Integration of Lean and Industry 4.0 for Smart Manufacturing

by

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Abstract

The purpose of this study was to investigate the potential of integrating Industry 4.0 (I-4.0) technology with Lean Production (LP) systems to increase manufacturing productivity. LP has been in use for over four decades and has resulted in the development of a range of Lean tools and principles that have been proven effective in improving productivity and performance in different manufacturing sectors. However, since 2011, I-4.0 has also been increasingly utilized to enhance productivity. While both paradigms share the goal of enhancing productivity, Lean is a people-centered, while I-4.0 is a technology-centered approach. As a result, some researchers have raised concerns about the integration of I-4.0 into LP systems and the potential for a synergistic relationship between the two approaches. To analyze these concerns systematically, we conducted a Systematic Literature Review (SLR) investigating the relationship between Lean and I-4.0, identifying existing frameworks for combining the two, and identifying key factors that drive the successful integration of I-4.0 into LP systems. We also explored potential challenges that may arise during the integration process. The SLR findings revealed a lack of understanding of the relationship between Lean tools and I-4.0 technologies, particularly the one-to-one relationship. In addition, there is a lack of empirical studies exploring how these two paradigms can be integrated to enhance productivity. By addressing these gaps, we were motivated to conduct this dissertation research. The entire research work is divided into three studies. In the first study, we aimed to propose a conceptual framework for the successful integration of I-4.0 into the LP system. Besides the research gaps derived from the SLR in designing the framework, we employed basic principles of system thinking. The proposed framework is designed with a clear direction of the relationship between Lean and I-4.0, while also taking into account potential key driving factors and challenges. In the second study, we attempted to implement the proposed framework in a Lean Educational Automotive Manufacturing Lab. We demonstrated it as a small manufacturing floor to delineate the different phases of the proposed framework. To measure its performance, we defined the overall equipment effectiveness (OEE) as the primary key performance indicator (KPI). To explore the synergistic impact of Lean and I-4.0, we defined four treatments, namely 'Control,' 'Lean,' 'Industry 4.0', and 'Lean & Industry 4.0'. In this study, 48 research subjects assembled SUV model

cars using Lego parts to test the framework's performance based on the research protocol. The subjects assembled the cars individually under each treatment and also in combination. After conducting a comprehensive analysis, we found that the 'Industry 4.0' approach resulted in significantly higher OEE compared to the other treatments. However, the study is limited to a small sample size. To overcome the limitation of a small sample size and to evaluate the effectiveness of workflow layout followed by subject, we were motivated to conduct the third study. In the third study, we explored whether the workflow layout impacts productivity or efficiency. To conduct our investigation, we randomly selected 12 research subjects to observe their performance during the car assembly process. We analyzed their performance based on recorded videos from our second study. Next, we created a discrete event simulation (DES) model to validate the observation using the empirical data of 12 research subjects. Through the observation, we found subjects followed eight different workflow sequences. Through the DES analysis, we discovered the significant impact of workflow on productivity and efficiency. In this study, we employed Throughput (TP) and Time In System (TIS) performance metrics to test our proposed hypotheses. Overall, it is worth mentioning that the study makes three contributions. Firstly, it presents a conceptual framework for integrating I-4.0 technologies into LP systems. Secondly, the performance of the proposed framework is validated by using human subjects in a prototype environment. Finally, effective utilization of DES in determining an efficient workflow sequence for picking and placing parts during the assembly of SUV cars.

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Chapter 1

Introduction

1.1 Background of the study

Lean Production (LP) is a manufacturing method that emphasizes the reduction of waste and improvement of efficiency in the production process. The goal of LP is to minimize waste in all production areas, such as overproduction, waiting, defects, unnecessary processing, excess inventory, unnecessary motion, and underutilized employees [2, 3]. By eliminating waste, LP can reduce production costs, improve product quality, and shorten lead times [4]. The significance of identifying and minimizing faults in the manufacturing process is highlighted by this approach. It employs various lean principles for detecting and minimizing defects, such as recognizing the value, analyzing the flow, implementing a pull production system, continuously improving, and striving for perfection [5]. By recognizing the value that a product or service provides to the customer, mapping out the production process, producing in small batches, empowering employees to identify and address defects, and continuously improving production processes, companies can reduce waste, enhance product quality, and increase customer satisfaction. LP fosters a culture of quality and continuous improvement, focusing on meeting customer needs and expectations, eliminating defects, and enhancing overall production efficiency [6, 4, 7].

According to the literature, the Lean principles were first developed by Toyota in the 1950s as a response to the post-World War II economic environment in Japan, which was characterized by limited resources and intense competition and is known as the Toyota Production System (TPS). The TPS's goal was to develop a manufacturing system that was highly efficient, flexible, and capable of producing high-quality products at low cost [8]. The TPS methodology that Toyota developed emphasized the importance of reducing waste and maximizing efficiency in the production process [9]. Toyota identified seven types of waste: overproduction, waiting, defects, unnecessary processing, excess inventory, unnecessary motion, and underutilized employees [10]. By identifying and eliminating these wastes, Toyota was able to reduce production costs, improve product quality, and shorten lead times. Over time, the TPS has been commonly used in the manufacturing world, and in 1988 it was characterized by the term 'Lean' by John Krafcik [10].

Meanwhile, since 2011, the manufacturing industry has witnessed the emergence of I-4.0 (I-4.0), which involves the integration of digital technologies into the manufacturing process. I-4.0 is characterized by a cyber-physical system (CPS) where the physical and virtual worlds are connected, and the control system is distributed [11]. Nowadays, I-4.0 is considered a new paradigm for connecting people, machines, and processes within the changing operative framework conditions and distributed management systems [12]. Consequently, the appearance of I-4.0 in manufacturing creates pressure on manufacturers to speed up and be more competitive.

