An Integrated Support System with Internet of Things for Lean Manufacturing

Nur Ain Qistina Binti Muhammad Shafee

Doctor of Philosophy in Manufacturing Engineering

2025

Faculty of Industrial and Manufacturing Technology and Engineering

AN INTEGRATED SUPPORT SYSTEM WITH INTERNET OF THINGS FOR LEAN MANUFACTURING

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NUR AIN QISTINA BINTI MUHAMMAD SHAFEE

A thesis submitted
in fulfilment of the requirements for the degree of
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DECLARATION

I declare that this thesis entitled “An Integrated Support System with Internet of Things for Lean Manufacturing” is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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Date : 5th November 2025

APPROVAL

I hereby declare that I have read this thesis, and, in my opinion, this thesis is sufficient in terms of scope and quality for the award of Doctor of Philosophy in Manufacturing Engineering.

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DEDICATION

Dedicated For My,

Mother, Rohamiza binti Josoh

Father, Muhammad Shafee bin Atan

Life partner, Hashemi bin Hashim

Amazing Siblings,

Honorable Lecturers,

Loyal Friends,

Much Love, from Qistina.

ABSTRACT

Lean Manufacturing (LM) has been widely recognised as a systematic approach to improving operational efficiency and eliminating waste across industries. However, in the fast-evolving context of the Fourth Industrial Revolution (IR4.0), traditional LM approaches face significant limitations due to their lack of real-time responsiveness, data-driven adaptability, and intelligent decision-making capability. Current research remains largely conceptual, with many studies relying on simulated or theoretical models rather than live industrial data, which limits their reliability and industrial relevance. Moreover, there is still no comprehensive framework that effectively integrates LM, Decision Support Systems (DSS), and Internet of Things (IoT) technologies to support continuous improvement. Existing applications of data analytics in LM are often restricted to monitoring functions instead of enabling real-time optimisation, while the connection between LM tools such as Line Balancing, Single-Minute Exchange of Die (SMED), and Kanban with IoT-based systems remains insufficiently developed. To address these theoretical and empirical gaps, this study developed iDSS-ProLean, an integrated, sensor-driven DSS designed to align LM principles with IoT-based real-time data analytics for adaptive manufacturing environments. Implemented on a semiconductor backend line comprising seven sequential stages, the system utilised ESP32 microcontrollers and multiple sensors (HC-SR04, SW-420, DHT11, BMP280) connected to a Firebase database and Android interface for live monitoring. Results from sixty trial runs demonstrated significant performance improvements: Line Balancing Efficiency value increased from 0.82 to 1.00, SMED ratios improved from inefficient changeovers, greater than 1.0, to optimised setups in less than 1.0, and Kanban inventory levels were stabilised within the target range of 500 ± 5 units based on the best kanban card available on the production line. Statistical validation confirmed reliable data transmission ($p > 0.05$) and a significant correlation between the parameters and each LM Tools indicators. Expert evaluation further showed high user acceptance, confirming iDSS-ProLean as a reliable, economical, and scalable framework for smart manufacturing aligned with IR4.0 principles. The significance of this study lies in establishing the first empirically validated framework that unifies LM, DSS, and IoT within a single, scalable, and adaptive model tailored to semiconductor manufacturing. This study extends the boundaries of LM by embedding sensor-driven intelligence and real-time analytics into traditional continuous improvement systems. Methodologically, it demonstrates a novel approach for integrating sensor-based data acquisition with DSS modelling, thereby offering a replicable and reliable validation process for industrial-scale experimentation. Practically, iDSS-ProLean provides an economical, accessible, and scalable digital solution capable of transforming static LM practices into adaptive, self-optimising systems aligned with IR4.0 principles. By addressing long-standing theoretical and empirical deficiencies, this research contributes to the advancement of smart manufacturing and positions iDSS-ProLean as a viable model for sustainable, data-driven industrial excellence.
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SISTEM SOKONGAN BERSEPADU DENGAN INTERNET BENDA (IOT) UNTUK PEMBUATAN KEJAT (LM)

ABSTRAK

Pembuatan Kejat (Lean Manufacturing, LM) telah lama diiktiraf sebagai satu pendekatan sistematik untuk meningkatkan kecekapan operasi dan menghapuskan pembaziran dalam pelbagai industri. Namun demikian, dalam konteks Revolusi Industri Keempat (IR4.0) yang berkembang pesat, pendekatan LM tradisional menghadapi batasan ketara disebabkan kekurangan keupayaan untuk bertindak balas secara masa nyata, menyesuaikan diri berasaskan data, serta menyokong pembuatan keputusan secara pintar. Kajian semasa masih banyak bersifat konseptual, dengan kebanyakan penyelidikan bergantung pada model simulasi atau teori semata-mata tanpa pengesahan menggunakan data industri sebenar, sekali gus mengehadkan kebolehpercayaan dan kerelevanan praktikalnya. Tambahan pula, masih tiada rangka kerja menyeluruh yang berupaya mengintegrasikan LM, Sistem Sokongan Keputusan (Decision Support Systems, DSS), dan Internet Benda (Internat of Things, IoT) secara bersepadu bagi menyokong penambahbaikan berterusan. Aplikasi analitik data yang wujud dalam LM juga kebanyakannya terhad kepada fungsi pemantauan, bukannya pengoptimuman masa nyata, manakala hubungan antara alat LM seperti Line Balancing, Single-Minute Exchange of Die (SMED), dan Kanban dengan sistem berasaskan IoT masih belum diterokai secara mendalam. Bagi menangani jurang teori dan empirikal ini, kajian ini telah membangunkan iDSS-ProLean, iaitu sistem sokongan keputusan bersepadu berasaskan penderia yang direka bentuk untuk menyepadukan prinsip LM dengan analitik data masa nyata berasaskan IoT bagi menyokong persekitaran pembuatan yang adaptif. Sistem ini dilaksanakan pada barisan pengeluaran belakang semikonduktor yang terdiri daripada tujuh peringkat berturutan. Ia menggunakan mikropengawal ESP32 serta beberapa jenis penderia (HC-SR04, SW-420, DHT11, BMP280) yang dihubungkan kepada pangkalan data Firebase dan antara muka aplikasi Android bagi tujuan pemantauan langsung. Hasil daripada enam puluh siri percubaan menunjukkan peningkatan prestasi yang ketara: nilai Line Balancing Efficiency (LBE) meningkat daripada 0.82 kepada 1.00, nisbah SMED bertambah baik daripada pertukaran acuan tidak efisien (lebih daripada 1.0) kepada penyediaan yang dioptimumkan (kurang daripada 1.0), manakala tahap inventori Kanban distabilkan dalam julat sasaran 500 ± 5 unit berdasarkan kad Kanban terbaik di barisan pengeluaran. Pengesahan statistik mengesahkan penghantaran data yang boleh dipercayai ($p > 0.05$) serta menunjukkan korelasi yang signifikan antara parameter dan setiap penunjuk alat LM. Penilaian pakar turut menunjukkan tahap penerimaan pengguna yang tinggi, di mana hasilnya mengesahkan bahawa iDSS-ProLean merupakan rangka kerja yang boleh dipercayai, ekonomik, dan berskala untuk pelaksanaan pembuatan pintar yang sejajar dengan prinsip IR4.0. Signifikannya, kajian ini telah mewujudkan rangka kerja pertama yang disahkan secara empirik yang menggabungkan LM, DSS, dan IoT dalam satu model berskala serta adaptif yang disesuaikan khusus untuk industri semikonduktor. Kajian ini memperluas sempadan teori LM dengan menggabungkan kecerdasan berasaskan penderia serta analitik masa nyata ke dalam sistem penambahbaikan berterusan tradisional. Dari segi metodologi, ia memperkenalkan pendekatan baharu dalam mengintegrasikan pemerolehan data berasaskan penderia dengan pemodelan DSS, seterusnya menyediakan proses pengesahan yang boleh diguna semula dan dipercayai untuk eksperimen berskala industri. Dengan menangani kekurangan teori dan empirikal yang telah lama wujud, kajian ini menyumbang secara signifikan kepada kemajuan bidang pembuatan pintar dan meletakkan iDSS-ProLean sebagai model yang berdaya maju untuk mencapai kecemerlangan industri berasaskan data yang mampan.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AM	Additive Manufacturing
CFA	Confirmatory Factor Analysis
CI	Confidence Interval
CPS	Cyber-Physical Systems
CT	Cycle Time
DA	Data Analytics
DBMS	Database Management System
DSS	Decision Support Systems
FL	Factor Loadings
IMAGE	Identify, Measure, Analyze, Generate, and Execute
IoT	Internet of Things
IR 4.0	Industrial Revolution 4.0
IaaS	Infrastructure as a Service
JIT	Just-In-Time
LBE	Line Balancing Efficiency
LM	Lean Manufacturing
LMS	LM Systems
LMP	LM performance
MITI	Ministry of Investment, Trade, and Industry
MOF	Ministry of Finance
MBSM	Model Based Management

NIMP	New Industrial Master Plan
NoM	Number of Machines
OEE	Overall Equipment Effectiveness
PaaS	Platform as a Service
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SaaS	Software as a Service
SMED	Single-Minute Exchange of Dies
SOP	Standard Operating Procedure
Std.Dev.	Standard Deviation
TPT	Total Processing Time
TQM	Total Quality Management
VSM	Value Stream Mapping
WIP	Work-In-Process
WOS	Web of Science

LIST OF APPENDICES

LIST OF PUBLICATIONS

The following is the list of publications related to the work of this thesis:

JOURNAL

Shafee, N. A. Q. M., Mohamad, E., Nordin, S. K. S., Abd Rahman, M. S., Zaidi, M. K. H. M., Ito, T., and Abd Shukor, M. H. (2025). Can IR4.0 work together with lean? An investigation from Malaysian LM sector. *Multidisciplinary Science Journal*, *7*(2), 2025055-2025055.

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Shafee, N. A. Q. M., Mohamad, E., Abd Rahman, M. S., Rahman, A. A., Abd Shukor, M. H., and Ito, T. (2025). An IoT-enabled Decision Support System for Real-Time Line Balancing in Semiconductor Manufacturing, Concurrent Engineering: Research and Applications. 11th of July 2025. **Indexed WOS.**

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CHAPTER 1

INTRODUCTION

This chapter provides an endorsement of Lean Manufacturing (LM) as the fundamental basis of this research, aligning with the advancements of Industrial Revolution 4.0 (IR 4.0). The integration of IR 4.0 components, such as Internet of Things (IoT) and Cloud Systems, has redefined industrial practices, yet existing Decision Support System (DSS) have struggled to fully adapt to this transformation. Current DSS often face challenges in real-time decision-making, data accuracy, and system responsiveness, limiting their effectiveness in optimizing production efficiency. To address these gaps, this research formulates key research questions derived from a comprehensive literature review, which builds upon the problem statement identified before this research. The research objectives are then outlined, followed by the corresponding research questions that guide the research. Finally, a chapter summary is presented to define the research's scope and structure.

1.1 Research Background

LM is widely recognized as a business process improvement strategy aimed at minimizing waste without compromising value to end users (Uriona-Maldonado et al., 2020). It emphasizes understanding customer needs and applying key principles to fulfill those requirements through value creation with zero waste (Nhat, 2020). From the LM perspective, value is defined from the customer's viewpoint rather than internal manufacturing perceptions (Klein et al., 2022).

LM principle identifies different types of waste, analyzes their causes, and implements solutions for their permanent elimination, forming the basis for continuous improvement (Nakamura, 2020; Kumar et al., 2021). On the other hand, IR 4.0 had historically been perceived as a disruptive force that reshaped the industrial landscape, often associated with social challenges and labour exploitation (Dewanarayana and Wimalaratana 2021; Zhu et al., 2021). Over time, IR4.0 has transformed economies from agrarian and handicraft-based systems into mechanized industries, marked by new materials, energy sources, machinery, organizational structures, and scientific applications driving mass production (Testik & Sarikulak, 2021). Introduced by the German government in 2011, IR4.0 compels manufacturers worldwide to shift from traditional business models to a interconnected production (Hamid et al., 2022). Its goal is to achieve highly flexible production with real-time communication among products, machines, people, and devices (Javaid et al., 2022).

Malaysia's Gross Domestic Product (GDP) growth rate has shown a positive trajectory, increasing from 4.8–5.3% to 4.4-5.5%, driven significantly by the manufacturing sector as illustrated in Figure 1.2 (Ministry of Finance Malaysia, MOF 2025). The semiconductor industry alone had contributed 7.5% to the National's GDP (MOF, 2025). Nevertheless, these positive Indicators, manufacturers had faced ongoing challenges due to inflationary pressures, necessitating continuous adaptation to maintain competitiveness and profitability (Gao et al., 2023). As a result, manufacturers had been required to remain competitive by adopting emerging technologies to sustain operations and meet market demands (Blinchfeldt and Faullant 2021). The rapid transformation of the industrial sector had necessitated swift and efficient information transfer, a challenge that IR 4.0 sought to address through digitalization and automation (Martell et al., 2023).

Figure 1.2 Malaysia Annual Gross Domestic Product Growth (MOF, 2025)

This research focused on three primary paradigms: LM, DSS, and IR4.0 Despite its potential, LM adoption across industries remained limited due to barriers such as insufficient knowledge, resistance to change, management constraints (Jaiswal et al., 2020; Maware & Parsley, 2022), and financial limitations (Shukla, 2020). Lack of understanding of LM tools often led to weak problem-solving and increased waste (Purushothaman et al., 2021), as seen in the misinterpretation of Kanban cards causing longer production response times (Thurer et al., 2020). Changing market demands, high attrition rates, and disruptions like pandemic restrictions further emphasized the need for digital automation through advanced technologies (Lehmacher, 2021). Power (2014) noted that analyzing unstructured, machine-generated data is impossible without advanced IT, and no widely adopted simulation system exists for enhancing LM using IR 4.0 technologies such as IoT, Big Data, AI, or Virtual Reality (Sony & Naik, 2020). Recognizing this, Rahman et al. (2021) confirmed strong industry interest in integrating IR 4.0 technologies into LM-based DSS frameworks. Accordingly, this study aimed to develop a method for sustaining LM principles within DSS by engaging DA and simulation through IR 4.0 enablers. The research aligned with two UN

Sustainable Development Goals, Goal 9 (Industry, Innovation, and Infrastructure), promoting sustainable industrialization through innovation, and Goal 12 (Responsible Consumption and Production), emphasizing resource efficiency and sustainable competitiveness (Chen & Xu, 2022). Thus, this study serves as an academic initiative to support IR 4.0 adoption in Malaysia's manufacturing sector, advancing data-driven decision-making, LM optimization, and industrial sustainability.

1.2 Problem Statements

Over the past decades, LM has been widely applied to enhance operational performance and eliminate waste. However, traditional LM faces challenges adapting to the fast-paced, data-intensive IR4.0 environment. Theoretical gaps persist, particularly the lack of an integrated framework combining LM, DSS, and IoT technologies. Existing studies on DA in LM largely focus on monitoring or tracking, rather than enabling continuous improvement (Massafra et al., 2023; Rahman et al., 2020), and few provide holistic frameworks linking LM tools with IoT for real-time decision-making (Payandeh, 2020; Brochado et al., 2024). Empirically, most research remains conceptual, relying on simulations (Rahman et al., 2021; Skere et al., 2023). Methodological gaps also exist, as current DSS models struggle with industrial-scale data in complex, high-precision environments like Malaysia's semiconductor industry (Zhai et al., 2020; Balayn, 2021). Practical barriers such as high costs, and complexity, further hinder sensor-driven DSS adoption (Geng et al., 2021; Brochado et al., 2024).

To address these gaps, this study introduces iDSS-ProLean, an integrated DSS framework aligning LM principles with IoT-based real-time DA for continuous improvement. Implemented within a semiconductor production line using ESP32 microcontrollers, sensors, and a Firebase database, the system enables real-time monitoring.

It integrates LM tools into a unified digital platform for dynamic, data-driven efficiency improvement. The novelty of this research lies in developing and validating the first empirical, real-time integrated framework connecting LM, DSS, and IoT for manufacturing setting.

1.3 Research Questions

To conduct a comprehensive research for the proposed research, several key questions were formulated to guide the investigation.

RQ 1: What are the most commonly used LM Manufacturing tools in existing DSS frameworks?

RQ 2: What are the input parameters required to implement the framework based on real-world production lines in the manufacturing industry?

RQ 3: How can DA be effectively managed within LM tools for its application in production modelling?

RQ 4: How can DA be integrated with production models in the framework development of DSS within the context of IR 4.0?

1.4 Research Objectives

The following research objectives were established:

RO 1: To investigate the existing DSS frameworks in the implementation of LM

RO 2: To formulate the Inherent Correlation DA Model through the integration of an IoT-based sensor architecture.

RO 3: To verify the proposed Inherent Model through a Modular Architectural Setup.

RO 4: To validate the proposed Inherent Model through a feasibility research using selected LM tools.

1.5 Research Scopes

This research was conducted within the context of Malaysia's manufacturing industry. The study was carried out during the ongoing IR4.0 phase transitioning towards data-driven and technology-enabled production systems. The research specifically focused on the semiconductor sector, representing one of Malaysia's most advanced and high-value manufacturing domains, characterised by high precision, high-mix production. The investigation adopted a system-integration approach, developing and testing iDSS-ProLean framework, which merges LM principles with IR4.0 technological enablers including the IoT and real-time monitoring. Three LM tools were strategically selected for their operational significance within semiconductor manufacturing: Line Balancing to optimise process flow and machine utilisation, SMED to minimise setup time and enhance flexibility, and Kanban to stabilise inventory and regulate production control. Through this integrated scope, the study aimed to provide both theoretical insight and empirical validation for intelligent LM implementation within Malaysia's semiconductor context, contributing to the nation's broader aspiration of achieving sustainable, high-technology manufacturing excellence under the IR4.0 vision.

1.6 Research Structure

This thesis comprises five main chapters. Chapter 1 introduces the research background, identifies the research gap, formulates research questions and objectives, and defines the study's scope.

Chapter 2 presents a comprehensive literature review, establishing the theoretical foundation of the proposed DSS framework integrated with LM based on systematic analysis of reliable journal sources.

Chapter 3 details the research methodology, including tool selection, data collection, and analysis procedures grounded in ethical and philosophical considerations.

Chapter 4 discusses the research findings, interpreting data according to the proposed framework and research objectives.

Finally, Chapter 5 concludes the study with a summary of results, research limitations, recommendations for future work, and reflections on the overall research process.

CHAPTER 2

LITERATURE REVIEW

This chapter presents the key issues, concepts, and techniques underpinning the present investigation. It aims to provide a comprehensive understanding through critical arguments that strengthen the study's justification. The discussion synthesizes fundamental knowledge related to the main research issues and integrates them with current industrial applications. By reviewing prior studies on LM implementation within the context of Industry 4.0, the chapter identifies the underlying challenges and research gaps. Ultimately, it establishes a strong theoretical foundation to support the development of appropriate conclusions for this study.

2.1 The Philosophy Paradigms

Philosophical paradigms play a pivotal role in shaping the epistemological and methodological foundation of this research. The study is informed by three primary paradigms, positivism, interpretivism, and pragmatism (Mumtaz, 2021) each offering distinct yet complementary perspectives on DSS and LM. The positivist stance aligns with DSS and LM modelling through its emphasis on objective, empirical, and quantifiable realities (Patil & Romice, 2024). Here, sensor architectural modelling and statistical analysis are employed to evaluate system performance and the effectiveness of LM tools within DSS applications, ensuring that outcomes are verifiable and grounded in empirical evidence (Davoudi et al., 2022).

Conversely, interpretivism acknowledges the influence of human behaviour, perception, and organizational context on manufacturing processes (Sharma et al., 2021). It highlights the subjective dimensions of DSS automation, where user engagement, managerial support, and process culture determine implementation success (Alomari et al., 2020). Accordingly, this study employs a Feasibility Study approach that integrates social and organizational frameworks in examining DSS adoption.

Finally, pragmatism introduces methodological flexibility, integrating quantitative and qualitative techniques to address complex, multifaceted problems (Prasad, 2021). By synthesizing the strengths of positivism and interpretivism, the pragmatist perspective facilitates a holistic examination of LM optimization through DSS under the IR4.0 context, balancing technical precision with human and organizational considerations (Fadda et al., 2022). Collectively, these paradigms establish a balanced methodological foundation, ensuring comprehensive understanding of DSS applications in LM from both analytical and socio-organizational dimensions.

2.2 The Research Pragmatism

Pragmatism focuses on the resolution of issues through efficient means and implements knowledge in practical ways (Nguyen et al., 2024). In contrast with positivism's focus on objective measurements or interpretivism's emphasis on subjective experiences, pragmatism is focused on methods that find practical solutions. In DSS and LM, pragmatism provides a blended framework that allows flexibility and the use of both quantitative and qualitative approaches to solve complicated, multilayered problems (Izu et el., 2020).

This is particularly useful for manufacturing settings that are dynamic and continually evolving where the primary goals of the environment are enhancing execution, minimizing waste, and improving the efficiency of automated and human decisions based on the data available alongside human intuition. The practical stance of this research considers alongside human perception the effectiveness of DSS within LM, as both empirical data and intuition are important. Take for example; production metrics as quantitative data can be complemented with the qualitative data regarding employees' attitudes towards the system and their engagement it all plays a role in determining the success of DSS implementation (Duggan et al., 2022).

With regard to these considerations, it is within pragmatism that mixed methods like surveys, interviews, case studies, statistical analysis, and simulations modelling are integrated to understand the impact of DSS on LM practices. Within these considerations, focusing on the resulting practical consequences of the research empowers its navigation through the intricacies within the manufacturing landscape ensuring that the technical and contextual requirements of the developed DSS are met. It is the knowledge that stems from this surgical precision that can, for example, guide industry shapers and inform them of the actions to undertake based on reliable evidence.

2.3 LM Background

LM system, which evolved from Toyota's production system- the world's largest automobile manufacturing factory, aims at minimizing waste throughout the production process. Phatale (2020) and Mostaghimi and Behnamian (2022) have defined waste as any action or step in a process that does not add value to the end product or services provided to customers. Losses in terms of time, money, and space for the company, includes all the following: unproductive time, unproductive labour, unproductive capital, storage and unproductive materials all of which do not add value towards the system (Harolds, 2021; Jessani et al., 2024).

To increase operational efficiency by eliminating waste, millions of companies around the world, have adopted LM Systems (LMS) in the attempt to increase production rates and productivity (Memari et al., 2022). In turn, these companies are capable to evaluate the enhancements in production rate along with meeting their benchmarks in benchmarks in previous operational states (Szabo et al., 2024). LM System provides multiple advantages and one of them is lower lead time, alongside with better communication among the personnel and higher communication efficiency. Supporting this statement, Leksic et al. (2020) and Purushothaman et al. Implementing a LM system requires employees to know how to distinguish with value-added and non-value-added activities (Emphasize, 2021). With this understanding, the execution of LM principles is assured to be maintained throughout the company.

In LM thinking the objective is to achieve the greatest increase in value in relation to the cost incurred by the resources spent, while minimizing or eliminating non-value-added activities (Azelya and Thabrani 2020). To support, non-value-added activities, though they do not contribute directly to customer value, often exist due to inefficiencies, delays, or other factors within the production system (Shou et al., 2020). However, some non-value-added activities are necessary and cannot be eliminated entirely (Peimbert-Garcia et al., 2021). These should be minimized to create smoother, an efficient processes. Non-value-added activities that do not contribute to the production or customer satisfaction can be eliminated completely to improve efficiency and reduce waste (Wang et al., 2020). By focusing on this balance, organizations can enhance overall productivity and ensure that all processes contribute to value creation. Table 2.1 illustrates the distinction between value-added and non-value-added activities and their relevance to LM practices.

Table 2.1 Distinction between value-added and non-value added

Value Added	**Non-Value Added**
a) Increase the value, usage, function of the product produced by the customers.	a) Decrease or do not give any of thevalue, usage, function of the product produced by the customers.
b) Increase the customers'satisfaction, happiness, and worth in receiving the service provided.	b) Decrease or do not give any of the customers' satisfaction, happiness,and worth in receiving the service provided.
c) No rework should be done after the final stage of productprocessing	c) Non-value added but necessary to the production system and cannot be eliminated totally.
d) Customers would be happy to purchase the service and would like to repeat	d) Non-value added but not necessary and can be eliminated totally.

2.3.1 LM Philosophy, Principles, and Methods

LM can result in significant improvements in efficiency, cycle time, productivity, and cost for a company, but these outcomes are achieved through the correct application of key principles. This section discusses the five key principles of LM adoption. In their influential work, *LM Thinking: Banish Waste and Create Wealth in Your Corporation*, Womack and Jones (1997) present a comprehensive approach to LM, beginning with a general overview and extending to the functional business horizon. The researchers define the LM Principes as a systematic approach to specifying value, organizing the value-creating activities in the most effective sequence, and performing these actions with the least possible waste.

Although the book was published in 1997, the principles and ideas presented by Womack and Jones remain highly relevant today. Their approach to LM thinking continues to guide modern organizations in reducing waste and improving efficiency across various industries (Minh et al., 2023). To achieve these objectives, LM adoption requires addressing challenges that may arise across various business units, particularly those with different cultures and management processes. Womack and Jones (1997) outline five key principles to guide LM implementation as referred to Figure 2.1.

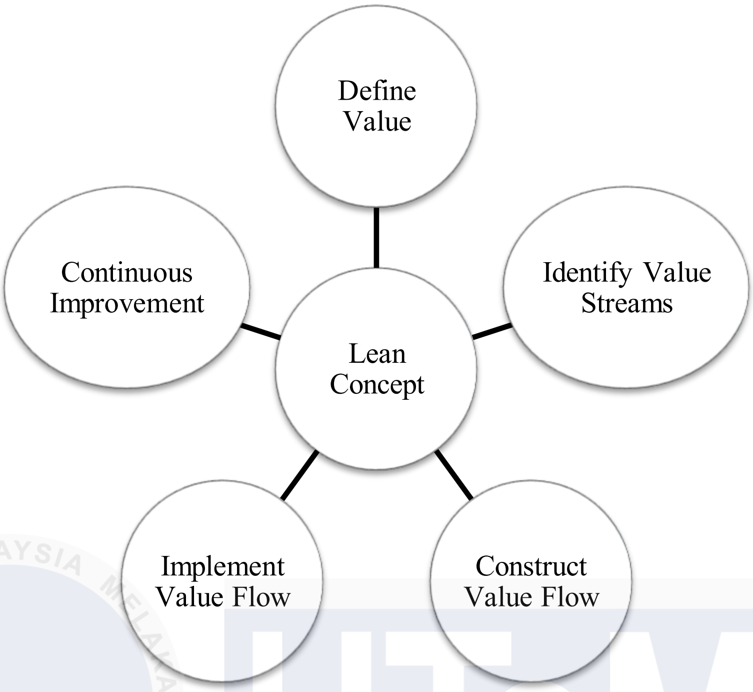


Figure 2.1 LM Principles (Wang et al., 2022)

a) Define the Values

The first key principle is to define the value from the perspective of the customers or the users (Zeithml et al., 2020). The principle conducts organization to evaluate and reconsider on who are actual target market and what is the correct demand that needby them in fully optimize the products value, function, and usage in any way possible of the products or service (Pallan et al., 2020). Define value means identifying the form, feature,or function that a customer is willing to purchase in the circumstance where they cannot perform the required task on own or without consider the cost and time(Zeithamal el at., 2020). The company needs to define value precisely in terms of specific products with specific capabilities offered at specific process through a dialogue with specific customers (Blut et al., 2023). This urge the company to really understand the demand and need required by the customers, thus optimize the product or service function for a comprehensive reorganization of currently practiced business process and organization culture.

b) Identify the Value Streams

Value stream is a concept distinguishes from the traditional supply or the value chain concept (Cornejo et al., 2020). The former is a focused view on the value adding process, referring only to the specific product or service in an organization; company whereaslatter include the complete activities that demanded by the organization objectives (Farajpour et al., 2022). Italso defines as the set of all specific actions required to bring a specific product through the three critical management task of a business units: problem solving task, information management task, and physical information task (Riccotti et el., 2020). The identifying the value stream principle drives the organizations to review and identifies all the activities involved in creating a product, determine activities that add values, as wellas eliminate the activities that result in waste or brings nothing to the value deliver tothe customers or end users (De Assis et al., 2021and Kihel et al., 2022).

c) Construct the Value Flow

Constructing or creating the flow principles that urges the management to recognize the need for a very efficient flow of the production process that reducethe production cost and reduce the waste as reduced as possible (Hesran et al., 2020). The basic concept of the term flow is to make pars ideally one piece at a time from raw materials to finished goods and to move them one by one to the next workstation with no waiting time in between (Incekara, 2022).The main value that must be kept in the components flow is it is should be constant and smooth from one station to another without any interruption or minimum to zero waiting time in between with the goals of zero inventories between the process flow (Kurniawan et al., 2024). However,the process of transforming from a conventional manufacturing to a flow-based production is challenge itself as the continual improvement are super essential to establish a smooth flow in the operation (Bait et al., 2020; Filipe and Pimentel 2023).

d) Implement the Pull

The pull-based production principle, often considered counterintuitive in the context of LM adoption, emphasizes that upstream production should only occur when there is a request from downstream customers or users (Chatterjee et al., 2021). This principle is different from the traditional push system which is fundamentally based on demand forecasts where production takes place ahead of time based on predicted demand to avoid unforeseen backlogs (Zhang et al., 2023). This creates inventory that has to be stored, managed, and controlled as it builds up which can lead to excess inventory and inefficient use of resources (Huang et al., 2020). While useful, this concept can lead to issues like improper planning, inaccurate data, and idling inventory between workstations which can result in a halt in production (Neve and Schmidt, 2021).

In comparison, pull-based production offers the simplicity of linking actual production activities to customer orders, eliminating the excess and idle inventory along the production line. This approach allows companies to respond to real-time demand, producing only what is necessary to prevent excess, minimize costs associated with inventory, as well as the cost of storing, monitoring, and securing products (Lu et al., 2020). To successfully implement a pull-based model companies have to rely on close collaboration with their customers to address their expectations and requirements (Alfares and Ghaithan, 2022). Cooperation with suppliers is just as important to guarantee raw material delivery which meets these new demand requirements in a timely fashion to make the entire production process agile (Dizbin and Tan, 2020). The essence of pull-based production lies in its focus on demand-driven manufacturing, in contrast to the push-driven inventory management system (Satolo et al., 2021; Araoujo et al, 2023).

e) Continuous Perfection

The final key principle in LM adoption is the constant pursuit of perfection (Yadav et al., 2020). With the effective implementation of the first four principles, a company becomes transparent in its value stream, enabling it to strive for continuous improvement (Al-Nuaimi and Al-Emran, 2021). This principle encourages management to relentlessly explore new opportunities for improvement that arise as a result of applying the earlier principles, recognizing that there is no endpoint in the effort to reduce energy, time, cost, space, and mistakes within the production process (Arica et al., 2022). Achieving waste elimination is an ongoing process that requires continuous effort over time, not a quick fix (Mostafa and Dumrak, 2020).

There is no one-size-fits-all approach for a company to fully implement theoretical suggestions; instead, companies must engage in trial and error to identify what best complements their unique policies and production ethics (Szabo et al., 2024). This principle fosters a culture of constant searching for ways to improve both product and service quality (Yadav et al., 2020). The key insight for any company is that failure to achieve perfection in an initial attempt should not be viewed as a setback but rather as an opportunity for further improvement. The potential for refining business operations is limitless, and a state of complete perfection is unattainable, yet the pursuit itself ensures ongoing progress and refinement (Patel and Patel 2021).

2.4 The Seven-LM Waste

According to the LM principle, the main goal of its adoption is to remove or eliminate the waste as much as it is possible (Klein et al., 2020). A core principle in LM methodology Is the removal or waste within the operations. LM waste can result in various form, time, materials, and labor (Khakpour et al., 2024). This is also associated by the lack of skill sets as well aspoor planning. The waste is any expense or energy or materials that not transformthe end product into what the customers need or desired (Botchway et al., 2023). Therefore, by eliminating the waste, the true effort into the product can be sustained and improved so that the core value can be delivered to the customers or end users. Nowadays, LM waste canbe categorized into eight different main aspects; that is coming from the seven original idea by the Toyota production system. In the Table 2.2 shows seven wastes according to the LM adoption in the company.

Table 2.2 Seven Waste Category in LM Adoption (Sodhi, et al. 2020)

Waste	Description
Defects	The final product that does not follow the specification declared by the company thatfollows the customers need or requirement.
Excess Processing	Producing the final product over or excess to the numbers need by the demand made.
Overproduction	Producing the final product before it is actually required.
Waiting	The time taken for the final products or thematerials to pass from one step to another that also including the bottleneck issue and the delayed in supplier delivery.
Inventory	The space occupied to store the final products or the materials; including the monitoring andsecurity of the products or materials.
Transportation	Movement of the product or even the materials from one place to another; be it by just inside thesame building or room to different state and country.
Motion	Unwanted movements of the workers that distract from doing the actual work of production; including the walking around the space to look for the tools resulting from a very poor designed ergonomics space.

2.5 Challenges in LM Implementation

LM tools provide structured methods, steps, and techniques for companies to adopt LM principles effectively (Qayoudhi 2022). These tools aim to enhance productivity and efficiency by maximizing resource utilization, aligning with LM adoption goals to streamline operations, reduce effort, shorten process time, minimize resource consumption, and eliminate waste (Battisella et al., 2023). Selecting the most suitable LM tools is crucial, as they must align with the company's objectives, available resources, and specific challenges whether within management, production processes, or communication across the supply chain (Aslam et al., 2020). An informed selection ensures that LM implementation addresses operational inefficiencies while fostering continuous improvement (Hastono et al., 2023).

LM implementation, whether in manufacturing or service industries, has gained widespread attention for its potential to enhance productivity and operational efficiency. Nonetheless, there is an alarming gap between the number of projects initiated for the purposes of LM and their successful completion. At least 70% of LM implementation projects are recorded as failures regardless of the sector undertaken. In the United Kingdom, in 2006, the figure for successfully meeting set organization-specific LM Implementation targets was 10% (Rigen and Holtskog 2013; Tortorella et al., 2021). In the other specialized sectors like aerospace, while less than 50 percent of the firms were satisfied with their LM undertakings, in the medical and healthcare sector, 54% of the surviving firms have expressed a lack of expectation to employ Six Sigma (Patel and Patel 2021).

A systematic review of literature in healthcare comprising 47 studies found that out of the total investigated LM initiatives, 62% of the initiatives were considered failures and lack of stakeholder's engagement and poor management of the workforce were cited as the primary reasons (Tiso, et al., 2022). As far as organizational improvement schemes or monetary limitations are concerned, there is no absence in such expenditures (Swarnakar et al., 2020). Rather these failures are a result of not paying attention to the LM implementation prerequisites (Kumar et al., 2023). The commitment and active participation of top management, effective organizational wide communication, proper project choice, thorough training, and many others are critical to LM success (Bader et al., 2023).

2.5.1 The Drawbacks in LM Manufacturing Industry

LM was recognized for its capabilities in waste reduction, productivity enhancement, and overall quality improvement at an organizational level. However, as with many things, it came with a set of complications during its adoption in different industries (Maware and Parsley 2022). It is no secret that a major hurdle was the cost associated with deployment and the sustained focus it needed long-term. LM tools like value-adding processes or value stream mapping, kanban systems, training, and provide cutting-edge technology at times needed heavy investments (Abu et al., 2021). These costs, accompanied by long-term prospects, challenged adoption, which proved difficult for smaller companies and businesses with low cash flows (Yadav et al., 2020). On the other hand, monitoring truly LM systems posed maintenance challenges and made staffing a primary operational bottleneck for these organizations (Qureshi et al., 2023).

A further problem faced in LM was the reluctance from employees to embrace changes, especially in the context of organizations which have set procedures and some form of custom (Tortorella et al., 2021). To adopt LM, a cultural shift was required and employees had to change how they thought and worked (Maware et al., 2021). According to Womack and Jones (1997), one of the principles of LM was to create an environment that encourages continual improvement, but fostering this in highly resistant environments was challenging. Changes were perceived as disruptive, resulting in heightened anxiety around job security, as well as general discomfort with operational changes (Lopez-Valeiras et al., 2022). Addressing this resistance was possible, but only with well-defined change management strategies such as training, effective communication, and active participation of organizational leaders (Kewalramani and Mandal, 2024). These activities, however, were resource intensive which delays the early stages of LM implementation, creating a cascade of issues in a time sensitive program (Li, 2024).

Furthermore, if not specifically crafted to suit the organization's requirements, LM blurred the lines between inefficiency and improvement (Antony et al., 2021). Even though LM was designed to get rid of waste, there was already some over-optimization in other areas which reduced flexibility (Kuiper et al., 2021). For example, the minimum inventory and stock control policies, which are core to LM, sometimes resulted in materials shortages or production halts when the supply chain encountered disruptions (Maqueira et al., 2020).

In addition, too much emphasis on the standardization of processes led to a lack of innovation which hampered the organization's responsiveness to rapid shifts in market conditions or advancements in technology (Mandler et al., 2021). Thus, while trying to increase efficiency, LM applied too much of a blanket approach lacking contextual sensitivity which in many cases turned out to be detrimental and negated the advantages that were intended (Usai et al., 2021).

2.5.2 Critical Failure Factors in LM Implementation

It is the execution of the adoption that affects the use of LM in any given industry (Martins et al., 2021). Structured implementation, with commitment to leadership oversight, active engagement, strategic plans, and monitoring, has support from Swarnakar et al (2020). Organizations need to shift their view where they see LM as a long-term cultural change instead of a short-term cost cutting measure, as noted by Hardcopf et al., (2021). If a company addresses the critical failure factors and takes a systematic approach, it enhances the probability of achieving sustainable LM success. In all industries, these are the critical failure factors in LM adoptions.

a. Lack of Top Management Commitment and Involvement

Effective LM requires active sponsorship from upper management to properly align company missions, objectives, and resource allocation, in addition to providing proper organizational training (Van Beers et al., 2021). To streamline misunderstanding gaps, management should tackle the perception gaps ensuring every employee understands their contribution in LM. Uniformity in manufacturing is key in sustaining operational efficiency and long-term success (Alnadi and McLaughlin 2021).

b. Insufficient Training and Education

An insufficient training issue at all levels of the organization creates a significant obstacle to successful LM implementation. The Company perceives training as expensive, which contributes to ineffective execution of LM tools (Salma et al., 2020). Equally, every employee needs proper training in order to employ LM practices accurately. For example, effective execution of PDCA requires thorough knowledge of all stages. Without substantial training, LM initiatives are likely to be implemented in a piecemeal fashion resulting in divergent outcomes. (Salma et al., 2020; Puram et al., 2021).

c. Incorrect LM Tool Selection and Prioritization

Sustained competitive advantage LM requires that effective tools are designed for a specific firm's situation and limitations. The lack of understanding of a given company's needs, lack of knowledge of LM methodologies, or financial constraints may hinder proper tool selection and result in them failing (Saleem et al., 2020). Each tool addresses certain challenges. PDCA can be unsuitable if there are insufficient resources as it misalign with the company's expectations and goals. (Saleem et al., 2020; Aslam et al., 2020).

d. Lack of Leadership Skills and Visionary Support

Robust LM leadership is instrumental to the execution of LM efforts. Driving LM requires strong leaders who can shape the culture of a firm by demonstrating everyday communicative, analytical and determinative actions that reflect LM principles (Conor and Cormican 2021). Without visionary leadership, execution becomes fragmented, resistance to change increases, and improvements fail to last. Leaders play a key role in fostering a culture of continuous improvement, ensuring employee engagement, and reinforcing LM principles across the organization (Synder et al., 2024).

e. Failure to Consider Human Factors and Organizational Culture

LM implementation is not solely about technical tools and methodologies it requires active employee participation and cultural transformation. Resistance to change, fear of job loss, and a lack of motivation among employees can significantly hinder LM success (Warrick, 2022). Organizations must prioritize change management strategies, including employee engagement, incentives, and transparent communication, to foster a LM culture (Kokkinou and Van Kollenburg et al., 2022).

f. Lack of a Clear Vision and Performance Measurement

Without a well-defined roadmap, LM initiatives often lose direction. Companies must establish clear performance metrics to evaluate the effectiveness of LM implementation (Tang et al., 2023). Detailed performance measurement allows organizations to identify areas of improvement, detect inefficiencies, and make data-driven decisions to optimize LM strategies (Amin et al., 2020).

2.6 The Inception of the IR4.0

IR 4.0 delineate the future of fully automation and smart system industry that comprises a digitalization for every data transaction, thus required Big Data involvement into the revolution (Jagatheesaperumal et al., 2022).It is reported that by 2025, 463 million terabytes be produced from the entire universe of data such as data generated by machines and devices, cloud-based data system, and business management (Oluyisola et al., 2021; Xiang et al., 2022). Hence, the industry requires a process engineering techniques for the data transmitting stage, named the DA, as example the value chain data, structured data, and external data, creating a giant leap for the industry productivity via the data transaction to be faster and complex (Obukhov and Kransyansky 2021).

Figure 2.2 depicts the growing trend of internet users from its inception in 1990 to 2023 (DataReportal). The increasing number of internet users helps to improve DA studies by giving a larger and diverse dataset for analysis (Mumin et al., 2022). This richness of information makes a substantial contribution to big data, allowing researchers and organisations to obtain deeper insights into customer behaviour and market trends through operational efficiency (Hajli et al., 2020). Hence, the spike in data volume leaves a significant gap in the coupling of Big Data and LM via DSS, whereas the traditional LM manufacturing techniques frequently rely on smaller, controlled datasets, whereas big DA necessitates specialised tools and skills to extract useful information (Valamede and Akkari 2020). Bridging this gap requires developing advanced DSSthat can effectively integrate and analyse massive datasets to optimize LM manufacturing processes.

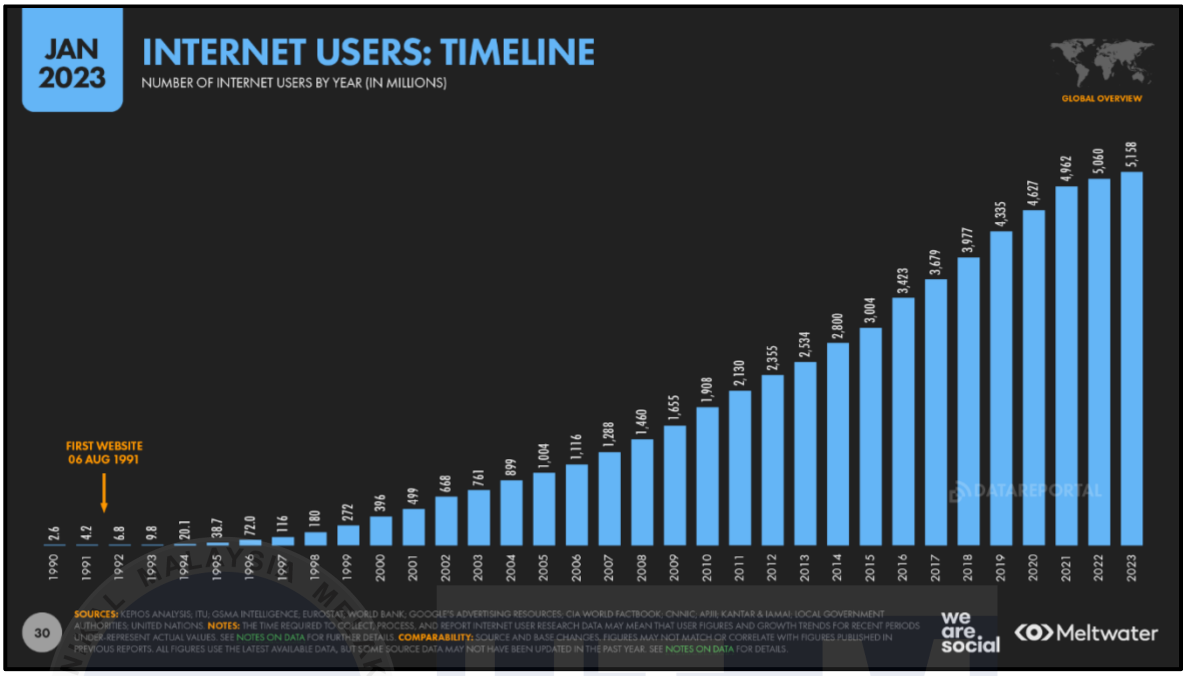


Figure 2.2 Growing Trend of Internet Users from its Inception in 1990 to 2023

(Dietzel, 2020)

2.7 The Component in IR4.0

IR4.0 is the industrial revolution that transforms the way people communicate among each other as well as how they control the machines, making it a vast adjustment for the humankind to experience as according to Ahmad et al., (2020). In a seminal work by Cinar et al., 2020), this revolution accentuate on the transformative actions among automation of the devices, data exchange, cloud data storage cyber-physical system, artificial intelligence, and IoT, creating a smart industry environment that combine the human intelligence with the modern technologies innovation. The rapid development of IR4.0 seems to lead towards the explosive data growth in every field, that resulted from the database exchange system into a real time manner. As for the manufacturing industry, the abundance of related data is from the data resources such as the sensors, IoT, and Cloud Computing resulting the data exchange process to become faster, as presented by Hamid et al., (2022).

