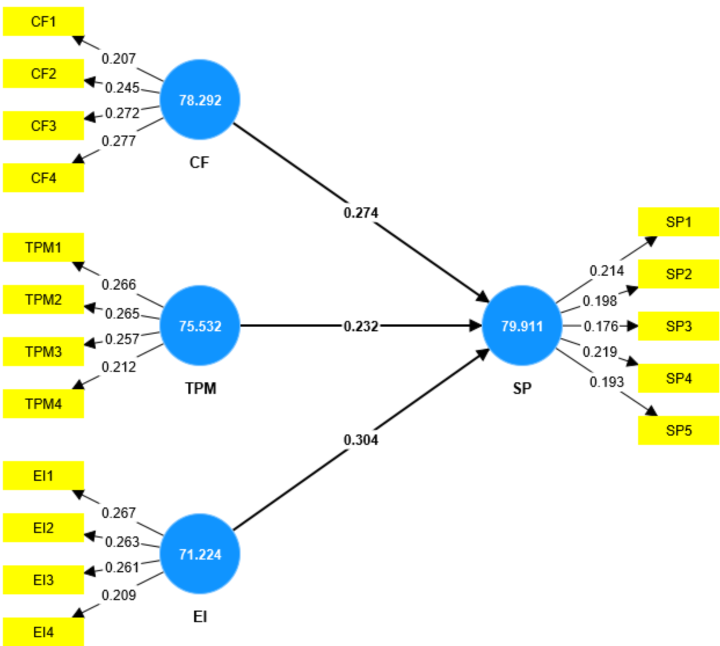

Figure 4.17: IPMA Model.

Table 4.3: Importance and Performance of Predecessor Constructs.

Predecessor Constructs	Importance	Performance
Continuous Flow	0.274	78.292
Total Preventive Maintenance	0.232	71.224
Employee Involvement	0.304	75.532
Average	0.27	75.016

Figure 4.18 demonstrates the importance-performance map guideline. Importance and performance data are displayed graphically on two axes, with "importance" displayed along the Y-axis and "performance" displayed along the X-axis. The data are plotted in four quadrants (Quadrant I, Quadrant II, Quadrant III, and Quadrant IV) to identify areas for improvement. According to Martilla and James (1977), the four quadrants are illustrated as Q1 (keep up with the good work), Q2 (possible overkill), Q3 (low priority), and Q4 (concentrate here). The four quadrants of the IPMA are defined by means of importance and performance (Deng, 2007). The calculated mean values of importance and performance were 0.27 and 75.016, respectively, which delimited the importance-performance map into four quadrants.

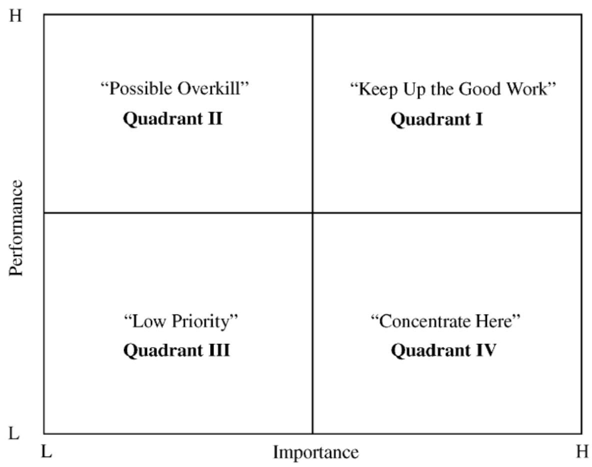

Figure 4.18: Importance-performance Map Guideline (Deng, 2007).

Figure 4.19 shows the importance-performance map. Based on Figure 4.19, CF and EI are recognised as key elements in explaining the target construct of SP. The constructs appearing in the lower-right quadrant of the importance-performance map show that they have high importance in influencing the target construct but exhibit low performance. This suggests that there is substantial potential to enhance the performance of the constructs in this region. In a ceteris paribus situation, an increase in EI performance of one unit leads to an increase in SP performance of 0.304 units. In particular, the EI's performance will increase from 75.532 to 76.532, and the SP's performance will increase by 0.304 points, from 79.911 to 80.215. Meanwhile, the performance of EI is comparatively low, indicating a significant potential for enhancing its performance. As a result, the most relevant construct for managerial actions in the PLS path model is the EI construct, due to its comparatively high importance and low performance in explaining the target construct. As shown in Figure 4.19, the CF, TPM, and EI were located in Q1, Q2, and Q4, respectively.