Although LP and I-4.0 aim to improve productivity, their approaches differ in emphasis. LP focuses on continuous improvement and harnessing human creativity to streamline processes and eliminate waste. It adheres to principles such as Just-In-Time (JIT), Kanban, and Pull production systems. However, in developing and implementing these production systems, leveraging human creativity to design efficient workflows, optimize resource utilization, and foster innovation throughout the organization is imperative [13, 14, 15]. On the other hand, I-4.0 emphasizes the strategic application of cutting-edge technologies, renowned for their robustness, to drive productivity improvements [16, 17, 18]. The key lies in effectively harnessing these I-4.0 technologies and applying them where they can yield the most significant impact, ensuring optimal results in modern manufacturing environments. Therefore, in light of the need to increase productivity, researchers have identified the importance of integrating both Lean and I-4.0 paradigms. However, the current literature suggests a lack of studies exploring the synergies between the two paradigms, and the few that do exist are largely limited to conceptual modeling rather than practical research in the field [19]. Furthermore, integration frameworks are lacking to successfully and sustainably merge Lean and I-4.0.

This study aimed to address some gaps in the manufacturing industry by investigating the synergies between Lean and I-4.0. A SLR will was conducted to achieve this, and a conceptual framework was proposed to integrate both paradigms. The study also aimed to evaluate the impact of the interaction between Lean and I-4.0 on the Overall Equipment Effectiveness (OEE). To do so, a prototype environment was created for assembling the SUV model car using lego parts. Furthermore, the study aimed to determine the best sequence of picking and placing the lego parts for assembling the SUV cars using DES.

1.2 Problem statement

The manufacturing industry is facing intense competition, which is putting pressure on it to improve its efficiency and productivity. One way to achieve this is by improving the overall equipment effectiveness (OEE) [20, 21]. OEE depends on three key factors: performance, quality, and availability. Lean principles have been instrumental in boosting OEE over the past 40 years by optimizing resource utilization, improving quality standards, and maximizing performance and availability. Meanwhile, since 2011, I-4.0 has been introduced to the manufacturing industry. As a result, there is a need to explore the effectiveness of integrating Lean and I-4.0 [15, 22] since both paradigms carry the same objectives to improve productivity.

Researchers and industry experts are increasingly interested in uncovering the synergies between Lean and I-4.0, striving to create an integration framework that harmonizes these two approaches [23, 24, 25]. The integration of I-4.0 into LP systems remains largely theoretical, with limited practical implementations [26, 22]. There's a scarcity of studies assessing the depth of their relationship. Additionally, there is a wide range of Lean tools and I-4.0 technologies, and it is necessary to investigate the one-to-one relationships among them and identify the factors that affect their successful integration [4, 6].

To better understand the relationship between Lean and I-4.0, we need to conduct further research. To explore the intensity of relationship between Lean and I-4.0, making one-to-one interaction between a specific Lean tool and a specific I-4.0 technology is required [27, 24]. It is essential to define the key performance indicators (KPI) to measure their combined impact. It is also important to explore the framework that exists or not for integrating I-4.0 technologies into LP systems. This requires investigating the direct relationships between specific Lean tools and I-4.0 technologies, as well as exploring integration strategies. This study aims to analyze the relationship between Lean and I-4.0 and propose an effective framework for integrating I-4.0 technologies into LP systems.

1.3 Research objectives

Three objectives are defined in the study:

1. To propose a conceptual integration framework to integrate I-4.0 technologies into the LP system
2. To make the interaction between mistake-proof devices of Lean tools and sensor technology of I-4.0 technologies and measure their mutual impact on operational performance in OEE
3. To investigate the impact of workflow layout in the performance improvement of an manufacturing process by using the Discrete Event Simulation (DES) modeling

1.4 Research questions

Based on the above-mentioned current developments in the respective fields, the following research question was formulated:

- RQ1: Does a complementary relationship exist between a Lean tool/principle and an Industry 4.0 technology?
- RQ2: Does an integration framework exist for integrating Industry 4.0 technologies into the Lean Production systems?
- RQ3: Does a balanced workflow layout significantly improve operational performance on a manufacturing floor?

1.5 Research contributions

This paper proposes three research contributions to enhance the OEE of manufacturing systems driven by Lean and I-4.0.

The **first**, contribution is investigating the synergistic relationship between Lean and I-4.0 through an SLR and explores the theoretical framework to integrate Lean and I-4.0. The current frameworks being used are examined, and existing gaps are identified. An improved conceptual integration framework is proposed based on these gaps and the context.

The **second**, research contribution is the one-to-one interaction between Lean and the I-4.0 technology. Specifically, the interaction is conducted between Poka-yoke or mistake-proof tool and vision technology. Four treatments were randomly assigned to each subject to identify the effect of Lean and I-4.0 interaction on the OEE improvement. To complete the experiment 48 subjects were invited. They assembled the SUV model cars using Lego parts and their performance and quality data were recorded to evaluate the impact of each treatment and make decisions against the hypothesis.

The **third** research contribution of this dissertation work is to identify the impact of a balanced workflow in improving the productivity and efficiency of a manufacturing floor. We observed that research subjects followed several workflow sequences in assembling the SUV cars during their participation. We recorded the time taken by each subject to pick and place each Lego part to assemble the car. Also, we observed the sequences are followed by subjects. Based on this information the whole process was mimicked virtually using a DES modeling. Finally, we explored the impact of a balanced workflow on the productivity and efficiency improvement of an automotive manufacturing process.

1.6 Dissertation outlines

This dissertation is structured as follows. Chapter 1 presents the introduction to the problem statement, research questions and hypothesis, contributions, and structure of the dissertation. Chapter 2 provides background on Lean principles, Lean tools, the concept of I-4.0, integration framework of Lean and I-4.0. Chapter 3 presents the basic tools and materials required to conduct the study, working procedures, and methods. Chapter 4 presents the experimental interaction between the mistake-proof tool and vision technology. Chapter 5 presents the role of a balanced workflow layout in improving the productivity and efficiency of a manufacturing floor using DES modeling. Finally, Chapter 6 presents conclusions, limitations, and future work.

Chapter 2

Background and Literature

2.1 What is Lean?

Lean is a philosophy that aims to produce more finished goods with fewer raw materials or parts [2]. It is an art of thinking to use scarce resources most efficiently in the respective production strategy. In the Lean philosophy, continuous incremental improvements are highly valued [14]. It is always focused on achieving zero-defect production through the continuous improvement strategy [28]. To obtain zero-defect production, it is essential to continuously identify different production types and eliminate those from the production system. The lean principle is also highly customer-centered; hence, it is often called production strategy from the customers' perspective [29]. Thus, it focuses on customer satisfaction. Alternatively, it can be stated that Lean focuses on identifying and solving the customers' problems persistently.