In certain way, this may create a complex data processing to be occurred through the whole processing line. In conjunction of the LM that focusing on the continuous improvement with the increase of the customers demand leading to the increase in variant diversity and intensity (Ferreira er al., 2023). Conversely, Zhang et al., (2020) found that with this complexity data processing, the manufacturers are require to respond to the customers' needs in a short lead time.Despite that, the computer based information named DSS was applied in the decision making activity as suggested by (Guo et al., 2020; Amalia et al., 2022; Gurtgarts 2023). This has led to a new query, how can the DSS assisted LM implementation in the IR4.0 era? In conveying this matter with the concomitance of the fact that the data is increasing in abundance from day to day, within this research, the researchers have investigate how to fill the gap of in coupling LM within DSS through the application of IR4.0.

Nevertheless, the emergence of IR4.0 has revolutionized industrial operations by integrating cutting-edge technologies that enhance efficiency, agility, and decision-making processes (Rosin et al., 2021). The effectiveness of IR4.0 is largely influenced by its core technological enablers, including IoT, Big Data and Analytics, Cyber-Physical Systems (CPS), Cloud Computing, Artificial Intelligence (AI), and Additive Manufacturing (AM) referred by Ministry of Investment, Trade, and Industry (MITI). The extent to which these enablers are implemented and harmonized directly impacts the rate of effectiveness of IR4.0 in modern industrial ecosystems.

IoT serves as the backbone of IR4.0, enabling seamless interconnectivity between machines, sensors, and systems (Majid et al., 2022). By facilitating real-time data acquisition, remote monitoring, and predictive maintenance, IoT enhances operational efficiency and reduces unplanned downtimes (Kommanaboina 2022). However, its effectiveness depends on the robustness of network infrastructure, cybersecurity measures, and data interoperability across multiple platforms that involved (Niraula 2022). Inadequate integration often leads to bottlenecks in data flow, affecting decision-making efficiency (Asante et al, 2021). Closely linked to IoT, Big Data and Analytics further strengthen IR4.0 by allowing manufacturers to collect, process, and analyse large volumes of data, leading to improved predictive maintenance, process optimization, and demand forecasting. Optimized Big Data technology use improves supply chain flexibility and lowers production overheads. However, the full realization of the benefits is hindered by issues like data silos, insufficient standardization, and inefficient computing a situation that, as Karadayi-Usta (2020) and Chauhan et al. (2020) claim, impairs the speed of IR4.0 adoption.

Alternatively, Lu and Asghar (2020) explained that Cyber Physical System (CPS) fortify the intelligent automation of manufacturing processes by integrating computation with physical elements, thus creating smart factories in which automated decision-making amplifies productivity and flexibility. Supporting this, Zhange et al (2020) claimed these systems allow for autonomous operations; however, their efficacy relies on security for data exchange and adaptation systems across old and new systems. Still, lacking seamless integration could result in workflow automation inefficiencies along with system downtimes that diminish the overall efficiency of IR4.0 (Del Gaudio and Hirmer 2020; Sony and Naik 2020). In further enabling this transformation, Cloud Computing offers a flexible framework for scalable storage, real-time processing, on-demand retrieval of information, data, and materials, thereby lessening reliance on outdated premise-based systems (Querashi et al., 2020). It enhances collaboration among industrial stakeholders and provides strong disaster recovery solutions. However, as Ciaza et al., (2020) put it, the reliance on cloud technologies brings exposure to security risks, issues with latency, and challenges with meeting compliance requirements that could negatively influence IR4.0 responsiveness.

AI has predictive analytics alongside process automation and quality control in IR4.0 environments. The use of machine learning algorithms optimizes accuracy in resource allocation, decision making, and even waste reduction (Javaid et al., 2021). However, as noted, AI manufacturing depends on high-quality available data, computational resources, and skilled labour (Johanesa et al., 2024). In the same way, AM, or 3D printing, improves production flexibility through rapid prototyping for customization, localized production, in turn reducing lead time and material waste (Khosravani and Reinicke 2020). Its limitations include material constraints, speed of printing and integration with current production systems (Dong et al., 2021). Addressing these challenges is critical for AM to realize its potential in IR4.0-driven industries.

The effectiveness of IR4.0 is integrated with the optimization level of its technological enablers. IoT, Big Data, CPS, Cloud Computing, AI and AM add value for industries, but the implementation of these technologies must resolve cybersecurity issues, interoperability, data adequacy, and infrastructure readiness (Paranitharan et al., 2020). Overcoming these hurdles is essential toward realizing the full potential of IR4.0 in transforming smart connected autonomous manufacturing systems and ecosystems (Oduro and Nisco, 2023). Research on framework standards and security line enhancements as well as improved machine learning for IR4.0 applications is highly recommended. In this regard, the current study intends to focus on these aspects.

2.7.1 Data Analytics

DA facilitates real-time decision making and historical data analysis in decision processes and thus has become irreplaceable in the modern manufacturing systems (Ghahramani et al., 2020; Wang et al., 2021). In a manufacturing setting, DA assists in optimizing workflows, managing maintenance scheduling, and allocating resources, as identifiedburm by (Burmister et al., 2023). Research (Adeniran et al., 2024; Saleh et al.,

2024) has acknowledged the analytics perspective in decision making, stressing its impact on core performance metrics such as operational efficiency and cost reduction. In semiconductor manufacturing, where precision is critical, adopting DA can guarantee that processes like etching, cutting, and assembly are performed with exceptional precision, as noted by (Li et al, 2020; Espadinha-Cruz et al., 2021). The studies by Mortada and Soulhi (2023) and Lai et al., (2021) highlighted that employing analytics in conjunction with LM manufacturing tools greatly enhances the detection of bottlenecks and optimizes cycle time and balance efficiency in production lines.

The incorporation of IoT and real-time data has transformed the domain of DA. Analytics are empowered thanks to data being generated from production equipment sent via IoT devices like sensors and microcontrollers (Fawzy et al., 2021). Petrillo et al., (2022) and He et al., (2023) examined the role of IoT-analytics in smart manufacturing not where data is collected to observe operations, but where advanced process control enables comprehensive performance, failure prognosis, and prescriptive maintenance solution implementation. Similarly, for a semiconductor manufacturing IoT-enabled DA offers detailed measurement of machine, environmental, and product quality metrics (Gharamani et al., 2020). In this context, proactively resolving the identified problems in a timely manner, when coupled with instantaneous processing of demand related data, helps ensure smooth production flow in accordance with the demand schedule (Morth et al., 2020; Wang et al., 2021; Fathy et al., 2021).

Implementing DA into the manufacturing ecosystem comes with its own set of problems, particularly in the realms of data integration as well as quality. The issues with data accuracy ascertain from disparate sources for meaningful analysis have been discussed in Yu et al., (2021), Escobar et al., (2021) and Bousdekis et al., (2022). To achieve the refined proposed framework, these challenges are solved using structured database architecture combined with Firebase as a centralized data repository. The coupling of this database with LM tools completes the void between analytics and actionable insights. In the literature, the lack of such integrations is emphasized as they capture the ability for manufacturers to utilize their data and converge their processes onto LM (Vieira et al., 2020). With the adapted strategy, production processes improve, and the foundation is laid for new research on the integration of DA into manufacturing processes.

2.7.2 Decision Support System

DSS have long been regarded as crucial in assisting decision-making processes in intricate settings, especially in manufacturing (Guo et al., 2020). These systems consist of data, an analytical model, and an interface which together facilitate prompt and accurate decision making. According to Marcos et al., (2020) DSS are described as systems that allow interaction with data and help users to resolve difficulties concerning semi-structured in nature. In manufacturing, these systems are indispensable for effective production scheduling, inventory control, and quality assurance (Oukhay et al., 2020), in which for semiconductor manufacturing where balance between precision and efficiency is critical, DSS contribute significantly by providing timely recommendations based on real-time data to help ensure production goals are accomplished, achieving optimum standards without compromise (Keswani et al., 2020; Yang et al., 2020; Psarommatis et al., 2021).

Consequently, the contemporary DSS have been enhanced with the addition of new technologies like the IoT, machine learning, and cloud computing. The DSS with IoT capability supports the real-time monitoring and decision-making processes by connecting the physical and digital layers of production systems, as noted by Castrignano et al. (2020) and Pan et al. (2020). For example, IoT-based sensors located onto the manufacturing machines can send data to the DSS, where advanced algorithms assess it to detect out-of-control processes or failure scenarios (Abdallah et al., 2022).

In LM the importance of DSS increases as it enables alignment of decisions taken with the key LM principles of DM such as waste, standardization, and continuous improvement. Integrated LM empirically studied by Yazici et al. (2020) and Ondra (2022) have found that applying these DSS in conjunction with LM techniques like line balancing and SMED enhances resource efficiency and production optimization suitable for advance manufacturing system. Just like any technological advancement, applying DSS in the manufacturing sector comes with its own unique challenges. Problems with data assimilation, system adoption, and scaling often emerge, as defined in Massarfa et al. (2023). Massarfa especially stresses the requirement of user-friendly DSS interfaces while also supporting the simultaneous management of vast amounts of disparate data.

2.7.3 Internet of Things

The IoT or Internet of Things is a new technology that allows the connecting of devices to permit the exchange of information and supervision in real-time (Laghari et al., 2021). Within the industrial domain, IoT is fundamental in creating smart factories, where interconnected sensors, machines and software systems work together to optimize operations in real-time (Soori et al., 2023). Ashton (2009) describes IoT as a development in which devices are capable of independent communication, allowing for its adoption across various fields. Within the semiconductor industry IoT ensures strict compliance with production standards by enabling environmental, machinery, and product quality conditions to be monitored in real time (Chen et al., 2020). Through the installation of IoT sensors on assembly lines, manufacturers are able to capture live data which allow for proactive maintenance and immediate action in case of irregular functions.

Implementing the IoT into manufacturing has been one of the IoT cornerstones of IR4.0 where smart factories leverage IoT to optimize efficiency, flexibility and scalability. As noted by Lee et al. (2015), adaptive manufacturing where production systems respond appropriately to varying demands and conditions is possible with IoT. An example would be the DHT11 sensor used for temperature monitoring and HC-SR04 distance measuring sensor that can be used to keep track of critical data for optimal handling (Vallabh et al., 2021). In iDSS-ProLean, IoT forms the foundation of data collection and IoT relays for data transmission. The data collected from the mimicked semiconductor production lines containing sensors integrated with ESP32 microcontrollers are sent to Firebase where the data is processed for real time decision making. Within iDSS-ProLean framework, information flows seamlessly between machines and the application making it possible to implement LM tools such as Line Balancing and SMED.

In spite of its many advantages, the use of IoT in manufacturing still poses greater challenges (Kalsoom et al., 2021). Data security, interoperability, and the scalability of IoT networks represent essential IoT concerns. Gubbi et al. (2013) has underscored the importance of having well-defined architectural structures for the proper control and management of data generated from the IoT system in a secure manner. For iDSS-ProLean, these issues are solved by using Firebase as a secure centralized backend which allows efficient data retrieval and storage. The system's ability to provide IoT-enabled LM tools yields actionable intelligence which closes the gap between data and decisions. The literature review highlights the importance of IoT not only for operational efficiency but also for achieving strategic goals in a manufacturing setting, thereby integrating it as a fundamental element of contemporary production systems (Ihekoronye et al., 2021; Okokpujie and Tartibu, 2024).

2.7.4 Cloud System

The encompassing characteristics of cloud computing make it exceptionally valuable in the implementation of a DSS system. One cloud computing feature that stands out is scalability, as cloud systems can dynamically scale up and down according to workload and data processing needs(Li et al., 2020).To add on, data integration is also easier to achieve with cloud computing, permitting cloud-based DSS to access systems to capture diverse data inputs from within and outside the system seamlessly (Sadeeq et al., 2021; Noguerra, 2023). This feature ensures that comprehensive and timely information is presented to decision makers. In addition, Kineber et al. (2022) highlighted the importance of the deployment model regarding cloud computing as it greatly impacts the implementation phase, user satisfaction and system efficiency.

As illustrates in Table 2.3 , the cloud system encompasses four deployment models and each serves contradictory purposes while complementing one another in the public, private, hybrid, and community clouds. The public cloud is proprietary of third-parties, as it provides resources that are greatly scalable and low priced. The private cloud, on the other-hand, is assigned to a single organization which enhances security and control. However, in serving these two purposes, the hybrid cloud incorporates both public and private clouds, ensuring scalable resource availability and security simultaneously. The community cloud is a model of cloud for enterprises with a common focus enabling greater cooperation (Tavbulatova et al., 2020; Ambica 2021; Garg 2022; Maniatis 2023). All these models work in tandem as they give organization the ability to enhance operational efficiency, security and cost all optimized to their individual needs.

Table 2.3 Cloud System Deployment Model (Eid et al., 2021)

Deployment Model	
Public Cloud	In this model, third-party providers like AWS, Microsoft Azure, and GCP own and manage resources, offering scalable, cost-effective services accessible to the public. Yet, it may not meet stringent data security needs for some organizations.
Private Cloud	This model provides exclusive cloud resources for a single organization, hosted on-premises or by a third-party provider. It is ideal for organizations prioritizing enhanced security, control, and customization of data and applications.
Hybrid Cloud	Combining elements of both public and private clouds, the hybrid model allows seamless data and application sharing while maintaining distinct identities. It is particularly advantageous for organizations seeking to balance scalability and flexibility with the need to secure sensitive information.
Community Cloud	This model involves a shared infrastructure used by organizations with common objectives, such as government agencies or academic institutions. While it offers enhanced control and security, it may involve higher setup and maintenance costs.

On the other hand, the deployment models are being supported by three main service models as showcased in the Table 2.4 - Infrastructure as a Service (IaaS), Software as a Service (SaaS), and Platform as a Service (PaaS) (Srivastava et el., 2023). Each of which satisfies a different type of user while still maintaining integration and synergy. IaaS offers proprietary controlled virtual machinery like server, storage, and network, allowing freedom to the organization to construct and trial run their own applications (Volkov and Stepanov, 2021). PaaS provides hosted application development platforms complete with all necessary design tools enabling the customer to construct, test and place applications seamlessly without dealing with the lower levels of digital architecture (Daradkeh and Agarwal, 2022). SaaS gives users application software over internet as needed without prior installation or post maintenance (Raghavan and Chandrasekaran, 2020). All these models offer the organization varying levels of control and management to optimize the system in place while providing scalability, effective resource use, and reduced operational costs (Vorobeva et al., 2022).

Table 2.4 Cloud System Service Models (Srivastava et el., 2023)

Service Models	
IaaS	Provides virtualized computing resources, including virtual machines, storage, and networking, over the internet. Users are responsible for managing the operating system and applications, while the service provider handles the underlying infrastructure.
PaaS	Delivers an environment for application development, deployment, and management. Users can focus on building and deploying applications, while the provider manages the infrastructure, including servers, operating systems, and middleware.
SaaS	Offers software applications via the internet on a subscription basis. Users can access these applications directly through a web browser without dealing with installation, maintenance, or infrastructure management. This model is highly convenient and efficient for businesses.

As previously discussed, all Deployment Models and Service Models while distinct, are interdependent (Srivastava et al., 2023). Deployment models define cloud accessibility and control, offers scalable, shared resources, ensures exclusive security supports shared industry needs. Service models determine cloud functionality in providing the virtualized infrastructure, offers development platforms, as well as delivers ready-to-use applications (Patel and Kansara, 2021; Segun-Falade et al., 2024). Together, these models optimize performance, security, and scalability based on business requirements (Awaysheh et al., 2021). Figure 2.3 illustrates the linkage of both models within Cloud System.

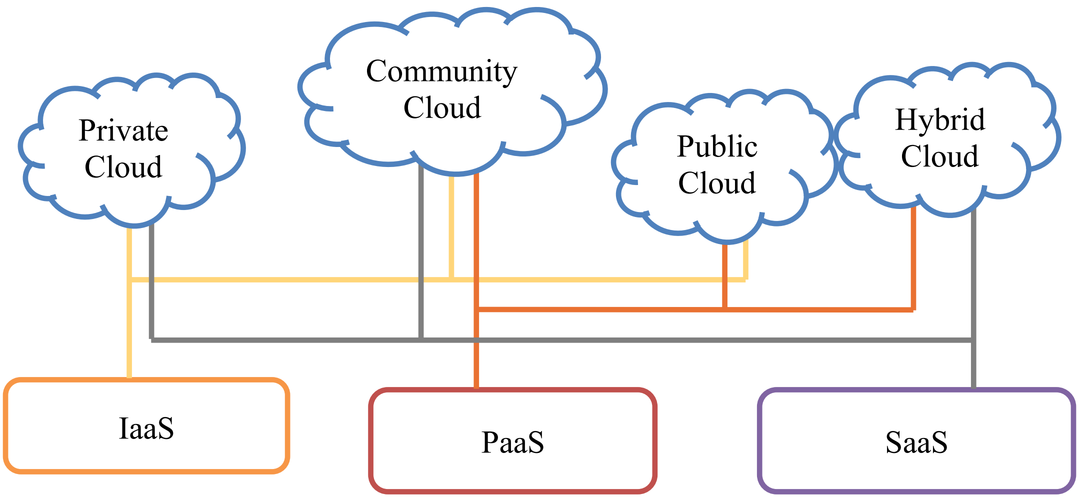


Figure 2.3 Cloud System linkage of Deployment and Service Models

Firebase, a cloud-based backend platform by Google, provides a scalable and integrated environment for real-time data management, making it ideal for modern DSS. The real-time database enables seamless data synchronization across multiple devices, ensuring up-to-date information for decision-making (Kamau et al., 2024). Firebase also offers authentication, hosting, and cloud functions, enhancing security and scalability. Firebase serves as a centralized backend for real-time data collection and analysis (Milojkovic et al., 2024). IoT sensors, such as DHT11 for temperature monitoring and HC-SR04 for distance measurement, transmit data via ESP32 microcontrollers to Firebase, where it is analysed for predictive maintenance, quality control, and efficiency optimization (Kaur, 2022). This real-time processing reduces downtime, enhances productivity, and supports LM tools like line balancing and SMED in advance manufacturing system system. Integrating Firebase with IoT Capable LM tools enables semiconductor manufacturers to enhance their operational effectiveness, minimise waste, and sustain superior product quality to remain competitive in the data-centric market.

2.8 The Rational of DA Model Formulation

Manufacturing processes benefit from the creation of a DA model since it utilizes the large volumes of production data while improving the decision-making process. As with any other industry, production decisions were previously made based on experience and gut feeling, but today's sophisticated production settings require real-time decisions based on data due to the ever-increasing complexity of the environment (Li et al., 2021; Sun and Braatz 2021). Enhanced DA combined with toolsets of LM allows precise forecasting, detection of inefficiencies, and optimization of processes which supports operational performance as suggested by Belhadi et al., (2020) and Marodin et al., (2022). This model assists in making evidence-based decisions specifically aimed at improving manufacturing processes, reducing operational costs, and enhancing competitiveness in the market.

Manufacturing systems, enabled with IoT sensors and real-time data collection systems, are capable of generating unprecedented volumes of data; however, without proper analytical approaches, such data remains dormant and underutilized (Chen, 2020). In addition, DA model converts raw data into actionable information employing optimally predictive analytics, machine learning, as well as statistical models to forecast information trends, detect patterns, and identify possible factors of unique repetitive occurrences, more commonly referred to as anomalies (Gupta et al., 2020; Rustagi and Goel, 2022; Jangam and Deshpande, 2023). With such capabilities, proactive decision making can be realized, aligning with DA's goal of reducing downtime and waste.

Moreover, combining DA tools with LM principles automates basic decision tasks which further strengthen process efficiency in line balancing, SMED, and Kanban. The analysis of real-time production data is performed in Subramaniyan's (2021) work, which permits dynamic adjustments to line balancing, alleviating bottlenecks and increasing throughput. This has created a continuous improvement cycle where LM principles refine the analytics model, and the model, in turn, automates decisions as supported by (Tu et al., 2021; Lai et al., 2021). Hence, a properly designed DA model, in addition to improving LM practices, allows industrial players to actively compete in the modern manufacturing environment.

2.8.1 The Contemporary Concepts Vs Future Perspective

Manufacturing has long been impacted by LM techniques that strive to reduce waste, improve efficiency, and sustain quality. These techniques have been beneficial in improving operational efficiency and lowering costs. Still, as highlighted by Subramaniyan (2021), global manufacturing is undergoing shifts which add new complexities like heightened production intricacy, fast-paced innovation, the need for sustainability, and digitalisation, all of which concern these older methods. In response, manufacturing is moving towards an integrated technology-enabled model combining traditional LM with IR4.0. These technologies support real-time data acquisition which allows for advanced decision making like monitoring and maintenance performed in real time (Zonta et al., 2020; Kommanaboina, 2020). Predictive analytics enhances scheduling by anticipating equipment failure before it occurs, which reduces downtime (Patil et al., 2021). Additionally, machine learning algorithms applied to production data streamline processes, enhancing productivity and quality over time (Kang et al., 2020). This framework adds LM and smart technologies, increasing agility and resilience in manufacturing systems.

Likewise, Gholami et al. (2021) suggest socially responsible frameworks heighten adaptive strategies for the eco-friendly future of manufacturing. From the purchase perspective, manufacturers have compelling incentives to develop energy-efficient technologies that enable a reduced carbon footprint throughout the product lifecycle due to rising consumer demand for sustainable goods and increasing regulatory scrutiny (Wang et al., 2021; Nwabekee et al., 2024). On the contrary, digital technologies, more specifically DA and IoT, provide valuable information that aids in reducing resource consumption and waste, driving this change. Based on the findings by Bermeo-Ayerbe et al. (2022) and Cruz and Garcia (2024), the use of data measurement alongside energy optimisation increases productivity, while predictive maintenance eliminates wasteful energy expenditure. These technologies emerging today enable the future of manufacturing to adopt a more comprehensive model that balances efficiency, product quality and sustainable practices all at once, propelled by DA and automated intelligent control systems.

2.9 The Assessment of Current Decision Support System

To understand the current situation regarding the use of DSS in the manufacturing industry, it is important to understand the components of this study and their interrelations. This section starts with describing the classical structures designed for decision makers who, ostensibly, act in the best interest of the business and fulfil the expectations of the clients. In the views of Kwan et al., (2020), Zaytsev (2020), and Christ et al., (2022), DSS is an information system which enables an organisation to collect information concerning internal operations and the external market environment, analyse the data, and devise plans of action, which, given the dropping prices of relevant hardware and software, should allow companies to leverage these information systems for noticeable betterment in management. Conversely, Trentesaux et al., (1998) and Gonzalez-Castana et al., (2022) argue that a range of tools, techniques, and technologies are utilised in DSS within the manufacturing industry to assist the managers and operators in having accurate and timely information for effective decision-making in regards to the operations, production, and resource management.

DSS in general, by definition, is a computerized program used to support determinations, judgement, and courses of action in an organization or a business. A DSS collects the variables and analyze the data, then synthesis it into a comprehensive information report (Guo et al., 2020). This character distinguishes DSS from an ordinary established operation application, whose trial run to only data collection and not to the extent of formulating new resolution from the judgement made (Ruban et al., 2021). DSS can be completely computerized or powered by humans or hybrid. Meanwhile, the best possible one has the analyze information system then make the decision for the user or the very least allow the user to make decision in a short period of time and DSS is tightly dependent on the previous data collected and then, creating a conclusive epilogue of the culmination assumption (Fernandez et al., 2020).

While upper-level management most frequently utilizes DSS to organize organizational data into actionable intelligence, general operations management can also access and benefit from these systems (Gupta et al., 2021). What is more, DSS can be customized for various industries, professions, and domains, including healthcare, government agencies, agriculture, and corporate operations, showcasing their versatility in enabling data-driven decision-making across diverse sectors as found by Zhai et al., (2020) and Sutton et al., (2020). Additionally, a key feature of DSS is its user-friendly information presentation, which enhances accessibility and comprehension. With advancements in technology, DSS can now be seamlessly integrated into computer systems, including desktops, laptops, and mobile devices, further enhancing usability and accessibility (Cho et al., 2021). This flexibility continues by having a large data able to be processed, as the main drive for DSS is the IoT, whereby the devices can be connected to one another thus creating bulk figures to be collected as affirmed by Piccialli et al, (2020) and Zheng et al., (2022). Indeed, a real-time monitoring can be done throughout and can be adjusted based on users' specifications, making this system is reliable and fit enough to be used in the industry (Chen 2020) and Rácz-Szabó et al., (2020).

In this part, the systematic review was being utilized - Preferred Reporting Items For Systematic Reviews And Meta-Analysis (PRISMA), defined by a minimal set of parameters for reporting in systematic reviews and meta-analyses that is supported by evidence (Rainkie et al., 2020). This analysis is primarily concerned with reporting reviews which assess the effects of interventions, but it may also serve as a foundation for reporting systematic reviews with goals other than assessing treatments such evaluating aetiology, prevalence, diagnosis, or prognosis with a transparent and trustworthiness application as well as to reflect advances and guarantee recent database (Gourge et al., 2021; Bryne et al., 2022).

There are three main steps; the identification, screening, and document included, while the main variables are previous studies and identification of new studies via databases and registers. The process began with sorting and filtering relevant sources based on specific criteria to ensure the quality and relevance of the selected articles. This selection process was guided by the parameters in Table 2.5 .

Table 2.5 Four Keys Parameters in PRISMA

Four Key Parameters
▪ Document had to be in journal format
▪ Discussion had to focus on the manufacturing industry
▪ Publication timeframe needed to be from 2011 to 2023, reflecting the evolution of IR4.0
▪ Keywords used for the search included "Decision Support System" and "Lean Manufacturing"

The sources were acquired through an extensive search in academic databases like Scopus and Web of Science (WOS). These databases were selected due to their strict criteria for indexing, providing access to validated scholarly articles that enhance the credibility and trustworthiness of the review. During the search, specific criteria were set to locate appropriate documents that studied the application centralisation for DSS and principles of LM. After the collection of articles was done electronically, the title and keyword selection were manually screened to check if they met the selection criteria. At this stage, I was able to collect 2,023 titles, which were further examined by going through the table of contents to ascertain relevance to DSS applications in manufacturing.

This selection process is crucial in ensuring that the boundaries defined are precise while the academic credibility of the literature review is upheld. With a clear goal to accomplish, limiting the review scope to only focus on what Scopus and WOS provide drastically improves the gathered peer-reviewed research that features high-impact studies relevant to the latest developments in the domain. Furthermore, only articles published in the last decade were eligible which ensured that the centred focus is on recent changes around DSS within LM and IR4.0.

The results confirm that applying a DSS integrated with LM principles significantly enhances efficiency, optimises processes, and improves overall decision-making. In addition, the development in technologies in IR4.0 has enabled the capabilities of DSS Technologies to be more sophisticated with real-time data collection, analytics, and predictive decision making, which are highly critical for competitiveness in modern manufacturing sectors.

Table 2.6 illustrates how the papers were published in multiple journals and indicates the amount of papers each journal contained and classified as a DSS per matter of subjects. Overall, out of all the papers published during 2012 and 2023, 30.15 percent were focused on DSS. The originating journal, DSS, from the United States had the highest claim earning 87.84% of their publications reflecting the central focus on DSS Information Systems highly. Other non-specialised IS, or multi-disciplinary journals, such as DS and Journal of Manufacturing Technology Management also extensively contribute to DSS. Journals from Europe, EJIS and JIT, released low proportions of DSS articles indicating the presence of broader IS related research subjects. Overall, out of 6,709 total articles, 30.15% are directly related to DSS, emphasizing its growing significance in academic research across multiple disciplines and geographic regions.

Table 2.6 Journal Distribution from Scopus and WoS

Journal	*Origin*	*Journal Orientation*	*Number of DSS-Related Journals*	*Total Number of Articles Published*	*%*
Decision Sciences	US	Multi-discipline	496	963	51.50
Decision Support System	US	General IS	788	897	87.84
European Journal Of Information Systems	Europe	General IS	24	432	5.55
Grouped Decision and Negotiation	US	Specialist IS	123	323	38.08
Information and Management	US	General IS	89	238	37.39
Information and Organization	Europe	General IS	113	765	14.77
Information Systems Journal	Europe	General IS	14	176	7.95
Information Systems Research	US	General IS	43	185	23.24
Journal of Information Technology	Europe	General IS	22	667	3.30
Information of Management Information System	US	General IS	67	245	27.34
Journal of Manufacturing Technology Management	UK	Multi-discipline	78	329	23.70
Industrial Engineering and Management Systems	Korea	Multi-discipline	87	587	14.82
ARPN Journal of Engineering and Applied Sciences	Pakistan	Multi-discipline	45	657	6.85
Concurrent Engineering Research and Application	US	General IS	34	245	13.87
		TOTAL	2023	6709	30.15

Following this classification, all 2,023 articles identified in the previous stage were systematically reviewed and analyzed using the PRISMA framework, as illustrates in Figure 2.4.

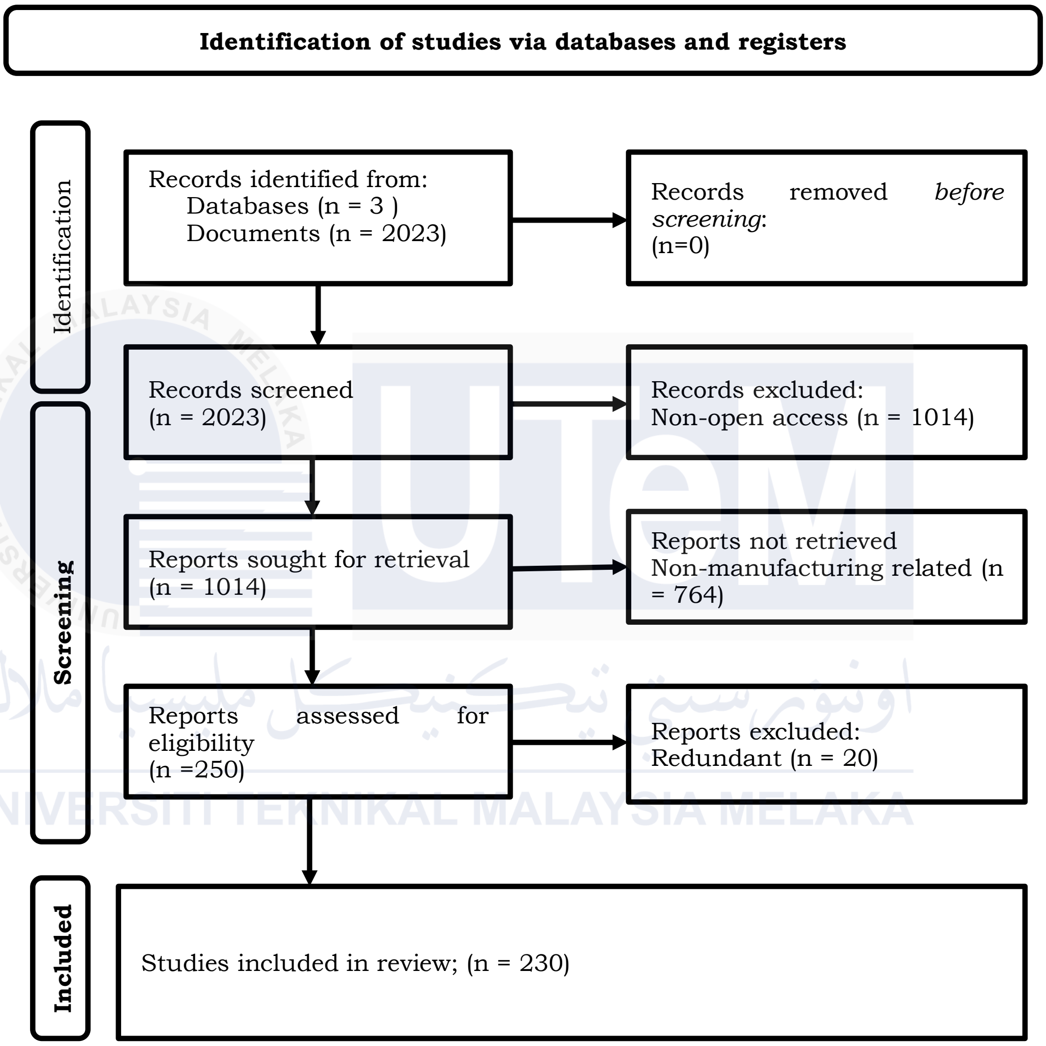


Figure 2.4 PRISMA Flowchart

From this process, a final selection of 230 relevant documents was made, and the extracted information was examined in relation to several key areas: the objectives and benefits of DSS, its core components and features, recent advancements in development, and user adoption trends. The discussion was further expanded to explore emerging issues identified in the literature, including case study applications, design science methodologies, professional relevance, industry funding, and theoretical foundations.

Finally, the findings were synthesized to outline future research directions, focusing on essential features for DSS development and potential collaborations with emerging technologies, such as IR4.0. These insights serve as a foundation for guiding future advancements in DSS integration and application across various industries.

2.9.1 The Intellectual Structure and the Development of DSS

DSS is known by its purpose, which is to support the decision maker in decision making process as there is no universally-accepted definition in the terms as individually (Whyte 1986). It has been more than half decade since DSS was first introduced in the middle of 1960s. The term of *DSS* is used as defined by Scott Morton to include all forms of information systems and technologies designed to assist one or more decision makers in deciding or choosing a course of action in a nonroutine, episodic situation that requires judgement (Little 1979). Originally coined by Peter Keen (1980), DSS encompasses a broad range of information systems and technologies that are specifically designed to aid decision-making process by providing data, models, and analysis tools to help in the judgement of the alternatives or solution, improving personal efficiency, increase organizational control, and speeds up problem-solving.

Another key elements of DSS are include both software and hardware components to operate successfully together. Pursuant to this claim made by Bonczek et al., (1980), the concepts and methods used in DSS have had the most impacts on the development of a potent business-oriented DSS. The framework and problem analyses are part of the design framework model. Hence, there are different steps involve in the process of decision making; Intelligence Phase, Design Phase, Choice Phase, and Implementation Phase as depicted in Figure 2.5 .

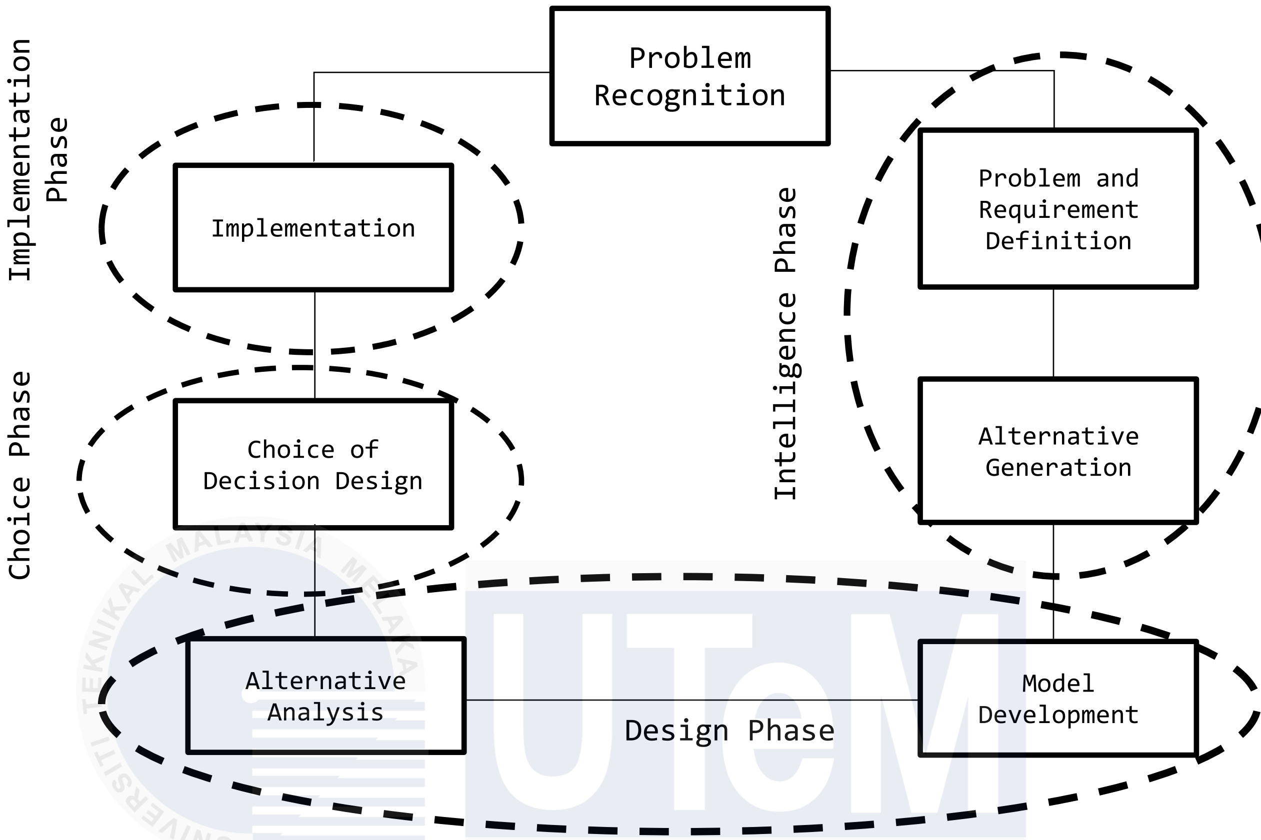


Figure 2.5 Phases in Decision-making process (Bonczek et al., 1980; Mumani et al., 2021)

On the other hand, the primary aspects of DSS for the Manufacturing Industry are the analytical tools and information management capabilities that facilitate the resolution of relatively large, unstructured problems (Watkins et al., 1995; Naim 2021; Waruwu 2022). A DSS for Manufacturing can facilitate decision-making by equipping decision-makers with the resources and knowledge needed to make prudent decisions and improve the performance of the manufacturing industry (Mokrozub and Malygin 2019). One research documented the development of a DSS involving those five elements is to configure the spare parts supply chains by considering different manufacturing technologies, improving the effectiveness of LM, integrating manufacturing processes in micro-factories production line, and automating decision-making in towards the era of zero-defect manufacturing (Rocha et al., 2021; Sala et al., 2021: Montgomery et al., 2023).

DSS provides real-time data and analytics to decision-makers to improve supply chain management, expedite decision-making, and optimise production procedures since the primary objectives of a DSS in the manufacturing industry are to improve decision-making procedures, boost productivity, and enhance performance outcomes. (Taipalus et al., 2021) claims that fundamental first element in a software component is referred to as the Database Management System (DBMS) which uses different mathematical models in the analysis of complex data for the presentation and engagement with the user via the interface utilized by the user. Following that, supported by Duncan and Etienne-Cummings (2019)the other two components of Model Based Management (MBSM) and Dialog Generation (User Interface).

(Rahman et al 2020; Gleim et al., 2022) also claim that the primary aspects of a DSS for the manufacturing industry are the analytical tools and information management capabilities that facilitate the resolution of relatively large, unstructured problems. A DSS for manufacturing should facilitate decision-making by equipping decision-makers with the resources and knowledge needed to make prudent decisions and improve the performance of the manufacturing industry (Alfawaer and Halimi 2022).

Consequently, advance manufacturing system framework was architected through the integration of three core technological components, each serving a distinct yet interrelated function aligned with the intellectual structure of a DSS. Firebase was employed as the cloud-based DAmanagement system due to its capacity to handle real-time data storage, synchronization, and query operations essential for supporting analytical decision-making. The Android Studio platform was utilized for designing the user interface, enabling end-users namely engineers and production managers to interact intuitively with LM tools, visualize sensor inputs, and receive data-driven recommendations in a mobile environment.

Concurrently, the Arduino IDE facilitated the configuration and deployment of IoT-based data acquisition using microcontrollers and connected sensors, enabling the capture of critical production parameters from the shop floor in real-time. This triadic integration was deliberately constructed to fulfil the functional model of a DSS: data acquisition Arduino, data processing and storage Firebase, and user interface Android Studio, thereby ensuring that the system could not only retrieve relevant information but also translate it into actionable insights within the LM context. Figure 2.6 illustrate advance manufacturing system architectural component in throughout the development process.

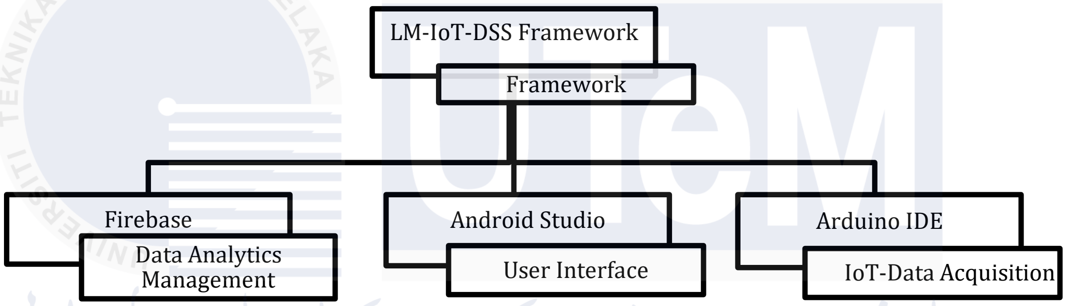


Figure 2.6 Advance manufacturing system framework Components

2.9.2 Current Trend of DSS in LM Industry

Recent advancements in DSSs have centred on enhancing decision-making through the incorporation of diverse technologies and analytical tools, as well as the evaluation and analysis of DSSs via social networks. A different article incorporated the expanded and revised versions of selected papers concentrating on topics such as decision analysis for enterprise systems and non-hierarchical networks, utilising the statistical modelling technique to find the relationship between events and factors related to that event (Pareek at el., 2021).