Moreover, the IPMA suggests that Malaysia's manufacturing firms should maintain their performance on continuous flow (CF), as CF has high importance and high performance. On the other hand, TPM has relatively low importance but high performance. In this case, the firms may choose to maintain the performance on TPM or focus on other constructs with high importance and performance. Notwithstanding, the possible effects of enhancing performance on TPM must also be taken into account. Additionally, in the importance-performance map, the construct with lower importance compared to other constructs is considered to have a lower priority for performance improvements.

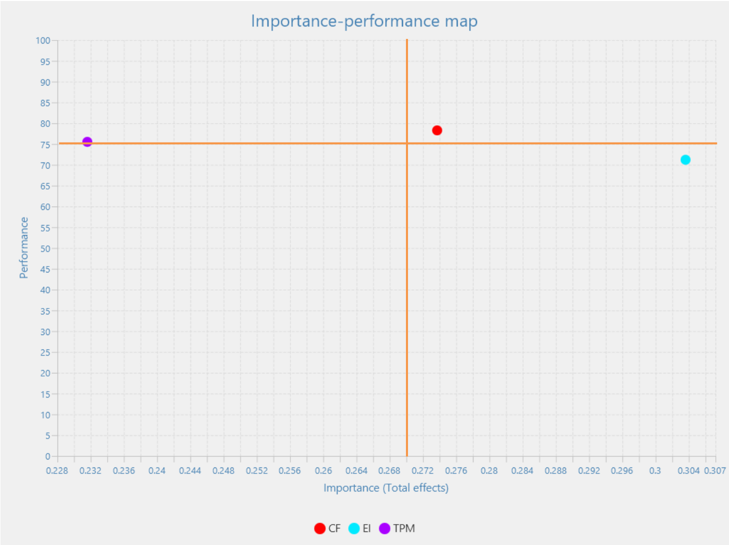

Figure 4.19: Importance-performance Map.

4.5 Discussion

A structural equation modelling (SEM) analysis was conducted with SmartPLS software to investigate the hypothetical correlation between the study's independent and dependent variables. In the meantime, the measurement model and structural model were accessed using the features of the SmartPLS software. Essentially, a measurement model is used to measure the reliability and validity of latent constructs in research. The evaluation of the measurement model involves internal consistency, convergent validity, and discriminant validity. All the internal consistency values were above the threshold, which implies that the constructs have an outstanding level of reliability and the indicators used to measure them are consistent. Besides, the substantial correlation between the indicators and the latent construct is demonstrated by the high value of outer loadings. Apart from that, the development of discriminant validity is supported by the results of cross loadings, the Fornell-Larcker criterion, and the HTMT ratio.

Additionally, a structural model is also employed to illustrate how variables in a system relate to one another. The structural model assessment involves collinearity statistics, path coefficient, coefficient of determination (R^2), effect size (f^2), predictive model assessment, and goodness-of-fit. The result showed that the variables have positive relationships that are statistically significant. Other than that, the predictive model assessment showed that the model has supportive predictive power.

The hypotheses can be explained through the findings of bootstrapping. In this study, the two-tailed test was selected as the test type, and the significance level was 0.05. Therefore, the critical value for a two-tailed test with a significance level of 5 % probability of error is 1.96. In other words, the path coefficient is considered statistically significant when the t-value exceeds 1.96. The hypothesis (H1) has been proved, as the t-value was 2.113 and the p-value was 0.035. This indicates that the continuous flow has a positive impact on safety performance. A good design of facility layout can improve safety performance in manufacturing industries. For instance, a well-planned factory layout can help to avoid, prevent, or reduce certain types of risks, particularly to health and safety (Amri et al., 2016).

The second hypothesis (H2) states that total preventive maintenance and safety performance are significantly correlated. The positive relationship between variables is supported by a t-value of 2.251 and a p-value of 0.024. The effective implementation of the pillars of TPM resulted in a rise in production output, as shown by the overall equipment effectiveness (OEE), which rose from 75.17 % to 85.25 % with no customer complaints and zero accidents (Kocher et al., 2012).