The lean approach performs the activities that add value for the customers. It focuses on eliminating those activities from the production systems, which are not adding value for the customers [30, 3]. The associated people with the production system, such as the operators, managers, and plant managers, are all trying to employ their creativity to add value to their products for customer satisfaction [31, 32]. They are being involved in a continuous improvement project for better quality, lower cost, and shorter lead time. Thus, the Lean implementing organization is highly adaptive and flexible with the customers' demand fulfillment. The enterprise is supported by management systems designed for the specific needs of the organization and its customers, suppliers, community, and employees. Consequently, the Lean organization continuously focuses on improving customer satisfaction through three viewpoints [8]:

1. Value creation with the respective products
2. Adaptability and
3. Use of the products

Lean thinking and practice can occur wherever products or services are designed, produced, and distributed, regardless of sector. However, there are many failed applications of Lean. These are often marked by early progress followed by back-sliding [33, 34]. Although we can point to many causes of such failure, the most common seems to be applying Lean practice without sufficient Lean thinking. The application of Lean problem-solving tools in isolation often yields quick positive results that prove to be difficult to sustain [35, 14]. In contrast, a more sustainable Lean transformation requires deeper thinking about purpose, process, capabilities, behaviors, and the management system required to make it all work [36, 37]. It also requires reflection on underlying assumptions in the organization and how they might have to change.

2.2 Lean principles

Lean principles, also known as the Toyota Production System (TPS), are a set of management practices that aim to optimize processes and minimize waste [2]. These principles were developed by Toyota Motor Corporation (TMC) in the 1950s and have since been widely adopted by organizations in various industries [3]. According to Womack and Jones, the five core principles of lean are: specify value, identify the value stream, flow, pull, and strive for perfection [5]. These principles aim to create a culture of continuous improvement, eliminate non-value-added activities, and focus on delivering value to the customer. By adopting lean principles, organizations can achieve greater efficiency, reduce costs, and improve quality. Moreover, lean principles emphasize respect for people and aim to empower employees to identify and solve problems. Overall, lean principles offer a systematic approach to process improvement that can benefit organizations in various sectors [5]. A brief description of these basic principles of Lean is depicted as follows:

1. **Value**: The primary principle of Lean Thinking is centered on understanding value from the customer's perspective [8]. This requires organizations to assess who their real customers are and what they consider valuable. This approach highlights the importance of defining value based on how customers perceive it, as they ultimately determine the

value of a product or service [38]. This way of thinking contrasts with the conventional practice adopted by most companies, which tends to specify value from a departmental perspective such as research and development, engineering, or finance. Defining value involves identifying the form, feature, or function that a customer is willing to purchase, especially when they cannot perform the required task on their own or without investing considerable cost or time [39]. Enterprises must precisely define value in terms of specific products with specific capabilities offered at specific prices through a dialogue with specific customers. This enables enterprises to understand and define the aspects of a product or service that are valuable to a customer [40].

2. **Value Stream**: Identify the value stream, which is the sequence of steps and activities required to deliver a product or service, and eliminate any steps or activities that do not add value or contribute to the final product. This principle is based on the idea that value is created through a series of interconnected activities and that companies should focus on optimizing the value stream as a whole, rather than optimizing individual steps in isolation [41].

3. **Flow**: Establish a continuous flow of work through the value stream, ensuring that work moves smoothly and efficiently from one step to the next, without delay or interruption. This principle is based on the idea that interruptions and delays in the production process create waste and reduce efficiency, and that companies should strive to establish a continuous flow of work that minimizes these interruptions [5]. The key steps involved in achieving flow include identifying bottlenecks, balancing workloads, establishing pull systems, and using visual management tools to monitor and improve flow [3].

4. **Pull**: Pull is another key principle of Lean Manufacturing (LM), which involves using customer demand to drive the flow of materials and work through the system. This is achieved by creating a pull system that responds to customer demand in real-time, rather than producing based on forecasts or guesses. Establish a pull system, where work is initiated and completed based on customer demand, rather than through a push system where work is initiated based on forecasted demand [3, 5].

5. **Continuous Improvement**: Continuous improvement is a core value of LM, which involves constantly seeking out opportunities to improve processes, reduce waste, and increase efficiency. This is achieved through the use of tools such as kaizen, or continuous improvement events, and the adoption of a culture of continuous improvement throughout the organization [3, 5].

One of the primary principles of LP is to define the value from the customer's perspective. The principal guides organizations to evaluate and reconsider who are their actual customers and what those customers regard as value. This principle emphasizes defining value from the way customers perceive it as customers ultimately decide the value of a product or service [38, 39]. Referring to Emiliani [40], this way of thinking differs from the common practices used by most companies, where they generally tend to specify value from a departmental point of view, such as research and development, engineering, and finance. Defining value is the means of identifying the form, feature, or function that a customer is willing to purchase in the circumstance where they can't perform the required task on their own or without investing considerable cost or time [42, 43]. Womack and Jones stated that enterprises need to "define value precisely in terms of specific products with specific capabilities offered at specific prices through a dialogue with specific customers" [7]. This urge drives us to understand and define whether the aspects of a product or service are valuable or not to a customer.