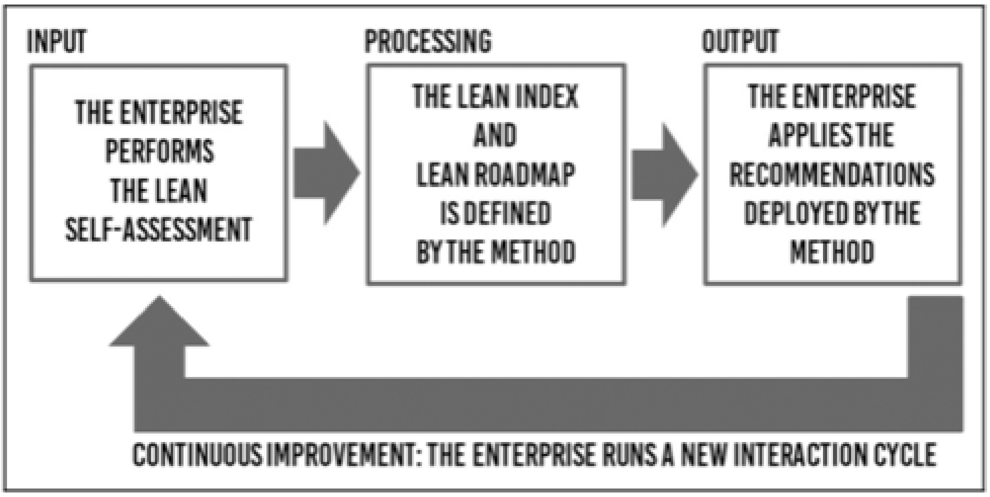


Figure 2.7 Roadmap in LM transformation (Silvério et al. 2020)

Silvério et al. (2020) proposed a roadmap aimed at guiding companies in their transformation into fully LM organizations as shown in Figure 2.7. The framework centers on the development of a quantitative self-assessment method that enables firms to evaluate their current leanness level. By doing so, it helps organizations identify suitable LM tools aligned with their operational maturity. This method produces a structured roadmap to determine which LM practices to adopt and in what sequence. In the context of this research, the framework is relevant as it emphasizes strategic selection of LM tools, which aligns with the rationale behind choosing Line Balancing, SMED, and Kanban within the framework. Moreover, the idea of using data-driven assessments to guide LM implementation closely mirrors the decision-support orientation adopted in this study.

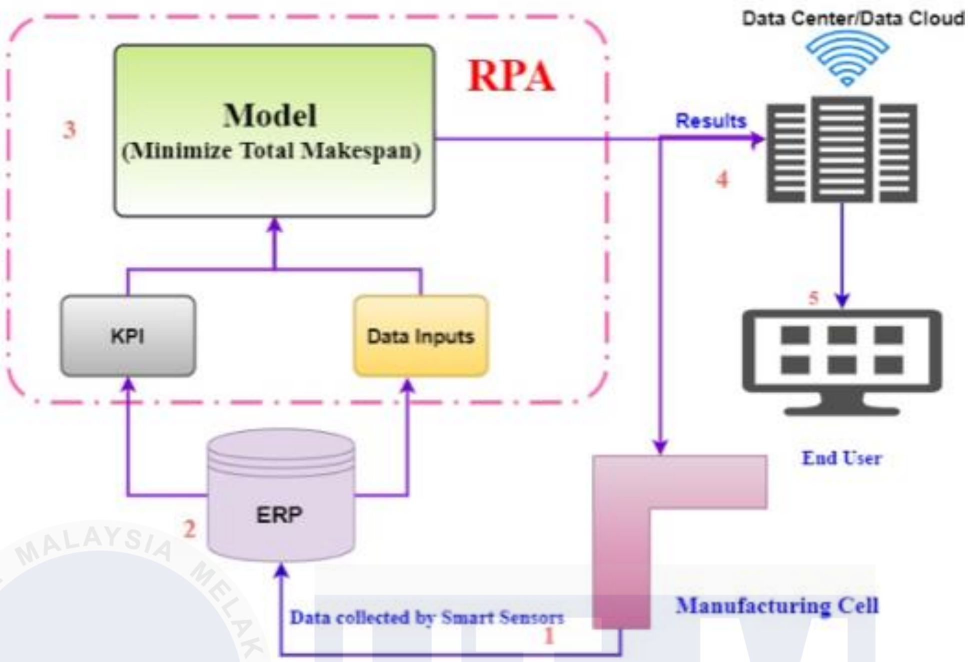


Figure 2.8 Conceptual framework of real-time DSS for
High-Mix Low-VolumeBalázs et al. (2020)

Balázs et al. (2020) introduced a conceptual real-time DSS designed specifically for High-Mix Low-Volume production scheduling within IR4.0 environments environments as shown in Figure 2.8. The framework incorporates the MB–GA scheduling method, which leverages a mutation-based genetic algorithm where random values are introduced into the population parameters to enhance solution diversity and adaptability. This approach is designed to be highly flexible, easy to automate, and not bound to any specific industry, as it utilizes general Key Performance Indicators (KPIs) and input parameters. The relevance of this framework to the current study lies in its emphasis on real-time decision-making and automation in complex manufacturing settings, which aligns with the core aim of advance manufacturing system. Specifically, it supports the notion that DSS can be optimized for dynamic, data-rich environments as in semiconductor manufacturing and reinforces the importance of flexibility and generalizability in DSS design.

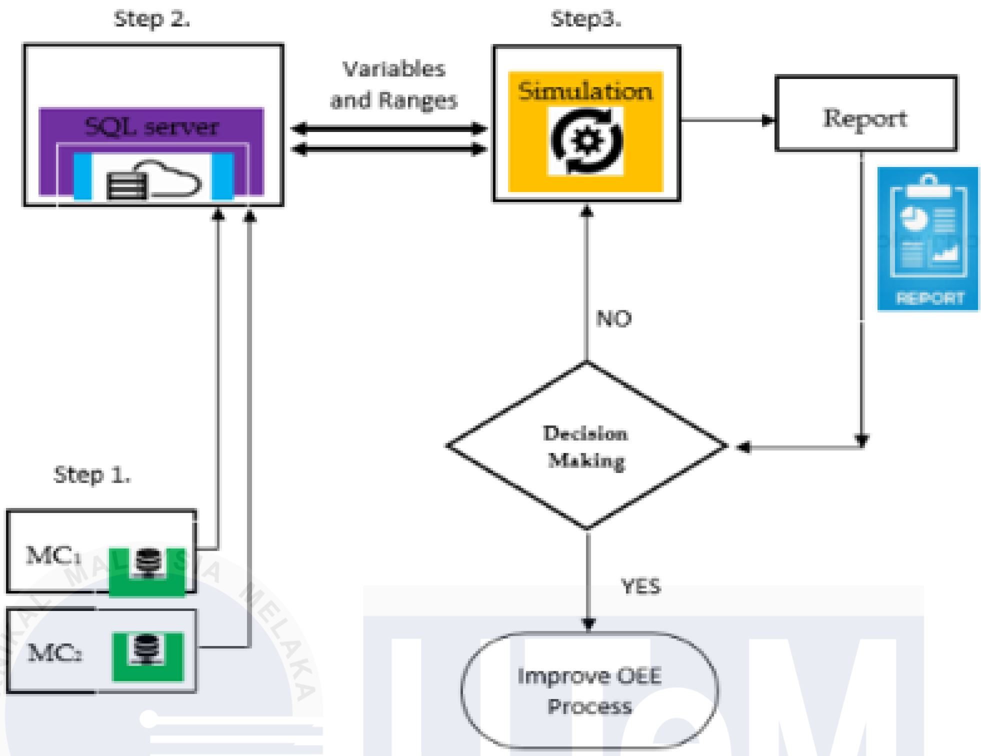


Figure 2.9 Model-driven DSS framework for OEE Abd Rahman et al. (2020)

Abd Rahman et al. (2020) developed a model-driven DSS that integrates data simulation with communication technologies, focusing on enhancing Overall Equipment Effectiveness (OEE) within the Malaysian manufacturing industry as shown in Figure 2.9. The framework utilizes simulation as a core technique to improve decision-making, particularly in addressing line balancing challenges. On the other hand, the system also incorporates real-time data communication to enable responsive adjustments to production constraints. Besides that, the study highlights how data-enhanced insights can be operationalized to support LM goals such as minimizing downtime and optimizing equipment utilization. In relation to the present research, this framework reinforces the role of DSS in facilitating data-informed LM practices. Moreover, its application within a local Malaysian context lends valuable insight into how DSS models can be adapted to regional industry dynamics, including production patterns and technological readiness.

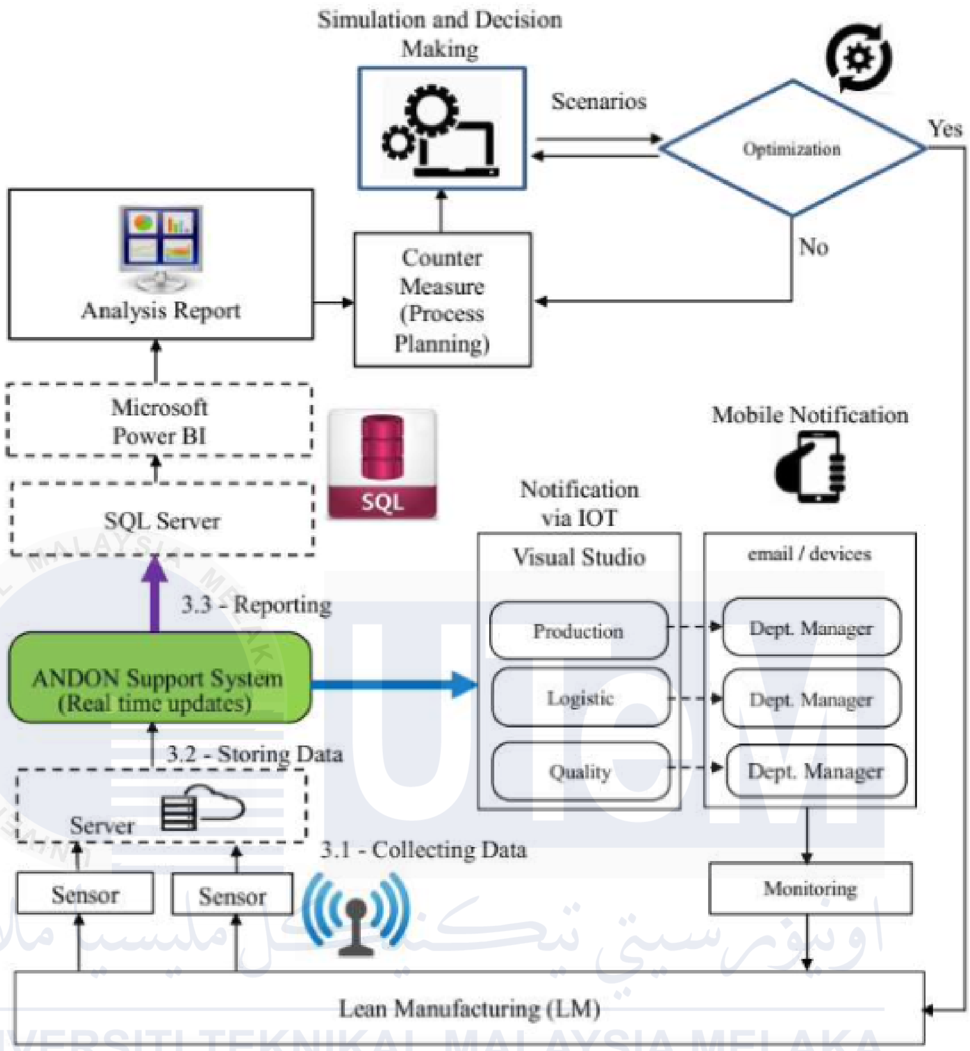


Figure 2.10 Andon-based DSS framework for IoT (Ito et al. 2020)

Ito et al. (2020) introduced an Andon-based DSS that combines IoT technologies with simulation approaches, specifically tailored for automotive part assembly lines as shown in Figure 2.10. The aim of the framework was to support digital transformation in manufacturing by offering a low-cost and easily adoptable solution. By integrating IoT for real-time data collection with simulation for predictive insights, the system enables immediate response to disruptions and production inefficiencies. In contrast to more complex, high-investment IR4.0 systems, this model emphasizes accessibility and simplicity, making it attractive for industries with limited digital maturity. Moreover, the use of the Andon concept traditionally used for visual signalling in LM shows how conventional LM tools can be enhanced through digitalization. In relation to this research, the framework supports the foundational idea of the whole research which also leverages IoT and simulation to enable real-time, low-barrier LM decision-making.

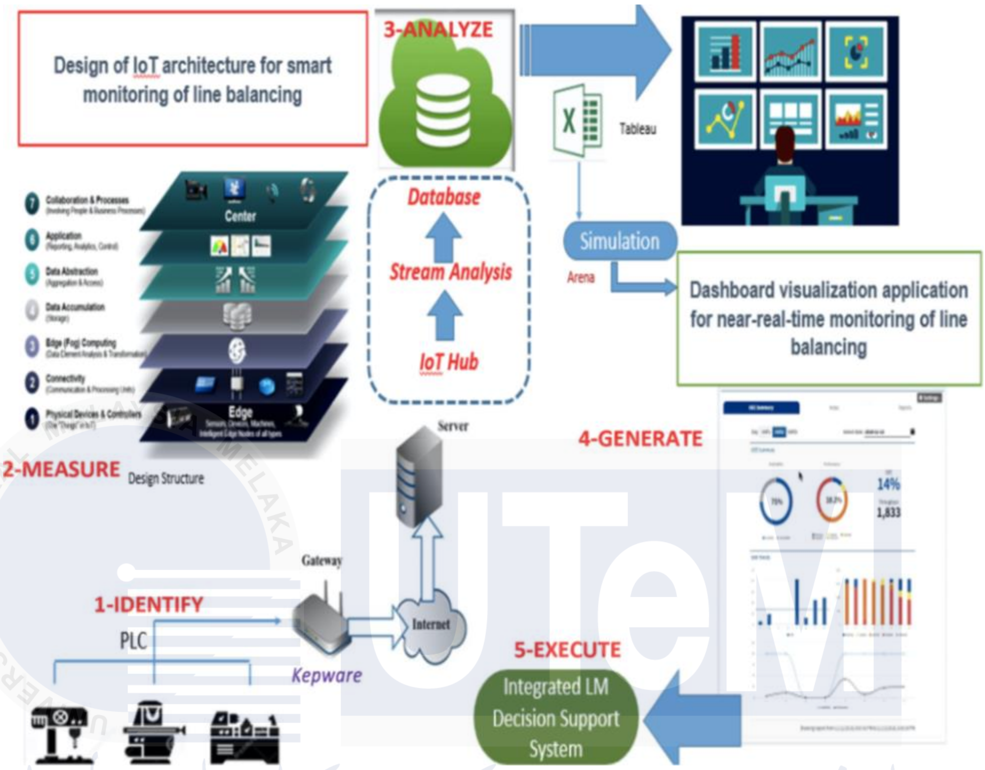


Figure 2.11 IoT-enabled DA model DSS (Abd Rahman et al. 2021)

Besides that, Abd Rahman et al. (2021) proposed the development of an IoT-enabled DA enhanced DSS aimed at improving LM process performance as shown in Figure 2.11. The framework adopts a dynamic approach by continuously capturing real-time data on both customer needs and production performance. This real-time responsiveness allows the system to readjust the "levers" of LM such as takt time, process flow, and inventory control thereby enhancing operational efficiency. In contrast to static LM implementations, this approach emphasizes adaptability and data-driven recalibration, aligning with IR4.0's emphasis on smart manufacturing. In the context of this research, the framework directly supports the underlying philosophy of this research, which also seeks to embed real-time responsiveness into LM tools. Moreover, its integration of IoT and dynamic analytics reinforces the importance of using sensor-driven insights for continuous LM improvement within a rapidly evolving production environment such as the semiconductor industry.

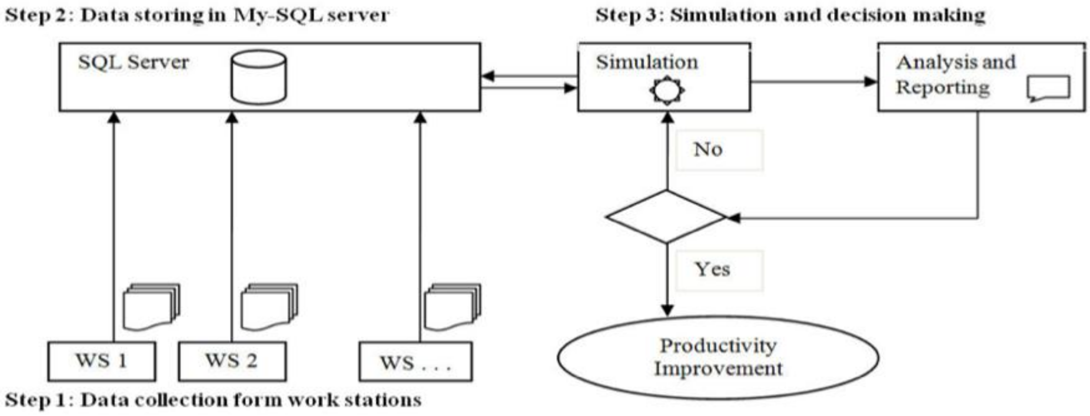


Figure 2.12 Model-driven DSS flowchart for garment industry Ivatury et al. (2022)

Ivatury et al. (2022) developed a Model-Driven DSS tailored to improve productivity in garment assembly lines, particularly in response to post-pandemic manufacturing challenges as shown in Figure 2.12. The framework integrates real-time data capturing with simulation and communication technologies to enable informed, responsive decision-making across production stages. By combining digital tools with productivity-focused strategies, the system provides manufacturers with the ability to simulate various production scenarios, assess their outcomes, and implement adjustments in real-time. In addition, it demonstrates how simulation-driven DSS can serve as a strategic recovery mechanism for industries facing volatile market conditions. In relation to this study, the framework reinforces the importance of simulation and real-time data integration, which mirrors the technical foundation of this research. Although it is applied in the garment industry, the core principles of adaptive scheduling, flow improvement, and efficiency tracking are transferable and highly relevant to the semiconductor sector.

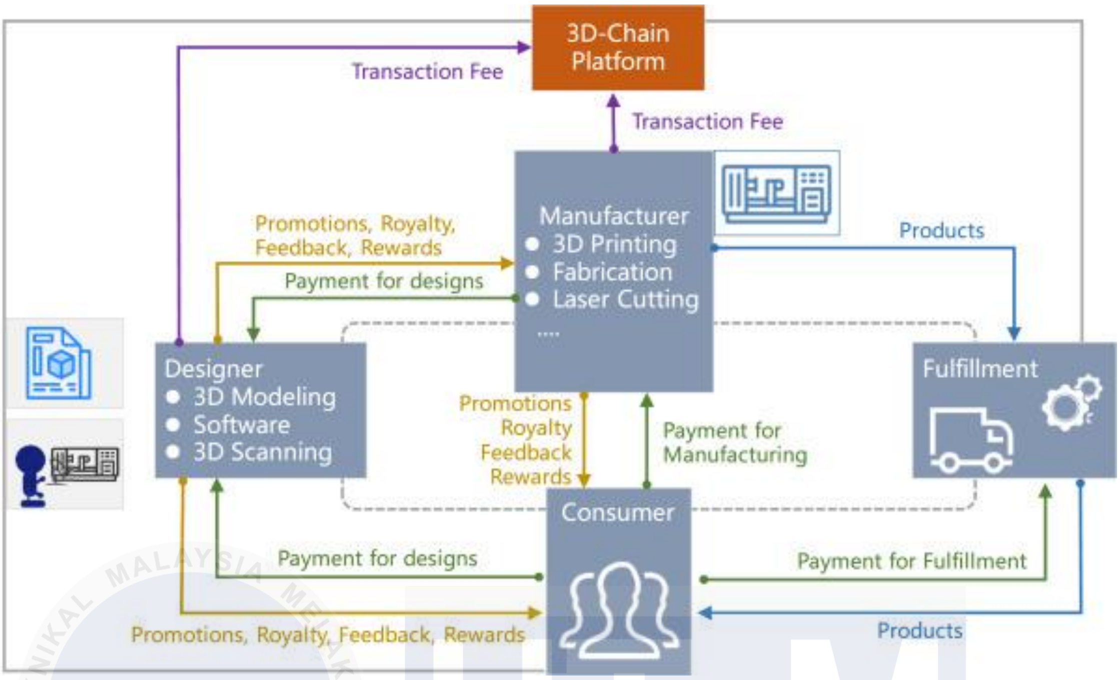


Figure 2.13 Technical model DSS for blockchain integration Dan et al. (2023)

Dan et al. (2023) introduced a highly technical DSS framework designed to address the integration of blockchain technology in sustainable manufacturing within the IR4.0 era as shown in Figure 2.13. The framework Pythagorean Fuzzy-Entropy-Rank Sum-Combined Compromise Solution combines multiple decision-making techniques to support consensus algorithms and computational models, particularly in environments requiring strict privacy protection and data security. This approach is significant in managing sensitive manufacturing data while promoting transparency and trust across interconnected systems. On the other hand, the use of fuzzy logic enhances decision robustness in uncertain industrial scenarios. Although this framework is more focused on data privacy and global decision optimization, its contribution to this study lies in showcasing advanced DSS integration within IR4.0, especially in terms of multi-criteria decision-making and intelligent system design. While this research does not incorporate blockchain, this study highlights how complex algorithmic logic and structured DSS approaches can be adapted for industrial environments, reinforcing the relevance of intelligent systems in supporting LM initiatives under digital transformation.

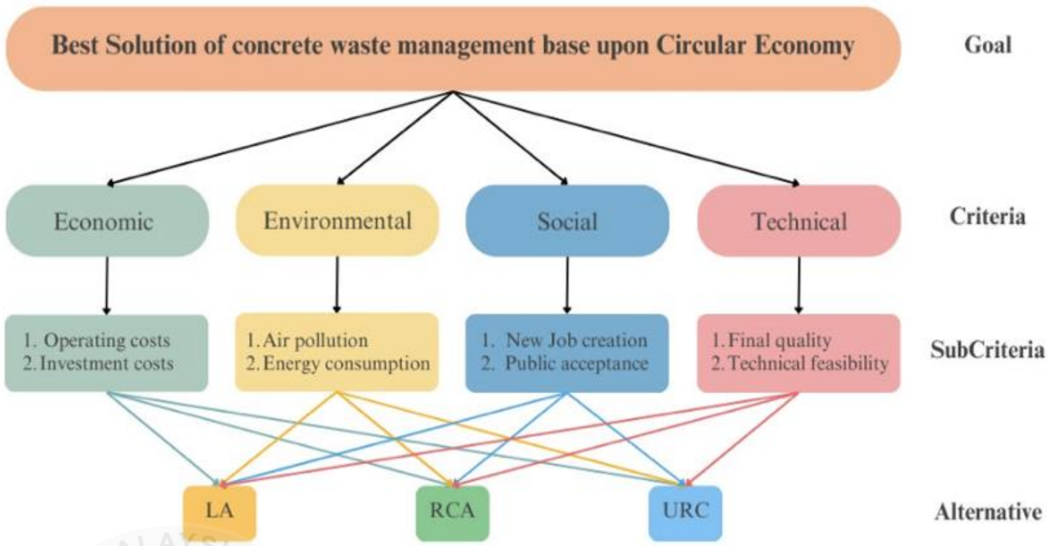


Figure 2.14 Fuzzy Analytic Hierarchy Process for DSS in concrete industry

(Prin et al., 2023)

Prin et al. (2023) developed a DSS aimed at facilitating smart decision-making in managing construction and demolition waste, with the ultimate goal of supporting a transition to a circular economy as shown in Figure 2.14. The framework utilizes the Fuzzy Analytic Hierarchy Process to estimate the priority weights of various decision criteria, enabling users to select the most appropriate concrete waste management method. The results revealed that environmental criteria held the highest priority, with a weight of 0.334, reflecting the increasing emphasis on sustainability in industrial practices. Besides that, the DSS offers a structured, criteria-based approach to support complex decision-making scenarios in the construction industry. Although the domain differs from semiconductor manufacturing, this study contributes to the current research by highlighting how multi-criteria decision frameworks can be used to evaluate and prioritize LM or sustainability strategies. It reinforces the importance of structured, data-informed decision logic.

2.9.3 DSS in Improving Manufacturing Industry

Consequently, the following discussion touch on recent advancements in DSSs that focus on the incorporation of diverse technologies and the facilitation of LM Performance (LMP) via the selection of solutions for relatively large, unstructured problems. The current trend in DSSs is the development of an agile and data-driven systems, which means using the categorised data provided to illuminate the decisions made (Mannina et al. 2022). The quantity and scope of the information provided by information technology have become overwhelming, resulting in cognitive excess, confusion, and an inability to function effectively (Guo, 2020). DSSs are being developed to expedite data analysis and the selection of a viable course of action. Another trend in the creation and administration of DSSs is the use of data mining (Arnott, 2019).

In conjunction with that, another literary gem has revealed a procedure for constructing a DSS backward is using a analysis sensitivity model specifically for effective interventions and maintenance in manufacturing using the example of a predictive mode from the electronics industry (Shojaeinasab et al., 2022), where this model is being used in the steel industry for the development and testing of production execution systems. Overall, the literature strongly suggests that DSSs should be utilised in the manufacturing industry to assist decision-makers in various aspects, including effective interventions. It can be concluded from this discussion that the impact of DSSs on the performance of LM can be sorted by comprehending three important aspects; waste identification and elimination, accurate and up-to-date information, and the integration of LM and agile production.

2.9.4 Issues and challenges in DSS for Manufacturing Industry

This section further discusses the strengths and weaknesses of DSSs from the literature. The powers of a DSS provide decision makers with the capabilities to analyse vast amounts of data and information for them to make substantiated decisions (Okunlaya et al. 2022). A DSS also aids the decision makers in complex problem analyses and assists them in solution identification (Dennehy et al., 2019). However, these systems also have vulnerabilities. One of their weaknesses is reliance on incomplete or inaccurate datasets, resulting in decisions that are biased or completely incorrect (Kühl et al. 2022). Overall, the strengths and limitations of these systems suggest that they are useful in the decision-making process; however, their usefulness means reliance on the data and algorithms used as well as the know-how of the decision makers who trust such systems.

For Intelligent Manufacturing, the boundaries of these systems would be their inability to manage multi-faceted and continuously evolving manufacturing processes, non-rigid flexibility and adaptability, and ignorance of human expertise and knowledge within the reasoning frameworks of decision-making (Hammond et al., 2023). As a whole, the boundaries of these systems should be contemplated throughout the creation and operation of such systems because ethical guidelines promoting the use of these systems should be structured in terms of verifiable standards devoid of arbitrary clearly defined standards based on accountability, responsibility, and unbiased action. Furthermore, innovative generations of DSS must be created to improve upon the existing systems and address the evolving needs of decision-makers across various sectors.

2.10 The Research Gap Analysis

The lack of system integration is one of the most important factors which has hindered the usage of DSS in manufacturing. During DA stage, DSS attempts to resolve problems by merging data and expert knowledge. Unfortunately, the presence of fragmented systems makes this process especially difficult. With the recent spikes in digitalisation and concurrent engineering, the utilisation of simulation as the primary engine for data analysis still faces a multitude of data-related challenges, like capturing, storing, and analysing large datasets. The existing DA systems do not go beyond data tracking and therefore lack effective decision-making capabilities, which limits their usability. Stalemated software development combined with frequent updates also disconnects DA from simulation software, resulting in further WLAN integration challenges due to a lack of standardisation.

These restrictions severely compromise the efficiency for improvements enhanced by DA in manufacturing processes while wrong configurations that result from incorrect parameters complicate the situation even further. The prevalence of small data paradigms greatly constrains the scope of automated decision-making analyses, while a lack of proper interconnects delays DSS execution. Ineffective LM practices coupled with poor data exchange protocols dramatically reduce DSS capabilities in resolving superset manufacturing challenges. As IR4.0 progresses, it has dominated the focus of research owing to its technology advancements in use with manufacturing. It has also been studied in the context of the Proposed Inherent Model to LM and IoT technologies. This is captured in the following important findings:

a) Integration of LM into DSS remains underdeveloped due to challenges in aligning DSS with LM Principles. The limited understanding of LMS and Tools among managers and engineers further complicates this process. Misapplications of these tools can fail to address problems effectively and may even lead to increased waste, causing financial losses for organizations.

b) Data utilization within Malaysian manufacturing companies remains limited, with data primarily used for visualization rather than problem-solving or predictive purposes. In the Proposed Inherent Model framework, DA is fundamental as the chief intelligence entity which synthesises multiple parameters for adequate decision making. This integration aims at improving organisational productivity by optimising decisional acceleration and eliminating redundancies.

c) The role of network communications based on IoT technologies is a vital aspect in the contemporary IoT world for manufacturing purposes as they allow interaction of sensors with databases and simulations. The IoT acts as a platform for gathering enormous amounts of data which is later studied through simulations to enhance the manufacturing processes. Despite the increasing interest in IoT integration, a comprehensive framework linking IoT and LM within the IR4.0 model remains absent. IoT enables real-time data acquisition and analysis, providing an opportunity to enhance human-to-human and human-to-machine interactions. This research recognizes the significance of IoT network architecture in supporting the Identify, Measure, Analyze, Generate, and Execute phases, which are essential for efficient decision-making in LM-based DSS frameworks.

In conclusion, the literature highlights the transformative potential of IoT-driven DSS in modern manufacturing. Advance DSS system builds on this foundation by integrating real-time data retrieval within LM principles and IoT infrastructure. By enhancing the production efficiency, process optimization, and decision accuracy, this system contributes to the broader evolution of IR4.0 technologies in semiconductor manufacturing. Table 2.7 reveals that such LM thinking is neither unrecognised nor embedded in the decision-making process along with IoT and DA in DSS potentials. This is the problem which this research has focused of for solution discovery through this research.

Table 2.7 Research Gap Analysis

Authors	*LM*	*DSS*	*IR4.0 Technology Enablers*										
			Simulation	**IoT**	**Add. Man.**	**Cloud Cop.**	**Smart Man.**	**Big Data**	**AI**	**CPS**	**Auto Robot**	**Aug. Reality**	**Cyber Security**
Taraglio et al. (2019)	X	X				X							
Unkovskiy et al. (2019)		X	X										
Pareek and Kaur (2019)	X	X		X									
Mannina et al. (2019)	X		X										
Alshamrani et al. (2020)	X	X	X	X									
Colorni andTsoukiás (2020)	X	X											
Shahin et al. (2020)	X	X											
Ramadan et al. (2020)	X	X	X		X			X		X			
Kamble et al.(2020)	X		X										
Trakadas et al. (2020)	X	X	X										
Utomo et al. (2020)		X	X								X		
Abd Rahman et al.(2020)	X	X	X	X				X					
Kocsi et al. (2020)	X			X				X					
Ito et al. (2020)	X	X	X	X				X					
Guo et al. (2020)	X	X		X									
Rahman et al. (2020)	X	X	X	X				X					
Farshidi et al. (2021)		X	X								X		
Sharma et al.(2021)		X											
Abd Rahman et al. (2021)		X											
Bergmann et al. (2020)	X		X										
Ivatury and Bonsa (2022)		X					X	X					
Kholil et al. (2022)		X			X								
Nouno et al. (2022)	X	X	X					X					
Logesh and Balaji (2020)		X	X										X
Yadav et al. (2020)		X											
Possik et al. (2022)	X	X											
Tanasić et al. (2022)	X	X											
Boonkanit and Suthiluck (2023)		X											
Su et al. (2023)	X	X											
Sekhar et al. (2023)	X	X	X	X			X		X				X

Based on the analysis in Table 2.7, previous studies have validated the effectiveness of the constructed framework, IoT, and LM Philosophy as its foundation. The relevance of the Proposed Inherent Modelis strongly supported by the current findings, demonstrating its potential application in the decision-making processes of Malaysian manufacturing companies. However, the connection required to measure improvements in the decision-making process remains unclear. Therefore, this research aims to explore both the direct and indirect impacts of the proposed inherent model in enhancing the efficiency of decision-making to support the growth of Malaysia's manufacturing sector.

2.11 The Development of The Conceptual Formulation

Given the problem highlighted in the Research Gap, this research's objective is to find a solution, specifically by developing more robust strategies to minimize human errors, particularly those related to data entry. Several key elements, as suggested by various researchers, contribute numerous concepts for understanding decision-making criteria through data utilization (Li et al., 2021; Bregar, 2022; Liou et al., 2023) However, the proposed framework places a significant emphasis on simulation modeling as a crucial aid for decision-makers.

2.11.1 System Architecture and Integration

IoT sensors are strategically placed across various stages of the production line, such as etching, cutting, and assembling, to capture real-time data on machine performance, cycle times, throughput, and material usage (Kasie et al., 2017; Liebrecht et al., 2021; Soori et al., 2023). This data is continuously transferred to a centralized cloud-based database, such as Firebase, where it is organized and stored for further analysis (Goodall et al., 2019; Wang et al., 2021; Ayvaz and Alpay, 2021).

2.12 LM integration

The system uses Line Balancing techniques to monitor production flow and control task allocation to workstations to reduce idle time and increase throughput (Lopes et al., 2021). Machine setup times are monitored through an integrated SMED system, with suggestions provided aimed at lowering setup times to increase production flexibility (Yazici et al., 2020). Additionally, the system incorporates a Kanban stock control system to maintain the availability of materials precisely when needed, thus lowering inventory costs while preventing wasteful overproduction (Gobachew et al., 2021). This prevention of overproduction is accomplished through the dynamic application of these LM tools which, based on information from IoT sensors, are implemented as needed (Kagermann et al., 2013).

2.12.1 Data Analysis and Decision-making

Potential disruptions are forecasted and production processes are optimised using predictive analytics along with statistical extrapolation (Gatla and Mandati, 2020). Based on continual study of data patterns, the system views and identifies inefficiencies, bottlenecks and various avenues for improvement (Bazargan-Lari and Taghipour, 2022). Integrated decision support models offer an analysed and synthesised form of insight that is actionable as output on dashboards and reports while also providing alerts in real time (Doukas and Nikas, 2020). Optimisation models were executed to provide specific LM tools and strategies that resolve the issues (Santos and Camacho, 2022). Additionally, the feedback loop observes the results of decisions made, where the system flexibly modifies its model based on the feedback, ensuring continuous improvement (Jelodar et al., 2021).

2.12.2 Reporting and Performance evaluation

DSS incorporates reporting features that allow production performance evaluation alongside the impact assessment of LM initiatives. These reports assist managers in understanding the performance dynamics of the production line, tracking their progress, and making informed decisions (Fera er al., 2019; Chen et al., 2021). DSS has becomes a holistic answer for integrating real-time data automation with LM tools, enhancing operational performance, eliminating non-value-adding activities, and enabling systematic refinement. This system conceptualisation guarantees that the structure is flexible, driven by a need for data, responsive to the demands of LM, and effective for strategic, tactical, and operational decisions across all layers of the production hierarchy.

2.13 Chapter Summary

This chapter presented a comprehensive review of LM principles and DSS within the context of Industry 4.0. It outlined the fundamental LM principles and highlighted how DSS enhances their implementation through data-driven decision-making and system optimization. The discussion incorporated three key philosophical paradigms, positivism, interpretivism, and pragmatism, which collectively underpin the methodological approach of this study. A systematic review of prior research from Scopus and WoS databases was conducted to identify gaps, particularly the limited integration of LM principles with intelligent DSS frameworks for manufacturing improvement. The chapter concludes by emphasizing that the synthesis of existing literature provides both the theoretical.

CHAPTER 3

METHODOLOGY

This research comprised three main phases. The Research Investigation phase employed a holistic approach to develop initial strategies and address RQ1, identifying the most used LM tools within existing DSS frameworks, thus fulfilling RO1, which established a foundational understanding of current DSS and LM implementations. Theory Development phase involved close-ended interviews with six experts and cross-sectional analyses of real production lines to address RQ2 and RQ3, fulfilling RO2 by formulating a novel correlation between DA and production models through IoT for LM integration. The final System Testament phase focused on verifying and validating the proposed framework, where verification tested IoT sensor connectivity and validation assessed technical and operational feasibility. This phase addressed RQ4 and fulfilled RO3 and RO4, confirming the model's functionality, practicality, and alignment with IR4.0 requirements. Together, these phases fulfilled all research objectives and established a comprehensive, defendable framework, as illustrated in Figure 3.1.

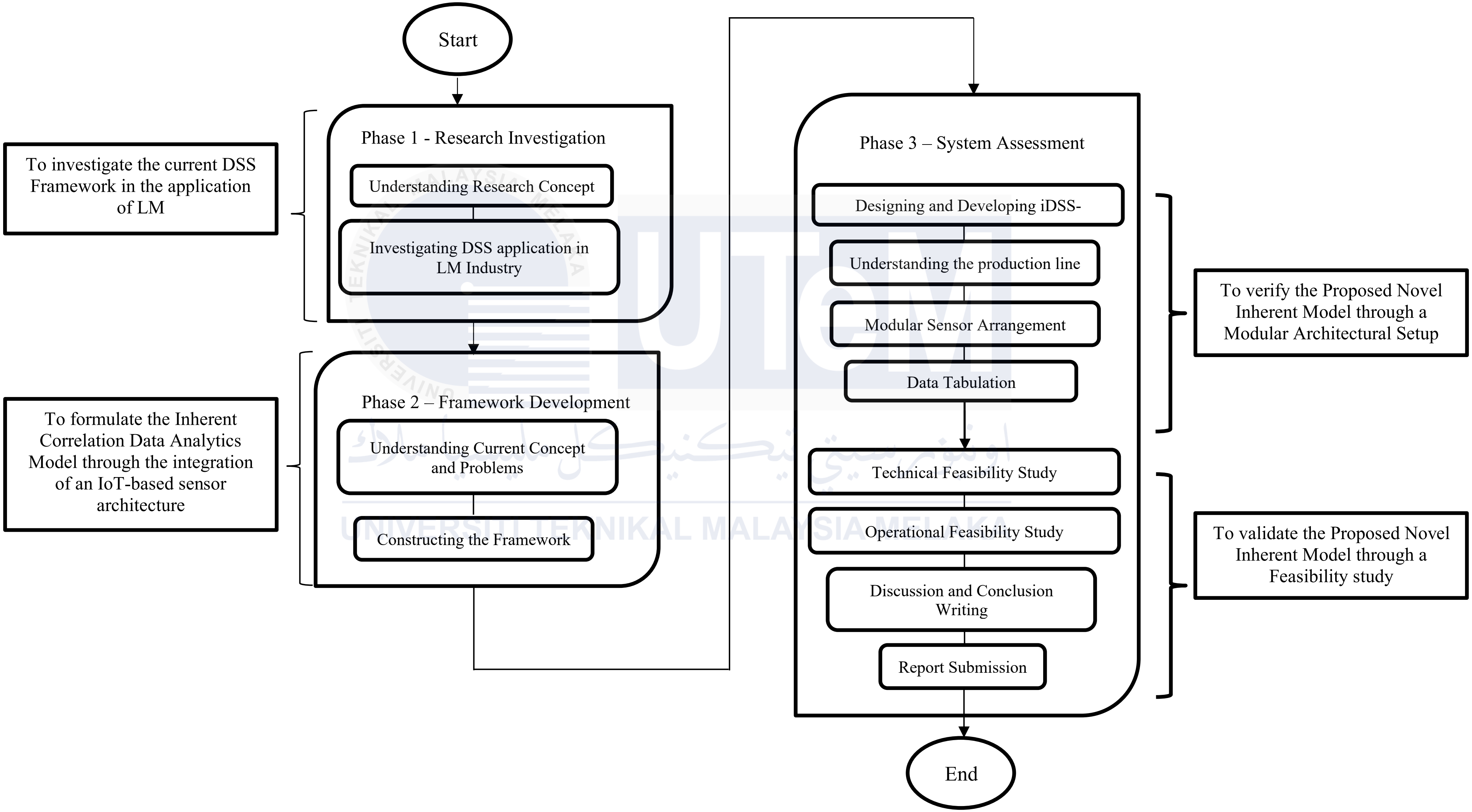


Figure 3.1 Research Phases According to Research Objective

3.1 Phase 1 - Research Investigation

This phase prioritised primary data collection, complemented by secondary sources, with a focus on exploring the convergence of DA and IoT within LM and their integration into existing DSS frameworks. To ensure the validity of the research instrument, the questionnaire was reviewed and validated by a panel of eight subject-matter experts. Their contributions helped refine the theoretical constructs by validating the relevance, applicability, and interdependencies among IR4.0 Enablers, Lean Manufacturing Systems (LMS), and Lean Manufacturing Performance (LMP). The experts' feedback enabled triangulation between existing literature, empirical data, and practical industry knowledge, thereby enhancing construct validity and contextual alignment.

In parallel, the cross-sectional analysis of quantitative data gathered from multiple manufacturing sectors facilitated the identification of consistent relational patterns across different operational environments. By integrating insights from both expert validation and cross-sectional evidence, the study established a robust theoretical foundation linking digital transformation to LM philosophy, ultimately advancing the conceptualisation of the iDSS-ProLean framework as a hybrid, data-driven decision support model for IR4.0-oriented Lean environments. The instrument achieved a Cronbach's alpha value of 0.762, indicating acceptable internal consistency and confirming that the items reliably measured the intended constructs, as presented in Table 3.1.

Table 3.1 Cronbach Alpha Interpretation

Cronbach's Alpha	**Interpretation**
>=0.9	Excellent reliability
0.8 – 0.9	Good reliability
0.7 – 0.8	Acceptable reliability
0.6 – 0.7	Questionable reliability
<0.6	Poor reliability

Determining the minimum sample size is not universally applicable, as it depends on various statistical factors and the specific research context. Although rigid rules do not exist, the determination of respondent size for quantitative analysis followed methodological standards. Based on Hair et al. (2017), at least 100 participants are recommended for operational analysis, while regression studies require 50 respondents or a 5:1–10:1 subject-to-item ratio. To confiem the adequacy of the sample size, this study employed the open sourced G*Power 3.1 calculator (Uakarn et al., 2021), for multiple linear regression with five predictors, Background Information, Impact on LM System, Impact on IR4.0 technologies, Impact of LM Performance, Understanding the current trend of IR4.0, a medium effect size ($f^2 = 0.15$), $\alpha = 0.05$, and power = 0.80 indicated a minimum of 300 respondents, ensuring sufficient statistical power.

A fixed-mode, closed-ended questionnaire ensured consistent data collection and minimized bias, with descriptive statistics and reliability testing via SPSS. Confirmatory Factor Analysis (CFA) validated construct reliability and model fit by assessing factor loadings confirming the accuracy of latent constructs, IR4.0 Technology Enablers, LM Systems, and LM Performance. In parallel, a systematic literature review supported the primary data, focusing on DSS applications aligned with LM and IR4.0. Searches in Scopus, WoS, and Emerald Insight (2011–2023) using "Decision Support System" and "Lean Manufacturing" yielded 2,023 articles, refined to 230 high-relevance papers following PRISMA guidelines, as shown in Figure 3.2.