Next, the third hypothesis (H3) demonstrates that employee involvement significantly affects safety performance. The hypothesis (H3) is supported by the t-value of 2.524 and the p-value of 0.012. Compared to continuous flow and total preventive maintenance, employee involvement has the greatest t-value and p-value; thus, it can be stated that employee involvement has the greatest impact on safety performance in manufacturing firms. Lawler, Mohrman and Ledford (1995) reported that 60 % of the organisations that exercised employee involvement procedures saw an improvement in workers' safety and health.

Other than that, the beta coefficient was evaluated to test the relationship between variables. The relationships between CF and SP, TPM and SP, and EI and SP were shown to have beta coefficients of 0.274, 0.232, and 0.304, respectively. The independent and dependent variables are positively correlated, as indicated by the positive beta coefficients. Apart from that, the higher the beta coefficient of a construct, the greater the impact on the dependent variable. Hence, in this instance, the EI has the greatest impact on the SP, followed by the CF and TPM.

Furthermore, the importance-performance map analysis was conducted to evaluate the importance and performance of each predecessor construct in influencing the target construct. The importance-performance map was delimited into four quadrants by the calculated mean values of importance and performance, which were 0.27 and 75.016, respectively. The EI was shown to be located in Q4, which indicates that the EI is the most pertinent construct for managerial actions. In addition, the IPMA suggests Malaysia's manufacturing companies keep up their performance on CF, as CF has high performance and importance. On the contrary, TPM was found to appear in Q2, in which the importance of TPM was relatively low but the performance was high. In this manner, the industries may choose to maintain their existing performance on TPM or refocus on other constructs with high importance and performance. However, the possible advantages of enhancing TPM performance must be considered as well. For example, improved uptime of machines, improved quality of the products, and improved equipment reliability. In short, all of the hypotheses are accepted, and the safety performance is positively impacted by each independent variable.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The findings of the present study clearly show that the implementation of lean tools has improved the safety performance of Malaysia's manufacturing firms. The occupational health and safety considerations are key aspects of manufacturing firms, along with profitability. The objectives of this study have been achieved, and all of the hypotheses are accepted. The values of Cronbach's alpha and composite reliability of the exogenous and endogenous constructs were substantially over the threshold of 0.70, indicating an excellent degree of internal consistency reliability for all the constructs. This implies that the constructs are highly reliable, and that the indicators employed to assess the underlying constructs are consistent. In addition, the constructs' AVE values exceeded the minimum required threshold of 0.5, showing that the construct has a good level of convergent validity. The bootstrapping findings seem to corroborate the substantial correlations among both dependent and independent variables, in which all t-values were over 1.96 and all p-values were below 0.5. It was concluded that employee involvement has the greatest impact on safety performance, with the highest beta coefficient of 0.304. It was followed by continuous flow and total preventive maintenance. The beta coefficients for the relationships between CF and SP, TPM and SP, and EI and SP were 0.274, 0.232, and 0.304, respectively. Besides, the t-value of 2.113 and the p-value of 0.035 indicate that the variables have positive relationships that are statistically significant. Furthermore, the IPMA indicates that EI is the most relevant construct for managerial action. Lastly, the implementation of lean tools is believed to significantly improve the safety performance of Malaysia's manufacturing firms.

5.2 Recommendations for future work

Considering the limitations of this study, there are several recommendations for future studies aimed at obtaining more reliable and effective research outcomes. Many organisations do not take the issue of a safe working environment and safety and health standards seriously. This will lead to an increase in occupational accidents and injuries at work. Future research should focus on enhancing safety and health procedures in safe working environments for employees in order to reduce accidents and injuries at the workplace. Another recommendation for future work is that the researcher may examine the connection between the implementation of lean tools and safety performance outside of manufacturing. Instead, the relationship between variables in this study only focuses on manufacturing firms.

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APPENDICES

Appendix A: Questionnaire

Section A: Demographic Profile

INSTRUCTION: Please fill up the information below accordingly by placing a tick (✓) in the box of your answer.