2.3 Development of lean and lean tools

After World War II, manufacturing companies like TMC faced severe resource scarcity. To overcome this situation, the TMC investigated how to produce more using less and discovered an effective way under Taiichi Ohno's leadership [44]. Ohno focused on reducing the activity, which does not add value for the customer. Eventually, he discovered seven activities that do not add value to the customer, currently known as the seven wastes [45, 44]. In short, between 1948 and 1975, a systematic production approach was developed by Taiichi Ohno, Kiichiro Toyota, and Shigeo Shingo, widely known as TPS and later as LP [2]. Thus, it infers that the underlying goal of LP is to use the minimum resources for maximum production towards reducing production costs [46]. While many researchers and production practitioners have provided several definitions of Lean concepts, it is generally believed that the Lean philosophy helps companies achieve more with less effort, cost, and time [2]. LP follows a simple production idea, producing the right goods using less towards making the company more responsive to the customer [47]. A bundle of Lean tools has been used in manufacturing and service companies to conduct a systematic investigation for the sake of continuous elimination of waste since the 1950s [48, 49, 50]. These tools and techniques are used to achieve production by eliminating waste and enhancing production efficiency [51]. Likewise, LP is an integrated manufacturing system that uses several tools to produce the commodities at the rate of customer demand [7]. There is no definite number of Lean tools, however, 22 Lean approaches are quoted in several studies [49]. The most common Lean tools are Value Stream Map (VSM), Total Productive Maintenance (TPM), Just-in-Time (JIT), single-minute exchange of dies (SMED), Mistake-proofing, 5S, Kanban, and the Ishikawa diagram [46, 49, 52]. In a study, authors stated that 101 Lean tools and principles could be used for waste elimination [53]. In this context, numerous studies have been conducted to review Lean tools and principles and their effective and efficient utilization. However, the goal of this study is not to review the Lean tools/principles in detail but to investigate the most critical Lean tools that may have a synergistic relationship with I-4.0 technologies.

2.4 Mistakes, defects, and errors in Manufacturing

Defects are a common phenomenon in the manufacturing world. According to Shingo, every defect is derived from the consequence of human mistakes. On the production floor, defects appear when the operator makes any mistakes [28]. Shingo proved this phenomenon by conducting a cause-and-effect analysis between human errors and defects [28]. Others widely approve his experimental analysis in many research [54].

The issue at hand could be how to define a mistake. In this context, many practitioners and scientists have defined the mistakes. Hinckley & Barkan defined a mistake as any execution of prohibited actions, the failure to perform a necessary action, or the misinterpretation of required information for the correct execution of an action [54]. They also discovered a significant number of mistakes, which increased the total defect rate in production [54]. It is brought to light that defects are somehow associated with the consequences of human mistakes [55]. In other words, there is a close association between human mistakes and defect productions [55]. It refers to a causal relationship between defects and human mistakes. In this context, the authors categorized ten different types of human mistakes, that have occurred in manufacturing and safeguards and ultimately produce the defects in production [55]. Misunderstandings, forgetfulness, and errors in identification were recognized as the most frequent mistakes. The author also identified several important manufacturing defect sources [55], as presented in Figure 2.1. However, in some cases, one specific type of defect may derive from several human errors, and thus, root causes analysis is required to identify the sources of each defect [55].

According to Stewart & Grout [56], a mistake is defined as the failure to perform the routine activities, and they defined routine activities as repetitive actions that become routine over time, and mistakes are common in situations where routine action activities are triggered in false cases. In manufacturing, an example could be repetitively making similar products, and a slightly different product might trigger the regular action activity, leading to a manufacturing mistake [56]. Fast-Berglund et al. recognized in their case study that the number of errors in manufacturing increases when the products become more complex [57]. It was recognized that the most common error types in the automotive industry included forgetting to connect and tighten parts, fitting parts incorrectly, and missing parts. In their research, these error types covered almost 80 percent of all errors. They suggested that mistake-proofing methods should be used so that decision-making could be done automatically [57]. Numerous studies have identified diverse types of defects. The present study lists several defects, as depicted in the Figure 2.1 [57, 58, 59].

2.5 The conceptual development of poka-yoke

As it is mentioned, the concept of Lean is to produce more using fewer resources [44]. To obtain this goal, a set of Lean tools and production principles were developed, including Poka-Yoke. Poka-Yoke is a Japanese term that means ‘mistake-proofing’ or ‘error-proofing’ [60].

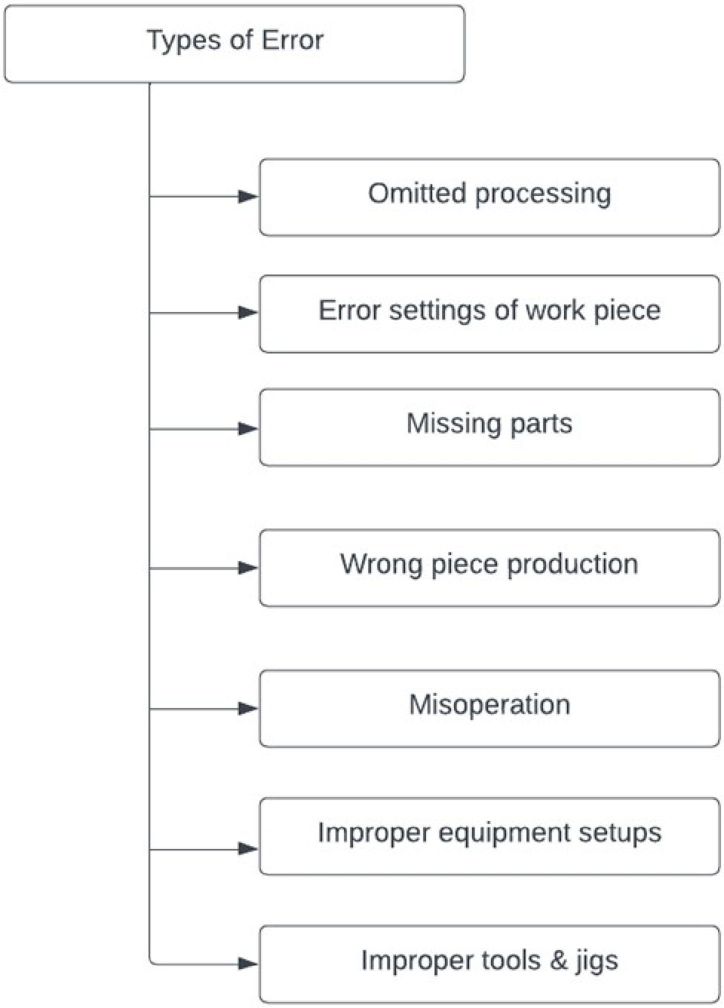


Figure 2.1: Most common types of errors reported in the literature

The concept was developed by Dr. Shigeo Shingo, a renowned Japanese industrial engineer and TPS expert [28]. Shingo believed that the majority of errors in manufacturing were not caused by workers' incompetence but were due to the design of the manufacturing process itself [28]. In the early 1960s, Shingo developed a quality control system that relied on simple, low-cost devices to detect and prevent errors before they occurred. This system, which he called 'Zero Quality Control' (ZQC), became the foundation of poka-yoke. Shingo believed that the use of poka-yoke devices would make it impossible for workers to make mistakes, thereby eliminating the need for inspection and improving overall quality [28]. He developed a range of poka-yoke devices, including color-coding, checklists, sensors, and feedback systems, that were designed to catch errors at the source and prevent them from becoming defects. Toyota, which was already implementing Shingo's ZQC system, began incorporating poka-yoke devices into its manufacturing processes in the 1960s. Using poka-yoke helped Toyota improve quality, reduce defects, and increase productivity, ultimately leading to the company's rise to become one of the most successful car manufacturers in the world [28]. Over the years, many other companies have adopted the concept of poka-yoke. It is a widely used quality control tool in manufacturing and other industries today. Using poka-yoke devices has expanded beyond the manufacturing process and into service industries, such as healthcare, where they are used to reduce errors and improve patient safety [61].