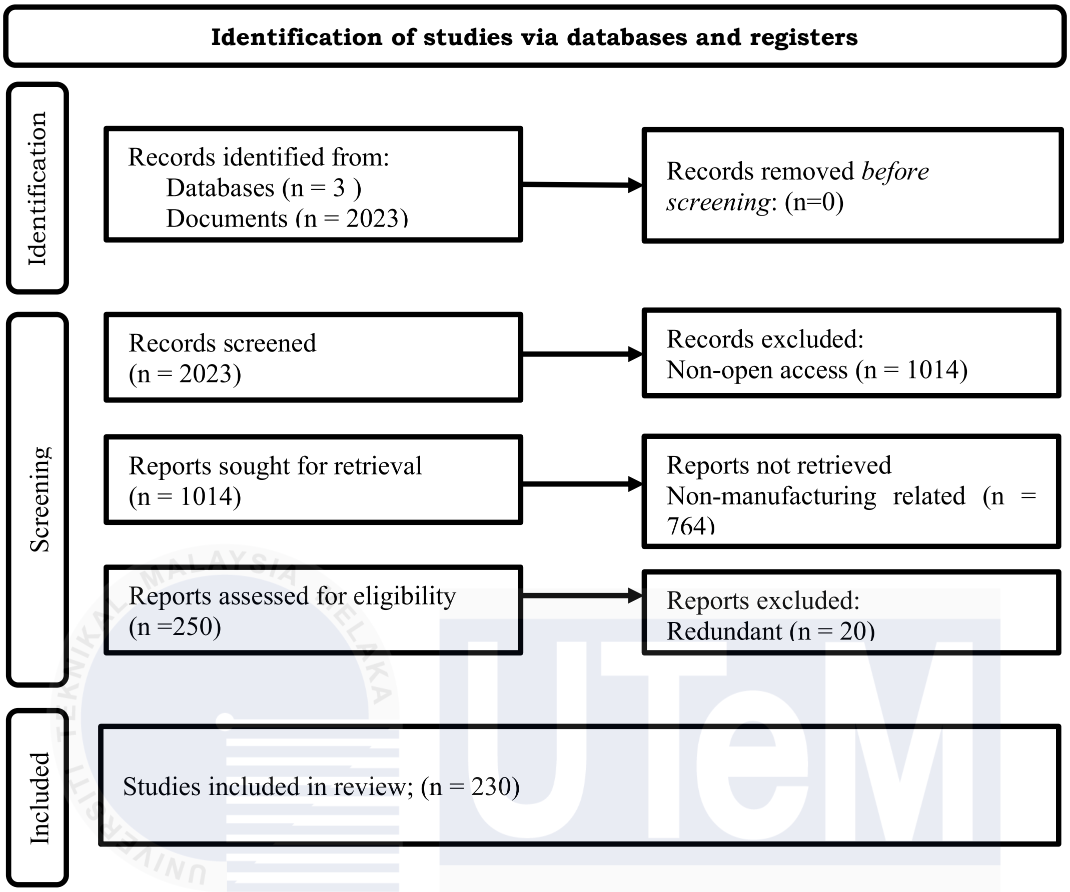


Figure 3.2 PRISMA Flowchart for 230 academic journals

These 230 articles were further analysed with respect to several dimensions, including: Objectives and benefits of DSS implementation, key components and features of DSSs, trends in technological development, user acceptance and adoption, case studies and application areas, design science methodologies, professional and industrial relevance, theoretical foundations, emerging challenges and future research directions and integration of DSSs with IR 4.0 technologies and the foundational design features required for building adaptable and intelligent decision-making systems in manufacturing contexts. By integrating these two methodological perspectives, this investigation captured both macro-level technological integration challenges and micro-level decision-making effectiveness. This combined approach ensured a comprehensive understanding of the current DSS framework within LM, addressing aspects required to achieve Objective 1. The complete process and findings from this phase are depicted in Figure 3.3 .

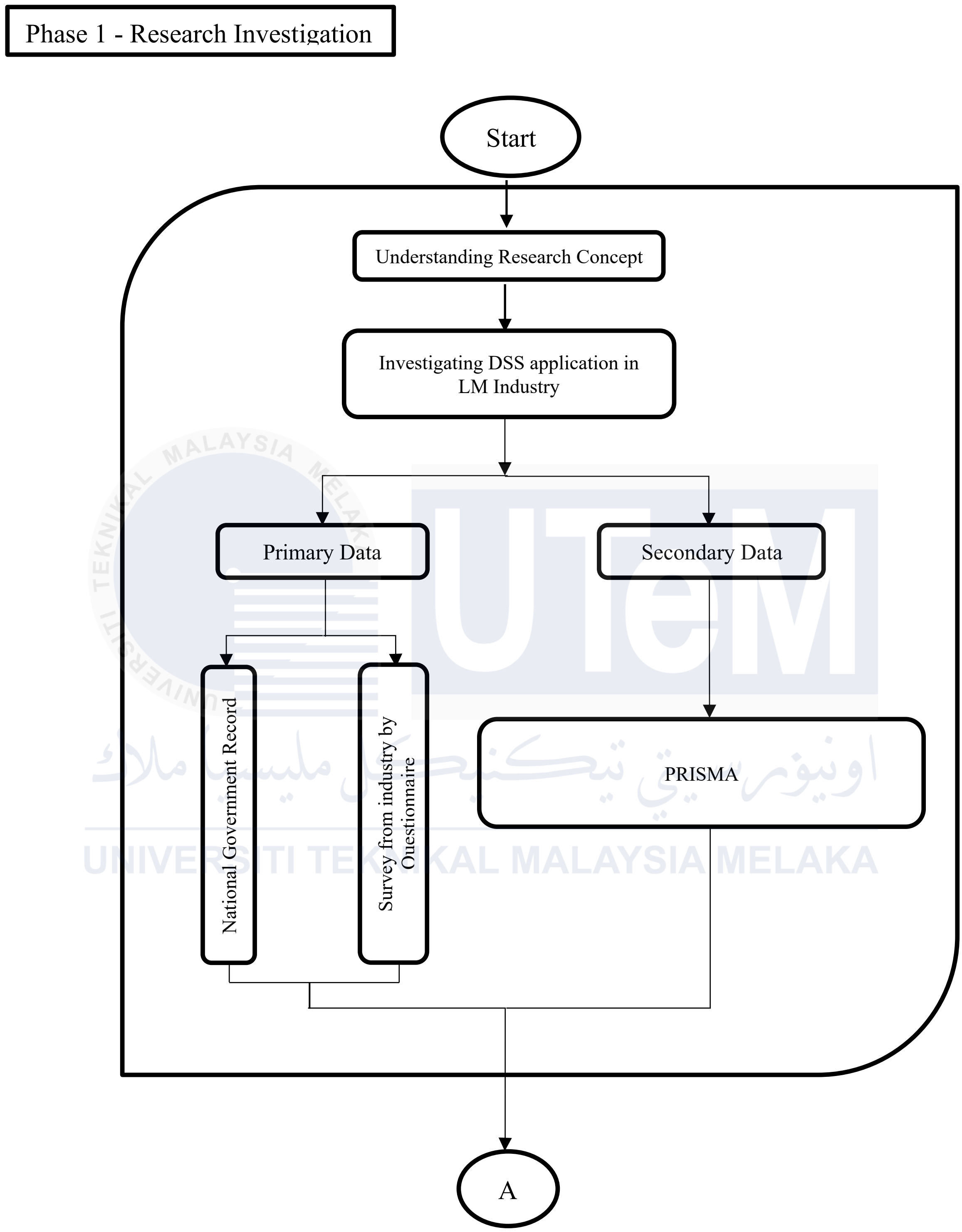


Figure 3.3 Research Phase 1

3.2 Phase 2 - Framework Development

The investigation conducted in the previous phase demonstrated that the application of DSS in LM required the development of iDSS-ProLean framework, which led to the initiation of Phase 2 of this research as shown in Figure 3.4.

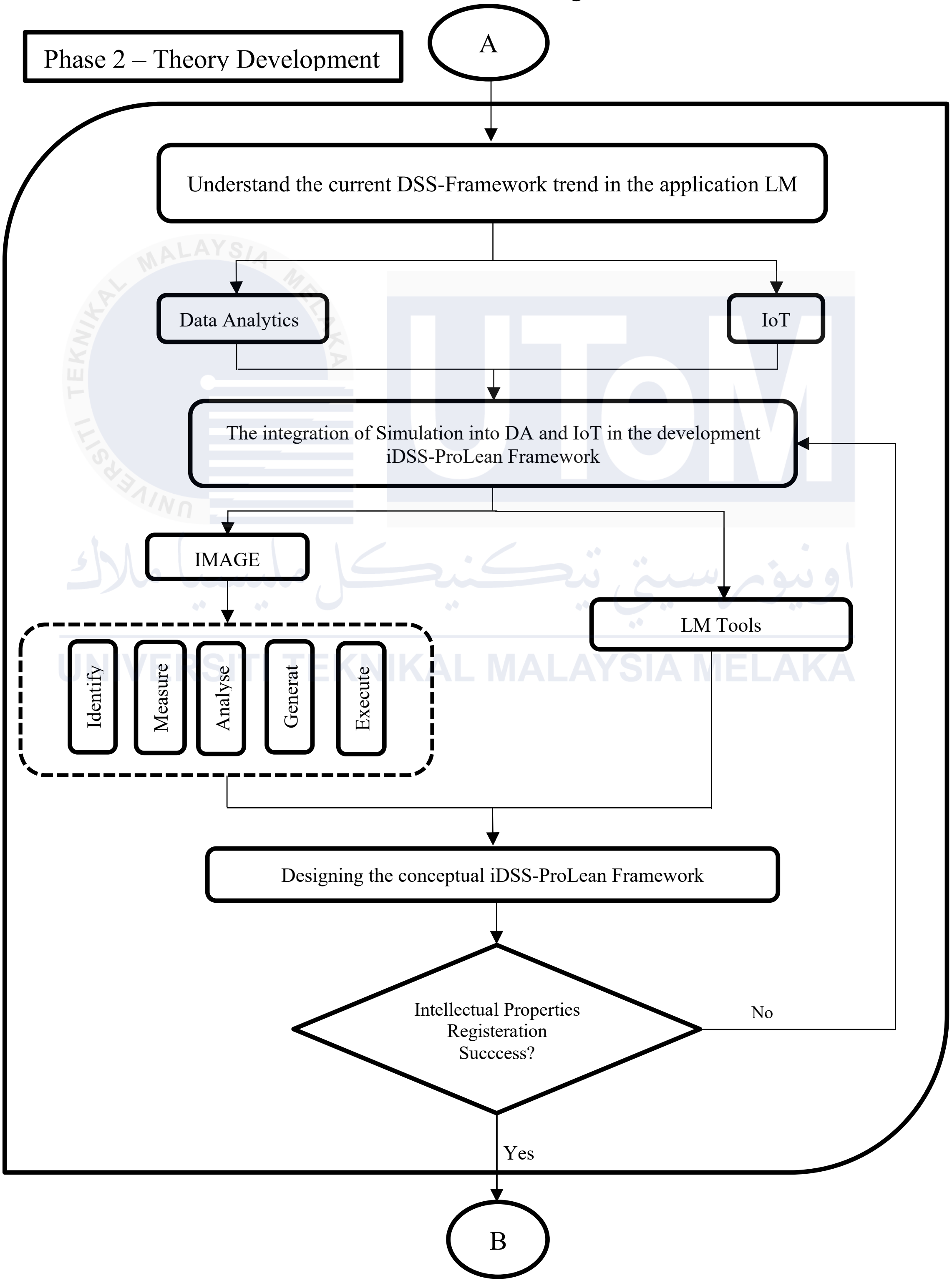


Figure 3.4 Research Phase 2

The development of iDSS-ProLean framework in this research was grounded in the integration of LM and the IoT to create a robust DSS for production line optimization. Central to this initiative was the incorporation of IoT enabling real-time data-driven decision-making. IMAGE formed the backbone for applying LM tools.. This structured approach ensured that decisions were based on actionable insights derived from real-time sensor data, addressing the gaps identified in Phase 1 of the research. The proposed *iDSS-ProLean*,Integrated Decision Support System in Manufacturing Production Line for Lean Manufacturing, was designed as a conceptual framework capable of identifying LM-specific needs, measuring key operational parameters via IoT sensors, analysing data through analytics techniques, generating actionable recommendations, and executing decisions in real time. The interactive, computer-based platform utilised IoT-enabled data management to support complex DSS processes and was structured into four key components: decision-maker, data management, and communication system. Figure 3.5 shows the proposed iDSS-ProLean framework.

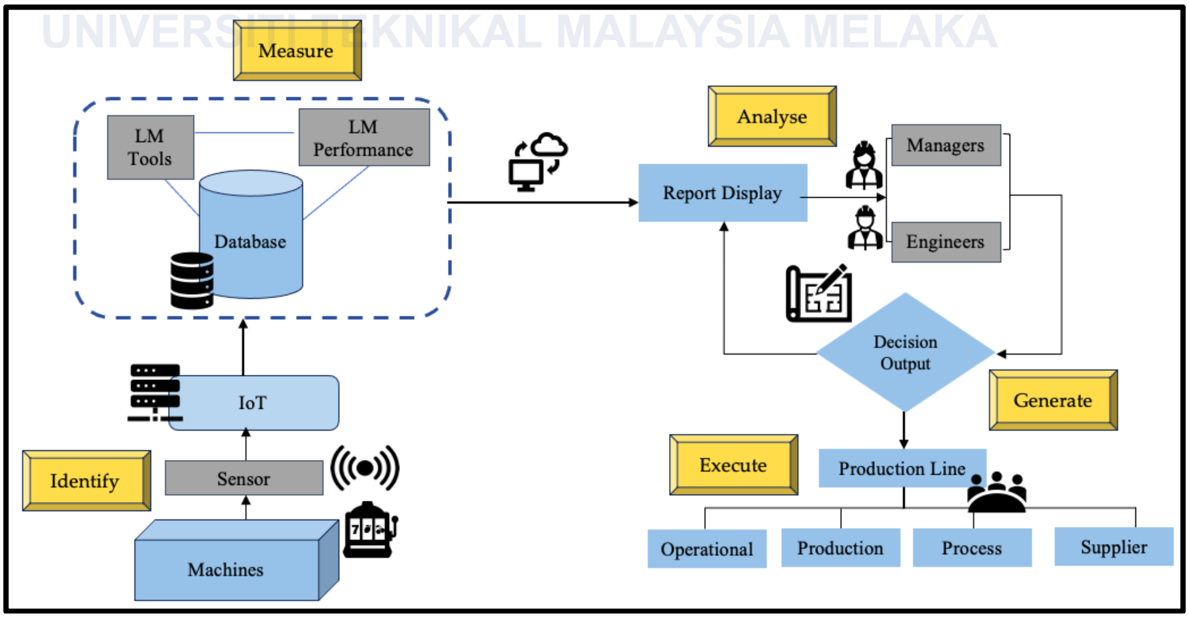


Figure 3.5 iDSS-ProLean Framework

The development of iDSS-ProLean framework incorporated a phased approach guided by LM principles and supported by appropriate technologies to optimize production line decision-making. The IMAGE process Identify, Measure, Analyze, Generate, and Execute was conceptualized to align with LM principles, ensuring a systematic transformation of production operations.

3.2.1 Identify

In the Identify, corresponding to the LM principle of specifying value, the use of sensors enabled the identification of key problems in the production line. Significant LM tools were used to uncover root causes and prioritize issues to address. iDSS-ProLean identifies issues specific to flow imbalance, prolonged setup times, and inventory mismatches by mapping them to respective LM tools: Line Balancing, SMED, and Kanban. Real-time data from integrated IoT sensors allows precise identification of problem areas across all machine stages, from etching to packing.

3.2.2 Measure

Measure phase, guided by the principle of value stream identification, employed Wi-Fi–enabled technologies to capture real-time operational data. These datasets were systematically uploaded to a centralised Firebase database and subsequently integrated into the LM formulations. Sensor-based parameters are recorded in real-time via the ESP32 module and sent to Firebase, capturing key values such as object distances for Line Balancing, temperature and vibration for SMED, and pressure for Kanban. These raw data streams are converted into relevant LM inputs like processing time, setup time, and material movement quantifying performance across the production line.

3.2.3 Analyze

Analyze phase, based on the LM principle of establishing flow, leveraged server-based sensors models to the replicate the production layout. Validation and verification of the models were conducted to align simulations with actual conditions, allowing planners and industrial engineers to identify waste and improve the process. The focus here was to streamline value delivery by removing inefficiencies and bottlenecks. Table 3.3 shows the Indicators used in for this phase.

Table 3.3 iDSS-ProLean Indicators

LM Tools	**Purpose**	**Indicators**		
		= 1	>1	<1
Line Balancing	Distribute workload evenly across workstations to prevent bottlenecks and underutilization	Perfect	Bottleneck	Underutilized
SMED	Reduce setup/changeover time to increase machine availability	Underutilized	Bottleneck	Perfect
	Baseline	50	>50	<50
Kanban	Manage inventory flow by producing or delivering materials only when needed	Stable	Stockouts	Overstocking

3.2.4 Generate

In Generate phase, the developed application delivered automated recommendations corresponding to each selected LM tool module. Users were granted the flexibility to select the specific LM tool most aligned with their operational objectives. Based on the system's analytical evaluation, the resulting output was categorised as either "Pass means Compliant" or "Fail means Inefficient", thereby enabling users to instantly assess their production performance without the necessity for manual computation or external analysis.

3.2.5 Execute

In Execute phase, corresponding to the pull value principle, applications were put into service to activate the enhanced processes. Scenarios derived from the prior step were executed according to the direction of the decision makers who ensured that the pre-defined objectives were achieved. The move cultivated a self-improving organisational culture that embraced the value of perfection and improved processes continuously. The illustration in Table 3.4 highlights the application of LM with IoT, DA and simulation technologies across the IMAGE phases where iDSS-ProLean framework with described emphasis creates a new solution framework on DSS for LM.

Table 3.4 LM Principles and IoT Technologies through iDSS-ProLean Framework

Phase	LM Principle	Technologies	Description
Image	Specify Value	Sensor	iDSS-ProLean identifies issues specific to flow imbalance, prolonged setup times, and inventory mismatches by mapping them to respective LM tools: Line Balancing, SMED, and Kanban. Real-time data from integrated IoT sensors allows precise identification of problem areas across all machine stages, from etching to packing.
Measure	Identify the Value Stream	WIFI	Sensor-based parameters are recorded in real-time via the ESP32 module and sent to Firebase, capturing key values such as object distances for Line Balancing, temperature and vibration for SMED, and pressure for Kanban. These raw data streams are converted into relevant LM inputs like processing time, setup time, and material movement quantifying performance across the production line.
Analyse	Establish Flow	Server	Using LM-specific formulas, the system calculates core performance Indicators: Line Balancing, SMED value, and Kanban number. This phase interprets the measured data to highlight whether a bottleneck, setup inefficiency, or overstocking condition exists. The analysis is fully automated within the app dashboard, allowing real-time interpretation aligned with LM thresholds.
Generate	Pull Value	Application	Based on the analysis output, the system generates a decision outcome. For example, SMED shows 'Pass' if setup is successfully reduced, and Kanban logic calculates whether inventory size meets LM requirements. This phase does not provide prescriptive recommendations but instead produces a binary or numerical result for user judgment.
Execute	Strive For Perfection	Dashboard	The final phase involves taking informed action based on the decision generated. Users typically engineers or managers can choose to rebalance machines, adjust setup protocols, or revise container sizes. The decision-making is supported by the app interface, making LM tool execution quicker and guided by real-time evidence.

3.3 Phase 3 – System Assessment

The final phase of developing iDSS-ProLean framework concentrated on assessing the framework which was crucial in guaranteeing that the proposed framework was effective and trustworthy. This phase was subdivided into two distinct categories: Verification and Validation. Verification focused on testing the modular sensor architecture framework; confirming that the sensor hardware and software components were functioning properly. Validation, in contrast, was performed via a Feasibility Research that analysed the practical aspects of implementing the system within real-world conditions. The validation focused on two dimensions: Technical Feasibility defined as the effort placed on measuring the actual work the system would be able to perform under the constraints of the production line's technology, and Operational Feasibility which measured the degree to which the output met the users satisfaction. All these assessments combined guaranteed that the framework was citing the convergence of being operationally ready to support LM-driven data-informed decision making in real time. Figure 3.6 displayed the last phase.

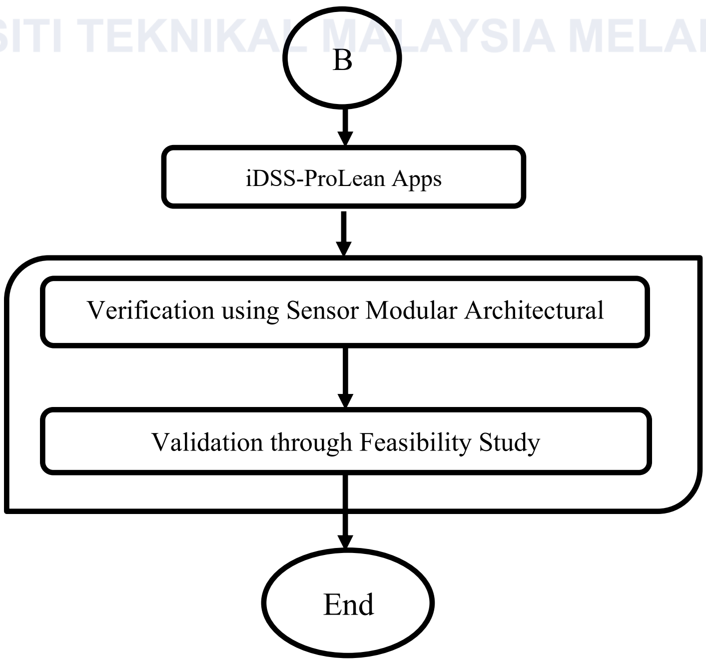


Figure 3.6 Research Phase 3

3.3.1 Verification using Sensor Modular Architecture Setup

a) Data Types Definition through LM Tool Integration

iDSS-ProLean framework integrates a comprehensive suite of functionalities designed to enhance production systems and reinforce LM principles. Collaboration with LM was essential, as its philosophy of waste reduction, process standardisation, and continuous improvement aligns directly with the framework's goal of achieving data-driven operational excellence. Through this integration, the framework not only automates decision support but also embeds LM Principles into every stage of production analysis. Collectively, as summarised in Table 3.5, Line Balancing ensured equitable workload distribution within the etch process, SMED minimised setup time, and Kanban streamlined material flow across operations.

Table 3.5 LM Formulation for iDSS-ProLean

LM Tools	*Data Formulation*	*Citation*
Line Balancing	$\text{Line Balancing Efficiency (LBE)} = \frac{\textit{sum of actual processing times}}{\textit{cycle time X number of workstation}}$ Cycle time = the maximum time allowed for each workstation to complete its tasks to meet the production demand. Number of Workstation = total number of station in the production line. For all processes; etching, cutting, assembling LBE should be as close to 1 as possible to indicate balanced workloads. If LBE < 1, some stations are underutilized If LBE > 1, there might be bottlenecks or inefficiencies	Chapman (2006), Womack and Jones (1997), Hitomi (2017),
SMED	$\text{SMED Value} = \frac{\textit{Total setup time before SMED}}{\textit{Total Setup time after SMED} - \textit{time reduction achieved}}$ Setup time before SMED = the time taken to prepare machines or switch tasks before implementing SMED. Setup time after SMED = The reduced time after applying SMED techniques.	Dennis (2017), antony et al., (2017), and Shingo (2019)
Kanban	$\text{Kanban Number (K)} = \frac{\textit{Demand Rate x Lead Time X } (1 + \textit{Safety Factor})}{\textit{Container Size}}$ Demand Rate = the number of units needed per time period. Lead Time = The time it takes from when an order is placed until its fulfilled. Safety Factor = a buffer to account for variability in demand or supply. Container size = the number of units per kanban card or signal.	Anderson (2010), Nicholas (2018), Ohno (2019)

b) Functional Description of Database Tables

The database for iDSS-ProLean framework was composed of several interconnected tables, each serving a specific purpose to manage and analyze production line data effectively. PROCESSES_TABLE was the central table containing critical production processes like etching, cutting, and assembling. It was the primary hub connecting to other tables in order to optimise the integration of LM tools and resources.

Meanwhile, MACHINES_TABLE contained machine-specific information related to each process, including their available time, capacity, and utilisation, which are critical for assessing machine efficiency in the operational workflow. MANPOWER_TABLE also monitored employees like technicians and engineers allocated to each process so that each workforce can be effectively used. For the integration of LM tools, the database contained KANBAN_TABLE, SMED_TABLE, and LINE_BALANCING_TABLE, which contained specific data relevant to inventory controls, setup time reduction, and process balancing respectively. These tables had a one-to-one relation with PROCESSES_TABLE, which ensured that each process was uniquely associated with an LM tool approach. In addition, the system recorded PRODUCTION_DATA_TABLE which contained real-time data of production including the demand, output, and performance of the processes. This table had one-to-many relationships with PROCESSES_TABLE where several data entries were permitted related to the ongoing production cycles.

Collectively, as illustrates in Table 3.6 , these tables provided a unified framework which helped iDSS-ProLean system in assessing, refining, and forecasting production results.

Table 3.6 Database Table for iDSS-ProLean

Production_Data Table:	**linebalancing Table:**
- timestamp	- total_processing_time
- temperature	- cycle_time
- pressure	- LBE_value
- humidity	
- vibration	**smed Table:**
- energy_consumption	- internal_setup_time
- daily_demand	- external_setup_time
- defects	- time_reduction
- quality_check_result	- smed_value
Processes Table:	
- process_id	**kanban Table:**
- process_name	- demand
- description text	- safety_stock
	- container_size
Manpower Table:	- kanban_size
- staff_id	
- staff_utilization_num	
Machines Table:	
- machine_id	
- machine_name	
- machine_utilization_num	

c) iDSS-ProLean Database Interrelations

After that, the systematic information configuration for iDSS-ProLean included the relationship schemas of tables which guaranteed the synchronisation of data, resources, and LM tools. The combination of one to many and one to one relationship provided optimum data circulation and functional interconnectivity. In accordance with Table 3.7, the PROCESSES_TABLE acted as a nucleus linking the MACHINES_TABLE and MANPOWER_TABLE by one-to-many relationships. This arrangement for each process, say etching, cutting, or assembling, allowed assigning multiple machine and manpower entries which provided flexible resource allocation.

Furthermore, the PROCESSES_TABLE was also linked to PRODUCTION_DATA_TABLE in a one-to-many relationship so that production pertaining to demand fulfilment, cycle times, and output can be tracked in real time. LM tools were incorporated through one-to-one relationships with PROCESSES_TABLE ensuring each methodology is applied accurately. In addition, the MACHINES_TABLE incorporated one to one relationship with LM tool tables for the machines and thus enabled tracking with regard to the specific machine. The MANPOWER_TABLE incorporated one to one relationship with the LINE_BALANCING_TABLE to allow control over workforce allocation concerning process balancing. These relationships enabled the database to capture various elements of production as a system providing optimised real-time processing and accurate automated decision-making.

Table 3.7 Database Relationships

Parent Table	*Child Table*	*Relationship*	*Relationship Name*
PROCESSES_TABLE	MACHINES_TABLE	One-to-Many (1:M)	Process-Machine Relationship
	MANPOWER_TABLE	One-to-Many (1:M)	Process-Manpower Relationship
	KANBAN_TABLE	One-to-One (1:1)	Process-Kanban Relationship
	SMED_TABLE	One-to-One (1:1)	Process-SMED Relationship
	LINE_BALANCING_TABLE	One-to-One (1:1)	Process-Line Balancing Relationship
	PRODUCTION_DATA_TABLE	One-to-Many (1:M)	Process-Production Data Relationship
MACHINES_TABLE	KANBAN_TABLE	One-to-One (1:1)	Machine-Kanban Relationship
	SMED_TABLE	One-to-One (1:1)	Machine-SMED Relationship
	LINE_BALANCING_TABLE	One-to-One (1:1)	Machine-Line Balancing Relationship
MANPOWER_TABLE	LINE_BALANCING_TABLE	One-to-One (1:1)	Manpower-Line Balancing Relationship
PRODUCTION_DATA_TABLE	KANBAN_TABLE	One-to-One (1:1)	Production-Kanban Relationship
	SMED_TABLE	One-to-One (1:1)	Production-SMED Relationship
	LINE_BALANCING_TABLE	One-to-One (1:1)	Production-Line Balancing Relationship

In addition, iDSS-ProLean database was designed to centralize key resources processes, machines, manpower, and production data as parent tables to ensure a stable and flexible foundation for LM analysis. This structure simplified relationships by allowing LM Tools to reference these core entities independently, ensuring modularity and adaptability. PROCESSES_TABLE defined essential production steps, guiding the allocation of resources and forming the basis for linking analysis tools like LINE_BALANCING_TABLE and KANBAN_TABLE. MACHINES_TABLE captured critical equipment data, enabling tools like SMED to optimize setup times, while its role as a parent table supported configuration flexibility. PRODUCTION_DATA_TABLE recorded real-time outputs and demand, integrating performance validation directly into the framework and enhancing the relevance of LM tools through real-time metrics. Table 3.8 depicted the significant of having Parents Table.

Table 3.8 Parents Table Significant

a) Centralize Key Resources: These represent the core entities that are foundational to the production line. b) Simplify Relationships: By focusing on these entities as parents, the database can establish clear and hierarchical relationships with other analysis tools. c) Flexibility In Analysis: This Structure allows LM Tools to be applied independently while referencing these core entities.	
processes_table	a) PROCESSES_TABLE defines the core steps in the production workflow, which are central to the semiconductor production line. b) Processes are crucial because they determine how resources were utilized. c) Other tables, like LINE_BALANCING_TABLE and KANBAN_TABLE, might have been linked to processes to analyze specific aspects like balance and inventory control.
machines_table	a) Machines are critical physical assets in the production line. b) Associating other tables with MACHINES_TABLE ensures a clear connection between machine performance and tools like SMED, which optimizes setup times and changeovers. c) Machines being a parent table allows for modular data management when new machines are introduced or configurations change.
production_data_table	a) PRODUCTION_DATA_TABLE encompasses the actual outputs and demands, which are essential for decision-making and validating framework performance. b) Linking KANBAN_TABLE and SMED_TABLE to production data ensures that real-time production metrics are integrated into the framework.

d) iDSS-ProLean IoT Network

Subsequently, the IoT architecture designed for iDSS-ProLean framework integrated key components necessary for real-time data collection, processing, and decision support in the semiconductor production line. At the core of this architecture, as illustrates in Figure 3.7, was the seamless communication between the frontend developed using Android Studio and the backend hosted on Firebase. Android Studio served as the user-facing interface, where production metrics, recommendations, and analytics were displayed in an intuitive format. On the backend, Firebase provided a robust platform for real-time data storage and synchronization, ensuring fluid interaction between the interface and data received from the IoT sensors embedded in the machines. The JSON-Android interchange acted as the communication protocol, facilitating structured data exchange between frontend and backend. In this architecture, IoT acted as the "vehicle" that delivered essential information from the physical machines to the decision-making dashboard, facilitating the framework's information handling capacity and providing large scale computations, automated insights, and in-the-moment production decisions all in a timely and efficient manner.

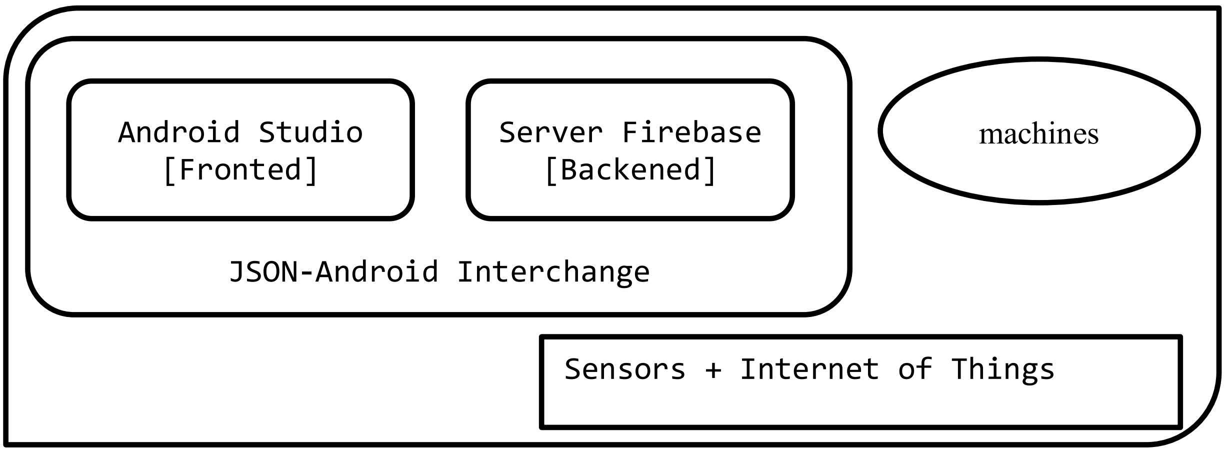


Figure 3.7 IoT Architecture for iDSS-ProLean

i) Frontend Development with Android Studio

iDSS-ProLean system used Android Studio as the main development environment in the user interface design, which simplified the interaction for the users of the system. Production stakeholders could rely on Android Studio to tailor their experience via an intuitive interface that adjusted responsively to their needs and expectations. Frontend was designed to enable interaction with the simulation models of the system, as well as monitor real-time data updates and issue alerts based on the simulations performed within the framework. The decision-makers could set model parameters and navigate through different scenarios using the application's rich features. The optimisation aimed at reducing the complexity of the interfaces so that the stakeholders could easily manipulate advanced IoT controls. Android Studio provided the means to develop fully fledged applications for any Android mobile device, enhancing usability and magnitude.

ii) Backend Integration and JSON-Android Interchange

Firebase, a cloud-based database and server, was responsible for managing data storage, synchronisation and real-time updates. As the machines' sensors captured data, the information was sent to be stored and processed in Firebase to be analysed in further steps. The JSON-Android interchange served as the interface between the front and backend sides of the system, performing data communications interchange. The Android application and the Firebase server were able to communicate through the JSON format, enabling the loading of data whilst adhering to the structure of JavaScript Object Notation. Through this format, the application was able to receive updates in real-time, while the processes from the user interface were sent to the server to be executed. Altogether, the architecture provided a solid and mutually responsive data flow which enabled iDSS-ProLean framework to facilitate dynamic decision making on demands.

e) iDSS-ProLean Interface

iDSS-ProLean interface acted as the focal point through which every user engaged with the decision support framework, synthesising links with a variety of LM Tools and real-time IoT system data. This interface was designed to permit effortless accessibility to the information relevant to production activities including production efficiency, machine performance, manpower utilisation, and the availability of raw materials for the managers, engineers, and decision makers concerned. The combination of data visualisations, dashboards, and real-time feedback guaranteed that users were enabled to make decisions that would improve operations, sustain optimum production levels, and ensure that LM tools. were properly utilised in operational performance enhancement.

Login and Register Screen, welcomed users into iDSS-ProLean framework. The interface displayed conspicuously the Login Button, which users could click to access the framework after providing their usernames and passwords, ensuring their identity ascertained the privacy and security of the framework. In consideration of user-friendliness, the login screen had “Forgot Password” as well as “Remember Me" options that expedited access. Additionally, for users without accounts, the interface featured a Register Button that took such users to a registration form where they captured key information such as passwords alongside name details. Requiring submission of the essential password along with the name ensured protected access as designed. Achieving both tasks on the same interface ensured that user experience was seamless while only entitled users could access the framework. Afterwards, users were expected to go back to the login screen where they would enter credentials to command the main dashboard. This systematic method ensured there was no reckless exposure of sensitive production information, analysis tools, or decision-making functionalities to unauthorised personnel while enabling them to work directly through the framework interactively.

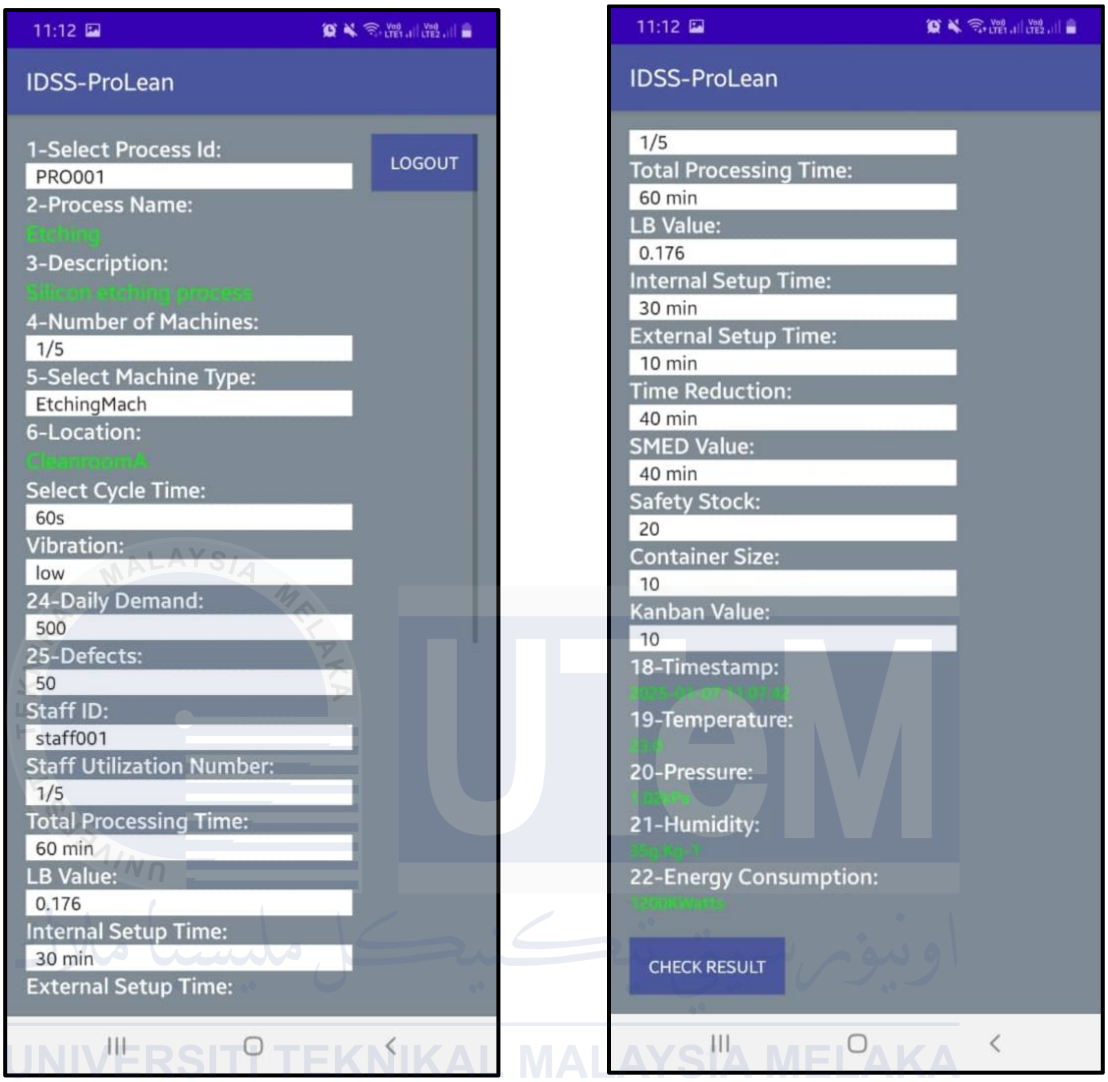


Figure 3.8 Data Display Screen for iDSS-ProLean

The second interface, as depicted in Figure 3.8, was termed the Data Display Screen, and it was here that the framework performs its core functionality. It provided a production line display dashboard that offered real-time information retrieved from the IoT sensors situated on the production line. The information received was multi-faceted, capturing elements such as the machine in operation, the raw materials being consumed, and the staff being utilised, enabling the engineers to control the entire production process instantaneously. In addition, users were able to set a production target for the day, which was monitored in terms of goals set and modifications needed regarding a set of defined metrics.

Figure 3.9 LM Tools Selection Interface

Completing iDSS-ProLean application interface with a focus on LM Tools Selection is shown in Figure 3.9 was built to work with real-time data and information collected from embedded sensors within the production machines. The set of predefined formulas served as the core or "brain" of the application. Based on this interface, users could choose the LM tool tailored therein to best match their preferences or areas of attention. Users were enabled to customise analysis as per their needs and make a prediction on the possible demand fulfilment efficiency. The users were empowered by the interface to make outcomes based on forecasts by LM Tools in relation to the organisational goals and pre-defined benchmarks.

Users had the option to log out of the framework after performing their analysis through a dedicated option on the user interface. Logging out ensured the session was securely closed while all the collected and calculated data remained accessible in Firebase for the future and the continuity of the framework. This systematic manner improved the decision-making process and at the same time ensured security and controlled access to the data.

f) Empirical Study using Sensor Modular Architecture

A sensor modular architecture referred to the flexible integration of multiple IoT-based sensors such as vibration, ultrasonic, and environmental sensors via a common microcontroller unit like the ESP32. Kalsoom et al. (2020) demonstrated how an IoT-enabled Kanban system using environmental sensors improved inventory transparency and production responsiveness in smart factories. Similarly, Duobiene et al., (2021) used vibration sensors to optimize SMED processes, reporting a 40% reduction in setup time. For line balancing, Ahmed et al. (2020) successfully applied ultrasonic sensors to track workpiece movement, enabling immediate feedback for station efficiency and bottleneck reduction.

The role of the ESP32 microcontroller in consolidating these sensor modules was further validated by Rendeiro et al. (2023), who confirmed its low-cost, Wi-Fi-enabled suitability for real-time LM data streaming. Collectively, these empirical studies affirm the methodological significance of adopting a sensor modular architecture in manufacturing environments, particularly for its scalability, cost-effectiveness, and ability to align IoT capabilities with LM objectives. Building upon the foundations laid by previous studies, this research advanced the field by integrating a sensor modular architecture specifically designed for LM decision support.

While prior studies, such as those by Zhang et al., (2020) and Ahmed et al., (2021), focused on isolated LM tools using sensor technologies, iDSS-ProLean framework provides a holistic approach that simultaneously monitors and optimizes multiple LM metrics Kanban, SMED, and Line Balancing through a unified, modular sensor system. Unlike the predominantly focused on one-to-one sensor-tool integrations, the modular architecture in this study enabled dynamic and flexible reconfiguration of sensors to cater to evolving LM needs across various production stages. This study contributed by utilizing a multi-sensor, multi-tool approach, integrating ESP32 as a central controller, and demonstrating real-time data transfer via Firebase, which ensures seamless communication between sensors and DSS. Table 3.9 shows the benchmark studies that supporting the sensor modular architecture used for iDSS-ProLean framework.

Table 3.9 Benchmark Studies Supporting the Sensor Modular Architecture

Study	*Sensor Type*	*LM Tools*	*Key Findings*	*Iot Platform*	*Contribution To LM*
Kalsoom et al. (2020)	Environmental Sensors (BMP280)	Kanban System	Improved inventory visibility and production flow	IoT-based system	Real-time Kanban control
Duobiene et al., (2021)	Vibration Sensors (SW-420)	SMED Optimization	40% setup time reduction	IoT-based system	Optimized machine setup time
Ahmed et al., 2021	Ultrasonic Sensors (HC-SR04)	Line Balancing	Efficient workpiece flow monitoring	IoT-enabled sensors	Balanced assembly line stations
Silva et al., 2022	ESP32 Microcontroller	Lean Manufacturing Implementation	Real-time monitoring capability	ESP32 with Wi-Fi	Low-cost solution for liveLM tracking

This modular architecture represented a semiconductor production line which is made up of three main stations: Etching, Assembling, and Cutting. Data collected in real-time from the production line was sent to Firebase and processed by iDSS-ProLean app. The conceptual understanding of semiconductor manufacturing processes was established through extensive literature review and critical engagement with scholarly resources. These interactions, coupled with a rigorous examination of current industrial practices, have informed the sensor arrangement for the mimicked production line in this study. As seen in Figure 3.10 , this research has implemented sensors to measure the production line activities to gather operational data.

In iDSS-ProLean framework, automation through sensors coupled with a microcontroller enabled real-time tracking and control of responsive production process optimisation. Environmental conditions such as temperature and humidity across the production line were monitored by the DHT22 to keep the operations within set parameters. The distance and movement of the materials were measured and tracked by the HC-SR04 ultrasonic sensor. The SW-420 vibration sensor tracked setup and changeover activities. The ESP32 microcontroller served as the main controller and coordinator in data gathering to be sent wirelessly to the Firebase database where the framework could conduct real-time evaluation and help automate the LM processes.