1. Company Location:
   - ☐ Johor
   - ☐ Kedah
   - ☐ Kelantan
   - ☐ Kuala Lumpur
   - ☐ Labuan
   - ☐ Melaka
   - ☐ Negeri Sembilan
   - ☐ Pahang
   - ☐ Perak
   - ☐ Perlis
   - ☐ Pulau Pinang
   - ☐ Putrajaya
   - ☐ Sabah
   - ☐ Sarawak
   - ☐ Selangor
   - ☐ Terengganu

2. Company Businesses Size
   - ☐ Small Enterprise (Full time employee below 75)
   - ☐ Medium Enterprise (Full time employee between 75-200)
   - ☐ Large Scale Company (Full time employee more than 200)

3. Type of Businesses
   - ☐ Chemical Industry
   - ☐ Metal Industry
   - ☐ Electronic Industry
   - ☐ Semiconductor Industry
   - ☐ Furniture Industry
   - ☐ Paper Industry
   - ☐ Food Industry
   - ☐ Leather Industry
   - ☐ Oil and Gas Industry
   - ☐ Rubber Industry
   - ☐ Plastic Industry
   - ☐ Other: ___________________________

4. Gender
   - ☐ Male
   - ☐ Female

5. Age
   ☐ < 20
   ☐ 21 – 30
   ☐ 31 – 40
   ☐ 41 – 50
   ☐ > 50

6. Educational Level
   ☐ Primary education
   ☐ Secondary education
   ☐ Diploma
   ☐ Bachelor’s degree
   ☐ Master’s degree
   ☐ PhD

7. Working Experience in the Industry
   ☐ < 1 year
   ☐ 1 – 5 years
   ☐ 6 – 10 years
   ☐ 11 – 15 years
   ☐ 16 – 20 years
   ☐ > 20 years

Section B: Measurement of Dependent and Independent Variable

This section and onwards are used to measure the dependent and independent variable in this study.

INSTRUCTION: Please read the statements below attentively and pinpoint your agreement level by indicating the scale that best represent your judgement.

Evaluation of the impact of Lean tools on safety performance in Malaysia's manufacturing firms

Continuous Flow

Continuous flow requires manufacturers to operate continuously and produce goods at a constant rate, in contrast to traditional batch production. The implementation of continuous flow strategy can significantly reduce the work-in-progress, shorten cycle times, improve the quality of the product and provide a safe working environment.

1 = No implementation; 2 = Little implementation; 3 = Some implementation; 4 = Extensive implementation; 5 = Complete implementation

	Continuous Flow	1	2	3	4	5
1.	Products are classified into groups with similar processing requirements					
2.	Products are classified into groups with similar routing requirements					
3.	Equipment is grouped to produce a continuous flow of families of products					
4.	Families of products determine our factory layout					

Adopted from Shah, R. and Ward, P., 2007. Defining and developing measures of lean production. Journal of Operations Management, 25(4), pp.785-805.

Total Preventive Maintenance

TPM is a method to maximise equipment efficiency, to enhance quality, to promote safety, to minimise costs, and more importantly, to boost team morale. Implementing TPM aims at preventing all accidents, injuries, and fires. The practices of TPM helps to reduce the waste caused by unorganised working environment and unexpected downtime and provide a safer working environment.

1 = No implementation; 2 = Little implementation; 3 = Some implementation; 4 = Extensive implementation; 5 = Complete implementation

	Total Preventive Maintenance	1	2	3	4	5
1.	We dedicate a portion of everyday to planned equipment maintenance related activities					
2.	We maintain all our equipment regularly					
3.	We maintain excellent records of all equipment maintenance related activities					
4.	We post equipment maintenance records on shop floor for active sharing with employees					

Adopted from Shah, R. and Ward, P., 2007. Defining and developing measures of lean production. Journal of Operations Management, 25(4), pp.785-805.

Employee Involvement

An effective employee involvement practices could lead to higher job satisfaction, quality improvement, productivity improvement, and reduction of the possibility of work-related accidents.

1 = No implementation; 2 = Little implementation; 3 = Some implementation; 4 = Extensive implementation; 5 = Complete implementation

	Employee Involvement	1	2	3	4	5
1.	Shop-floor employees are key to problem solving teams					
2.	Shop-floor employees drive suggestion programs					
3.	Shop-floor employees lead product/process improvement efforts					
4.	Shop-floor employees undergo cross functional training					

Adopted from Shah, R. and Ward, P., 2007. Defining and developing measures of lean production. Journal of Operations Management, 25(4), pp.785-805.