2.6 Definition of poka-yoke

Different organizations, scientists, and practitioners have varying definitions of Poka-yoke, but their perceptions are similar. According to the Lean Enterprise Institute, Poka-yoke is a Japanese term that means mistake-proofing or error-proofing, which refers to any mechanism, device, or procedure that helps to prevent errors or mistakes in a process [62]. The ASQ Quality Glossary defined the Poka-yoke as a quality assurance technique that aims to prevent human errors and detect them in advance through the use of automatic devices or methods, thus improving product quality and reducing costs [58]. According to the Daily Six Sigma, a Poka-yoke prevents errors by designing the manufacturing process, equipment, and tools to make it impossible for an operator to make a mistake [63].

Besides the organization's perspective, according to Shigeo Shingo, Poka-yoke is a mechanism to detect defects during the production run of a process or machine [28]. This mechanism has facilitated the inspection of 100 percent of the pieces produced by a particular process or machine. According to Grout, a Poka-yoke is a device associated with the process or machine's operation to prevent errors or defects derived from human mistakes [64]. According to Plonka, Poka-yoke is a systematic way of eradicating errors by identifying and eliminating the sources of respective errors [65]. According to Middleton's definition, Poka-yoke is a methodical strategy for removing mistakes by recognizing the origins of such mistakes [66]. The effectiveness of Poka-yoke in creating an environment free from errors, particularly in the field of manufacturing, has been widely acknowledged [67].

The Poka-yoke approach has been acknowledged as a reliable method for creating an error-free environment, particularly in the context of manufacturing. Also, it can be considered as a method of LM that uses uncomplicated and efficient approaches to get rid of flaws by anticipating, rectifying, or bringing focus to errors made by people before they happen [68].

According to Stewart and Grout, a mistake is defined as the failure to perform the routine activities, and they defined routine activities as repetitive actions that become routine over time, and mistakes are common in situations where routine action activities are triggered in false cases [56]. In manufacturing, an example could be repetitively making similar products, and a slightly different product might trigger the regular action activity, leading to a manufacturing mistake [56]. Fast-Berglund et al. recognized in their case study that the number of errors in manufacturing increases when the products become more complex [57].

Nowadays, many practitioners consider the Poka-yoke as an effective device such as sensors and jigs, and something like these, which can be used as a means of mistake-proofing or error-proofing [59, 3]. According to Saurin et al. Poka-yoke is the device primarily used to detect and prevent abnormalities detrimental to product or service quality or the health and safety of employees [69]. These devices can be physical or functional [69]. In a study, authors considered the Poka-yoke as a control system that prevents defective products from ending up with the customer either passively or actively [59]. Poka-yoke devices are tools that eliminate the effect of human error. Poka-yoke devices do this by shutting down the system when defects are about to occur, making them obvious to identify after they have been made [1]. The two main benefits that poka-yoke devices offer are immediate feedback and 100 percent inspection. Immediate feedback makes it possible to take corrective actions right after the error. The benefit of 100 percent inspection is that defective products will not end up with the customer. These benefits enable poka-yoke applications in self-checks, successive checks, and source inspections [28].

2.7 Functional principles of poka-Yoke

Overall, the functional principles of Poka-yoke are focused on ensuring that processes and systems operate correctly, safely, and efficiently by detecting and preventing errors before they can cause harm or damage. The basic principles of this approach are bulleted as follows:

- **Prevention of errors**: Poka-yoke devices are designed to prevent errors or mistakes from occurring in the first place. They eliminate the possibility of errors by ensuring that the correct steps are taken in a specific order or by making it impossible to perform a task incorrectly [61].

- **Detection of errors**: Poka-yoke devices can also detect errors that have already occurred. They use sensors or other mechanisms to identify deviations from the correct process or product specifications [70].

- **Immediate feedback**: When a Poka-yoke device detects an error, it provides immediate feedback to the operator or the system. This feedback can be visual, auditory, or tactile, depending on the nature of the error [71].

- **Simple and easy to use**: Poka-yoke devices are designed to be simple and easy to use. Operating effectively should not require complex training or extensive knowledge [61].

- **Robustness**: The Poka-yoke device should be designed to withstand environmental or system variations and operate reliably over time. This can be achieved using durable materials, redundant sensors, and fail-safe mechanisms [72].

- **Continuous improvement**: Poka-yoke devices are part of a continuous improvement process. They are regularly reviewed and refined to improve their effectiveness in preventing errors and improving quality [73].

2.8 The implementation strategy of poka-yoke

Poka-yoke is a unique approach to quality control compared to traditional methods. There is no single or specific strategy to implement the concept of Poka-yoke or mistake-proofing. In literature, numerous approaches are available for implementing the Poka-yoke. However, in many studies, Toyota's problem-solving wheel is used [74], which consists of six steps, as shown in Figure 2.2. The team involved in mistake-proofing follows these six steps to identify potential mistake-proofing processes. The initial step involves prioritizing and selecting the problems to be mistake-proofed based on their frequency of occurrence, impact on process flow, and impact on the company and customer. The problem is then analyzed to identify the root cause and determine whether it is due to unnecessary task complexity, a mistake, or variation, which each requires different control methods. In case of unnecessary complexity, the process or product is simplified; in case of variation, traditional variation control methods are used; and in case of mistakes, mistake-proofing methods are employed [74]. If an error has been identified as the root cause of an issue, further investigation can aid in finding solutions.