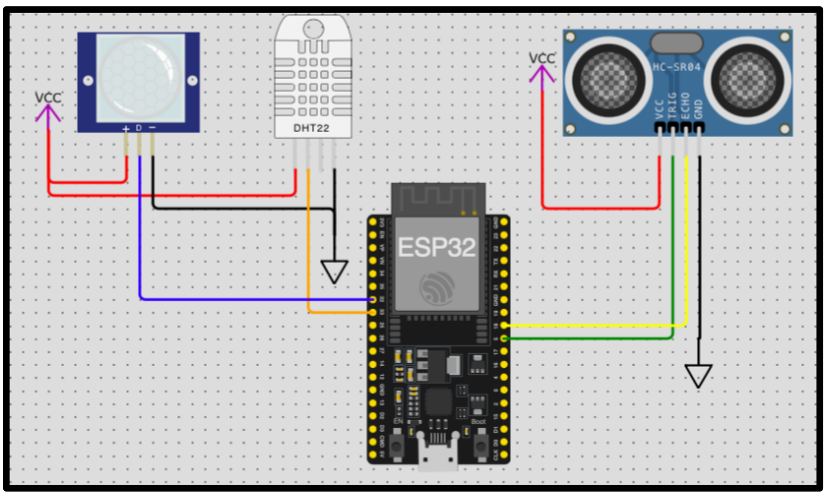


Figure 3.10 Sensors Architecture for iDSS-ProLean

iDSS-ProLean framework simulated a semiconductor production line including Etching, Cutting, and Assembling as major stages with sensors for real-time monitoring at each stage as shown in Table 3.10. Such input from the sensors made it possible to achieve precise data capture relative to each stage of the framework and thus improve performance, robust decision-making, and precision of iDSS-ProLean framework.

Table 3.10 Overview of Production Line Stages in the Mimicked Setup

Real Process	*Stage Description*
Etching	Simulates the process of imprinting patterns onto semiconductor wafers. An ultrasonic distance sensor is installed to measure the movement of wafers in and out of the station. This data is crucial for determining the cycle time and ensuring smooth flow into the next station.
Cutting	Mimics slicing wafers into smaller chips. A vibration sensor detects operational status and interruptions. This helps calculate processing time and identify bottlenecks, especially when the machine setup time increases.
Assembling	Represents the final stage where chips are assembled and packaged. A temperature and humidity sensor monitors environmental conditions that could impact assembly quality.

3.3.2 Validation through Feasibility Study

The final phase of developing iDSS-ProLean framework included verification and validation processes focused on determining the overall value of the framework, which was referred to as framework assessment. The initial verification of the framework was conducted using collected data from sensors where real-time sensor data was compared with simulated results to ensure the model operated within the expected bounds. This verification step ensured that the framework's calculations based on data were precise and trustworthy. After verification, iDSS-ProLean framework was subjected to validation in the form of an exhaustive feasibility study which was then divided into two primary parts these being Technical Feasibility and Operational Feasibility.

a) **Technical Feasibility**

Technical Feasibility Study evaluated the framework's operational suitability within actual industrial environments. In the beginning, a descriptive summary was created which included calculating the mean, median, Standard Deviation (Std. Dev.), and range for the collected data. This summary was useful in determining the distribution of data and in spotting any anomalies or trends that could potentially affect the framework's functionality in a practical context. To identify any differences in operational metrics prior to and following the incorporation of the framework, a paired T-test was performed on the sensor data from before and after its implementation. It was determined that the framework impacted production efficiency and LM operations significantly if the P-value obtained was 0.05 because the chances that observed changes where a product of random occurrence would be minimal.

60 trial runs was selected based on the Central Limit Theorem, which guarantees that the sampling distribution of the mean approximates normality when the sample size (n) is sufficiently large, typically $n \geq 30$ (Field, 2018; Tabachnick & Fidell, 2019). A conventional significance level of $\alpha = 0.05$, where the limit for the Type I error was controlled at $p \leq 0.05$. With 60 runs (df = 59), the corresponding t-critical value ($t = \pm 2.00$) confirmed that the distribution was stable and followed a normal assumption. Beyond theoretical justification, 60 runs were chosen to ensure reliability and stability of the sensor-based real-time measurements, providing low variability and consistent readings. The sample size also aligned with statistical power guidelines for paired T-test values stabilized beyond 60 observations and no longer fluctuate. From a practical standpoint, running thousands of tests was deemed infeasible; thus, 60 runs represented a balanced compromise, large enough to achieve statistical rigor while remaining feasible within production constraints.

A correlation test was carried out to test how closely related the most important variables, for example, the sensor values and production results, were. Strong and positive correlation between parameters confirmed the hypothesis that improvement in one aspect translates to gain in another in the formulation. The practical steps and estimated time to impact the production workflows are described in detail within the Technical Feasibility section of this report. Overall strategies and considerations in estimate accuracy were presented in Figure 3.11.

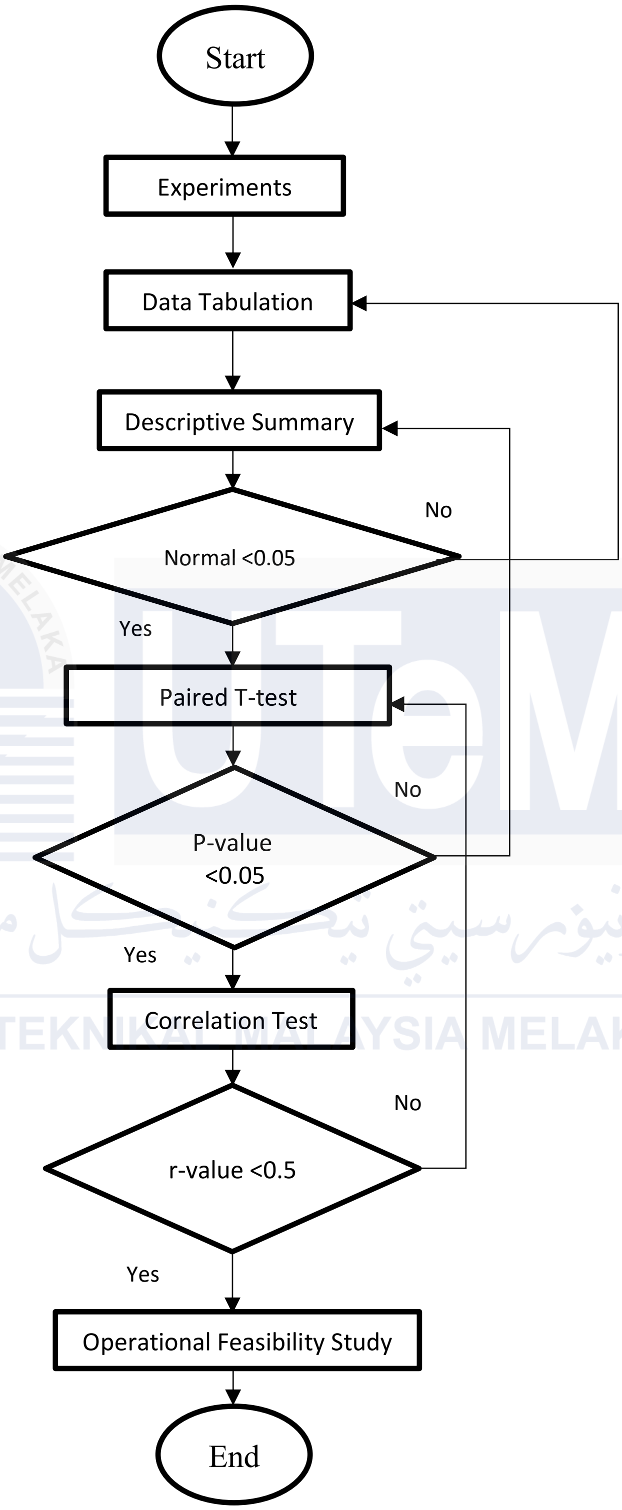


Figure 3.11 Technical feasibility flow chart

b) **Operational Feasibility Study**

This phase was crucial in appreciating LM practitioners' considerations regarding efficacy, flexibility and impact in evaluating a framework's actual use. To convert user feedback into measurable data, a fixed-mode, closed-end loop questionnaire served as the data collection tool to transform qualitative insights into quantitative measures. It was divided into three main parts: Demographics, Framework Adaptation, and User Experience. Demographics section gathered contextual information such as participants' experience, company sector, and IR4.0 knowledge, ensuring representation across diverse manager and engineering role. These details enriched the analysis by linking technical engagement levels to user expectations. Consistency and reliability between in-person and online questionnaire data collection were ensured through the use of identical instruments, question sequences, and response formats across both modes. The online version was pre-tested to confirm that its layout, structure, and Likert scale mirrored the printed version precisely. Additionally, time restrictions and submission controls were implemented online to replicate supervised conditions in in-person sessions.

Framework Adaptation section analysed heuristic alignment of iDSS-ProLean frameworks with workflows alongside their processes and digital tools. It evaluated the framework's alignment on the accuracy of information inputs and outputs. At the same time, the User Experience section examined how iDSS-ProLean frameworks interface and contributed to the productivity and efficiency of daily operational tasks in congruence with LM principles. Participants evaluated real-time information provision and framework-enabled decision-making in addition to interface aesthetic and step-less work conduct. The 20 items surveyed of the subject's experiences used a 5-level Likert scale for analysis, with '1' being Strongly Disagree and '5' Strongly Agree, thus framing open-ended opinion analyses for diverse evaluative factors on user experience design.

The results from this tool confirmed the operational efficiency of the proposed framework. In their responses, users claimed that the framework was simple, did not require much disruption and adequately supported primary LM functionalities like Line Balancing, SMED, and Kanban. The framework was able to seamlessly integrate with the workflows or business processes in place without major resource or effort expenditures. Moreover, participants recognised the framework's potential for improving processes, reducing operational footprint, improving real-time decision-making capabilities, and decision-making advanced through real-time DA and insights.

i) Respondents Size Determination

Respondent sample size for this phase was determined using the same procedure employed in the first phase, through the G*Power 3.1 calculator. Based on a multiple linear regression model with two predictors, Framework Adaptation and User Experience, and applying a medium effect size ($f^2 = 0.15$), an alpha level of 0.05, and a desired statistical power of 0.80, the analysis indicated that a minimum of 70 respondents was required. Adopting the same methodological parameters ensured consistency and comparability across the research objectives, while guaranteeing that the statistical tests conducted possessed adequate power to detect significant relationships among the variables examined in the operational feasibility study.

ii) Pilot Study for Reliability Analysis

Prior to the main study, a pilot study was conducted with 11 participants to test the reliability of the survey instrument using Cronbach's Alpha technique. This test evaluated the internal consistency between the questionnaire items. For the pilot study to run smoothly, all items on the questionnaire were configured as Scale in the SPSS Variable View.

Each participant's response was subsequently entered into the Data View section in SPSS. The reliability analysis to compute Cronbach's Alpha was done in SPSS. It entailed navigating to Analyse → Scale → Reliability Analysis, ensuring all Likert-scale responses were included in the analysis. The calculated value of Cronbach's Alpha for the pilot study was 0.835, which confirms the pilot study results have claimed, stated reliable in accordance with standards. Hence, no significant alterations were necessary to the reliability instrument for it to be used in the full study.. The pilot study further confirmed the reliability of the questionnaire, validating it for the full data collection achievement stage.

iii) Data Collection

Respondents were chosen for this study based on their work in LM ecosystems as well as their knowledge of IoT networks. They were sourced from professional networks such as LinkedIn and other colleagues who were directly engaged with LM and IoT applications. All respondents worked for companies that implement IoT frameworks in their production processes, meaning that they possessed at least some understanding of data transfer processes through the internet an important aspect for this study. For this purpose, participants were contacted through various professional channels, including Zoom, phone, LinkedIn chats, and emails. This method of recruitment was effective since it targeted participants with relevant hands-on experience of IoT applications in manufacturing industries. To maintain ethical standards, all responses were collected with full assurance of anonymity and confidentiality. No personally identifiable information was recorded or disclosed, and all data was handled with strict discretion to protect the privacy of the participants. Respondents were informed of the study’s purpose and voluntarily consented to participate.

3.4 Chapter Summary

This chapter presented the research methodology developed to achieve the stated objectives systematically through three interconnected phases. The Research Investigation phase established the foundation by identifying knowledge gaps, understanding the relationships between key factors, and defining the essential dimensions of DSS and LM to enhance comprehension of the existing DSS framework in LM implementation. Theory Development phase expanded this foundation by acquiring data through literature reviews and expert interviews to determine the input parameters required for integrating DSS and IoT within LM Tool, leading to the formulation of an empirically grounded theoretical framework. The final System Testament phase verified and validated the framework through rigorous technical and operational feasibility studies, ensuring its practicality, functionality, and performance in real production environments. Collectively, these phases provided a structured and defendable approach that guided the overall research process, contributing significantly to the development of an integrated and reliable DSS framework for LM implementation within the context of IR4.0.

CHAPTER 4

RESULT AND ANALYSIS

4.1 The Investigation of the Current DSS Framework in the LM Implementation

The investigation of the current DSS framework within LM formed the foundation of the study. As LM evolved under the IR4.0 paradigm, it became crucial to examine how DSS could bridge conventional LM principles with modern technological demands, enhancing decision-making efficiency while aligning with LM Tools and IR4.0 enablers. A total of 303 valid responses were obtained from 208 manufacturing firms nationwide, reflecting a 68.6% response rate, with all firms reporting prior or ongoing LM implementation. Collected data were analysed using hypothesis testing via P-values and CFA focusing on the interrelationships among IR4.0, LMS, and LMP through Path Coefficient values. Statistical significance was assessed at the 0.05 level, where P-values > 0.05 indicated insufficient evidence to reject the null hypothesis (H0). While the P-value alone did not confirm a hypothesis, it provided statistical evidence supporting or refuting the tested relationships.

The results were as follows:

- **Case 1**

  H0: There is a correlation between IR4.0 and LMS.

  H1: There is no correlation between IR4.0 and LMS.

  → Therefore, there was a correlation between IR4.0 and LMS ($p = 0.897$).

- **Case 2**

  H0: There is a correlation between IR4.0 and LMP.

  H1: There is no correlation between IR4.0 and LMP.

  → Therefore, there was a correlation between IR4.0 and LMP ($p = 0.980$).

- **Case 3**

  H0: LMP affects the indirect correlation between IR4.0 and LMS.

  H1: LMP does not affect the indirect correlation between IR4.0 and LMS.

  → LMP did affect the indirect correlation between IR4.0 and LMS ($p = 0.876$).

Table 4.1 was utilised to draw conclusions based on the P-values determined during the hypothesis testing process. At the 0.05 significance level, all null hypotheses were retained. The three elements IR4.0, LMP, and LMS demonstrated significant relationships, with path coefficient values of 0.897, 0.980, and 0.876, respectively. The structural interrelationships between IR4.0, LMS, and LMP were validated through path coefficient analysis. The results revealed a strong dependence between IR4.0 and LMS, with a path coefficient of 0.897, indicating that the adoption of IR4.0 technologies significantly supported the implementation of LMS. A direct and statistically significant relationship was also observed between IR4.0 and LMP ($p = 0.980$, ***), signifying the pivotal role of IR4.0 technologies in enhancing manufacturing outcomes. Furthermore, the indirect relationship between IR4.0 and LMP, mediated through LMS, yielded a path coefficient of 0.876, thereby confirming that LMS acted as a crucial mediating variable in translating digital transformation efforts into measurable performance gains.

Table 4.1 Hypothesis Test Results

Hypothesis	*Path Coefficient (P)*	*Significance*	*Conclusion*
IR4.0 – LMS	0.897		Dependence
IR4.0 – LMP	0.980	***	Dependence
LMP – IR4.0 – LMS	0.876		Dependence

*** indicates significance at $p < 0.05$

Several existing studies support the significant relationships among IR4.0, LMP, and LMS, particularly in promoting sustainability, production synergies, and operational efficiency. Buer (2018), Totorella (2018), and Ito et al. (2020) argued that integrating IR4.0 technologies with LMS enabled optimisation of production processes and improved resource efficiency through waste minimisation. For instance, IoT-enabled sensors facilitated real-time collection of machine performance data, enabling predictive maintenance and reducing downtime, while AI and Big Data applications enhanced production control and supported continuous improvement initiatives. Ghobakhloo (2019) further emphasised that IR4.0 functions as an LM enabler, with success contingent on the degree of LMS integration with IR4.0 technologies and LM tools such as Jidoka and Value Stream Mapping (VSM). Additionally, Ghaithan et al. (2021) highlighted the tangible benefits of IR4.0 and LMP within the Malaysian manufacturing context.

Following the path analysis, CFA was conducted to determine the direction and strength of correlations among all variables across the cases. CFA validated the factor structure of observed variables and assessed the construct validity of the measurement model, ensuring that the observed variables accurately represented the underlying latent constructs, namely IR4.0 enablers, LMS elements, and LMP, including indicators such as employee involvement, cost reduction, and waste elimination. After CFA validation, Factor Loadings (FL) were extracted to quantify the strength of association between observed indicators and their respective constructs.

Table 4.2 CFA for IR 4.0, LM Systems, and LM Performance

Instrument Details	Factors Loadings	Mean	Std. Dev.
IR 4.0			
Our organizations implement;			
Additive Manufacturing	0.833	3.733	1.325
Cyber Physical Framework	0.820	3.727	1.326
Smart Manufacturing	0.733	3.689	1.261
Artificial Intelligence	0.685	3.444	0.791
Big Data	0.935	4.866	1.204
Simulation	0.905	4.487	0.785
Cloud Computing	0.835	3.834	1.216
Augmented Reality	0.882	3.754	1.197
IoT	0.998	4.575	0.694
Automation	0.854	3.706	1.233
System Integration	0.821	3.963	1.114
LM Systems			
Our organizations implement			
Kaizen	0.789	3.522	0.532
Kanban	0.765	3.214	0.783
PDCA	0.643	3.252	0.671
OEE	0.891	3.524	1.453
5S	0.876	3.523	0.897
JIT	0.756	3.135	0.732
Jidoka	0.745	3.512	0.712
TQM	0.934	4.165	1.867
KPI	0.835	3.421	0.783
VSM	0.982	4.231	1.781
TPM	0.761	3.452	0.321
LM Performance			
Our organizations notice;			
Employee Involvement	0.876	3.546	0.918
Cost Reduced	0.765	3.765	0.831
Waste Reduced	0.987	4.453	1.398

Based on the results in Table 4.2 , the structured relationship model was developed to examine the interactions among IR4.0 technologies, LMS, and LMP. The objective of this analysis was to validate the hypothesised constructs and understand the strength of associations between key elements influencing LM implementation outcomes in the context of digital transformation.

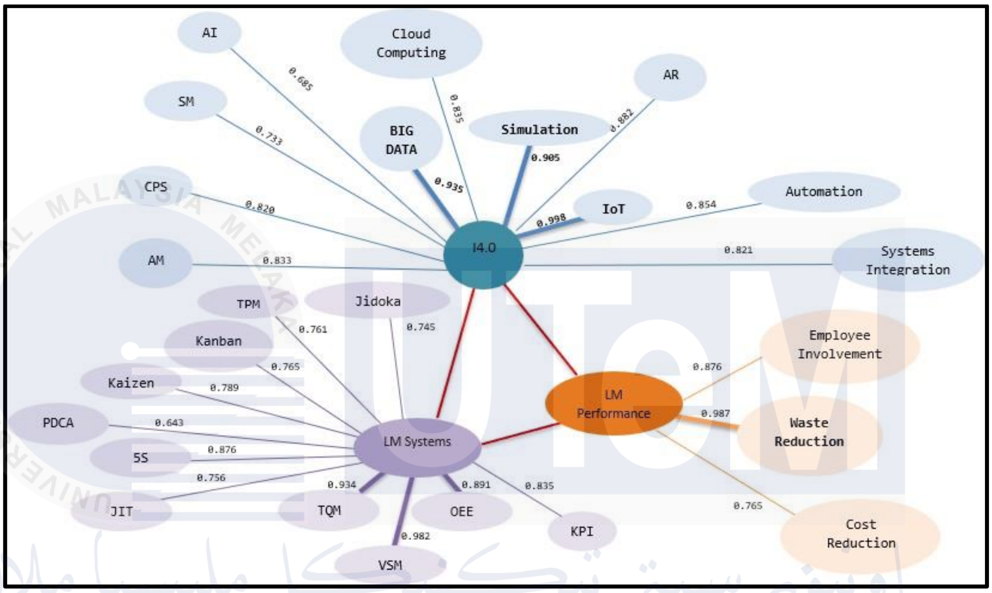


Figure 4.1 Relationship Model based on the Factor Loading Value

As illustrated in Figure 4.1, the model highlights the interconnected roles of IR4.0 technologies and LMS in enhancing overall LMP. CFA analysis confirmed the construct validity and reliability of latent variables, with factor loadings sufficiently high to support each observed variable under its respective construct. The results revealed that IR4.0 technologies strongly influence LMS implementation (path coefficient = 0.876), with Big Data (0.935), Simulation (0.995), and IoT (0.990) being the most impactful indicators. Among LM frameworks, Total Quality Management (TQM, 0.934), Value Stream Mapping (VSM, 0.982), and Overall Equipment Effectiveness (OEE, 0.891) had the strongest effects, while the relationship between LMS and LMP was also robust (0.794).

A moderately strong direct effect was observed from IR4.0 to LMP (0.684), with waste reduction identified as the most significant performance measure (0.987), followed by cost reduction and employee involvement. These findings indicate that IR4.0 technologies positively impact performance metrics, but their effect was maximised when mediated by robust LMS, supporting a synergistic integration of digital technologies. The study provided a data-driven foundation for the thesis by quantifying the influence of IR4.0 on LMS and LMP, identifying the mediating role of LMS, and revealing gaps in current DSS applications and industrial readiness. These insights informed the development of the iDSS-ProLean framework, ensuring it is both theoretically grounded and practically applicable for future LM environments in the IR4.0 era.

4.2 The Formulation of the Inherent Correlation DA with IoT Framework iDSS-ProLean

Following the prior investigation of the interrelationship between IR4.0, LMS, and LMP, the framework established in this study was strategically designed to address the identified gaps and benchmark insights. IDSS-ProLean framework was systematically formulated around five progressive phases, IMAGE, each representing the inherent correlation between DA and IoT) within LM decision environments. These five phases aligned directly with the five core principles of LM: (1) Specify Value, (2) Identify the Value Stream, (3) Establish Flow, (4) Strive for Perfection, and (5) Pull Value. This alignment ensured that each step of data acquisition, processing, and decision-making remained grounded in LM formulation while leveraging the speed and scalability of IR4.0 technologies as illustrates in Figure 4.2 .

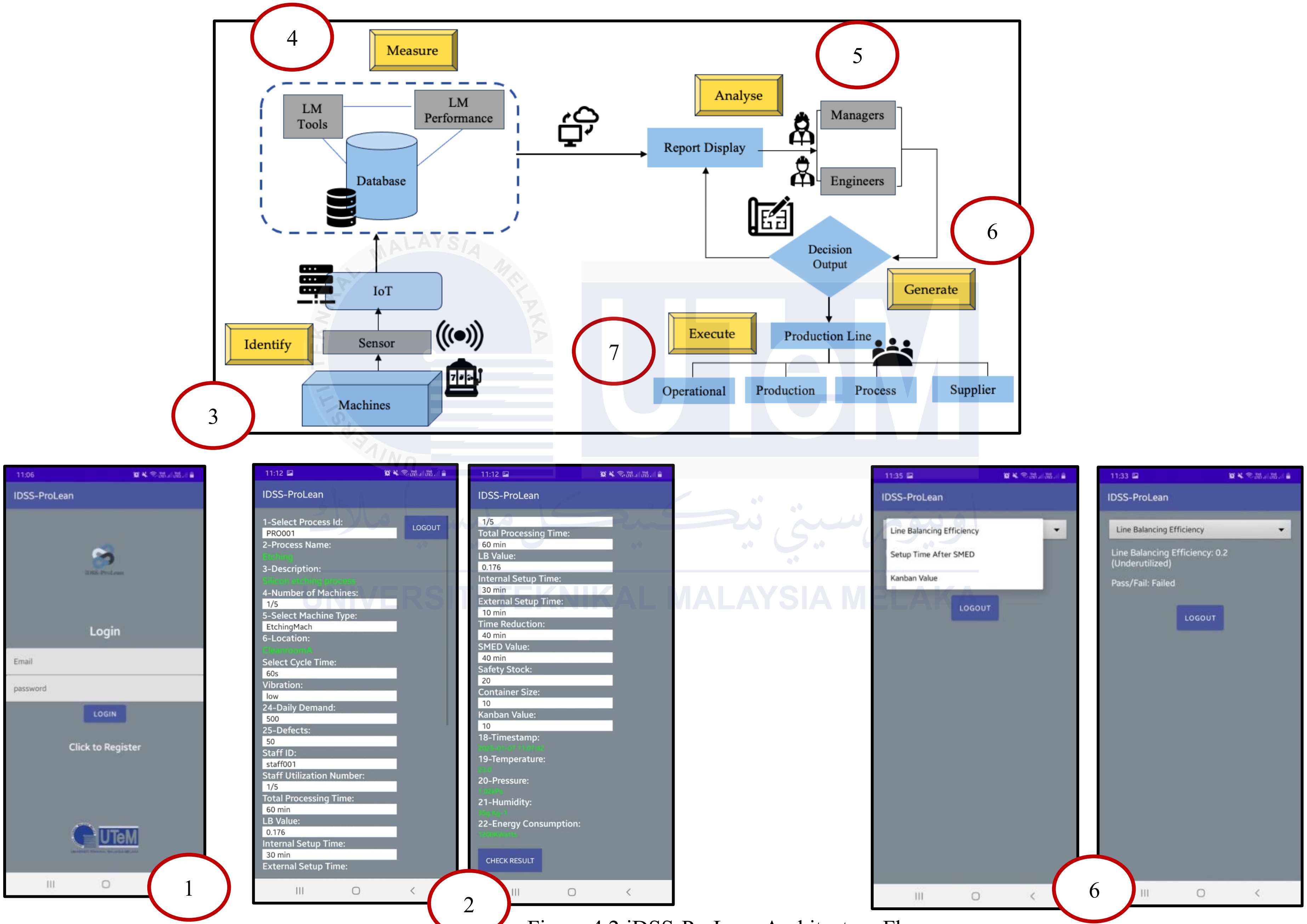


Figure 4.2 iDSS-ProLean Architecture Flow

The detailed operational flow is described to provide a transparent understanding of how each phase in the iDSS-ProLean framework functions in practice. This step-by-step explanation is essential to demonstrate how the application translates real-time sensor input into structured LM decisions through IMAGE phases.

1 **The user launched the iDSS-ProLean mobile application**

The process began when the user launched the iDSS-ProLean mobile application via the Android home interface, initiating interaction with the system's user interface layer developed in Android Studio. Upon launch, the user was immediately prompted to log in using existing credentials or register a new account an essential step that enabled secure, traceable access to the system, with authentication managed through Firebase to ensure seamless connectivity with backend processes.

2 **The application autonomously received real-time sensor data**

After successful authentication, the app transitioned to the data reception interface. At this point, the system began streaming live input from the attached ESP32 microcontroller, which had been interfaced with multiple sensors:The data transmission occurred wirelessly over WiFi and required no manual user input. All sensor readings were automatically recorded in Firebase.

3 **The system performed the Identify phase**

During this phase, the system categorized the production conditions based on sensor input, identifying which machine or process stage was currently active. This allowed the system to map each reading to a specific LM tool context, ensuring relevant analytics were applied.

4 **The system proceeded with the Measure phase**

The app quantified operational parameters in real-time, including processing times, bin levels, setup durations, and ambient conditions. This information was essential for calculating performance against LM standards. Data integrity was preserved through timestamped logs, all of which were synced to the Firebase cloud backend.

5 The system analyzed the collected data through embedded LM logic

In this Analyse phase, the system computed the key LM indicators based on the input received:

$$LBE = \frac{Total\ Processing\ Time}{Cycle\ Time\ x\ Number\ of\ Machines} \quad \text{(i)}$$

$$SMED = \frac{\text{Setup Time Before}}{(\text{Setup Time After} - \text{Time Reduced})} \quad \text{(ii)}$$

$$Kanban = \frac{(Demand\ x\ Lead\ Time\ x\ (1-Safety\ Factor))}{Container\ Size} \quad \text{(iii)}$$

Using these formulas, the system evaluated whether each module met LM efficiency thresholds. The outcome was displayed on the decision interface in the form of visual cues and binary outputs.

6 The application generated a decision output for the user

In Generate phase, the app provided a clear recommendation for each selected Lean tool module. Users had the flexibility to choose which LM tool they wished to engage with Line Balancing, Kanban, or SMED based on their operational focus. Depending on system evaluation, the output was marked as either "Pass – Compliant" or "Fail – Inefficient", allowing users to immediately understand the status of their current production state without the need for manual calculations.

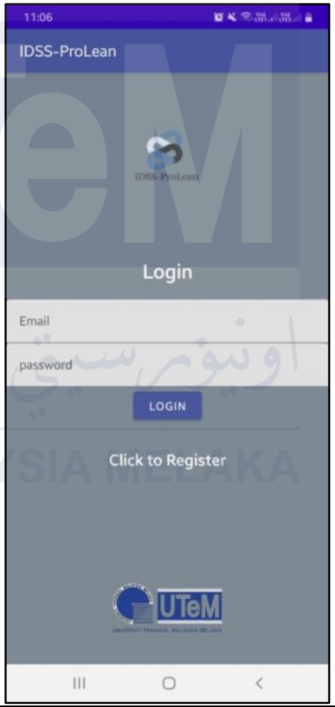
7 The user executed action or exited based on system recommendation

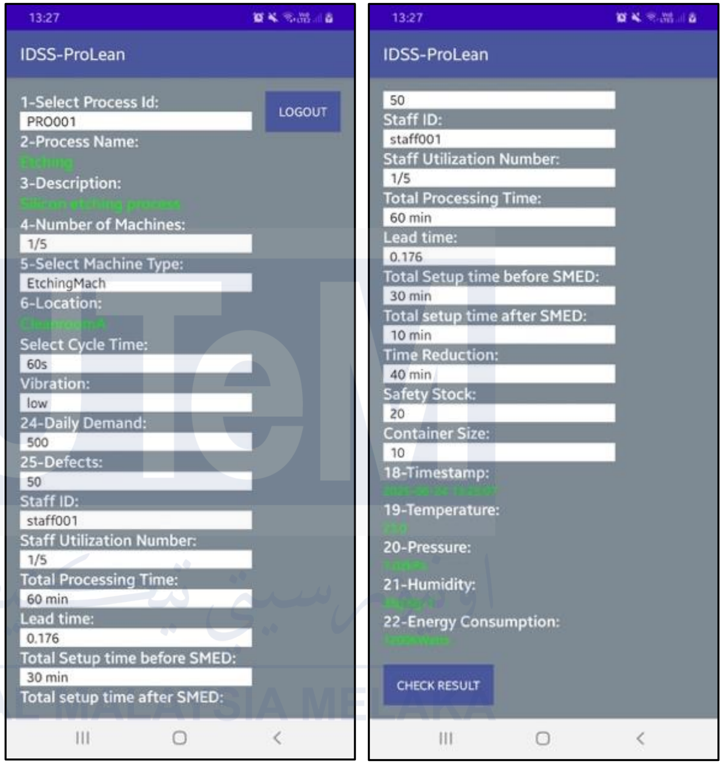
Finally, in the Execute phase, users were given the option to take corrective actions based on the output. For instance, they could reconfigure workstation allocation for LBE, reduce changeover steps for SMED, or adjust container sizes for Kanban. Regardless of action taken, all session data were automatically saved in Firebase, ensuring traceability for future decision-making. The user could then choose to log out, completing the operational cycle.

4.2.1 Standard Operating Procedure for iDSS-ProLean apps

To ensure effective and consistent usage of iDSS-ProLean system among industrial users, a SOP was developed to guide users through each step of the application's operation. This SOP outlines the sequence of actions required to operate the app, from launching the interface to monitoring real-time sensor data and generating reports. It serves as a reference manual for users to understand the modular components of the system, including Line Balancing, SMED, and Kanban. Each step is presented in a clear, numbered format accompanied by visual screenshots to enhance usability, especially for first-time users or those unfamiliar with IoT-integrated DSS. The following Table 4.3 details the complete SOP for iDSS-ProLean application.

Table 4.3 System Workflow SOP of iDSS-ProLean Mapped to IMAGE Framework Architecture

Framework Phase	***Procedures***	***Description***
Launch Application	User opens the iDSS-ProLean app from the Android home screen.	
	Login or Register	User logs in using existing credentials or registers a new account. 

Identify	***Data Reception Interface***	*Real-time sensor data (from HC-SR04, SW-420, DHT11, BMP280) is received via ESP32 microcontroller. No manual input is needed.*	

Analyse	**Decision Interface**	The app processes incoming data and displays a decision dashboard to the user.
	Select LM Tool	User selects one of the LM tools: – Line Balancing– SMED – Kanban 

	View Decision Output	Based on analytics, the app shows status such as: – “Pass” or “Fail”. 
Generate	**User Action**	User choose to follow the system’s suggestion or make adjustments to machine settings towards the production line
Execute	**Logout**	User logs out of the app. All session data is automatically stored in Firebase.

For recognising originality and contribution, iDSS-ProLean Framework was accurately registered under the Copyright Act 1987 [Act 332] and Voluntary Notification Regulations 2012. Categorized as a literary work, it was registered on 10 June 2024 under Notification Number: CRLY2024M03200. The registration was filed by Universiti Teknikal Malaysia Melaka as the owner, with authorship acknowledged to Effendi Bin Mohamad, Mohd Soufhwee Bin Abd Rahman, and Nur Ain Qistina Binti Muhammad Shafee. This recognition validated the novelty and intellectual contribution of the developed framework in integrating LM tools with IoT-based technologies for real-time manufacturing decision support.

4.3 The Verification of the Proposed Inherent Model – iDSS-ProLean, through Modular Sensor Setup using the Selected LM tools.

The case study was conducted on a semiconductor back-end assembly line comprising seven sequential stages, structured around three core processes: etching, cutting, and assembling. This production configuration served as the experimental foundation for validating the iDSS-ProLean framework, which integrates LM tools, IoT-based sensors, and real-time data retreived to enable informed and responsive decision-making. At the Raw Material Receipt stage where silicon wafers arrived in batches, sensors were not installed, as disruptions in this phase were primarily administrative rather than operational in nature. Nevertheless, downstream effects were indirectly addressed through the Kanban formulation within iDSS-ProLean.

In contrast, the Etching Machine, highly sensitive to humidity and pressure fluctuations, was equipped with DHT11 and BMP280 sensors to capture environmental conditions in real time, supporting improved setup optimisation and buffer stock planning. The Laser Cutter Machine, crucial for maintaining flow continuity, was fitted with an HC-SR04 ultrasonic sensor to monitor material movement and detect idle time. Meanwhile, the Die Bonder Machine, representing the assembly stage and identified as a major production bottleneck, was embedded with an SW-420 vibration sensor to detect setup fluctuations and operational delays. Conversely, the Inspection and Packing Machines were not instrumented, as their performance dependencies were largely upstream and did not directly influence the LM Tools under evaluation. The scalability of the iDSS-ProLean framework was demonstrated through its modular and adaptable architecture, which enables seamless application across varied production contexts such as etching, cutting, and assembling. The integration of IoT sensing, real-time analytics, and LM Tool allows the framework to be recalibrated to match specific process characteristics and operational requirements.

In the etching and cutting processes, sensors captured precision timing, vibration, and environmental parameters, whereas in assembly operations, the framework facilitated workload synchronisation and just-in-time material flow. Its cloud-based decision support structure enables rapid algorithmic adjustment and data-driven reconfiguration without requiring hardware modification, ensuring flexibility across product types and production scales. Finally, the Shipping Section functioned as the final control point to align daily production outputs with delivery targets. Although this stage was not equipped with sensors, it was incorporated into the Kanban formulation within iDSS-ProLean to ensure that upstream operations consistently met real-time demand and inventory thresholds. The overall semiconductor production layout is illustrated in Figure 4.3.

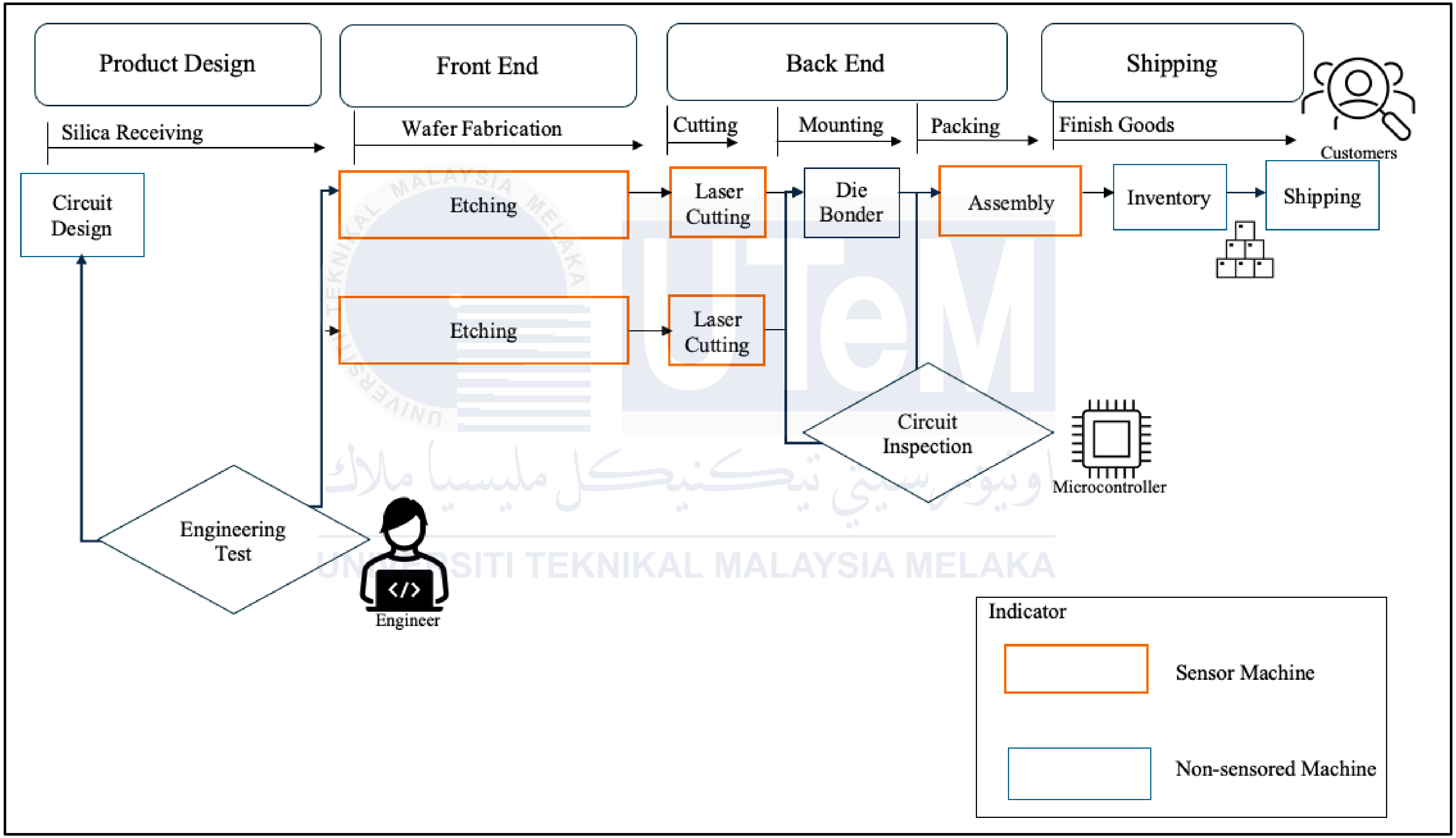


Figure 4.3 Overview of Sensor Deployment Across Semiconductor Stages

4.3.1 Case study 1: Line balancing

a) Identify Specify Value

In the semiconductor back-end assembly line examined in this study, a major issue identified was the uneven workload distribution among five key stations, Etching, Laser Cutter, Die Bonder, Inspection, and Packing, arranged in a serial flow. The Die Bonder often exhibited longer processing times, while downstream machines such as the Packing Station remained idle, disrupting production rhythm and causing delays, underutilisation, and missed output targets. Conventional line balancing relied on manual observation and shift-end reports, lacking accuracy and real-time responsiveness, which led teams to respond only after inefficiencies occurred.

To overcome this, the iDSS-ProLean framework introduced a sensor-integrated architecture for real-time workload monitoring and automated Line Balancing Efficiency (LBE) computation. Each station was fitted with an HC-SR04 ultrasonic sensor to detect workpiece entry and exit through distance changes, generating precise timestamps for processing activities. Data were transmitted to an ESP32 microcontroller for initial processing and then uploaded to the Firebase Realtime Database via Wi-Fi.

The framework compared real-time processing data against the LM-based efficiency formula to locate and quantify line imbalances, providing immediate feedback for corrective action in line with LM's goal of continuous, waste-free flow. Data were managed through structured tables, LINEBALANCING_TABLE, MACHINES_TABLE, and PROCESSES_TABLE, which stored metrics such as processing time, cycle time, and LBE values, continuously updated from sensor input.

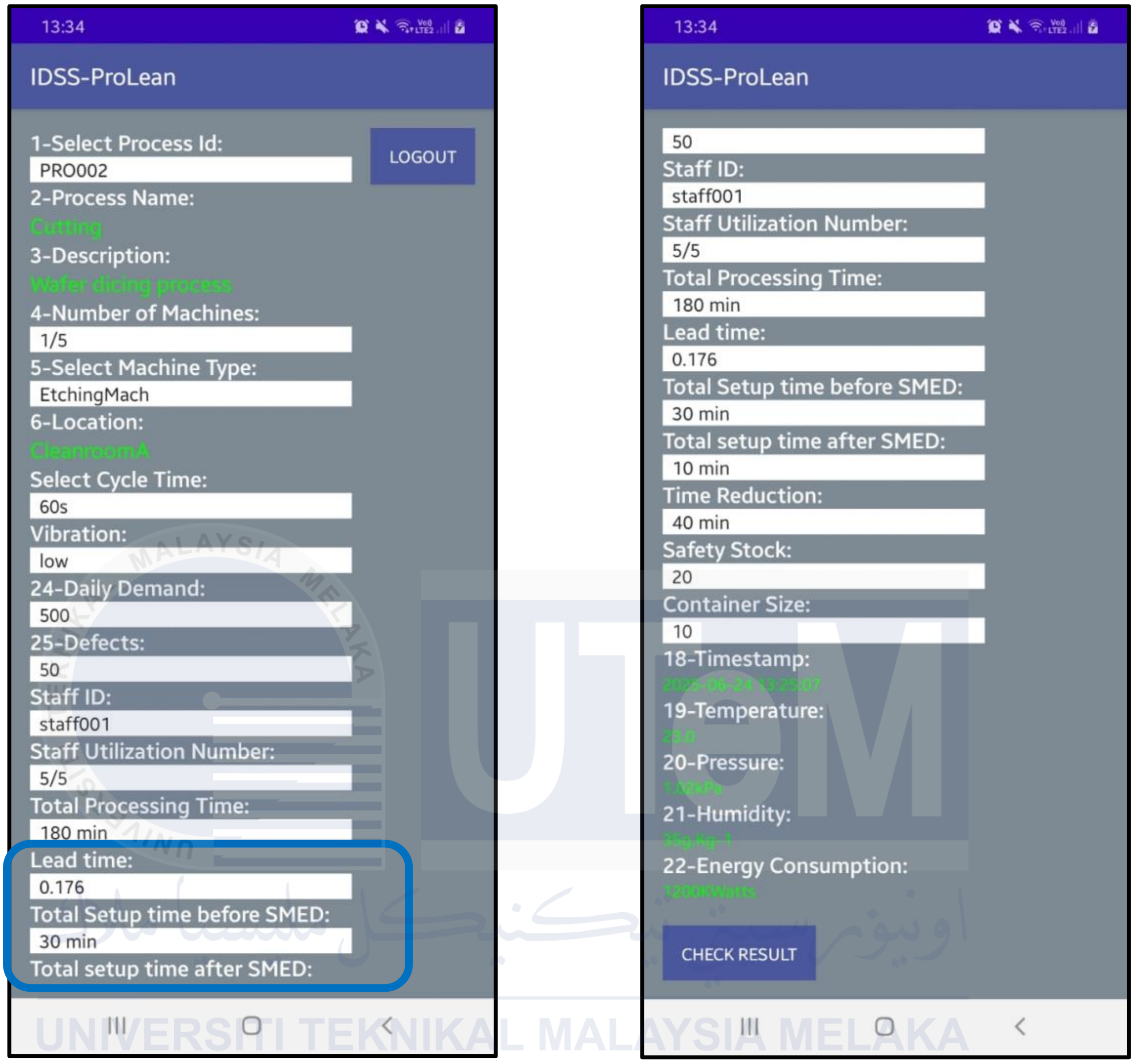


Figure 4.4 iDSS-ProLean Interface for data retrieval from sensor

As illustrated in Figure 4.4, the iDSS-ProLean Line Balancing interface captures and visualises real-time processing times for each workstation, together with the calculated LBE value. This interface provides operators and decision-makers with an intuitive, real-time overview of machine performance and workload distribution across the line. The displayed data are dynamically retrieved from the LINEBALANCING_TABLE, which stores parameters such as TOTAL_PROCESSING_TIME, CYCLE_TIME, and the computed LBE_VALUE, ensuring that all values reflect live production conditions rather than estimations or post-shift reports.

b) **Measure Value Stream Mapping**

In this case, the NoM was fixed at five. The framework automatically calculated LBE for every completed trial run, based on the time data retrieved from the sensors and structured through the Firebase backend. A total of 60 trial runs were conducted and recorded using this architecture as shown on Table 4.4 . The resulting LBE values served as the primary performance metric to assess whether the line was balanced and capable of achieving flow efficiency.