<u>Safety Performance</u>

Safety performance indicators are used to evaluate operational safety performance through monitoring. Lagging indicators analyze historical accident records to evaluate an organization's accidents. Leading indicators analyze foregoing and forthcoming event to prevent and minimize the accident in the manufacturing firm. Accidents in workplaces can be prevented and reduced by studying safety performance.

1 = Strongly disagree; 2 = Disagree; 3 = Neither agree nor disagree; 4 = Agree; 5 = Strongly agree

	Safety Performance	1	2	3	4	5
1.	Accident frequency rate reduced					
2.	Accident severity rate reduced					
3.	Accidents involving death and/or loss of limb reduced					
4.	Tangible losses reduced					
5.	Near-miss rate reduced					

Adapted from Bayram, M., Ünğan, M. and Ardıç, K., 2016. The relationships between OHS prevention costs, safety performance, employee satisfaction and accident costs. International Journal of Occupational Safety and Ergonomics, 23(2), pp.285-296.

Appendix B: Google Form Response

Evaluation of the impact of Lean tools on safety performance in Malaysia's manufacturing firms

Dear sir/madam,

I am an undergraduate student of Bachelor of Engineering (Hons) Mechanical Engineering at Universiti Tunku Abdul Rahman (UTAR) and I am currently conducting a research namely

Evaluation of the impact of Lean tools on safety performance in Malaysia's manufacturing firms

This research study is a compulsory subject to partially fulfil the requirement of the degree program. This questionnaire is carefully designed to be completed in no more than 10 minutes. This questionnaire mainly focuses on manufacturing companies in Malaysia. The attached questionnaire consists of a series of sections which are demographic profile and measurement of dependent and independent variable of this study.

I would appreciate if you would spend some of your time to complete the enclosed questionnaire based on your knowledge and understanding. Your cooperation is highly appreciated and thank you for spending your precious time to fill in this questionnaire.

Lastly, your responses will be kept strictly **PRIVATE AND CONFIDENTIAL** as they will and only be used solely in research purpose.

Student
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Evaluation of the impact of Lean tools on safety performance in Malaysia's manufacturing firms

PERSONAL DATA PROTECTION NOTICE

Please be informed that in accordance with Personal Data Protection Act 2010 ("PDPA") which came into force on 15 November 2013, Universiti Tunku Abdul Rahman ("UTAR") is hereby bound to make notice and require consent in relation to collection, recording, storage, usage and retention of personal information.

1. Personal data refers to any information which may directly or indirectly identify a person which could include sensitive personal data and expression of opinion. Among others it includes:
a) Name
b) Identity card
c) Place of Birth
d) Address
e) Education History
f) Employment History
g) Medical History
h) Blood type
i) Race
j) Religion
k) Photo
l) Personal Information and Associated Research Data

2. The purposes for which your personal data may be used are inclusive but not limited to:
a) For assessment of any application to UTAR
b) For processing any benefits and services
c) For communication purposes
d) For advertorial and news
e) For general administration and record purposes
f) For enhancing the value of education
g) For educational and related purposes consequential to UTAR
h) For replying any responds to complaints and enquiries
i) For the purpose of our corporate governance
j) For the purposes of conducting research/ collaboration

3. Your personal data may be transferred and/or disclosed to third party and/or UTAR collaborative partners including but not limited to the respective and appointed outsourcing agents for purpose of fulfilling our obligations to you in respect of the purposes and all such other purposes that are related to the purposes and also in providing integrated services, maintaining and storing records. Your data may be shared when required by laws and when disclosure is necessary to comply with applicable laws.

4. Any personal information retained by UTAR shall be destroyed and/or deleted in accordance with our

retention policy applicable for us in the event such information is no longer required.

5. UTAR is committed in ensuring the confidentiality, protection, security and accuracy of your personal information made available to us and it has been our ongoing strict policy to ensure that your personal information is accurate, complete, not misleading and updated. UTAR would also ensure that your personal data shall not be used for political and commercial purposes.

Consent:
6. By submitting or providing your personal data to UTAR, you had consented and agreed for your personal data to be used in accordance to the terms and conditions in the Notice and our relevant policy.

7. If you do not consent or subsequently withdraw your consent to the processing and disclosure of your personal data, UTAR will not be able to fulfill our obligations or to contact you or to assist you in respect of the purposes and/or for any other purposes related to the purpose.