By categorizing the error, teams can easily locate a list of solution principles and instances that pertain to resolving their issue. The subsequent step is to employ these principles and ideas to devise solutions. It is not sufficient to accept a single proposed solution [75]. Several solutions should be generated, regardless of the problem's complexity. The rationale for creating multiple solutions is to evaluate their comparative strengths and weaknesses. This assessment simplifies the selection of the best solution and highlights common flaws that may be addressed with new solutions that were not initially considered [55]. After selecting the concept, it is put into practice, and its efficacy is assessed. If the solution proves to be effective and can be employed in other areas of work, it is standardized across the organization. The best alternative

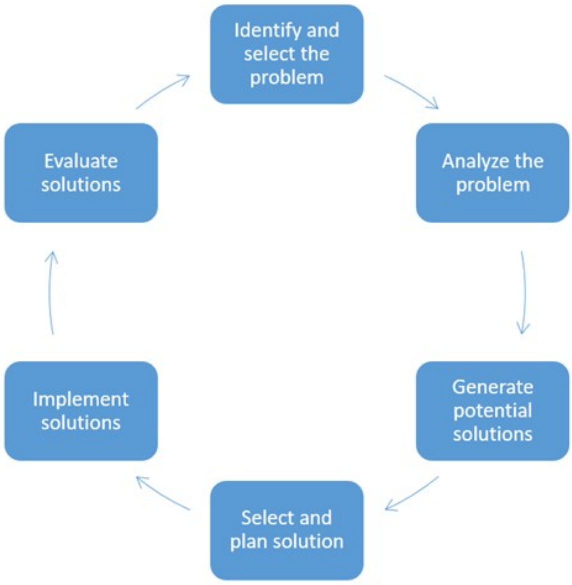


Figure 2.2: Toyota's problem-solving wheel

solution is used to solve the problem. After implementing the solution, its efficacy is evaluated for standardization and further use [55]. Likewise, these six steps are employed towards implementing the concept of Poka-yoke.

However, becoming proficient in mistake-proofing takes practice. Mastery in mistake-proofing is achieved through practice. It can be challenging for beginners to come up with solutions because mistake-proofing is not widely practiced, and there are few examples available [76]. Those new to the skill may find it challenging to generate solutions as it is not commonly practiced, and there are few instances to draw from.

From the nature of Toyota's six-step strategy, it can be perceived that various circumstances should be considered towards formulating the solution of a specific error based on the production process. Since it was noted that human error could result in errors or flaws in the production line, the workers' experience is essential to consider in defining the Poka-yoke strategy. With regards to the implementation of mistake-proofing techniques, all respective components should be precise, specific, and appropriate to the individual error or mistake-proofing [56]. However, based on numerous studies, a few essential steps and points are documented as follows:

- **Identify and select the problem**: The first step is identifying potential errors that could occur in a process. This can be performed by analyzing data on past errors, observing the process, or conducting a failure mode and effects analysis (FMEA) [77].

- **Design mistake-proofing devices**: Once potential errors have been identified, the next step is to design mistake-proofing devices that will prevent those errors from occurring. This can involve designing new tools, modifying existing equipment, or implementing new procedures [70].

- **Verify the devices**: Before implementing the mistake-proofing devices, they should be tested to ensure they function as intended. This can be done through simulation, prototype testing, or a small-scale implementation [78].

- **Implement the devices**: After they have been verified and refined, they can be implemented. This may involve training operators on how to use the devices, updating procedures, or modifying the layout of the workspace [70].

- **Monitor the process**: Once the devices have been implemented, it is important to monitor the process to ensure that they are working as intended. This can be done through regular inspections, data analysis, or process audits [79].

- **Continuous improvement**: Finally, the implementation strategy of Poka-yoke should include a continuous improvement cycle. This involves regularly reviewing the process and the devices to identify opportunities for improvement and refining the mistake-proofing devices to make them even more effective [80].

2.9 The concept of industry 4.0

The improved manufacturing process known as the first industrial revolution began in the 1760s and continued until 1820-1840 [81, 38]. This period was characterized by mechanized production and steam power, which significantly increased human productivity. For instance, the output of a worker who operated a mechanized cotton spinning machine increased by 500 times, and the power of the traditional loom increased a worker's output by over 40 times [82].

The second industrial revolution started in the second half of the 19th century and lasted until the beginning of World War I, from 1870-1914. Mass production, scientific discoveries, and standardization characterized it. Mass production was introduced by Henry Ford, who applied the principles he observed in a Chicago slaughtering house to his automobile manufacturing process.

The third Industrial Revolution, also known as Industry 3.0 (1-3.0), refers to the period of industrialization from the 1960s to the late 20th century [83]. It was characterized by the introduction of computerization, automation, and the use of electronic and digital technologies in manufacturing processes. Critical features of I-3.0 include the use of programmable logic controllers (PLCs), computer-aided design (CAD), and computer-aided manufacturing (CAM) [84]. These technologies enabled manufacturers to streamline their operations, increase production efficiency, and reduce costs. Additionally, I-3.0 saw the emergence of new industries such as semiconductor manufacturing, information technology, and telecommunications. The Third Industrial Revolution significantly shaped the modern global economy and laid the groundwork for the Fourth Industrial Revolution or I-4.0 [85].

The Fourth Industrial Revolution, also known as I-4.0, refers to the ongoing digital transformation of manufacturing and production processes. Key features of I-4.0 include the integration of technologies such as the Internet of Things (IoT), artificial intelligence (AI), robotics, and big data analytics [86]. These technologies enable machines, products, and systems to communicate with each other in real-time, leading to increased efficiency, productivity, and customization. I-4.0 also emphasizes the use of cyber-physical systems (CPS), which are connected, intelligent systems that are capable of sensing and responding to changes in the environment [87]. This fourth industrial revolution is expected to transform manufacturing and production across industries and has the potential to create new business models and disrupt traditional ones.

The concept of I-4.0 originated in Germany, where it was seen as a way to maintain the country's competitive advantage in manufacturing [88]. The German government launched the 'Industrie 4.0' initiative in 2011, which aimed to promote the adoption of digital technologies in manufacturing. The initiative was led by a group of experts from industry, academia, and government, who published a report outlining the key principles of I-4.0 [1].