Table 4.4 Trial runs for LBE case study

Apps Running	*Number Of Machines*	*TPT*	*Cycle Time*	*LBE*	*Apps Running*	*Number Of Machines*	*TPT*	*Cycle Time*	*LBE*
1	5	150	30	1.0	31	4	141	34	1.0
2	4	100	25	1.0	32	3	77	25	1.0
3	3	80	28	1.0	33	3	100	32	1.0
4	4	133	34	1.0	34	5	159	32	1.0
5	3	90	29	1.0	35	3	65	22	1.0
6	5	160	32	1.0	36	4	132	34	1.0
7	3	65	22	1.0	37	3	73	25	1.0
8	4	131	34	1.0	38	3	100	32	1.0
9	3	75	25	1.0	39	5	155	30	1.0
10	3	100	32	1.0	40	4	100	25	1.0
11	5	155	32	1.0	41	3	80	28	1.0
12	3	65	22	1.0	42	4	133	34	1.0
13	4	130	34	1.0	43	3	90	29	1.0
14	3	74	25	1.0	44	3	69	22	1.0
15	3	97	32	1.0	45	4	142	34	1.0
16	3	67	22	1.0	46	3	77	25	1.0
17	4	132	34	1.0	47	3	100	32	1.0
18	3	72	25	1.0	48	5	155	32	1.0
19	3	100	32	1.0	49	3	65	22	1.0
20	5	156	32	1.0	50	4	130	34	1.0

21	3	69	22	1.0	51	3	77	25	1.0
22	4	134	34	1.0	52	3	100	32	1.0
23	3	78	25	1.0	53	3	65	22	1.0
24	3	100	32	1.0	54	4	131	34	1.0
25	5	155	32	1.0	55	3	77	25	1.0
26	3	69	22	1.0	56	3	100	32	1.0
27	4	131	34	1.0	57	5	157	32	1.0
28	3	78	25	1.0	58	3	65	22	1.0
29	3	100	32	1.0	59	3	65	22	1.0
30	3	66	22	1.0	60	4	132	34	1.0

For evaluation purposes, the LBE values were categorized into three key groups: values less than 1 indicated underutilization of resources, a value equal to 1 represented a perfectly balanced line, while values greater than 1 signified the presence of bottlenecks or overburdened stations. In the initial measurement phase Before, as shown in Figure 4.5 , the distribution of results revealed clear inefficiencies. Out of the 60 runs, only 2 trial runs achieved the ideal LBE of 1. Meanwhile, 20 trial runs recorded LBE values less than 1, indicating idle time or underloaded machines, and the remaining 38 trial runs exceeded an LBE of 1, pointing toward overworked stations or delays. This imbalance was likely due to inconsistent task allocation across machines and unstandardized processing times, both of which are common causes in manual or semi-automated production settings. These results emphasized the need for a systematic framework like iDSS-ProLean to facilitate data-driven balancing and optimize the flow of work across the line. This classification provided a clear quantitative baseline to assess the initial inefficiencies across the production line prior to the optimization process.

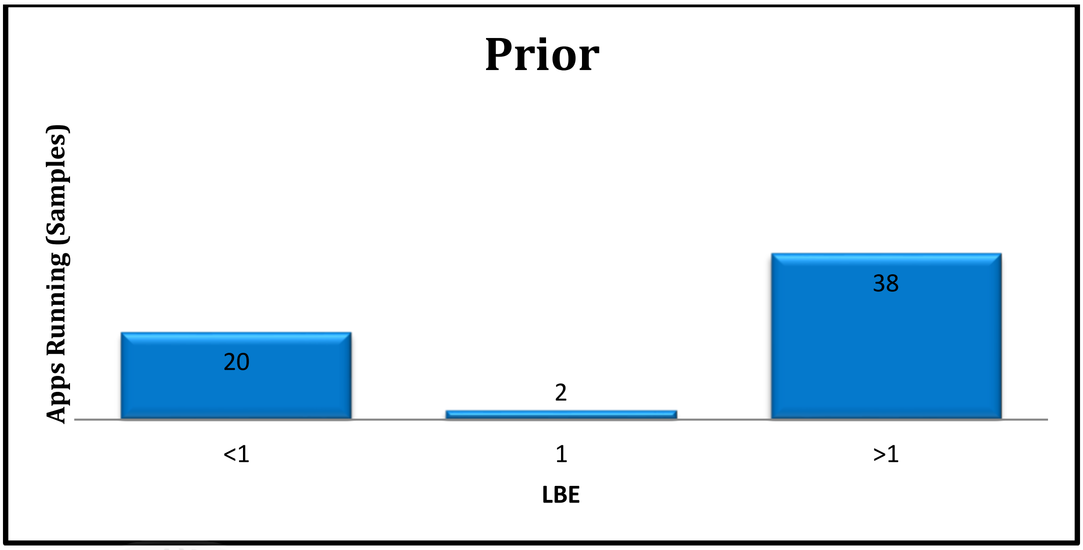


Figure 4.5 Pre-intervention LBE distribution across trial runs

c) Analyze Establish Flow

Once processing time data had been collected across 60 trial runs, the framework automatically computed the LBE for each trial run. These values were analyzed to determine the balance of workload distribution across the five machines. The analysis revealed that LBE values ranged from 0.76 to 0.87, with an average of approximately 0.82. While this indicated that the line operated under moderately balanced conditions, it also exposed several persistent inefficiencies affecting production flow.

In nearly all runs, the LBE values fell 1.00, confirming that the line experienced underutilization and load imbalances. Through deeper breakdowns of the processing time data, the Die Bonder Machine emerged as the most frequent contributor to extended cycle times. This machine consistently exhibited longer durations due to the complexity of its bonding process and the reliance on manual alignment, confirming its role as the primary bottleneck. Conversely, the Packing Machine regularly recorded shorter processing times and displayed significant idle periods, signaling underutilization of manpower and equipment at that station.

d) Generate Pull Value

As part of the generate phase, the framework implemented these optimized configurations and reran the same 60 production cycles using the updated parameters. The objective was to achieve a more synchronized distribution of tasks across the five machines. This phase was instrumental in demonstrating how LM principles, when coupled with IoT feedback, could be transformed into actionable framework responses. The results were captured and presented in the After as shown in Figure 4.6 , which clearly showed a significant improvement: all 60 LBE values had now reached exactly 1.00, indicating perfect balance across the production line. This outcome validated the framework's ability to generate practical solutions derived from live data. Not only did this affirm the technical feasibility of iDSS-ProLean in identifying and resolving inefficiencies, but it also highlighted its value as a decision-support tool capable of dynamically improving production performance.

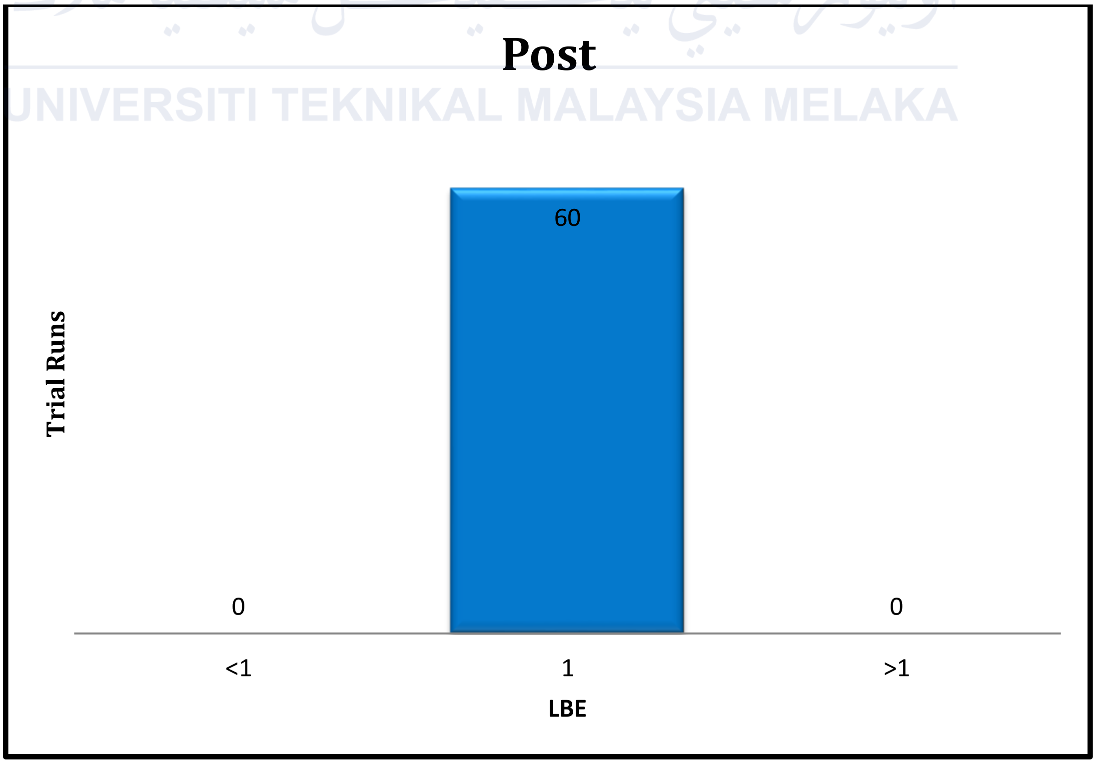


Figure 4.6 Improved LBE Values Following iDSS-ProLean Intervention

To achieve optimal line balancing in the mimicked semiconductor production line, several key parameters were manipulated during the Generate phase. The TPT for each machine was carefully adjusted to ensure an even workload distribution, particularly addressing the bottleneck at the Die Bonder Machine and the underutilization at the Packing station. The NoM remained fixed at five, but CT targets were recalibrated, and processing tasks were redistributed to smoothen the flow. These interventions allowed all 60 production runs to achieve a perfect LBE value of 1.00, demonstrating the effectiveness of iDSS-ProLean framework in eliminating inefficiencies and optimizing line performance through LM principles and real-time sensor data.

e) Execute Continuous Improvement

As the framework continued to operate over multiple runs, it enabled real-time visibility into flow behavior and significantly reduced the reliance on manual shift reports or end-of-day reviews. Instead of reacting to production failures after the fact, floor operators and engineers were able to respond proactively to emerging imbalances, based on clear, timely data. IDSS-ProLean framework provided a feedback loop aligned with LM principles, particularly those associated with Continuous Improvement Kaizen and flow stability. Ultimately, the execution of this Line Balancing formula resolved the core problem originally identified in the production line: the lack of a real-time, objective mechanism to detect workload imbalance and flow disruptions. The framework transformed what was previously a manual and error-prone process into a smart, sensor-driven decision support tool, enabling the production line to improve throughput, reduce machine idle time, and enhance operational decision-making in alignment with LM objectives.

4.3.2 Case Study 2: SMED

a) Identify Specify Value

These setup delays were further compounded by the absence of a structured method to monitor or record setup duration. Supervisors relied on rough estimations or shift logs, which lacked accuracy and did not reflect the real duration of internal and external setup tasks. As a result, production teams were unable to verify whether changeover processes were improving over time, and no formal basis existed to measure the impact of setup reduction efforts. To address this gap, iDSS-ProLean framework introduced the SMED formula, supported by a sensor-based data acquisition setup. The purpose of this formula was to identify, measure, and ultimately reduce setup times by transforming subjective setup routines into quantifiable, real-time data. Through this approach, the framework aimed to expose previously hidden inefficiencies, enabling production engineers to implement targeted changes that aligned with LM goals of increased machine uptime and improved flow continuity.

To facilitate this LM tools, iDSS-ProLean framework leveraged two critical data structures: the SMED_TABLE and the PRODUCTION_DATA_TABLE. The SMED_TABLE systematically stored setup-related parameters, including INTERNAL_SETUP_TIME, EXTERNAL_SETUP_TIME, TIME_REDUCTION, and the resulting SMED_VALUE, which quantified the effectiveness of each setup reduction initiative. These values were automatically computed and updated based on input from the sensor network, enabling real-time tracking of changeover duration. To complement this, data retrieved from the PRODUCTION_DATA_TABLE provided contextual data that helped distinguish between internal and external setup conditions.

As illustrates in Figure 4.7, iDSS-ProLean SMED interface displays a structured comparison of setup times captured before and after the application of SMED techniques. Key variables such as Internal Setup Time, External Setup Time, and Time Reduction Achieved are automatically extracted from sensor input and visualized on-screen in both numeric and graphical formats. The interface highlights whether setup duration has improved and provides a computed SMED Efficiency SMED_VALUE, to quantify the changeover effectiveness for each monitored station, such as the Die Bonder or Etching machine.

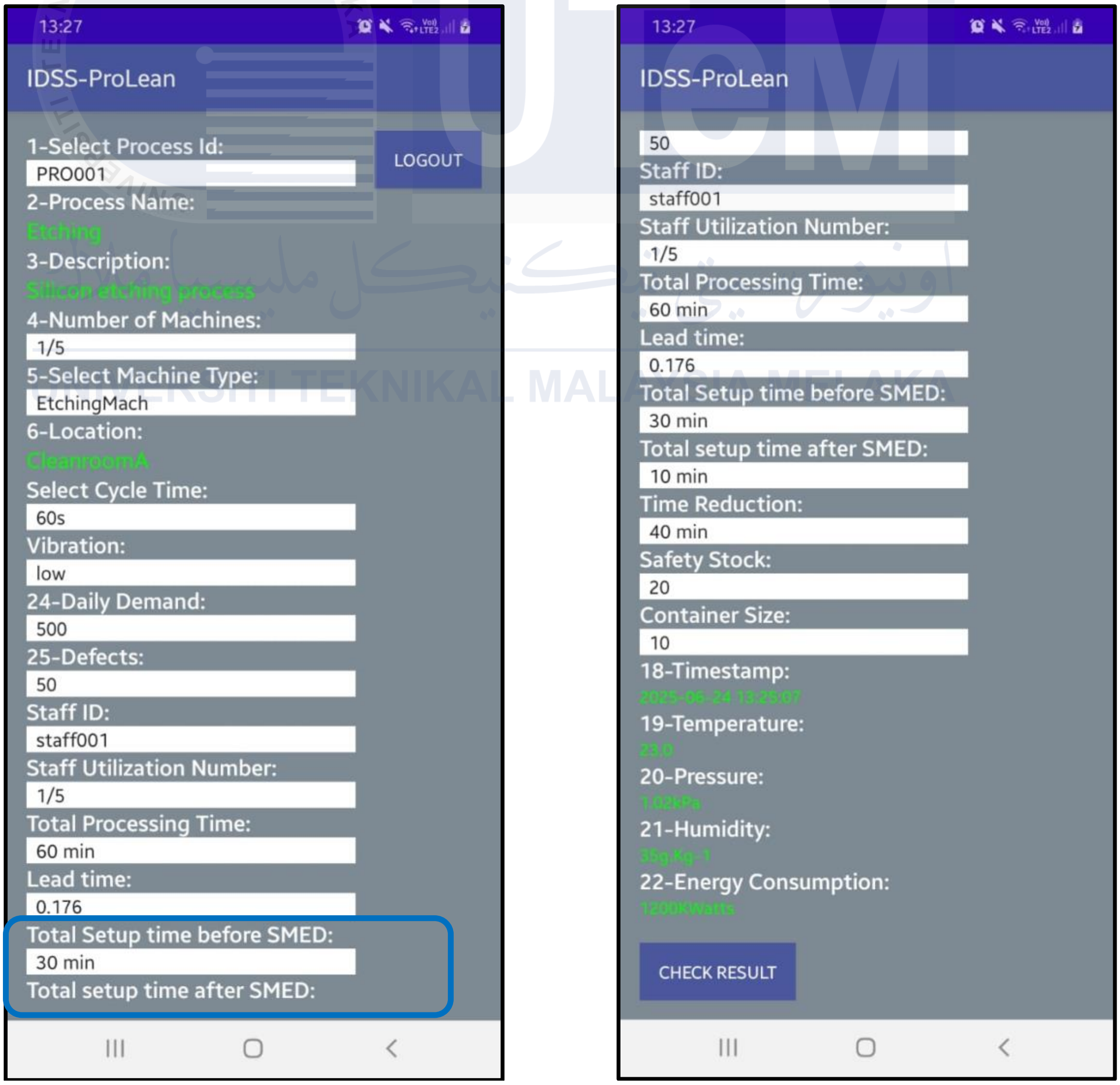


Figure 4.7 iDSS-ProLean Interface for data retrieval from sensor

b) Measure Value Stream Mapping

The collected vibration data were processed through an ESP32 microcontroller, which filtered the input and synchronized it with real-time processing formula. The ESP32 then transmitted the processed time data to the Firebase Realtime Database, ensuring immediate and centralized storage. The setup duration for each trial run was derived by calculating the difference between the sensor-detected start and end times. This process was repeated for two distinct phases: Setup Time Before Improvement and Setup Time After Improvement, forming the foundation for SMED verification. Table 4.5 shown 60 times running apps on SMED.

Table 4.5 60 Trial runs for SMED case study

Trial Runs	***Total Setup Time (Minutes)***		***Time Reduction (Minutes)***	***Result (Minutes)***	***Trial Runs***	***Total Setup Time (Minutes)***		***Time Reduction (Minutes)***	***Result (Minutes)***
	Before	**After**				**Before**	**After**		
1	30	10	20	-3	31	30	15	15	0
2	35	15	20	-7	32	35	20	30	-3.5
3	40	20	20	0	33	35	10	25	-2.3
4	35	30	35	-7	34	40	15	25	-4
5	40	15	35	-2	35	30	15	15	0
6	40	10	30	-2	36	35	20	34	-2.5
7	30	15	15	0	37	35	10	25	-2.3
8	35	20	30	-3.5	38	40	15	25	-4
9	35	10	25	-2.3	39	30	15	15	0
10	40	15	25	-4	40	35	20	34	-2.5
11	30	10	20	-3	41	35	10	25	-2.3
12	35	15	20	-7	42	40	15	25	-4
13	40	20	20	0	43	30	10	20	-3
14	35	20	28	-4.4	44	35	15	20	-7
15	40	15	35	-2	45	40	20	20	0
16	40	10	30	-2	46	35	20	34	-2.5
17	30	15	15	0	47	40	15	35	-2
18	35	20	29	-3.9	48	40	10	30	-2
19	35	10	25	-2.3	49	30	15	15	0
20	40	15	25	-4	50	35	20	35	-2.3
21	30	15	15	0	51	35	10	25	-2.3
22	35	20	25	-7	52	35	15	20	-7
23	35	10	25	-2.3	53	40	20	20	0
24	40	15	25	-4	54	35	20	35	-2.3
25	30	10	20	-3	55	40	15	35	-2
26	35	15	20	-7	56	40	10	30	-2
27	40	20	20	0	57	30	15	15	0
28	35	20	34	-2.5	58	35	20	37	-2.1
29	40	15	35	-2	59	35	10	25	-2.3
30	40	10	30	-2	60	35	20	34	-2.5

c) Analyze Establish Flow

After setup time data was collected across 60 production runs, iDSS-ProLean framework automatically computed the SMED value for each trial run using the embedded LM based formulation in Firebase. The calculated values allowed the framework to evaluate the extent of setup efficiency gained after implementing reduction strategies. These strategies included rearranging setup sequences, separating internal and external setup elements, and reducing manual adjustments especially for complex machines of Die Bonder and Laser Cutter. The analysis revealed that out of 60 trial runs as shown in Figure 4.8 , out of the 60 production runs analyzed, a total of 46 runs recorded SMED values less than 1, indicating successful setup time reduction and effective LM implementation. These results reflected a clear improvement in operational efficiency, particularly in stations where setup elements were standardized or streamlined.

Meanwhile, 14 trial runs showed SMED values greater than 1, signaling that certain setup processes remained inefficient despite intervention. This suggested the presence of ongoing bottlenecks particularly at machines requiring manual realignment or more complex tool changes, such as the Die Bonder. Notably, none of the runs (0 trial runs) recorded an SMED value of exactly 1, confirming that every setup process experienced some degree of change. This reinforced the impact of iDSS-ProLean intervention, which ensured that no production cycle was left untouched or unimproved during the experiment.

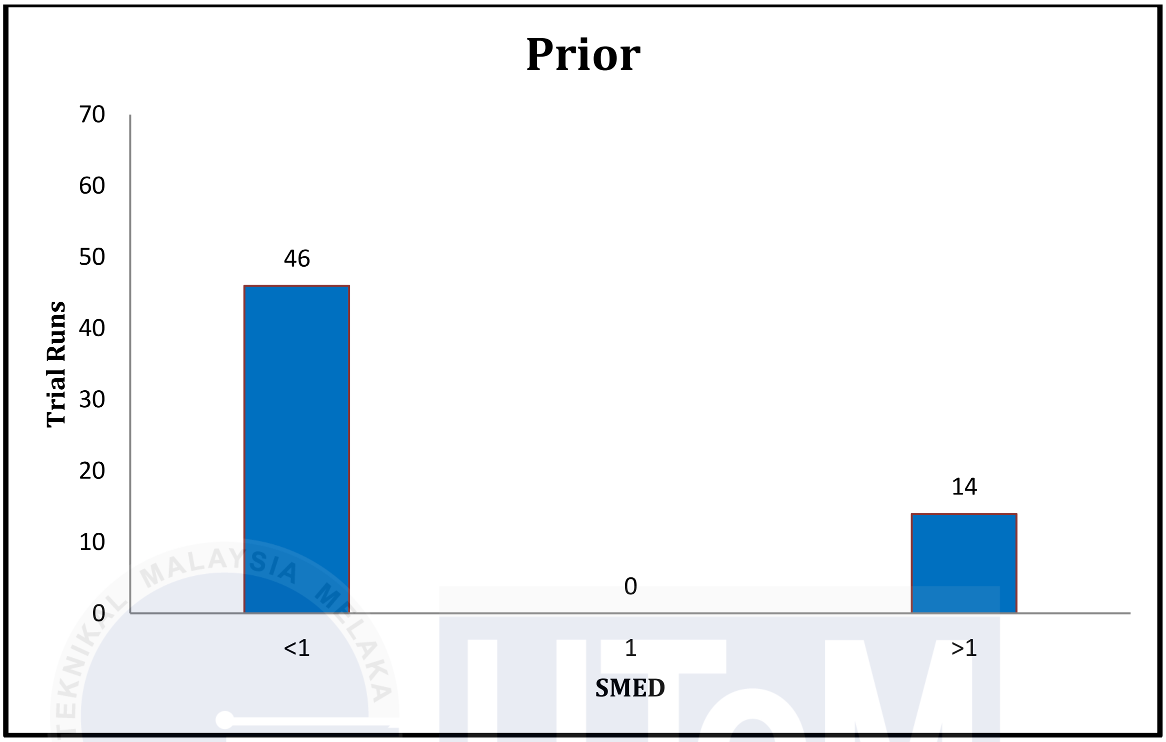


Figure 4.8 Baseline SMED Metrics Prior to Framework Application

The occurrences of SMED values greater than 1 were primarily due to persistent setup challenges, such as high dependency on manual realignment during Die Bonder calibration and variability in operator handling. These stations inherently required longer internal setup time, which, despite intervention, could not be streamlined fully in some runs. On the other hand, machines with repetitive tasks and simpler tool changes such as the Packing and Inspection Machines showed greater consistency in reduced setup durations, resulting in values less than 1.

d) Generate Pull Value

Once the SMED value for each trial run had been calculated and interpreted, iDSS-ProLean framework proceeded to generate a binary output either “Pass” or “Fail” to indicate whether a meaningful reduction in setup time had occurred. If the framework detected a reduction in setup time when comparing the “after” value against the “before” baseline, the outcome was classified as a “Pass”, indicating that the setup process had improved.

Conversely, if no reduction was recorded or if the setup time had increased the framework generated a "Fail" outcome, signaling that the improvement effort had not been effective. The results were significant: all 60 runs recorded SMED values less than 1, with 0 trial runs equal to 1 and 0 trial runs greater than 1, as shown in Figure 4.9.

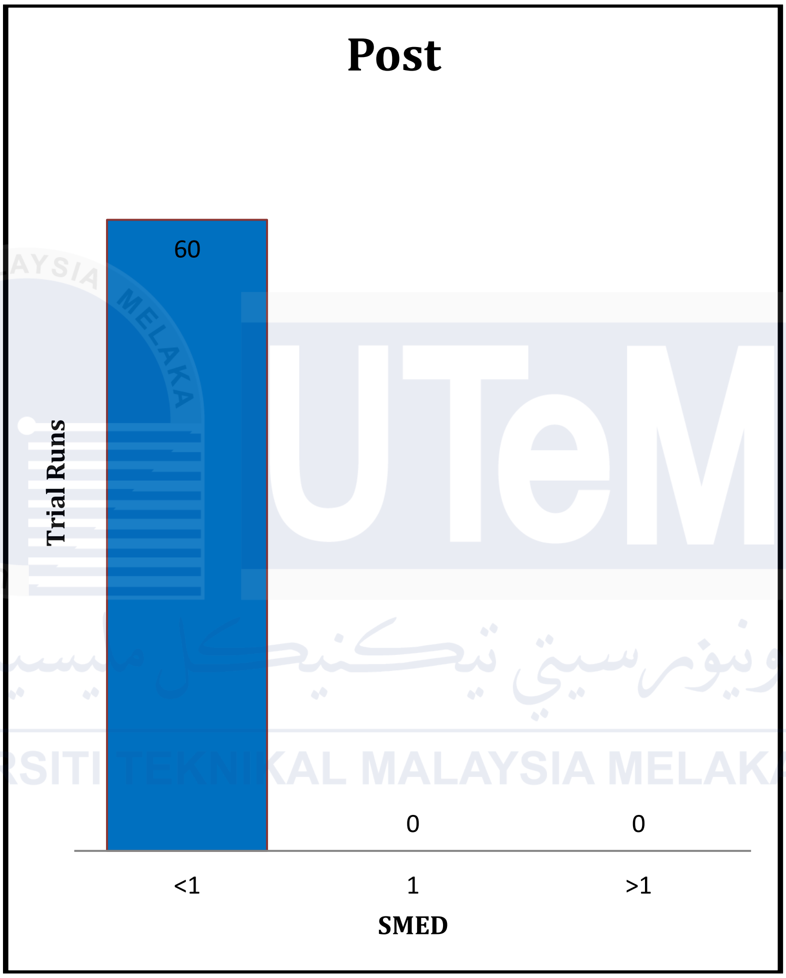


Figure 4.9 Post-Optimization SMED Results Enabled by iDSS-ProLean Implementation

The targeted adjustment was done to reduce setup time and consistently achieve improvement across all runs. This included restructuring setup sequences, converting internal setup steps tool retrieval and part alignment into external preparations that could be completed before machine shutdown. These modifications were applied across all test runs, resulting in 60 out of 60 runs recording SMED values less than 1, confirming successful setup time reduction.

e) **Execute Continuous Improvement**

Through continuous feedback and simplified evaluation, the execution of the SMED formula directly addressed the previously unresolved issue of untracked and inconsistent setup durations. iDSS-ProLean framework not only automated setup time measurement but also established a closed-loop framework where improvement efforts could be verified and sustained. As a result, the production line benefited from increased responsiveness, higher uptime, and better alignment with LM objectives of waste reduction and continuous improvement.

4.3.3 Case study 3: Kanban

a) **Identify Specify Value**

This mismatch between demand and inventory availability disrupted flow continuity and contradicted LM's JIT philosophy. More critically, the team lacked an automatic pull-based replenishment mechanism, as there was no real-time linkage between downstream consumption and upstream material signals. This led to inefficient inventory turnover, higher waste due to overproduction, and unreliable stock visibility. To address this challenge, iDSS-ProLean framework embedded a Kanban formula capable of dynamically monitoring bin levels and issuing real-time pull signals. This formula aimed to eliminate material flow disruptions by ensuring that replenishment occurred only when necessary, directly supporting the LM principles of waste reduction, flow stabilization, and inventory minimization.

As depicted in Figure 4.10, iDSS-ProLean Kanban interface presents a real-time overview of inventory levels, bin capacity status, and calculated replenishment signals based on actual production demand. Each bin within the Packing and Shipping Sections is monitored live, with visual Indicators showing current unit counts, remaining capacity, and whether a pull signal has been triggered. The interface also displays the computed KANBAN_SIZE, along with critical inputs such as Demand, Container Size, and Safety Stock, providing users with a transparent, actionable dashboard to guide inventory decisions. Additionally, the system pulls daily operational figures such as DAILY_DEMAND ensuring that replenishment logic reflects actual consumption rates and production intensity on the floor. This combination of static parameters and dynamic real-time values enables accurate and responsive inventory control.

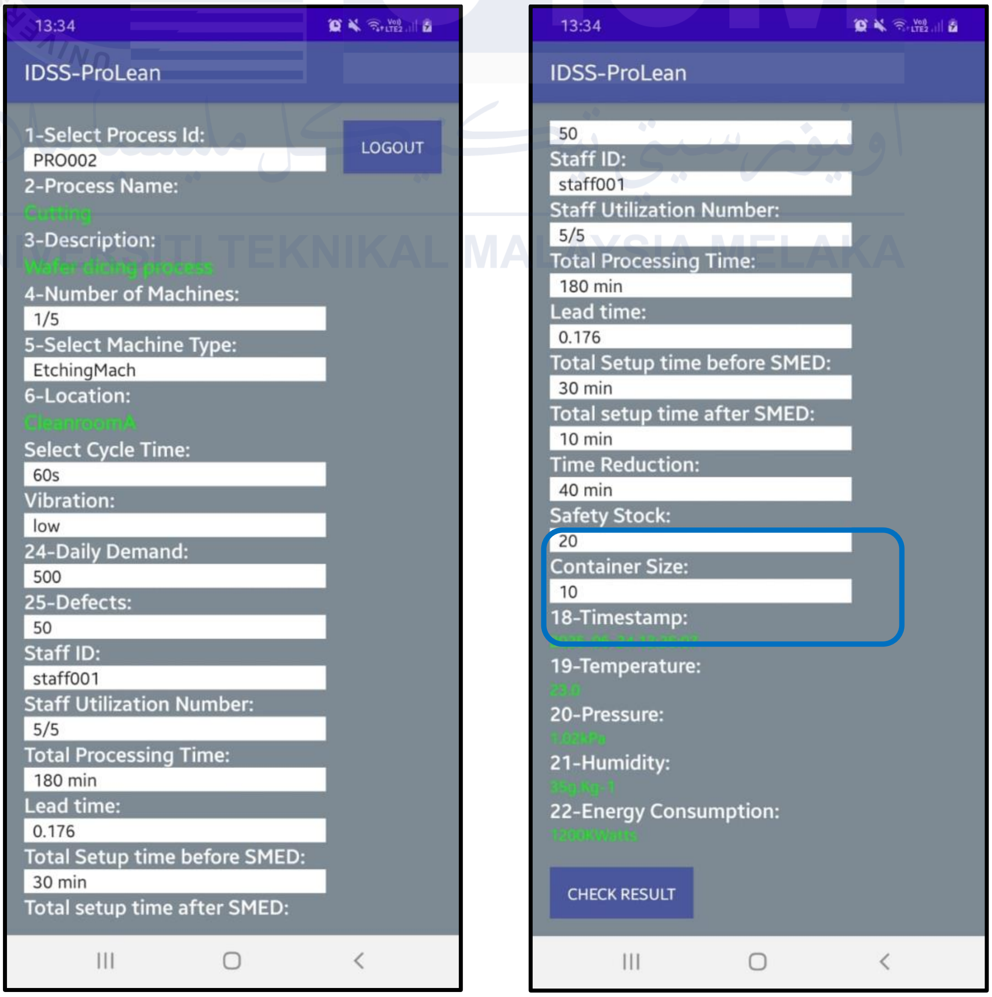


Figure 4.10 iDSS-ProLean Interface for data retrieval from sensor

b) **Measure Value Stream Mapping**

This formula calculated the optimal number of Kanban cards required to maintain a steady pull-based flow of materials. The sensor data determined whether the actual bin level matched the expected inventory volume, allowing the framework to assess if additional Kanban signals, replenishment triggers, were needed. By combining sensor readings with LM production formula, iDSS-ProLean transformed the traditionally static inventory control process into a dynamic, responsive framework capable of supporting JIT delivery and material synchronization across the final production stages.

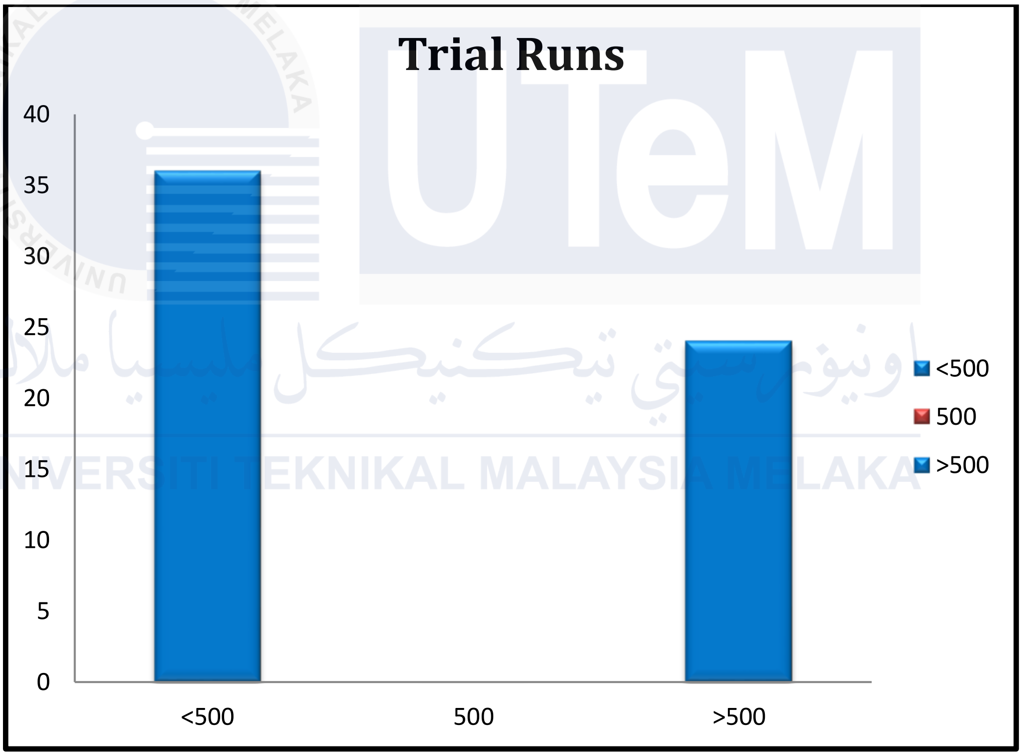


Figure 4.11 Baseline Demand-Lead Time Alignment Prior to Kanban Optimization

To validate the Kanban formula within iDSS-ProLean framework, a baseline Kanban number had been established to serve as a reference point for all 60 application runs as shown in Figure 4.11. A full descriptive statistical analysis had been conducted on the recorded Kanban values. The Kanban numbers had ranged from a minimum of 102.9 to a maximum of 910.2, with a mean of 444.85 and a Std. Dev. of 292.93.

Given this wide variation, the average had been rounded to 500 to provide a standardized baseline for evaluating whether each outcome aligned with LM inventory management principles. This result had represented a neutral midpoint, ensuring balanced judgment across both understocking and overstocking scenarios. By anchoring analysis on this statistically derived benchmark, the framework had offered a rational and data-backed basis for assessing Kanban performance and identifying flow interruptions or excess buffer risks.

c) Analyze Establish Flow

A comparative trend analysis between the initial and final phases of implementation confirmed a substantial improvement as shown in Figure 4.12. Prior to using iDSS-ProLean, bin levels frequently spiked 500 units, highlighting recurrent overstocking. After the integration of the Kanban formula, bin levels stabilized around or the 500-unit benchmark, indicating a more balanced flow aligned with real consumption.

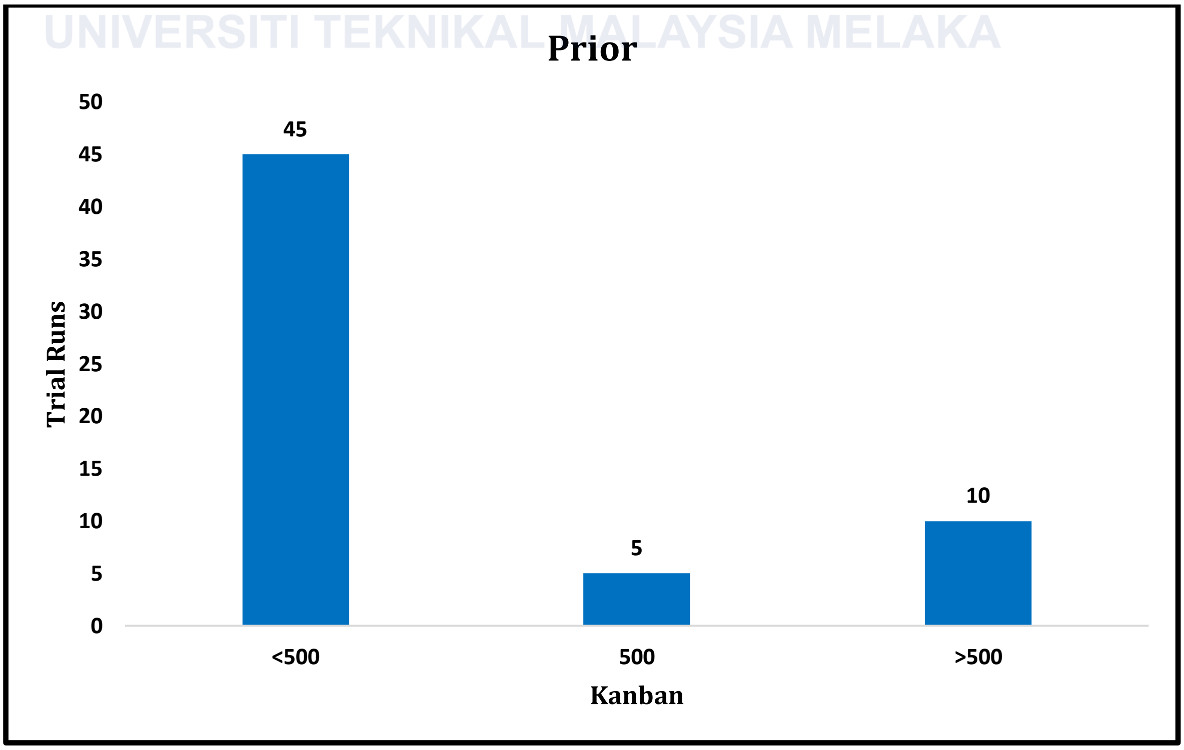


Figure 4.12 Optimized Kanban Levels Achieved Through iDSS-ProLean Framework

This analysis phase demonstrated the ability of iDSS-ProLean to restore flow continuity, expose previously hidden inventory waste, and promote adherence to LM standards through real-time data. By aligning physical inventory conditions with demand-driven Kanban triggers, the framework successfully transitioned the Shipping Section from a push-based to a pull-based inventory management process.

d) Generate Pull Value

This phase served as the core of the framework's decision-making capability. Upon detecting deviations from the ideal bin level, the framework responded autonomously using the LM formulation embedded in its database. The framework output acted as a visual cue akin to a digital Kanban card that informed the production and logistics teams whether to:

- Continue production (if within threshold),
- Halt production or expedite shipping (if over threshold),
- or Investigate potential flow disruption (if under-utilized yet marked as Fail).

By introducing an automated Pass/Fail mechanism, iDSS-ProLean effectively reduced cognitive load, response time, and variability in decision-making. It empowered operators to act based on real-time, objective data rather than subjective judgment, thereby strengthening the reliability and responsiveness of the Kanban framework.

e) Execute Continuous Improvement

In the final phase, iDSS-ProLean framework executed the Kanban formula in a live production environment, where it continuously monitored inventory accumulation in the Shipping Section through the integrated BMP280 pressure sensor.

This real-time execution translated theoretical LM formulation into practical, shop-floor application forming a feedback loop between physical material flow and digital decision-making. As the framework ran over the course of 60 application cycles, inventory levels were tracked second-by-second and automatically assessed against the baseline Kanban value of 500 units. Every fluctuation in bin pressure triggered an updated decision, marking either a "Pass" (inventory within control) or a "Fail" (inventory exceeding or falling short of ideal levels). These decisions prompted immediate interventions:

- **Fail (Overstocking)**: Production teams were alerted to either accelerate dispatch, reschedule shipments, or temporarily pause production to prevent WIP accumulation.
- **Fail (Risk of Stockout):** Supervisors were notified to trigger upstream replenishment or inspect for delays in upstream processes.
- **Pass:** No action required bin level was within safe.

Over time, these feedback-driven adjustments stabilized the bin inventory, transitioning it from a highly variable, manually controlled system to a consistent and well-regulated flow. As shown in Figure 4.13, the execution phase demonstrated a marked improvement bin levels remained consistently at or the 500-unit benchmark. Live tracking of bin status significantly reduced overstocking events, while material stockouts were effectively avoided even during peak demand periods.