8. You may access and update your personal data by writing to us at likhang0711@1utar.my (Wang Li Khang).

Section A: Demographic Profile

INSTRUCTION: Please fill up the information below accordingly.

1. Company Location *

- ○ Johor
- ○ Kedah
- ○ Kelantan
- ○ Kuala Lumpur
- ○ Labuan
- ○ Melaka
- ○ Negeri Sembilan
- ◉ Pahang
- ○ Perak
- ○ Perlis
- ○ Pulau Pinang
- ○ Putrajaya
- ○ Sabah
- ○ Sarawak
- ○ Selangor
- ○ Terengganu

2. Company Businesses Size *

- ○ Small Enterprise (Full time employee below 75)
- ◉ Medium Enterprise (Full time employee between 75-200)
- ○ Large Scale Company (Full time employee more than 200)

3. Type of Businesses *

- (selected) Chemical Industry
- Metal Industry
- Electronic Industry
- Semiconductor Industry
- Furniture Industry
- Paper Industry
- Food Industry
- Leather Industry
- Oil and Gas Industry
- Rubber Industry
- Plastic Industry
- Other: ____________________

4. Gender *

- (selected) Male
- Female

5. Age *

- ◯ < 20
- ◯ 21 - 30
- ◯ 31 - 40
- ◯ 41 - 50
- ◉ > 50

6. Educational Level *

- ◯ Primary education
- ◯ Secondary education
- ◯ Diploma
- ◉ Bachelor's degree
- ◯ Master's degree
- ◯ PhD

7. Working Experience in the Industry *

- ◯ < 1 year
- ◯ 1 - 5 years
- ◯ 6 - 10 years
- ◯ 11 - 15 years
- ◯ 16 - 20 years
- ◉ > 20 years

Section B: Measurement of Dependent and Independent Variable

This section and onwards are used to measure the dependent and independent variable in this study.

INSTRUCTION: Please read the statements below attentively and pinpoint your agreement level by indicating the scale that best represent your judgement.

Continuous Flow

Continuous flow requires manufacturers to operate continuously and produce goods at a constant rate, in contrast to traditional batch production. The implementation of continuous flow strategy can significantly reduce the work-in-progress, shorten cycle times, improve the quality of the product and provide a safe working environment.

Adopted from Shah, R. and Ward, P., 2007. Defining and developing measures of lean production. Journal of Operations Management, 25(4), pp.785-805.

Products are classified into groups with similar processing requirements. *

No Implementation

1 ○

2 ○

3 ○

4 ◉

5 ○

Complete Implementation

Products are classified into groups with similar routing requirements. *

No Implementation

1 ○

2 ○

3 ○

4 ◉

5 ○

Complete Implementation

Equipment is grouped to produce a continuous flow of families of products. *

No Implementation

1 ○

2 ○

3 ○

4 ◉

5 ○

Complete Implementation

Families of products determine our factory layout. *

No Implementation

1 ○

2 ○

3 ○

4 ◉

5 ○

Complete Implementation

Total Preventive Maintenance

TPM is a method to maximize equipment efficiency, to enhance quality, to promote safety, to minimize costs, and more importantly, to boost team morale. Implementing TPM aims at preventing all accidents, injuries, and fires. The practices of TPM helps to reduce the waste caused by unorganized working environment and unexpected downtime and provide a safer working environment.

Adopted from Shah, R. and Ward, P., 2007. Defining and developing measures of lean production. Journal of Operations Management, 25(4), pp.785-805.

We dedicate a portion of everyday to planned equipment maintenance related activities. *

No Implementation

1 ○

2 ○

3 ○

4 ○

5 ◉

Complete Implementation

We maintain all our equipment regularly. *

No Implementation

1 ○

2 ○

3 ○

4 ◉

5 ○

Complete Implementation

We maintain excellent records of all equipment maintenance related activities. *

No Implementation

1 ○

2 ○

3 ○

4 ○

5 ◉

Complete Implementation

We post equipment maintenance records on shop floor for active sharing with employees. *

No Implementation

1 ○

2 ○

3 ◉

4 ○

5 ○

Complete Implementation

Employee Involvement

An effective employee involvement practices could lead to higher job satisfaction, quality improvement, productivity improvement, and reduction of the possibility of work-related accidents.

Adopted from Shah, R. and Ward, P., 2007. Defining and developing measures of lean production. Journal of Operations Management, 25(4), pp.785-805.