The principles of I-4.0 include interoperability, which allows machines and systems to communicate with each other; virtualization, which creates virtual copies of physical systems and processes; decentralization, which allows decision-making to be distributed across the manufacturing process; and real-time capability, which enables data to be processed and analyzed in real-time [89].

Several scientists and Industrial practitioners defined the concept of I-4.0, although their focus points are similar. For example, Shrouf et al. stated that the concept of I-4.0 encompasses various technologies and cyber-physical systems, to enhance manufacturing through the integration of physical and digital systems, resulting in greater efficiency, flexibility, and intelligence [90]. Nieuwenhuis & Wells mentioned the term, 'I-4.0' denotes a fresh stage in the industrial revolution, which emphasizes greatly on interconnectivity, automation, real-time data, and machine learning [91]. According to Kagermann et al. I-4.0 is a revolutionary change that allows the integration of both operational and information technology. This integration creates advanced, self-optimizing systems that are capable of learning from data and adjusting to changes in their surroundings [92]. Porter and Heppelmann demonstrated that the term 'I-4.0' refers to the fourth industrial revolution, where physical, digital, and biological systems are integrated, and new business models are developed that take advantage of these technologies [93]. According to Shafiq et al. the fourth industrial revolution, it refers to the digitization of manufacturing, which includes the integration of cyber-physical systems, advanced analytics, and the IoT. This integration leads to the creation of intelligent factories that can cater to customer requirements more efficiently, flexibly, and responsively [94].

Based on the definition of I-4.0, it seems that I-4.0 aims to bring about the creation of digital factories that possess the following characteristics: intelligent networking, flexibility, mobility, incorporation of customers, and novel business models [86]. The fundamental concept behind I-4.0 is to utilize the latest information technologies to incorporate the IoT and services, resulting in the integration of business and engineering processes. This integration enables flexible, efficient, and environmentally sustainable production with consistently high quality at low cost [95]. Since the launch of the 'Industrie 4.0' initiative, the concept of I-4.0 has gained global recognition, and many countries have launched their initiatives to promote the adoption of digital technologies in manufacturing. The principles of I-4.0 are key to transforming traditional manufacturing into 'smart factories' that are more efficient, flexible, and responsive to customer needs [92].

In recent years, I-4.0 has become a research topic that has received significant attention due to its potential to transform manufacturing by leveraging digital technologies. The research topics primarily focus on integrating physical and digital systems, as well as incorporating advanced analytics, the IoT, and CPS. The ultimate goal of I-4.0 is to create smart factories that are more efficient, flexible, and responsive to customer needs while also maintaining high quality and low cost. However, the concept of I-4.0 is still evolving, and there is much debate and confusion about its scope and definition. As a result, researchers are continuing to explore various topics related to I-4.0, such as data analytics, artificial intelligence, cybersecurity, and human-machine collaboration, to advance the field further and realize its potential. For example, Brettel et al. [1] conducted a cluster analysis to demonstrate the disordered state of the I-4.0 research streams, as depicted in Figure 2.3 [1]. In their article, they listed over 20 research topics considered part of the fourth industrial revolution, with multiple articles associated with each stream.

2.10 Integration strategy of industry 4.0

There are three integration strategies of I-4.0: horizontal, vertical, and end-to-end, which are closely interconnected and crucial for the effective implementation of I-4.0 principles. Horizontal integration strategy refers to the seamless integration of different processes. Vertical integration strategy focuses on the integration of different tiers of the supply chain. The end-to-end integration strategy considers the entire product life cycle, from design to production to distribution [96]. Together, these integration strategies create a fully connected and integrated manufacturing ecosystem, with efficient communication, collaboration, and data sharing across all levels of the value chain, resulting in increased productivity, agility, and responsiveness to

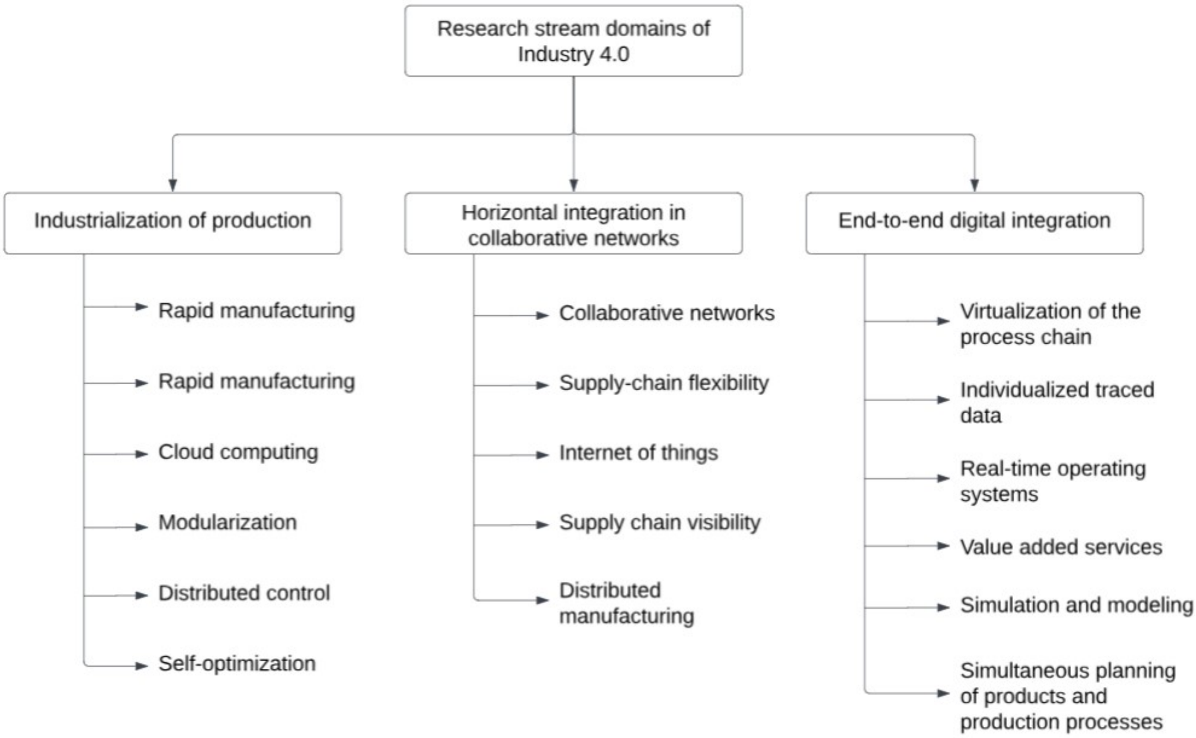


Figure 2.3: Research stream of I-4.0 [1]

customer demands [97]. A brief description of this integration is documented in the following sections.