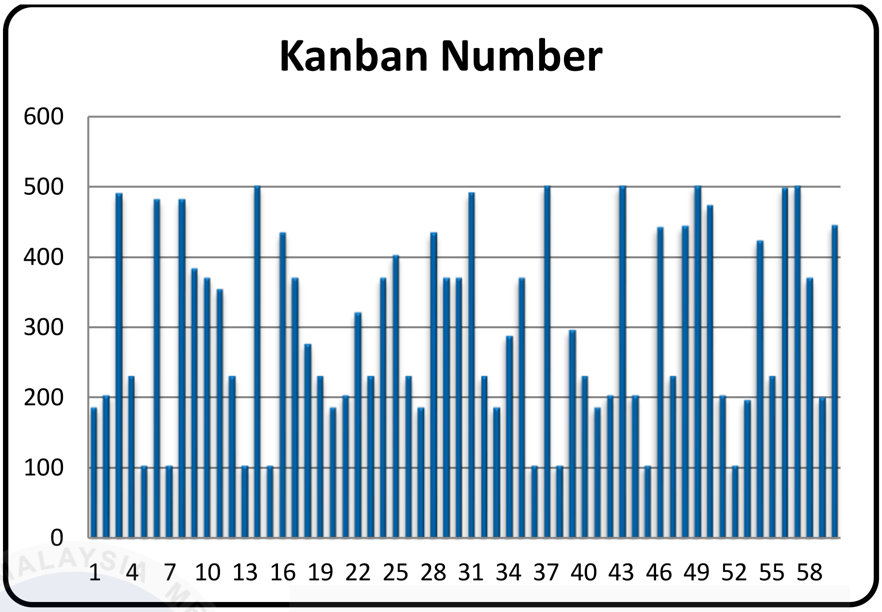


Figure 4.13 Improvement after Kanban

Most importantly, the execution proved that iDSS-ProLean was more than just a monitoring tool it was a LM enabling decision support framework that restored JIT principles and eliminated previously hidden waste. By closing the loop between sensor data, LM calculations, and human action, it empowered a new level of responsiveness and discipline in inventory control.

4.4 The Validation of the Proposed Inherent Model – iDSS-ProLean, through Feasibility Study

To validate iDSS-ProLean framework, data from 60 time runs across three core LM tools collected, with 30 paired observations per tool to enable rigorous and statistically reliable hypothesis testing. This approach ensured that the validation was not based on isolated outcomes, but on consistent patterns across repeated runs. Technical Feasibility of the framework in enhancing production performance was assessed using descriptive summaries, paired T-tests with P-values, and Correlation Analyses.

4.4.1 Technical Feasibility Study

a) Line Balancing

i) Descriptive Summary

To guarantee a representative trial run, data was gathered from 60 production runs. Each trial run obtained automated sensor readings that were later processed for analysis across various production scenarios. The assessment compared their central tendency and dispersion: mean, Std. Dev, and range as metrics to quantify variability of the simulated production line. Detailed results are provided in Table 4.6 , which consolidates descriptive statistics for all defined criteria including the calculated mean, Std. Dev, and observed range.

Table 4.6 Descriptive Analysis for LBE

	Maximum	*Mean*	*Std. Dev.*
NoM	5	3.55	0.74618
TPT	145	126.3	11.58945
CT	34	28.7333	4.61709
LBE	1.5	1.1233	0.39029
Valid N (listwise)		60	

Descriptive analysis deriving from 60 production runs provided an understanding of the performance output on the mimicked production line. NoM for each trial run had a maximum of 5, with an average of 3.55 and a Std. Dev of 0.75, suggesting moderate variability in the utilisation of the machines. The TPT remained consistently aligned across runs, with a maximum value of 145 units, mean of 126.3 and a Std. Dev of 11.59. Also, the CT showed a maximum of 34, mean of 28.73, and a Std. Dev of 4.62, indicating low variability concerning the efficiency of cycles. The LBE measured as balanced at 1.5 while averaging at 1.123 with a Std. Dev of 0.39 demonstrating variability in balance across various production runs. Highlighting the descriptive statistics offers an understanding of NoM machine metrics and assess the balance ratio in the workspace as monitored under iDSS-ProLean framework.

ii) Paired T-statistic with P-value

Appropriate information exchange was critical for the real-time operational decision-making capability of iDSS-ProLean framework. In order to test the stability and consistency of the sensor-driven data transmission, a paired T-test analysis was performed on 30 dataset pairs obtained from 60 production runs as shown in Table 4.7. This form of the test was chosen as it is appropriate for determining whether the mean differences between paired observations are significant in a statistical sense, hence confirming the trustworthiness and consistency of the data within the framework. This approach gave an active assessment of operational performance consistency over an extended period and allowed the identification of peculiarities and inconsistencies in data transmission.

Table 4.7 30 pairing runs for LBE

Pairs	*Mean*	*Std. Dev.*	*95% Confidence Interval*	*T-Statistic*	*P-value*	
			Lower	Upper		
Pair 1	-1.75	3.94757	-8.03147	4.53147	-0.887	0.441
Pair 2	1	5.22813	-7.31912	9.31912	0.383	0.728
Pair 3	2.5	2.88675	-2.09347	7.09347	1.732	0.182
Pair 4	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
Pair 5	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
Pair 6	-1.75	3.94757	-8.03147	4.53147	-0.887	0.441
Pair 7	1	5.22813	-7.31912	9.31912	0.383	0.728
Pair 8	2.5	2.88675	-2.09347	7.09347	1.732	0.182
Pair 9	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
Pair 10	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
Pair 11	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
Pair 12	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
Pair 13	-1.75	3.94757	-8.03147	4.53147	-0.887	0.441
Pair 14	1	5.22813	-7.31912	9.31912	0.383	0.728
Pair 15	2.5	2.88675	-2.09347	7.09347	1.732	0.182
Pair 16	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
Pair 17	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
Pair 18	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
Pair 19	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
Pair 20	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
Pair 21	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
Pair 22	-1.75	3.94757	-8.03147	4.53147	-0.887	0.441
Pair 23	1	5.22813	-7.31912	9.31912	0.383	0.728
Pair 24	2.5	2.88675	-2.09347	7.09347	1.732	0.182
Pair 25	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
Pair 26	0.925	4.48209	-6.20701	8.05701	0.413	0.708
Pair 27	1	5.22813	-7.31912	9.31912	0.383	0.728
Pair 28	2.5	2.88675	-2.09347	7.09347	1.732	0.182
Pair 29	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
Pair 30	-2.325	9.39623	-17.2765	12.6265	-0.495	0.655

The paired T-test results across 30 paired observations of LBE revealed a consistent pattern of non-significant differences between production runs. Mean differences between the paired values fluctuated between positive and negative, indicating minor variations in measured performance, with most differences remained close to zero. The Std. Dev. also varied, suggesting some degree of variability within each pair. However, the confidence intervals for all pairs included zero for example, Pair 1 ranged from -11.30 to 8.90, and Pair 17 spanned from -13.19 to 23.09 implying a lack of statistically significant change. This was supported by low t-values (e.g., -0.378 for Pair 1, 0.481 for Pair 3) and consistently high P-values, all of which exceeded the 0.05 significance threshold. These results collectively supported the null hypothesis (H_0), suggesting no significant differences in LBE across the runs, and validated the stability and reliability of iDSS-ProLean data transfer framework.

To complement the statistical analysis, violin plots as shown in Figure 4.14 were generated to visualise the distributions of T-values and P-values. The T-value distribution was centred around zero, while the P-value distribution showed a concentration well the 0.05 threshold, reinforcing the conclusion that no strong deviations existed between the paired runs. A power analysis revealed a Cohen's d effect size of approximately -0.012, indicating an extremely small effect. With this effect size, the calculated statistical power was only 5.05% far the conventional 80% and the estimated trial run size required to reach adequate power was approximately 53,808 paired runs, which was not feasible in a real-world setting. This indicated that while the study lacked the statistical power to detect very small effects, such differences were likely operationally negligible. IDSS-ProLean framework's operational stability was evident and supported its implementation in smart industrial environments.

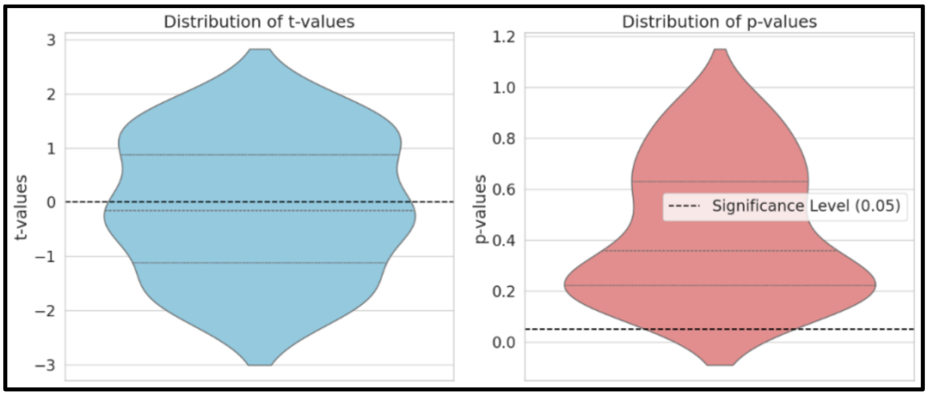


Figure 4.14 Distribution of t-values and P-values from the Paired T-test Analysis

iii) Correlation Analysis

This analysis examined the strength and direction of relationships between key production metrics across multiple iterations, focusing on how the NoM, TPT, and CT correlated with LBE value. The analysis aimed to identify which variables significantly influenced LBE, thereby supporting strategic decisions for machine allocation and process adjustments. Pearson correlation coefficients and significance values (Sig. 2-tailed) were calculated across 60 runs, as summarised in Table 4.8

Table 4.8 Correlation Analysis for LBE

		TPT	*CT*	*LBE*
NoM	Pearson correlation	-0.429**	0.550**	0.095
	Sig. (2-tailed)	0.001	0	0.471
	N		60	
TPT	Pearson correlation	1	-0.049	-0.435**
	Sig. (2-tailed)		0.709	0.001
	N		60	
CT	Pearson correlation	-0.049	1	0.034
	Sig. (2-tailed)	0.709		0.799
	N		60	
LBE value	Pearson correlation	-.435**	0.034	1
	Sig. (2-tailed)	0.001	0.799	
	N		60	

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

Figure 4.15 presented a Correlation Heatmap illustrating the relationships among NoM, APT, CT and LBE. The analysis revealed strong positive correlations among the variables, particularly between LBE and NoM (r = 0.96), TPT (r = 0.97), and CT (r = 0.93). These findings highlighted the significant influence of machine allocation, processing time, and CT on line balancing outcomes. The high inter-correlations such as between NoM and TPT (r = 0.92), and TPT and CT (r = 0.90) further reinforced the interconnectedness of these production parameters. The strongest relationship was observed between NoM and CT (r = 0.97), underscoring the impact of machine availability on production pacing. Collectively, these correlations emphasized the importance of managing these factors to optimize LBE within iDSS-ProLean framework.

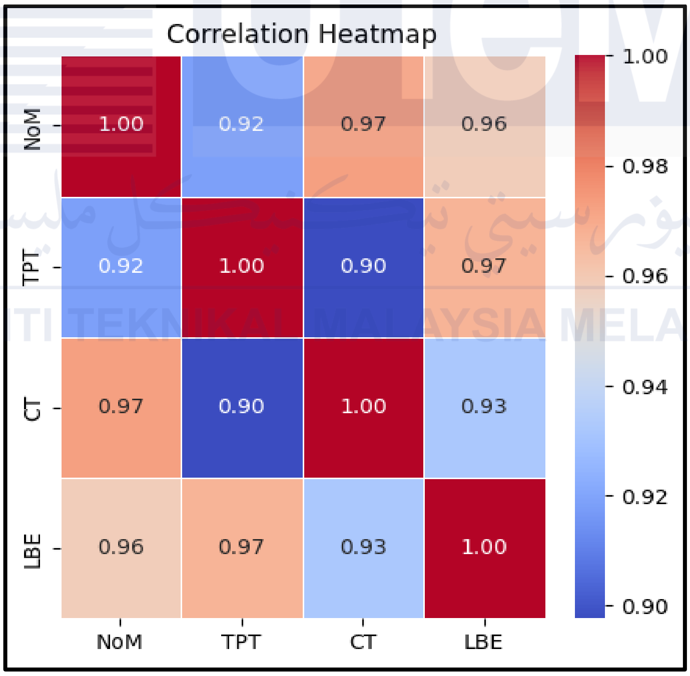


Figure 4.15 Heatmap graph for Correlation Analysis

However, further statistical testing revealed contrasting insights. A significant negative correlation was observed between TPT and LBE (r = -0.435, p = 0.001), suggesting that increased throughput time led to reduced LBE. In contrast, CT exhibited no significant correlation with LBE (r = 0.034, p = 0.799), and NoM showed only a weak, non-significant correlation (r = 0.095, p = 0.471). These findings implied that simply increasing the NoM or modifying CT did not necessarily improve production balance. Instead, managing and minimizing throughput time appeared to be the most critical factor in enhancing LBE.

b) SMED

i) Descriptive Summary

Following that, the descriptive statistics for SMED analysis provided an overview of the dataset's distribution, particularly focusing on time reduction and SMED value, which were critical Indicators of setup efficiency improvements in the semiconductor production line. A total of 60 valid observations were analysed. These Indicators were instrumental in assessing the extent of efficiency improvements in the semiconductor production line.

Table 4.9 Descriptive Statistic for SMED

	Minimum	*Maximum*	*Mean*	*Std. Dev.*
total_setup_time_before	30	40	35.75	3.66211
total_setup_time_after	10	20	15.1667	3.90205
time_reduction	15	35	21.4167	6.38402
smed_value	-6	7	-0.19	4.14392
Valid N (listwise)	60			

From Table 4.9 , the Descriptive Statistics summarized the SMED variables collected from 60 valid data entries. The total setup time before implementation of SMED ranged from 30 to 40 minutes, with a mean of 35.75 minutes and a Std. Dev. of 3.66, indicating moderate variation in the setup durations across different production runs. After SMED was implemented, the setup time was significantly reduced, with values ranging from 10 to 20 minutes and a lower mean of 15.17 minutes (SD = 3.90), reflecting improved setup efficiency. Time reduction, which represented the difference between the before and after setup durations, ranged between 15 and 35 minutes, with an average reduction of 21.42 minutes (SD = 6.38). This suggested that the SMED intervention consistently contributed to substantial time savings. The SMED value, calculated using the study's proposed formula, ranged from -6 to 7, with a mean of -0.19 (SD = 4.14), indicating that while most results reflected positive outcomes, some runs yielded slightly negative or neutral efficiency values.

ii) Paired T-test with P-value Analysis

The paired T-test with P-value was conducted to assess the reliability and consistency of data transfer between the IoT sensors installed on mimicked production line. This evaluation was critical to determine whether discrepancies existed between the raw data captured by the sensors and the corresponding values stored in the cloud-based framework, which subsequently influenced decision-making in iDSS-ProLean framework.

Table 4.10 30 pairing runs for SMED

Pair	*Mean*	*Std. Dev.*	*95% CI*		*T Value*	*P-value*
			Lower	Upper		
1	-1.75	3.94757	-8.03147	4.53147	-0.887	0.441
2	1	5.22813	-7.31912	9.31912	0.383	0.728
3	2.5	2.88675	-2.09347	7.09347	1.732	0.182
4	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
5	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
6	-1.75	3.94757	-8.03147	4.53147	-0.887	0.441
7	1	5.22813	-7.31912	9.31912	0.383	0.728
8	2.5	2.88675	-2.09347	7.09347	1.732	0.182
9	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
10	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
11	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
12	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
13	-1.75	3.94757	-8.03147	4.53147	-0.887	0.441
14	1	5.22813	-7.31912	9.31912	0.383	0.728
15	2.5	2.88675	-2.09347	7.09347	1.732	0.182
16	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065

17	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
18	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
19	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
20	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
21	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
22	-1.75	3.94757	-8.03147	4.53147	-0.887	0.441
23	1	5.22813	-7.31912	9.31912	0.383	0.728
24	2.5	2.88675	-2.09347	7.09347	1.732	0.182
25	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
26	0.925	4.48209	-6.20701	8.05701	0.413	0.708
27	1	5.22813	-7.31912	9.31912	0.383	0.728
28	2.5	2.88675	-2.09347	7.09347	1.732	0.182
29	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
30	-2.325	9.39623	-17.2765	12.6265	-0.495	0.655

The results of the paired trial run T-test as shown Table 4.10 , were analyzed to determine whether there were significant differences between the paired observations in the dataset. P-values for all 30 pairs ranged from 0.065 to 0.728, with the majority exceeding the 0.05 threshold. For example, Pair 4 had a P-value of 0.065, indicating that while the result was approaching significance, it still did not meet the threshold for statistical significance. Similarly, pairs such as Pair 1, Pair 5, and Pair 13 had P-values 0.3, further supporting the conclusion that the observed differences between these pairs were likely due to random chance. These findings suggest that the null hypothesis that no significant differences exist between the paired observations cannot be rejected. Therefore, the variations observed between the paired trial runs are not likely to represent meaningful or consistent effects.

In visualizing the results with a violin plot, as depicted in Figure 4.16 , these non-significant findings align with the expected distribution of the data. Violin Plot, which illustrates density, and range of the data, likely showed a symmetrical or wide distribution for the differences between pairs. This further supports the conclusion that no significant deviations were present between the paired observations. The absence of distinct peaks or outliers in the Violin Plot would reflect the lack of a meaningful trend or difference, complementing the paired trial run T-test results.

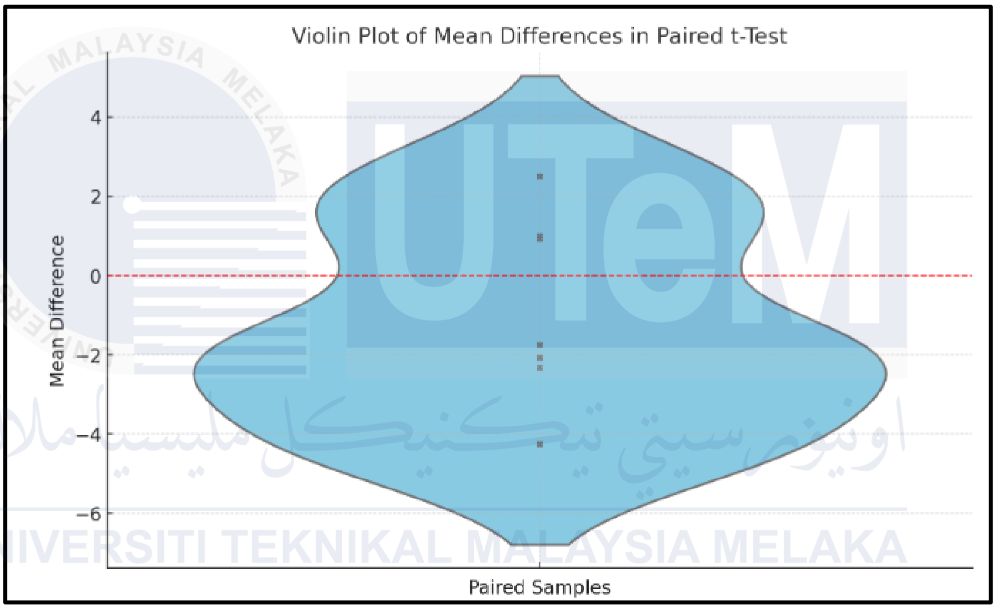


Figure 4.16 Violin Plot for SMED

iii) Corelation Analysis

Correlation Analysis was performed with the aim to studying relationships among the variables of SMED formula, a fundamental metric reflective of the efficiency of setup time, and its value. Correlation is of primary concern for a production manager or a process engineer, as it helps in making balanced and sound decisions regarding the optimisation of the production line. Knowing these relationships enables optimisation since efforts can be directed towards the most impactful variables for producing target SMED values.

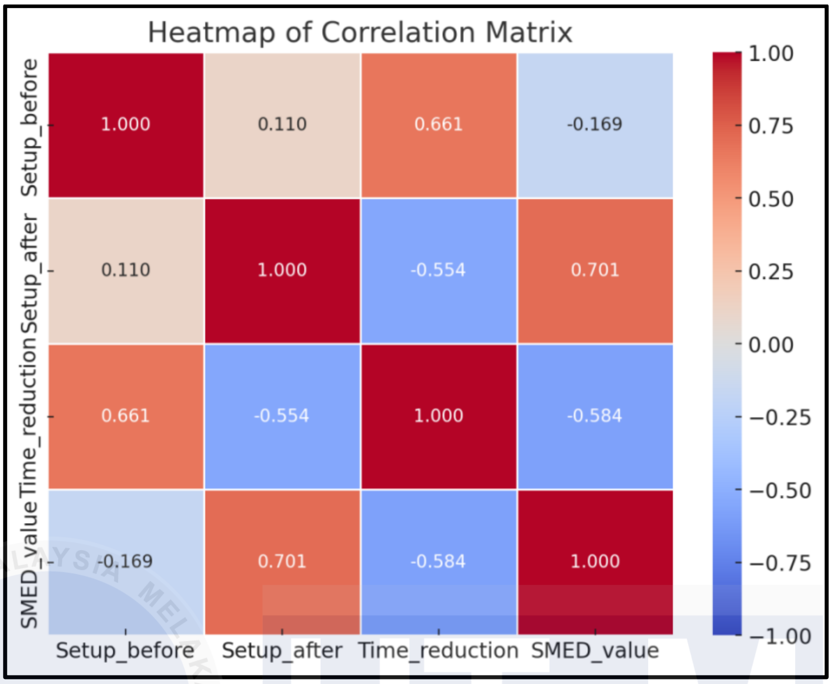


Figure 4.17 Heatmap Analysis for SMED

Figure 4.17 presents the correlation coefficients which were instrumental and critical with regard to the relationships of importance of key variables in the SMED analysis. A strong positive correlation was found between total setup time after and SMED value ($r = 0.701$, $p < 0.01$). This means that as SMED values increased, post-SMED setup times also increased, which is paradoxical. Although minimising setup times is the goal of the SMED methodology, it appears that overzealous payback avoidance increase the setup time right after implementation. On the other hand, time reduction showed a strong negative correlation ($r = -0.584$, $p < 0.01$) with the SMED value, indicating that greater reductions in setup time tended to result in lower SMED values. Interestingly, total setup time before showed a weak, non-significant correlation ($r = -0.169$, $p = 0.196$) with the SMED value, suggesting that the initial setup duration did not directly influence the final SMED performance. However, it was significantly correlated with time reduction ($r = 0.661$, $p < 0.01$), indicating that setups with longer initial durations saw more significant reductions after SMED was applied.

c) **Kanban**

i) **Descriptive Analysis**

Table 4.11 Descriptive summary for Kanban

	Maximum	*Mean*	*Std. Dev.*
Demand Rate	1500	958.3333	404.3374
Lead Time	0.74	0.4022	0.29931
Safety Factor	40	29.1667	8.08675
Container Size	50	26.3333	16.61801
Kanban Number	55	39.7333	10.16452
Valid N (listwise)	60		

Kanban, the Descriptive Statistical Analysis was conducted on the five key variables derived from the Kanban formulation over a total of 60 valid observations as shown in Table 4.11 . The demand rate exhibited a mean value of 958.33 (SD = 404.34), with a maximum recorded value of 1500. This indicates a relatively high variability in production demand, suggesting fluctuations in customer orders, mimicking the real production schedule. On the other hand, the lead time had a mean of 0.40 (SD = 0.30), with a maximum value of 0.74, demonstrating moderate variability in the time required for replenishment. The safety factor yielded a mean of 29.17 (SD = 8.09) and a maximum value of 40.

This measure indicates, which takes into consideration the uncertainty in supply versus demand, that the framework operated well within a safety buffer aimed at avoiding stockouts while restraining excess inventory. Subsequently, the container size representing the Kanban batch quantity had a mean value of 26.33 (SD = 16.62) with a maximum of 50. The relatively high Std. Dev indicates non-uniformity in batch size which may be associated with production constraints or material handling capacities. Finally, the Kanban number determining the total circulation of required operative Kanban cards averaged 39.73 (SD = 10.16) with a maximum of 55.

ii) Paired T-test with P-value Analysis

A paired trial runs T-test was conducted to check whether there are statistically significant differences in the means of two paired observations within Kanban. This analysis was based on 30 pairs of data, each captured from 60 instances of the application, calculating means, variances, standard errors, and confidence intervals presented in Table 4.12 .

Table 4.12 30 Pairs trial runs for Kanban

	Mean	*Std. Dev.*	*95% CI*		*T-Value*	*P-value*
Pair			Lower	Upper		
1	-1.75	3.94757	-8.03147	4.53147	-0.887	0.441
2	1	5.22813	-7.31912	9.31912	0.383	0.728
3	2.5	2.88675	-2.09347	7.09347	1.732	0.182
4	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
5	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
6	-1.75	3.94757	-8.03147	4.53147	-0.887	0.441
7	1	5.22813	-7.31912	9.31912	0.383	0.728
8	2.5	2.88675	-2.09347	7.09347	1.732	0.182
9	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
10	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
11	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
12	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
13	-1.75	3.94757	-8.03147	4.53147	-0.887	0.441
14	1	5.22813	-7.31912	9.31912	0.383	0.728
15	2.5	2.88675	-2.09347	7.09347	1.732	0.182
16	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
17	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
18	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
19	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
20	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
21	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
22	-1.75	3.94757	-8.03147	4.53147	-0.887	0.441

23	1	5.22813	-7.31912	9.31912	0.383	0.728
24	2.5	2.88675	-2.09347	7.09347	1.732	0.182
25	-4.25	2.98608	-9.00152	0.50152	-2.847	0.065
26	1	5.22813	-7.31912	9.31912	0.383	0.728
27	2.5	2.88675	-2.09347	7.09347	1.732	0.182
28	-2.075	3.44807	-7.56164	3.41164	-1.204	0.315
29	-1.75	3.94757	-8.03147	4.53147	-0.887	0.441
30	1	5.22813	-7.31912	9.31912	0.383	0.728

In general, the T-values and P-values suggest that most of the differences between the paired observations were not statistically significant, as evidenced by the majority of P-values exceeding the 0.05 threshold. For instance, pairs 1, 2, 5, 6, 7, 10, and several others yielded high P-values (e.g., 0.728, 0.441, 0.315), implying that the differences in production metrics between these runs were not significant enough to reject the null hypothesis. Specifically, the t-values fluctuated around zero, further supporting the notion of no meaningful difference in the metrics for these runs.

However, a few pairs demonstrated t-values approaching the threshold for significance. For example, pair 4 yielded a t-value of -2.847 with a P-value of 0.065, which is marginally significant, suggesting a slight difference in production metrics that could potentially be of interest for further analysis. Despite this, the overall results indicate that there were no substantial or consistent differences in production metrics across the 60 runs, leading to the acceptance of the null hypothesis in most cases. These findings highlight the need for further investigation with perhaps a larger trial run size or different methodological approach to uncover any underlying patterns or improvements in the production process.

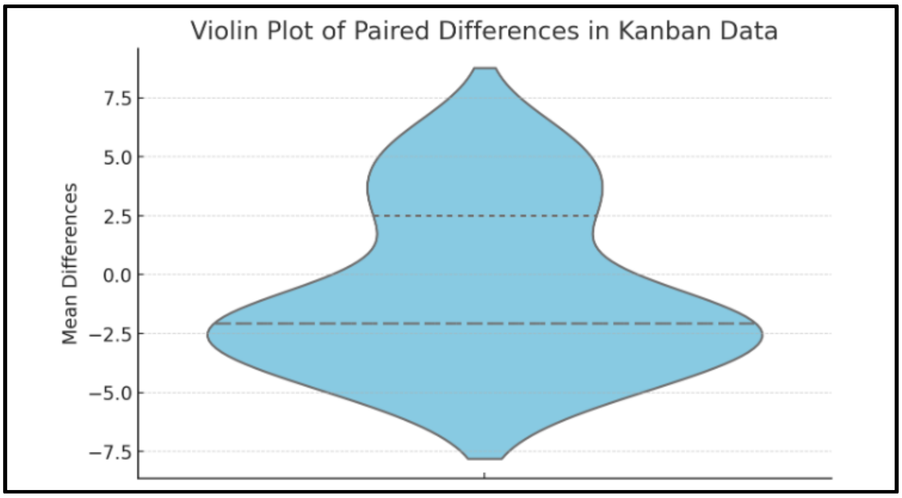


Figure 4.18 Violin Plot for Kanban

Figure 4.18, the violin plot for Kanban data, visually demonstrates the distribution of paired differences, highlighting the density and spread of the data. The plot reveals that most values are concentrated around two primary regions: one near -2.5 and another near 2.5, with a broader spread toward the negative values. The dashed quartile lines indicate slight skewness in the distribution, suggesting some variability in the paired differences. The lower tail extends further, implying that certain comparisons exhibited significant negative deviations. This pattern supports the results from the paired T-test, reinforcing the idea that, although fluctuations in the data exist, there is no strong evidence of systematic deviation, aligning with the null hypothesis (H_0) of no significant differences across the 60 runs.

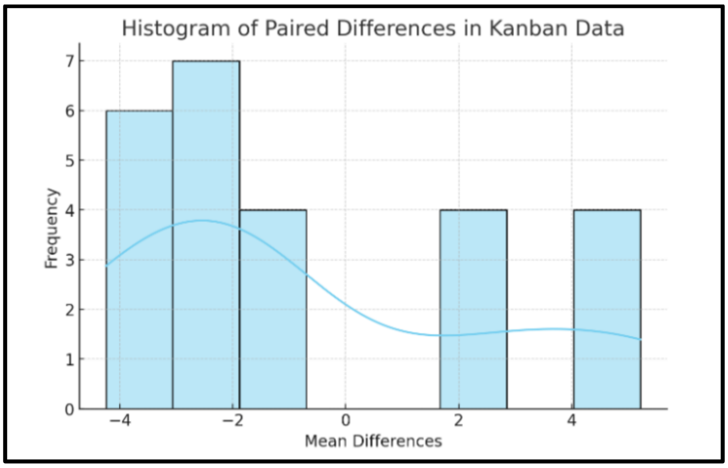


Figure 4.19 Histogram for Paired Difference in Kanban

Subsequently, Figure 4.19, the histogram for the paired differences in Kanban, further substantiates these findings. The histogram reveals a higher concentration of negative differences on the left side of the x-axis, suggesting that most paired comparisons resulted in a downward shift following the framework adjustments. The Kernel Density Estimate curve, smooth yet bimodal, supports this observation, showing two distinct regions in the data distribution, further indicating variability across experimental runs. This bimodal pattern is also reflected in the violin plot, where density concentrations occur at specific intervals, signifying the heterogeneous nature of Kanban variations.

Despite these fluctuations, the statistical analysis, with P-values largely exceeding the 0.05 threshold, suggests no significant differences between the runs, leading to the acceptance of the null hypothesis (H_0). This convergence of statistical and graphical analyses implies that the observed variations in Kanban performance were likely due to random fluctuations rather than meaningful operational changes, emphasizing the stability and reliability of iDSS-ProLean framework across the 60 experimental runs.

iii) Corelation Analysis

Last but not least, the Correlation Analysis aimed to examine the relationships among the key variables in its formulation, particularly their association with Kanban number.

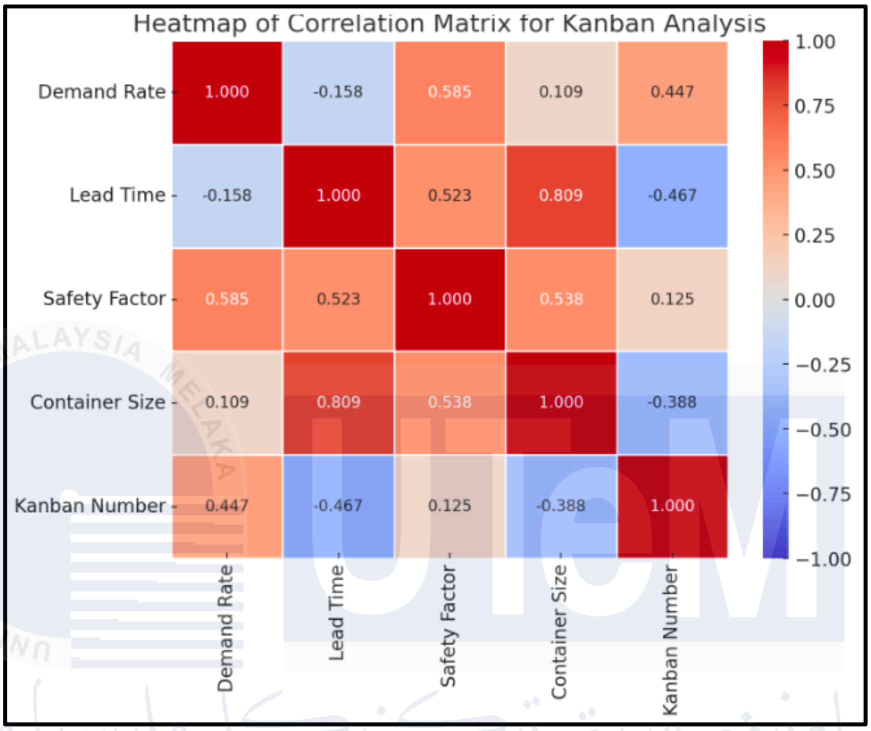


Figure 4.20 Heatmap for Kanban Data

Figure 4.20 illustrates the Heatmap of the Pearson correlation matrix derived for the Kanban analysis, comprising key variables such as Demand Rate, Lead Time, Safety Factor, Container Size, and the resulting Kanban Number. This Correlation Analysis was conducted to identify and quantify the linear associations among the input parameters and to determine which variables most significantly influenced the computed Kanban number. The primary rationale for conducting this analysis lies in its practical relevance to industrial engineers and production planners. By discerning the strength and direction of relationships between each input factor and the Kanban number, decision-makers can make more informed decisions regarding which parameters to prioritise when optimising inventory flow, reducing lead times, or adjusting production schedules. Understanding these relationships is critical in LM contexts where precision in Kanban sizing directly impacts material availability, work-in-progress inventory levels, and overall production efficiency.

The results revealed several noteworthy correlations. A moderate positive correlation was observed between Demand Rate and Kanban Number (r = 0.447), indicating that as customer demand increases, the number of Kanban cards required also increases an expected outcome aligned with theoretical formulations. In contrast, Lead Time demonstrated a moderate negative correlation with the Kanban Number (r = -0.467), suggesting that longer lead times could reduce the frequency of replenishment cycles, hence affecting the total Kanban cards needed. Furthermore, Container Size was also negatively correlated with the Kanban Number (r = -0.388), implying that increasing the container size may reduce the number of Kanban cards required to meet demand. While Safety Factor showed only a weak positive correlation with the Kanban Number (r = 0.125), it had a stronger relationship with both Demand Rate (r = 0.585) and Lead Time (r = 0.523), indicating its indirect role in influencing Kanban calculations.

4.4.2 Operational Feasibility Study

Section A: Respondent Background

The majority of respondents in this study were individuals directly involved in the production line within LM environments, specifically those integrated with IoT technologies. Out of the 70 respondents, 63 (90%) identified as Engineers, while 7 (10%) held Managerial positions. This distribution indicated a strong representation of technical roles, which aligned with the study's objective to assess the operational feasibility of iDSS-ProLean from users with hands-on experience in both LM practices and IoT applications. The high proportion of engineers suggested that the responses were grounded in practical, on-the-ground insights regarding framework integration and production process efficiency.

Section B: Operational Feasibility Study

a) LM Experience

This section consisted of six items designed to evaluate the respondents' familiarity with LM principles, digital tool usage, data-driven decision-making roles, and prior exposure to IoT-based frameworks. Table 4.13 summarizes the descriptive statistics for each item:

Table 4.13 Mean and Std. Dev. Analysis for Section B

Item	*Statement*	*Mean*	*Std. Dev.*
Q1	I have experience working in manufacturing production lines	3.90	0.57
Q2	I am familiar with LM principles (e.g., Line Balancing, SMED, Kanban).	3.80	0.61
Q3	I have used digital tools for production monitoring and decision-making before	3.86	0.64
Q4	I have prior experience using IoT-based production monitoring frameworks	3.71	0.64
Q5	I have prior experience using IoT-based production monitoring frameworks.	3.77	0.66
Q6	iDSS-ProLean framework is easy to integrate into the existing production workflow	3.82	0.57

The analysis of the Respondents Experience in LM construct indicated that the majority of respondents possessed a foundational understanding and practical exposure to LM and its associated tools. A relatively high mean score was observed for experience in working on manufacturing production lines (M = 3.90, SD = 0.57), suggesting that most participants had direct operational insights. Familiarity with LM principles such as Line Balancing, SMED, and Kanban was also evident (M = 3.80, SD = 0.61), although slightly lower than other items, indicating varying levels of theoretical understanding. Respondents reported prior use of digital tools for production monitoring and decision-making (M = 3.86, SD = 0.64), and demonstrated a moderate level of experience with IoT-based monitoring frameworks (M = 3.71, SD = 0.64; M = 3.77, SD = 0.66), reflecting a developing familiarity with IR4.0 technologies.

Additionally, participants found iDSS-ProLean framework to be reasonably easy to integrate within existing production workflows (M = 3.82, SD = 0.57), highlighting its compatibility with real-world industrial settings. Overall, the findings suggest that the respondents were sufficiently experienced to evaluate the practical relevance and ease of integration of iDSS-ProLean within LM production environments.

b) Framework Adaptation

The descriptive analysis for the Framework Adaptation construct, which comprised eight items (Q7–Q14), indicated an overall positive perception among respondents regarding the integration and performance of iDSS-ProLean framework within the existing production environment as mentioned in Table 4.14.

Table 4.14 Mean and Std. Dev. Analysis for Section C

Item	*Statement*	*Mean*	*Std. Dev.*
Q7	iDSS-ProLean apps effectively captures real-time production data without delays	3.90	0.59
Q8	IoT sensors provide accurate and reliable data for decision-making in iDSS-ProLean	3.85	0.58
Q9	The transition from manual to iDSS-ProLean data collection is smooth.	3.82	0.55
Q10	iDSS-ProLean does not disrupt existing production operations	3.85	0.60
Q11	iDSS-ProLean is easy and understandable	3.87	0.43
Q12	iDSS-ProLean is compatible with other digital tools	3.85	0.53
Q13	iDSS-ProLean reduces workload of managers and engineers	3.86	0.55
Q14	iDSS-ProLean is more efficient than traditional methods	3.86	0.55

Specifically, respondents perceived the framework as capable of effectively capturing real-time production data without delays (Q7), as evidenced by a mean score of 3.90 (SD = 0.59). Similarly, the accuracy and reliability of IoT sensor data for decision-making purposes (Q8) were positively received, yielding a mean of 3.85 (SD = 0.58).

In terms of the framework's usability, the transition from manual to automated data collection via iDSS-ProLean (Q9) was regarded as relatively smooth (M = 3.82, SD = 0.55), while its operation was not perceived to cause disruptions to existing production workflows (Q10), also with a mean score of 3.85 (SD = 0.60). Furthermore, respondents generally found the framework to be easy to learn and understand (Q11), which received a slightly higher mean of 3.87 (SD = 0.43), suggesting user-friendliness and accessibility. The framework's compatibility with other digital tools used in the production line (Q12) was also acknowledged (M = 3.85, SD = 0.53).

In terms of operational benefits, participants agreed that iDSS-ProLean helped reduce the workload of production managers and engineers (Q13), with a mean of 3.86 (SD = 0.55), and that decision-making processes were more efficient when using the framework compared to traditional methods (Q14), which garnered a mean score of 3.86 (SD = 0.55). Overall, the responses demonstrated a consistently favorable perception of iDSS-ProLean in terms of technical integration, ease of use, and operational efficiency. These findings suggest that the framework was well-adapted to the current manufacturing environment, thereby supporting its feasibility and alignment with IR4.0 principles.

c) User Experience

The construct of User Experience, encompassing Items Q15 through Q21, was evaluated to understand participants' perceptions regarding the practicality, usability, and overall satisfaction with iDSS-ProLean framework The results demonstrated a notably positive user sentiment, particularly in terms of framework interaction, usefulness, and alignment with LM objectives.

Table 4.15 Mean and Std. Dev. Analysis for Section D

Item	*Statement*	*Mean*	*Std. Dev.*
Q15	iDSS-ProLean provides meaningful insights that help improve production performance	3.89	0.62
Q16	iDSS-ProLean app interface is user-friendly and intuitive	4.05	0.55
Q17	iDSS-ProLean supports continuous improvement in production performance	3.90	0.61
Q18	iDSS-ProLean reduces the need for manual intervention in data analysis	3.90	0.59
Q19	iDSS-ProLean aligns well with LM objectives	4.08	0.47
Q20	Overall, I am satisfied with the performance of iDSS-ProLean framework	3.96	0.61
Q21	I would recommend iDSS-ProLean framework to other manufacturing operations.	4.08	0.71

Respondents acknowledged that the framework provided meaningful insights as summarized in Table 4.15, contributing to enhanced production performance (Q15), which yielded a mean score of 3.89 (SD = 0.62). The user-friendliness and intuitiveness of the app interface (Q16) received the highest rating within this construct, with a mean of 4.05 (SD = 0.55), indicating that the framework interface was accessible and easy to navigate for users of various technical backgrounds. In terms of continuous improvement, participants agreed that the framework supported ongoing enhancements in production performance (Q17), scoring a mean of 3.90 (SD = 0.61). Similarly, the ability of iDSS-ProLean framework to reduce manual intervention in data analysis (Q18) was well received (M = 3.90, SD = 0.59), reflecting the framework's automation strengths and alignment with data-driven manufacturing processes.

Importantly, the framework was perceived to align well with LM objectives (Q19), which obtained one of the highest mean values at 4.08 (SD = 0.47). This reflects strong acceptance of the framework's principles in facilitating waste reduction, process streamlining, and efficiency improvements. Additionally, general satisfaction with the framework's performance (Q20) was observed (M = 3.96, SD = 0.61), and a strong likelihood of recommending iDSS-ProLean framework to other manufacturing operations was indicated (Q21), which also received a high mean score of 4.08 (SD = 0.71). Collectively, these findings underscore a favorable user experience, highlighting both the functional and strategic value of iDSS-ProLean framework in supporting LM initiatives. The consistently positive ratings across all seven items suggest that the framework is not only operationally effective but also well-received by its end users, thereby reinforcing its feasibility and potential scalability in real-world industrial settings.

In conclusion, the descriptive analysis across the three constructs LM Experience, Framework Adaptation, and User Experience collectively affirmed the practical relevance, technical feasibility, and user acceptability of iDSS-ProLean framework. Respondents demonstrated substantial exposure to manufacturing operations and LM tools, indicating a well-informed participant group capable of providing insightful feedback. The framework adaptation results highlighted that iDSS-ProLean was perceived as reliable, accurate, and non-disruptive, with seamless integration into existing operations and compatibility with digital tools. Furthermore, the user experience findings revealed strong user satisfaction, with participants acknowledging the framework's ability to deliver meaningful insights, support continuous improvement, and reduce manual intervention. These insights not only validate the applicability of iDSS-ProLean within real-world manufacturing contexts but also support its potential scalability as a decision-support tool for digital LM implementation.

4.5 Chapter Summary

The chapter demonstrated the successful achievement of all four objectives of the iDSS-ProLean project: investigating the linkage between DSS, LM, and IoT, formulating the integrated framework, verifying the model through sensor-based simulations and validating its technical and operational feasibility. Although full-scale implementation on a live production line was restricted, the combined use of sensor-based modelling, statistical verification, and industry feedback provided strong evidence of reliability, practicality, and readiness for future industrial adoption. Overall, iDSS-ProLean represents a theoretically sound and practically applicable model, advancing LM by embedding sensor-driven intelligence for continuous, data-driven improvement. manufacturers require intelligent, data-driven systems to remain competitive. This study introduced iDSS-ProLean, an integrated DSS combining IoT, real-time data analytics, and key LM tools within a unified framework. Implemented on a semiconductor backend line with seven sequential stages, the system utilised ESP32 microcontrollers and sensors, HC-SR04, SW-420, DHT11, BMP280, connected to a Firebase database and Android interface for live monitoring. Across 60 trial runs, iDSS-ProLean effectively identified and optimised inefficiencies: LBE improved from 0.82 to 1.00, SMED reduced setup times from 14 inefficient runs (SMED > 1) to full optimisation (SMED < 1), and Kanban stabilised inventories within the 500-unit benchmark. Statistical validation confirmed reliable data transmission ($p > 0.05$) and a significant correlation between total processing time and LBE ($r = -0.435$, $p = 0.001$). A feasibility study involving 30 industrial engineers indicated that 78% agreed the system improved decision-making and found it easy to use.