Shop-floor employees are key to problem solving teams. *

No Implementation

1 ○

2 ○

3 ○

4 ◉

5 ○

Complete Implementation

Shop-floor employees drive suggestion programs. *

No Implementation

1 ○

2 ○

3 ○

4 ◉

5 ○

Complete Implementation

Shop-floor employees lead product/process improvement efforts. *

No Implementation

1 ○

2 ○

3 ○

4 ○

5 ◉

Complete Implementation

Shop-floor employees undergo cross functional training. *

No Implementation

1 ○

2 ○

3 ○

4 ◉

5 ○

Complete Implementation

Safety Performance

Safety performance indicators are used to evaluate operational safety performance through monitoring. Lagging indicators analyze historical accident records to evaluate an organization's accidents. Leading indicators analyze foregoing and forthcoming event to prevent and minimize the accident in the manufacturing firm. Accidents in workplaces can be prevented and reduced by studying safety performance.

Adopted from Bayram, M., Ünğan, M. and Ardıç, K., 2016. The relationships between OHS prevention costs, safety performance, employee satisfaction and accident costs. International Journal of Occupational Safety and Ergonomics, 23(2), pp.285-296.

Accident frequency rate reduced. *

Strongly Disagree

1 ○

2 ○

3 ○

4 ○

5 ◉

Strongly Agree

Accident severity rate reduced. *

Strongly Disagree

1 ○

2 ○

3 ○

4 ○

5 ◉

Strong Agree

Accidents involving death and/or loss of limb reduced. *

Strongly Disagree

1 ○

2 ○

3 ○

4 ○

5 ◉

Strongly Agree

Tangible losses reduced. *

Strongly Disagree

1 ○

2 ○

3 ○

4 ○

5 ◉

Strongly Agree

Near-miss rate reduced. *

Strongly Disagree

1 ○

2 ○

3 ○

4 ○

5 ◉

Strongly Agree

Appendix C: Ethical Approval Letter

UNIVERSITI TUNKU ABDUL RAHMAN DU012(A)
Wholly owned by UTAR Education Foundation Co. No. 578227-M

Re: U/SERC/97/2023

6 April 2023

Ts Dr Yeo Wei Hong
Head, Department of Mechanical and Material Engineering
Lee Kong Chian Faculty of Engineering and Science
Universiti Tunku Abdul Rahman
Jalan Sungai Long
Bandar Sungai Long
43000 Kajang, Selangor

Dear Ts Dr Yeo,

Ethical Approval For Research Project/Protocol

We refer to your application for ethical approval for your students' research project from Bachelor of Engineering (Honours) Mechanical Engineering programme enrolled in course UEGE4118. We are pleased to inform you that the application has been approved under Expedited Review.

The details of the research projects are as follows:

No.	Research Title	Student's Name	Supervisor's Name	Approval Validity
1.	Evaluation of the Impact of Lean Tools on Safety Performance in Malaysia's Manufacturing Firms	Wang Li Khang	Mr Cheong Wen Chiet	6 April 2023 – 5 April 2024
2.	The Effect of Lean Tools on the Sustainability of Malaysia's Manufacturing Firms	Cha Teng Siang		
3.	Study of the Impact of Industry 4.0 on Safety Performance in Malaysia's Manufacturing Firms	Zhang, Xiyue		

The conduct of this research is subject to the following:

(1) The participants' informed consent be obtained prior to the commencement of the research;

(2) Confidentiality of participants' personal data must be maintained; and

(3) Compliance with procedures set out in related policies of UTAR such as the UTAR Research Ethics and Code of Conduct, Code of Practice for Research Involving Humans and other related policies/guidelines.

(4) Written consent be obtained from the institution(s)/company(ies) in which the physical or/and online survey will be carried out, prior to the commencement of the research.

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Tel: (603) 9086 0288 Fax: (603) 9019 8868
Website: www.utar.edu.my

Should the students collect personal data of participants in their studies, please have the participants sign the attached Personal Data Protection Statement for records.

Thank you.

Yours sincerely,

Professor Ts Dr Faidz bin Abd Rahman
Chairman
UTAR Scientific and Ethical Review Committee

c.c Dean, Lee Kong Chian Faculty of Engineering and Science
Director, Institute of Postgraduate Studies and Research

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