CHAPTER 5

CONCLUSION AND FUTURE WORKS

iDSS-ProLean framework was developed and validated as the first DSS specifically designed for LM in semiconductor production lines. This research addressed the main gaps in existing DSS frameworks (RO1) by integrating real-time IoT data, simulation, and LM tools into a unified, modular system architecture featuring a structured database and interactive user interfaces for process optimisation. The framework was successfully validated with live sensor data from an actual production line (RO2), confirming its capability to manage, analyse, and visualise industrial-scale data accurately. Moreover, the use of low-cost sensors and open-source platforms demonstrated its technical feasibility and practicality for industrial adoption (RO3). Overall, iDSS-ProLean establishes a robust, data-driven foundation for continuous improvement in LM environments through real-time decision support and efficient production control.

5.1 Research Achievement

This research successfully achieved all four objectives established at the outset of the study, leading to the development and validation of the intelligent DSS framework known as iDSS-ProLean, which integrates LM and IoT-based Sensor Architecture within the context of IR4.0. The first objective (RO1) aimed to investigate existing DSS frameworks for LM implementation.

This objective was achieved through an extensive review and analysis of current DSS architectures, highlighting critical limitations such as the absence of real-time data integration, limited automation support, and weak connectivity between LM tools and operational data. The findings from this investigation formed the foundation for designing a more intelligent, responsive, and data-driven framework capable of overcoming these gaps. The second objective (RO2) was to formulate the Inherent Correlation DA Model by integrating an IoT-based sensor architecture. This was accomplished through the design of a modular sensor network that captures, transmits, and analyses production data in real time. The integration of IoT sensors with DA processes enabled the transformation of raw operational data into actionable insights, establishing a correlation between data flow, process parameters, and production efficiency. This innovation enhances visibility into manufacturing performance and supports predictive analytics for informed decision-making.

The third objective (RO3) focused on verifying the proposed Inherent Model through a Modular Architectural Setup. This was achieved by developing and testing the system prototype within a controlled environment, ensuring that the architecture could handle multiple LM tools and real-time sensor data simultaneously. The modularity of the setup proved essential in validating system stability, scalability, and interoperability across different production conditions, confirming the practicality of the model's design. Finally, the fourth objective (RO4) sought to validate the proposed Inherent Model through feasibility research using selected LM tools. This objective was achieved through industrial data validation using live semiconductor production inputs. The feasibility tests confirmed the framework's analytical reliability and capability to optimise processes in real manufacturing conditions Collectively, these achievements confirm that iDSS-ProLean providing a validated, intelligent DSS framework that enhances productivity, and supports sustainable LM practices in alignment with IR4.0 principles.

5.2 Research Impact

5.2.1 Technological Impact

This research demonstrates unprecedented innovation in LM through the development of iDSS-ProLean, which integrates key LM tools with IoT and real-time DA to modernise conventional manufacturing systems. The framework's intelligent decision support functionalities enhance production adaptability by responding to variable conditions and delivering real-time insights that optimise operational efficiency and minimise waste. Its implementation of IoT-enabled sensors and seamless data flow exemplifies a novel integration of IoT and DA in manufacturing, enabling continuous monitoring and data-driven improvement. Beyond the semiconductor industry, this integration offers a scalable model for other sectors aiming to improve process efficiency through intelligent technologies. The responsiveness and adaptability of iDSS-ProLean across etching, cutting, and assembling processes further demonstrate its versatility and potential for cross-industry application, reinforcing the role of LM when complemented with advanced, technology-driven frameworks.

5.2.2 Society Impact

New age technologies such as iDSS-ProLean can create new employment positions in tech support, data analysis, and framework management which illustrates a new hope for technology-driven roles in the industry. With the advancement of automation and data engineering in manufacturing, the skillset requirements for the workers need to change to be able to interface with such systems, automating the learning process, and enhancing the skillset of the workforce. Not only does this transform the empowerment of individuals to undertake complex, rewarding challenges, but it also aligns with government policies focused on cultivating a skilled workforce.

5.2.3 Knowledge Impact

The advancement and application of iDSS-ProLean is a notable contribution to the knowledge base of industrial engineering, IoT, and smart manufacturing. As a case study, it demonstrates the fusion of IoT technologies with LM tools and provides empirical evidence for both the development and application of theories in these fields. Documentation of the design, implementation, and results of iDSS-ProLean enable research into the IoT-enabled DSSin manufacturing regarding their features, enhancement and challenges. The information generated from the real-time monitoring of production processes enrich the study on the efficiency of production processes, the reliability of the framework, and the effects of IoT on operational excellence. Also, the integration of LM principles and this framework opens the discourse on the applicability of LM and other traditional manufacturing processes in high-tech environments, enhancing further literary and practical contributions in industrial engineering.

iDSS-ProLean app illustrates the fusion of several fields, such as industrial engineering, computer science and business management, creating new avenues for interdisciplinary research. The integration of IoT technologies with LM principles disrupts the conventional separation of these domains and initiates new ways of thinking that utilise elements from all branches. This convergence promotes an all-encompassing perspective of smart manufacturing systems while simultaneously driving multidisciplinary technological, operational, and managerial research divided by blended academic boundaries. The interdisciplinary characteristics of iDSS-ProLean broaden the scope of intellectual collaboration, thus transforming the optimised manufacturing paradigms, DA, and business strategies.

5.3 Future Recommendation

Building upon the outcomes and technological advancements demonstrated in this research, future studies should continue to explore strategic directions that strengthen and extend the capabilities of the iDSS-ProLean framework. These recommendations are intended to deepen its integration of intelligent technologies, enhance its adaptability across multiple industrial sectors, and support the long-term evolution of smart, data-driven, and sustainable manufacturing systems. Future research can focus on the following areas to further enhance and expand iDSS-ProLean framework:

a) **Integration of Hybrid AI Models:**

   Incorporate deep learning techniques to predict production bottlenecks, machine failures, and demand fluctuations.

b) **Data Fusion and Contextual Intelligence:**

   Combine structured sensor data with unstructured metadata, such as maintenance logs and operator notes, to enhance system intelligence and contextual understanding.

c) **Adaptive and Continual Learning**

   Implement continual learning algorithms to enable model adaptability and resilience in dynamic production environments.

d) **Explainable Artificial Intelligence (XAI)**

   Apply interpretability methods such as SHAP and LIME to ensure transparency, trustworthiness, and user confidence in AI-driven recommendations.

e) **Cross-Industry Applicability**

   Develop customized architectures that can be adapted to various industrial sectors, including automotive, pharmaceutical, and food production, while maintaining scalability and interoperability.

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APPENDICES

APPENDIX A Questionnaire for Objective 1

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

Faculty of Manufacturing Engineering
Universiti Teknikal Malaysia Melaka

Can IR4.0 work together with Lean? Evidence From Malaysian Manufacturing Lean Practitioners

- To investigate the impact of IR 4.0 technologies on the lean tools, and
- To rank the IR 4.0 technologies for the future transformation of the lean practices.

Prepared by
Nur Ain Qistina Binti Muhammad ShafeePhD Students
011-6991 5689

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All Response be kept Strictly Confidential.
This Form Contains Five (5) Section. Please Answer All Question by tick (/) where appropriate corresponding to your choice.

Section A: Background Information

1. Please state your gender
   a. Male
   b. Female
2. Age
   a. 20-30 years old
   b. 31-40 years old
   c. 41-50 years old
   d. More than 50 years old
3. Please state your experience in company
   a. 0-5 years
   b. 6-10 years
   c. 11-15 years
   d. 16 and
4. Please state your position in the company
   a. Executive boards
   b. Managers
   c. Senior Engineers
   d. Engineers
5. Company's sectors
   a. Electrical and electronic
   b. Automotive
   c. Metal processing
   d. Oil and gas
   e. Defense and security
   f. Food and beverage
   g. Transportation and logistics
   h. others
6. Type of company
   a. Multinational
   b. National
   c. SME
   d. GLC
   e. others
7. Awareness and Familiarity on IR 4.0
   a. Yes
   b. Maybe
   c. No

Section B: Impact on Lean System

This part is to translate the qualitative opinion into a quantitative data. Hence, please select the number according to the scale to indicate the extent to which the impact received from the items in your personal opinion.

SCALE	LABEL
1	*No Impact At All*
2	*Little Impact*
3	*Impact*
4	*Highly Impact*
5	*Strongly Impact*

ITEMS	1	2	3	4	5
I understand what lean is					
I notice there is/are:					
Defects-effort caused by rework, scrap, and incorrect part					
Overproduction-supplying the process with more than is needed to meet orderrequirements					
Waiting-wasting the time to wait for the next step in the process					
Non-utilized talent-underutilizing the talents, skills, and knowledge of a worker					
Transportation-unnecessary movement of products and materials					
Inventory-excess products and materials not being processed					
Motion- any movement of a man and/or equipment that does not add value to the productor service					
Extra processing – more work or higher quality that is required by the customer					
I notice my company used:					
Kaizen – continuous improvement					
Kanban – instruction or information card					
PDCA – plan, do, check, action					
OEE – Overall Equipment Effectiveness					
5S – housekeeping technique					
TPM – Total Productive Maintenance					
JIT – Just in Time					
Poka Yoke – mistake proofing for zero defects					
Jidoka - Automation					
Andon – an alert signal regarding current production status					
TQM- Total Quality Management					
VSM – Value Stream Mapping					
Takt Time – Average Production Time					
KPI – Key Performance Index					

Section C: Impact on IR 4.0 Technologies Enablers

This part is to translate the qualitative opinion into a quantitative data. Hence, please select the number according to the scale to indicate the extent to which the impact received from the items in your personal opinion.

SCALE	LABEL
1	*No Impact At All*
2	*Little Impact*
3	*Impact*
4	*Highly Impact*
5	*Strongly Impact*

ITEMS	1	2	3	4	5
Additive Manufacturing					
Cybersecurity					
Artificial Intelligence					
Big Data					
Advance Manufacturing					
Simulation					
Cloud Computing					
Augmented Reality					
IoT					
Automation Robots					
Systems Integration					

Section D: Impact on Lean Performance

This part is to translate the qualitative opinion into a quantitative data. Hence, please select the number according to the scale to indicate the extent to which the impact received from the items in your personal opinion.

SCALE	LABEL
1	*No Impact At All*
2	*Little Impact*
3	*Impact*
4	*Highly Impact*
5	*Strongly Impact*

ITEMS	1	2	3	4	5
Employee Involvement					
Cost Reduction					
Waste Reduction					

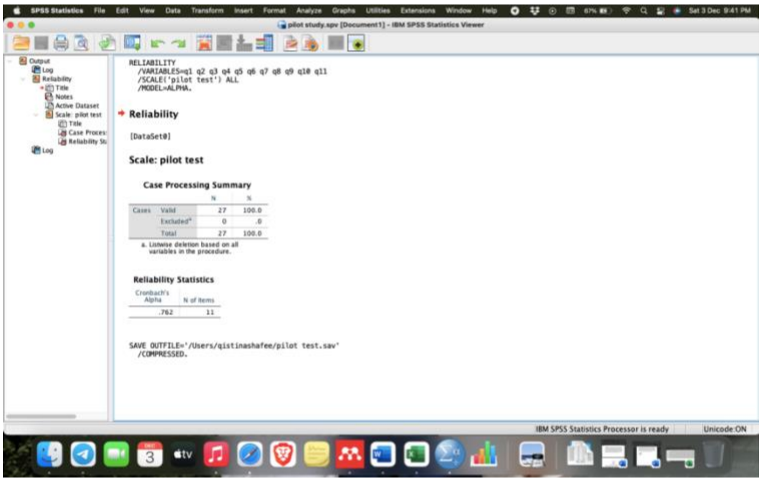
Section E: Understanding the Current Trend of Industry 4.0

1. The Main Source for Industry 4.0
   a. National news / website
   b. Professional course provided by the company
   c. Peer talk
   d. Self-search on internet
2. Level of the implementation of the current industry 4.0
   a. Beginner
   b. Elementary
   c. Intermediate
   d. Advance

3. Level of data services
   a. Beginner
   b. Elementary
   c. Intermediate
   d. Advance
4. Level of cybersecurity
   a. Beginner
   b. Elementary
   c. Intermediate
   d. Advance
5. Level of skills you already have to work in the industry technology in your company
   a. Beginner
   b. Elementary
   c. Intermediate
   d. Advance
6. Do you interested in upgrading your skills
   a. Yes
   b. Maybe
   c. No
7. Do you think your company should upgrade the level of IR4.0 implementation
   a. Yes
   b. Maybe
   c. No

APPENDIX A(ii) Pre-Test Panelist

Panelist	*Position*	*Organization*	*Expertise*	*Experience*
Assoc. Prof. Dr. Abdul Samad Bin Shibghatullah	Head Of Program, Bachelor Of Computer Science	College Of Computing and Informatics, Universiti Tenaga Nasional	Public Transport Scheduling, Information Technology	22 Years
Profesor Madya Dr Zuhriah Binti Ebrahim	Profesor Madya - Fakulti Teknologi Dan Kejuruteraan Industri Dan Pembuatan	Universiti Teknikal Malaysia Melaka	Lean Six Sigma	21 Years
Profesor Madya Dr Seri Rahayu Binti Kamat	Profesor Madya - Fakulti Teknologi Dan Kejuruteraan Industri Dan Pembuatan	Universiti Teknikal Malaysia Melaka	Manufacturing System	21 Years
Dr. Dani Yuniawa	Senior Lecturer	Universitas Merdeka Malang, East Java, Indonesia	Discrete Event Simulation, Quality Engineering, Quality Management, Quality Assurance, Six Sigma.	20 Years
Dr. Nadiah Binti Ahmad	Pensyarah Kanan - Fakulti Teknologi Dan Kejuruteraan Industri Dan Pembuatan	Universiti Teknikal Malaysia Melaka	Systems Optimization	16 Years
Dr. Primahasni Dalulia	Senior Lecturer	Universitas Merdeka Malang, East Java, Indonesia	Business Administration, Marketing, Consumer Economics, Industrial Engineering	10 Years

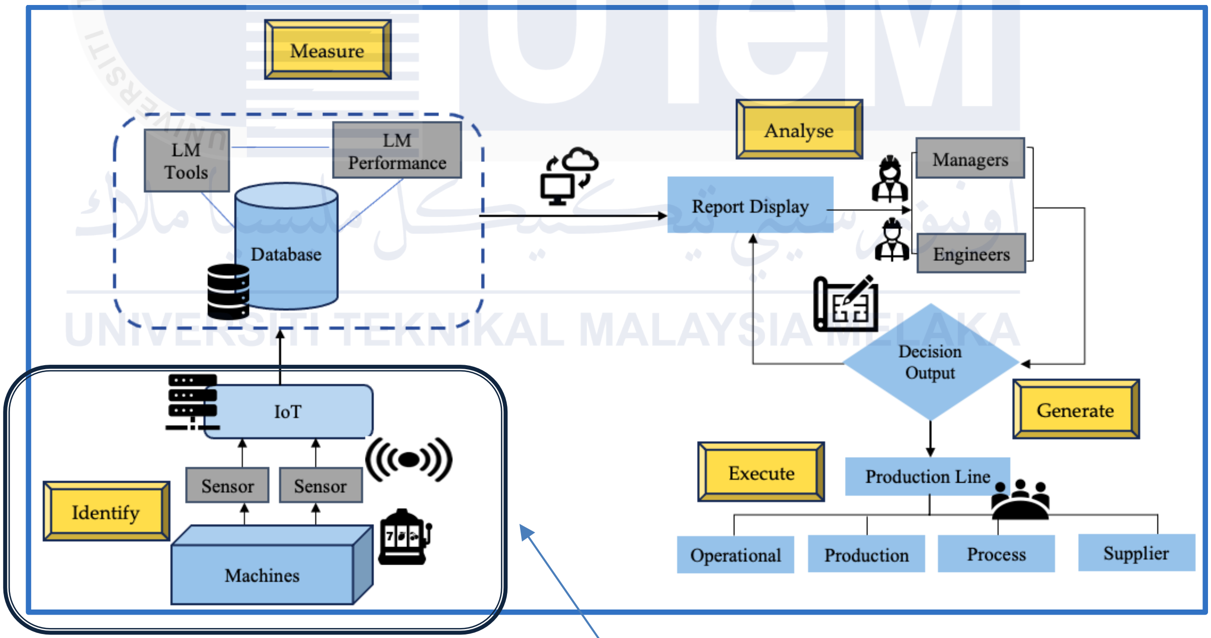


Cronbach's Alpha Reliability Coefficient Industry Survey on DSS, LM, and IoT Integration in Manufacturing

APPENDIX B iDSS-ProLean Intellectual Property for Objective 2

iDSS-ProLean

iDSS-ProLean Logo



Novelty: Machines-Apps Interconnection

iDSS-ProLean Framework

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Rujukan Tuan (Your Ref):
Tarikh (Date): 23 April 2024

Profesor Ts. Dr. Effendi bin Mohamad
Melalui dan salinan
Dekan Fakulti Teknologi dan Kejuteraan Industri dan Pembuatan

YBhg.Prof.,

KEPUTUSAN PERMOHONAN PENDAFTARAN HARTA INTELEK (IP) BIL.2/2024

TAJUK PERMOHONAN : A THEORITICAL FORMULATION OF NEAR-NET-SHAPE DATA ANALYTICS MODEL IN LEAN MANUFACTURING DECISION SUPPORT SYSTEM

JENIS IP : HAK CIPTA

Dengan segala hormatnya perkara di atas adalah dirujuk.

2. Sukacita dimaklumkan bahawa melalui Mesyuarat Jawatankuasa Penilaian Teknikal Harta Intelek Bil. 2/2024 yang telah diadakan pada 25 Mac 2024 yang lalu, permohonan pendaftaran IP di atas telah diluluskan dengan penambahbaikan seperti ketetapan berikut:

i. *Suit and recommended or copyright.*
ii. Disokong untuk *copyright*. Perlu penambahan penerangan mengenai *framework* ini.
iii. *The explanation is so generic that does not specifically refer to this type of work. It would be better to specifically relate the presentation to the work.*
iv. *The theoretical framework is recommended for copyright.*

3. Sehubungan dengan itu, YBhg.Prof. adalah dimohon untuk melengkapkan semula borang Permohonan Pendaftaran IP dan dokumen permohonan hak cipta sekiranya ingin meneruskan pendaftaran ini.

Sekian, terima kasih.

"MALAYSIA MADANI"
"BERKHIDMAT UNTUK NEGARA"
"KOMPETENSI TERAS KEGEMILANGAN"

Saya yang menjalankan amanah,

DR. MUHAMMAD ILMAN HAKIMI CHUA BIN ABDULLAH
Timbalan Pengarah
Bahagian Inovasi Kreatif (Blue Dot)
Pusat Pengurusan Kolaborasi RICE UTeM - Melaka

SEBUAH UNIVERSITI TEKNIKAL AWAM

Award from UTeM RICE (Research Innovation and Collaboration Centre)

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MELAKA (UTEM) HANG TUAH JAYA
76100 MELAKA
MALAYSIA

LCR01

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TAJUK KARYA	:	IDSS-PROLEAN FRAMEWORK
KATEGORI KARYA	:	SASTERA
TARIKH KARYA DICIPTA	:	01 DISEMBER 2022
TEMPAT PENERBITAN YANG PERTAMA	:	TIDAK BERKAITAN
NO. PEMBERITAHUAN	:	CRLY2024M03200
NO. PERMOHONAN	:	LY2024M03200
TARIKH PERMOHONAN	:	10 JUN 2024

BUTIRAN PENCIPTA

NAMA PENCIPTA	:	EFFENDI BIN MOHAMAD
NRIC / NO. SYARIKAT	:	780625015887
WARGANEGARA	:	MALAYSIA
NAMA PENCIPTA	:	MOHD SOUFHWEE BIN ABD RAHMAN
NRIC / NO. SYARIKAT	:	760406017083
WARGANEGARA	:	MALAYSIA

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NAMA PENCIPTA	:	NUR AIN QISTINA BINTI MUHAMMAD SHAFEE
NRIC / NO. SYARIKAT	:	970701035968
WARGANEGARA	:	MALAYSIA

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PEMEGANG LESEN	:	TIDAK BERKAITAN

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Pengawal Hak Cipta
Tarikh: 24 Jun 2024

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Title of Work	:	**IDSS-PROLEAN FRAMEWORK**
Category of Work	:	**LITERARY**
Date of Notification	:	**10 JUNE 2024**
Date of Creation	:	**01 DECEMBER 2022**
Date of First Published	:	**NOT APPLICABLE**

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APPENDIX C Coding table for Objective 3

CODING TABLE

SOFTWARE	Coding Component

Firebase
Writing backend code that is automatically triggered by Firebase events, such as when new data is added or updated in the database, is essential for processing IoT data as it arrives.

```
// Import Firebase Admin SDK
const admin = require('firebase-admin');
admin.initializeApp();

// Get a reference to the Firebase Realtime Database
const db = admin.database();

// Define a function triggered by database events
exports.onDataChange = require('firebase-functions').database
 .ref('/iot-data/{deviceId}') // Path to monitor for changes, with a wildcard for deviceId
 .onWrite((change, context) => {
 const beforeData = change.before.val(); // Data before the change
 const afterData = change.after.val(); // Data after the change

 // Log the changes
 console.log(`Data changed for device: ${context.params.deviceId}`);
 console.log('Before:', beforeData);
 console.log('After:', afterData);

 // Process the new data
 if (afterData) {
 // Example: Add a timestamp to the new data
 const updatedData = {
 ...afterData,
 processedAt: admin.database.ServerValue.TIMESTAMP,
 };

 // Save the updated data back to the database
 return change.after.ref.update(updatedData);
 }

 // Handle data deletion (if needed)
 if (!afterData) {
 console.log(`Data deleted for device: ${context.params.deviceId}`);
 }

 return null;
});
```

Arduino IDE
Integrate Firebase With Arduino IDE For Real-Time Data

```
// Include necessary libraries
#include <WiFi.h>
#include <FirebaseESP32.h>

// Define your Firebase and Wi-Fi credentials
#define FIREBASE_HOST "<YOUR_FIREBASE_PROJECT>.firebaseio.com" // Replace with
your Firebase project URL
#define FIREBASE_AUTH "<YOUR_FIREBASE_DATABASE_SECRET>" // Replace with
your Firebase database secret
#define WIFI_SSID "<YOUR_WIFI_SSID>" // Replace with your Wi-Fi SSID
#define WIFI_PASSWORD "<YOUR_WIFI_PASSWORD>" // Replace with your Wi-Fi
password

// Create Firebase and Wi-Fi objects
FirebaseData firebaseData;

void setup() {
 // Initialize Serial monitor
 Serial.begin(115200);

 // Connect to Wi-Fi
 WiFi.begin(WIFI_SSID, WIFI_PASSWORD);
 Serial.print("Connecting to Wi-Fi");
 while (WiFi.status() != WL_CONNECTED) {
```

```
 Serial.print(".");
 delay(1000);
 }
 Serial.println("\nConnected to Wi-Fi");

 // Connect to Firebase
 Firebase.begin(FIREBASE_HOST, FIREBASE_AUTH);
 Firebase.reconnectWiFi(true);
 Serial.println("Connected to Firebase");
}

void loop() {
 // Example: Sending data to Firebase
 if (Firebase.setInt(firebaseData, "/iot-data/device1/temperature", 25)) {
 Serial.println("Data sent successfully");
 } else {
 Serial.println("Failed to send data");
 Serial.println(firebaseData.errorReason());
 }

 // Example: Reading data from Firebase
 if (Firebase.getInt(firebaseData, "/iot-data/device1/temperature")) {
 Serial.print("Received temperature: ");
 Serial.println(firebaseData.intData());
 } else {
 Serial.println("Failed to read data");
 Serial.println(firebaseData.errorReason());
 }

 delay(5000); // Wait for 5 seconds before the next iteration
}
```

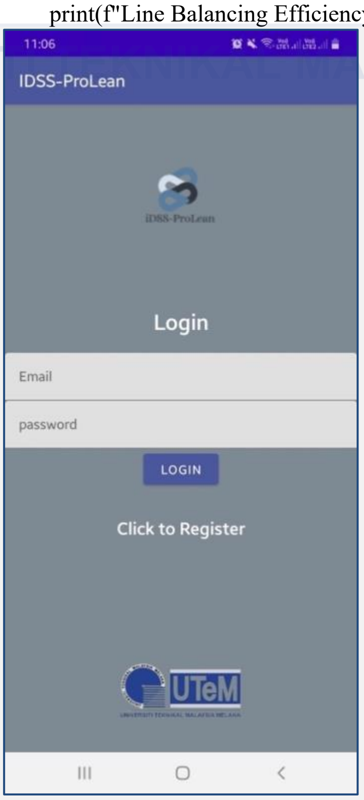
Sensor Simulation

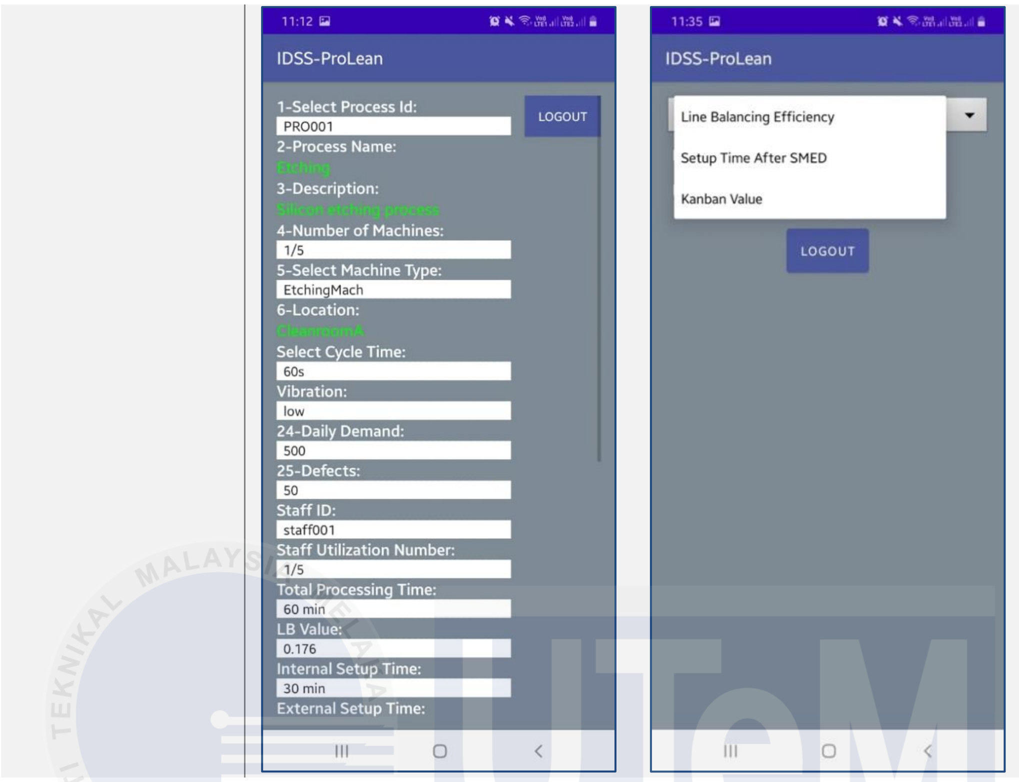
```
# Wokwi Simulation for Line Balancing using ESP32, HC-SR04, SW-420, and DHT11
# Simulating total processing time, cycle time, number of machines, and environmental factors
from machine import Pin, time_pulse_us
import dht
import time
import json
import random
# Sensor Pin Configurations
TRIG = Pin(5, Pin.OUT) # HC-SR04 Trigger
ECHO = Pin(18, Pin.IN) # HC-SR04 Echo
VIBRATION_SENSOR = Pin(21, Pin.IN) # SW-420 Vibration Sensor
DHT_SENSOR = dht.DHT11(Pin(4)) # DHT11 Temp and Humidity

# Constants
total_machines = 5 # Define number of available machines

def get_distance():
 TRIG.value(1)
 time.sleep_us(10)
 TRIG.value(0)
 duration = time_pulse_us(ECHO, 1)
 distance = (duration * 0.0343) / 2 # Convert to cm
 return max(5, min(distance, 100)) # Limit range (5cm to 100cm)
# Function to read vibration sensor
def get_vibration():
 return VIBRATION_SENSOR.value() # 1 = active, 0 = idle
# Function to read temperature and humidity
def get_environment():
 try:
 DHT_SENSOR.measure()
 temp = DHT_SENSOR.temperature()
 hum = DHT_SENSOR.humidity()
 except OSError:
 temp, hum = 25, 50 # Default safe values
 return temp, hum
# Simulating 50 production cycles
```

```
data_log = []
total_processing_time = 0
for cycle in range(50):
 cycle_time = get_distance() # Use distance to simulate process time
 vibration = get_vibration()
 temperature, humidity = get_environment()
 total_processing_time += cycle_time

 # Simulated JSON data storage
 data_entry = {
 "cycle": cycle + 1,
 "cycle_time": cycle_time,
 "vibration": vibration,
 "temperature": temperature,
 "humidity": humidity,
 "total_machines": total_machines
 }
 data_log.append(data_entry)
 print(json.dumps(data_entry, indent=4))
 time.sleep(1) # Simulate cycle delay

# Calculate Line Balancing Efficiency (LBE)
LBE = (total_processing_time / (sum(entry['cycle_time'] for entry in data_log) * total_machines))
* 100

# Save Data (Mock Firebase Upload)
output_data = {
 "simulation_data": data_log,
 "total_processing_time": total_processing_time,
 "LBE": LBE
}
with open("wokwi_line_balancing_data.json", "w") as file:
 json.dump(output_data, file, indent=4)

print("Simulation Complete. Data saved.")
print(f"Total Processing Time: {total_processing_time} sec")
print(f"Line Balancing Efficiency: {LBE:.2f}%")
```

Android Studio

- Build A Real-Time Dashboard




11:12
IDSS-ProLean
1-Select Process Id:
PRO001
LOGOUT
2-Process Name:
Etching
3-Description:
Silicon etching process
4-Number of Machines:
1/5
5-Select Machine Type:
EtchingMach
6-Location:
CleanroomA
Select Cycle Time:
60s
Vibration:
low
24-Daily Demand:
500
25-Defects:
50
Staff ID:
staff001
Staff Utilization Number:
1/5
Total Processing Time:
60 min
LB Value:
0.176
Internal Setup Time:
30 min
External Setup Time:
11:35
IDSS-ProLean
Line Balancing Efficiency
Setup Time After SMED
Kanban Value
LOGOUT

APPENDIX D Questionnaire for Objective 4

Faculty of Manufacturing Engineering
Universiti Teknikal Malaysia Melaka

Can IR4.0 work together with Lean? Evidence From Malaysian Manufacturing Lean Practitioners

- **The objective of this questionnaire is to assess the operational feasibility of iDSS-ProLean system by evaluating its effectiveness, usability, and impact on manufacturing processes from the perspective of industry professionals.**

Prepared by
Nur Ain Qistina Binti Muhammad Shafee
PhD Candidate
011-6991 5689

Supervised by
Prof. Ts. Dr. Effendi Bin Mohamad
Project Leader
012- 374 5208

All Response Be Kept Strictly Confidential And Exclusively For Academic Purpose Instruction:
This form has two (2) sections. Please Answer All Question by tick (/) where appropriate corresponding to your choice.

Section 1: Respondents Background

Please state your position in the company

a) Managers ☐
b) Engineers ☐

Section 2: Operational Feasibility Study

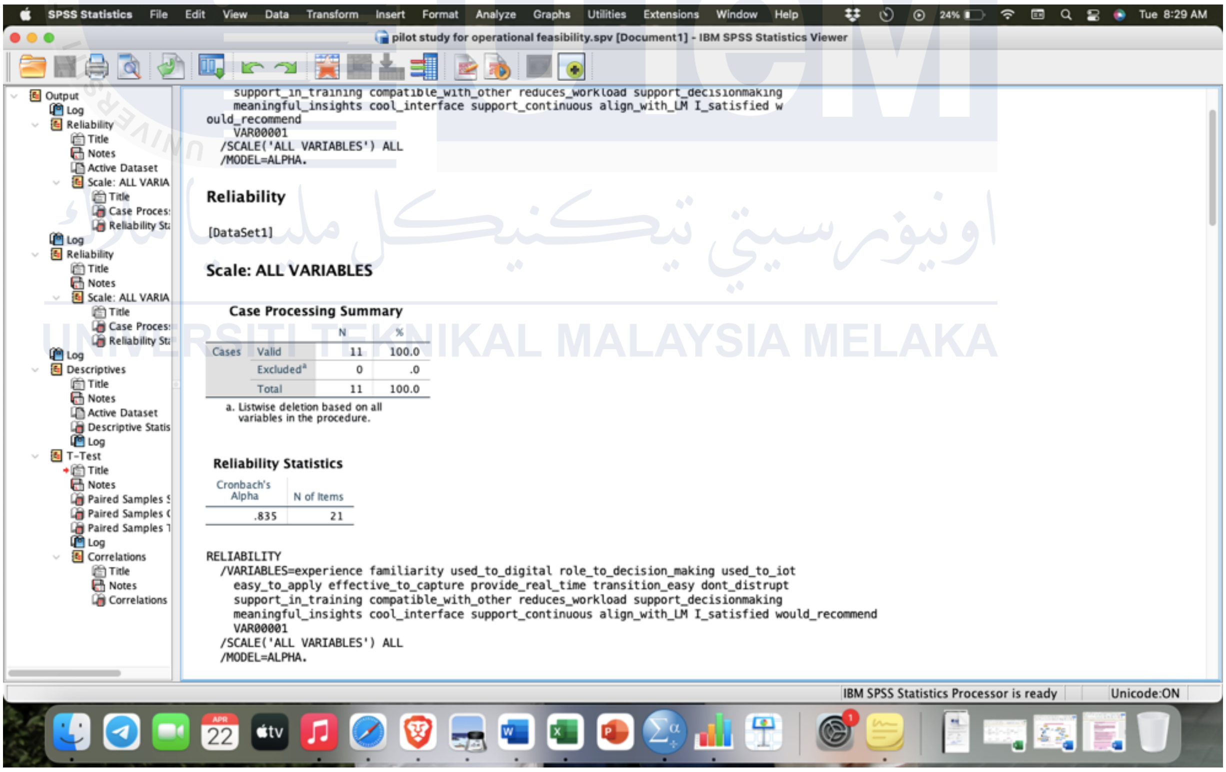
This part is to translate the qualitative opinion into a quantitative data. Hence, please select the number according to the scale to indicate the extent to which the impact received from the items in your personal opinion.

SCALE	LABEL
1	*Strongly Disagree*
2	*Disagree*
3	*Neutral*
4	*Agree*
5	*Strongly Agree*

QUESTIONS	1	2	3	4	5
Lean Manufacturing Experience					
1. I have experience working in manufacturing production lines.					
2. I am familiar with Lean Manufacturing principles					
3. I have used digital tools for production monitoring and decision-making before.					
4. My role involves making data-driven decisions for process improvements.					
5. I have prior experience using IoT-based production monitoring systems.					
6. iDSS-ProLean system is easy to integrate into the existing production workflow.					
Framework Adaptation					
7. The system effectively captures real-time production data without delays.					
8. The IoT sensors provide accurate and reliable data for decision-making.					
9. The transition from manual to automated data collection is smooth with this system.					
10. The system does not significantly disrupt existing production operations.					
11. The system is compatible with other digital tools used in the production line.					
12. The system reduces the workload of production managers and engineers.					
13. The decision-making process using iDSS-ProLean is more efficient than traditional methods.					
14. The system provides meaningful insights that help improve production performance.					
User Experience					
15. iDSS-ProLean app interface is user-friendly and intuitive.					
16. The system supports continuous improvement in production performance.					
17. The system reduces the need for manual intervention in data analysis.					
18. The system aligns well with Lean Manufacturing objectives					
19. Overall, I am satisfied with the performance of iDSS-ProLean system.					
20. I would recommend iDSS-ProLean system to other manufacturing operations.					

APPENDIX C (ii) Panellist for pre-test

PANELLIST	POSITION	ORGANIZATION	EXPERIENCE
Nor Akramin Bin Mohamad	Ketua Bahagian - Pusat Perkhidmatan Pendidikan Lanjutan Dan Berterusan	Universiti Teknikal Malaysia Melaka	21 Years
Dr. Ts. Chm. Anuar Bin Ishak	Principle Assistant Director	Seksyen Kawalan Punca-Punca Pencemaran Udara Dan Bunyi Bising, Jabatan Alam Sekitar	20 years
Ir. Dwi Hadi Sulistyarini, ST., MT	Head Of Basic Engineering Science Laboratory	Teknik Industri Universitas Brawijaya	20 years
Muhammad Faishal S.T.,M.Eng., Ph.D.	Lecturer	University Ahmad Dahlan	16 years
Mohd Khidir Osman	Administrative Officer	Angkatan Tentera Malaysia (ATM)	15 years
Nur Najiha Bin Amin	Production Engineer	In. d. Solution Sdn. Bhd.	4 Years



Cronbach's Alpha Reliability Coefficient for Operational Feasibility Questionnaire

APPENDIX E Letter of Invitation for the Experts

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+606 270 1022
www.utem.edu.my

PUSAT PENGURUSAN KOLABORASI RICE-UTEM MELAKA,
Tel: +606 270 1295 | faks: +06 270 1033

Rujukan Kami:
Rujukan Tuan:
Tarikh:

Kepada yang berkenaan,

Prof / Prof Madya / Dr / Ts / Encik / Puan / Cik,

Memohon Kerjasama sebagai Panel Pakar bagi Kajian *Decision Support System* dalam Industri Pembuatan *Lean* di Malaysia

Dengan segala hormatnya perkara di atas adalah dirujuk.

2. Adalah dimaklumakan pelajar di bawah seliaan saya iaitu Nur Ain Qistina binti Muhammad Shafee (P052210004) sedang menjalankan kajian bertajuk "*A THEORETICAL FORMULATION OF NEAR-NET-SHAPE DATA ANALYTICS MODEL IN LM DECISION SUPPORT SYSTEM*" untuk melengkapkan pengajian di peringkat Doktor Falsafah di Universiti Teknikal Malaysia Melaka (UTeM).

3. Bagi mendapatkan maklumat untuk mencapai objektif kajian beliau yang melibatkan input teknikal dari pakar di dalam bidang *Lean Manufacturing* di Malaysia. Pihak kami dengan rendah hati ingin menjemput Prof / Prof Madya / Dr / Ts / Encik / Puan / Cik, sebagai panel pakar dalam kajian ini.

4. Untuk makluman, metodologi kajian ini akan melibatkan sesi wawancara untuk menilai instrumen soal selidik yang dibangunkan, terutamanya bagi kesesuaian item skala Likert bagi setiap soalan. Pandangan serta kepakaran daripada ahli akademik dan pengamal industri amat penting dalam memastikan kesahan dan kebolehpercayaan kajian ini.

5. Kami percaya objektif kajian ini akan memberi manfaat kepada hala tuju pengurusan Industri Pembuatan *Lean* dan *Decision Support System* secara amnya. Kerjasama yang diberikan didahului dengan ucapan terima kasih.

Sekian,

"MALAYSIA MADANI"
KOMPETENSI TERAS KEGEMILANGAN"

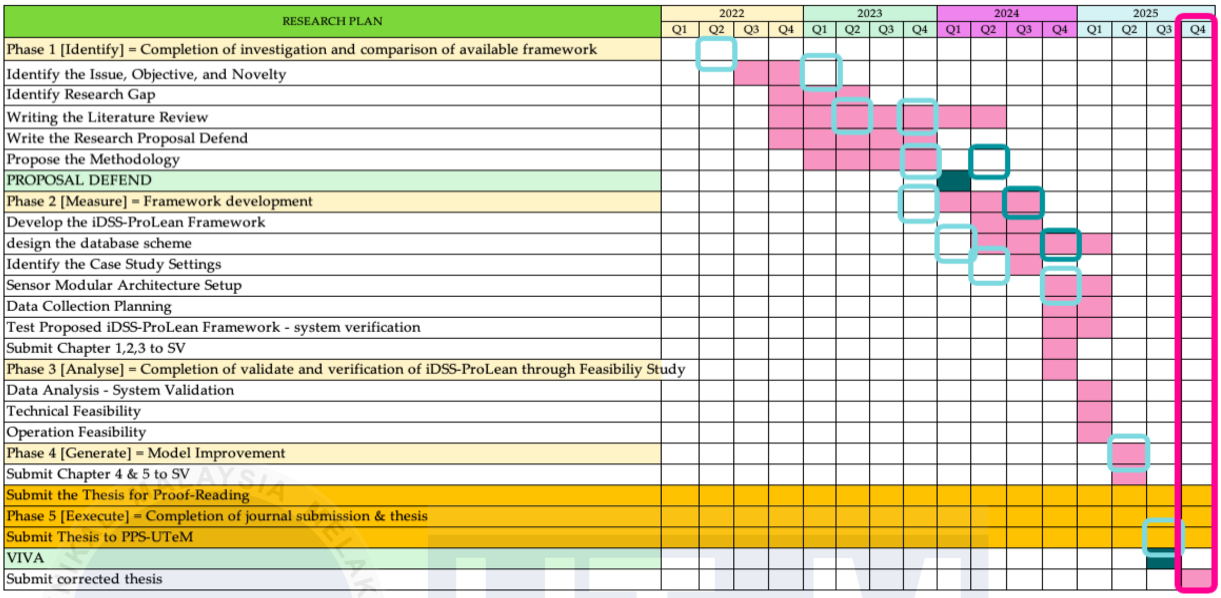
Saya yang menjalankan amanah,

Professor Ts. Dr Effendi bin Mohamad
Pengarah,
Pusat Pengurusan Kolaborasi RICE-UTeM Melaka,
Universiti Teknikal Malaysia Melaka.

SEBUAH UNIVERSITI TEKNIKAL AWAM

Letter of Invitation for the Questionnaires Participation

APPENDIX F Research Gantt Chart



Journal Published:

1. MULTIDISCIPLINARY REVIEW JOURNAL - How Well Do Decision Support System Help Decision-Makers? An Examination of Adopting Lean Manufacturing Process
2. JAMT JOURNAL - A Novel Material Flow System For Cast Manufacturing Firms
3. JHCD JOURNAL - Investigation On Decision Support System (DSS) in Lean Manufacturing Industry From Behavior and Technical Aspects.
4. MULTIDISCIPLINARY SCIENCE JOURNAL - Can IR4.0 Work Together With Lean? An Investigation from Malaysian Lean Manufacturing Sector

Proceedings Published:
1. JSME CONFERENCE '22 - Change Management Strategies for A Success Lean Adoption
2. JSME CONFERENCE '23 - Big Data and Simulation In Lean Manufacturing for IR4.0 perspective
3. JSME CONFERENCE '23 - Kanban Apps For Lean Practitioners
4. iDECONE 2023 - Application of Kaizen in Proposing A Hood Placement Design for the Milling Machines' Exhausting Ventilation System
5. MUCET 2023 - A Novel Material Flow System For Cast Manufacturing Firms: A Case Study
6. JSME 2024 - A Simulation-Based Decision Support System for Overall Equipment Effective (OEE)
7. iIRID 2024 - Bibliometric Review On Data Analytics In Lean-Decision Support System Development Based On Scopus Database
8. ICTeD 2024 - Structured database design for iDSS-ProLean: a Decision Support System for Lean Semiconductor Manufacturing
9. JSME 2025 - Modular Sensor Architecture in Enhancing Decision Support Via IoT Interchange for Line Balancing Production Line
10. From Framework to Feasibility, Developing an IoT-Based Decision Support System for Line Balancing in Semiconductor Production - concurrent engineering