2.11 Horizontal integration of industry 4.0

Horizontal integration is a strategy that involves merging two or more companies that operate in similar production modes rather than the merging of companies along the supply chain as in vertical integration. This strategy can be advantageous in reducing fixed costs by sharing expenses, leading to economies of scale, higher efficiency, and lower prices for consumers. In the IT and engineering fields, horizontal integration refers to the merging of companies to share resources such as energy, raw materials, logistics, skills, and information, resulting in mutual improvement in efficiency and cost reduction [92]. Also, successful implementation of this strategy can lead to increased flexibility and real-time optimization of networks [98].

According to Brettel et al., horizontal integration allows companies to enhance their capabilities without incurring additional investments [1]. Furthermore, as noted by Carvalho et al., it enables companies to meet their customers' demands sustainably by reducing lead times and ensuring expected quality [33]. This type of integration also promotes emerging and sustainable innovation, which is often challenging to achieve without merging companies, as Koch et al. suggest [81].

One of the advantages of horizontal integration is the transparency it creates, as comparative information and machine status become available, making it easier to optimize maintenance processes [81]. Also, as noted by Koch et al., this integration enables companies to share their complementary competencies, increasing their capability and flexibility and creating new business opportunities [81]. Additionally, tracking product flows and associated data for quality control can help companies make real-time decisions and improve customer satisfaction, as suggested by Moch et al. [99]. However, Brettel et al. noted that designing supply chains that allow for the adaptation of schedules and routes is crucial in the process of merging companies [1].

2.12 Vertical integration of industry 4.0

The implementation of I-4.0 principles in manufacturing involves a production strategy known as vertical integration. This approach involves a company taking ownership of the entire production process, from raw material collection to finished product distribution. Vertical integration integrates all levels of production, from the factory floor to the executive boardroom, using digital technologies [96]. This involves linking together different production process components, such as machines, sensors, software systems, and data analytics tools, to create a seamless and integrated workflow [100]. With vertical integration, data and information can flow seamlessly throughout the production process, allowing for greater coordination and collaboration between different departments and stakeholders [101]. By doing so, the company can streamline its production process by avoiding the need for outsourcing. This can result in cost reduction and greater control over the manufacturing or distribution process. This can lead to improved efficiency, reduced costs, increased quality, and the ability to respond quickly to changes in customer demand or market conditions [96]. According to Enrique et al. and Antony et al., vertical integration can be divided into forward and backward dimensions, as

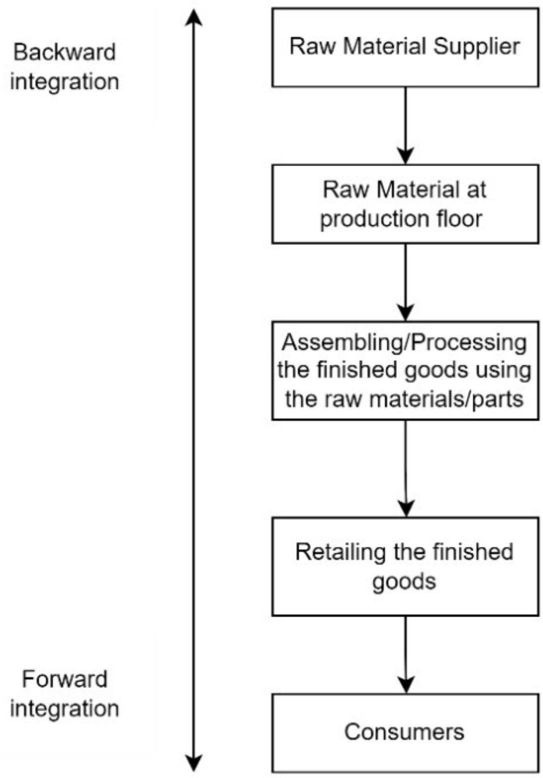


Figure 2.4: Vertical integration of I-4.0

shown in figure 2.4 [102]. However, this strategy requires significant capital investment, which can limit the company's flexibility.

Numerous definitions of vertical integration are available in the current literature. For example, Kagermann et al. defined vertical integration as the factory's architectural setup where a single entity owns various physical or informational subsystems such as sensors, actuators, manufacturing, and production management [92]. According to Wang et al., with vertical integration, the subsystems are integrated at different hierarchical levels to provide end-to-end solutions or services [103]. Kagermann et al. also mentioned that vertical integration allows the factory to be responsive to customers' needs by using CPS to make the plants actionable [92]. These configuration rules control the production process and its structure, leading to the automatic derivation of case-specific typologies. According to Brettel et al., the success of vertical integration in the production industry leads to the concept of a 'smart factory,' which benefits from real-time quality control, cost reduction, lead time shortening, and efficient resource allocation [1]. Furthermore, by utilizing a CPS-based vertical integration, the production system can be equipped with the ability to dynamically adjust the production schedule in response to changes such as order modifications, variations in price, and fluctuations in quality. This enhances the flexibility of the production process and enables the production systems to be tailored to meet customers' specific needs [104, 98].

2.13 End-to-end integration

End-to-end digital integration defines a holistic digital framework to mitigate the gap between product design and development, enabling the digital engineering view through the production planning, designing, engineering, processing, and other associated services [105]. The end-to-end integration strategy considers the product's entire life cycle and concentrates on value creation. One of the key features of this strategy is to enable real-time access for all associated suppliers for data monitoring so that they can make necessary decisions towards adding the values [1]. Thus, it allows significant optimization by using digital and virtual communication. Kagermann et al. stated that connecting the business process with the end-to-end integration using CPS is a big challenge [92]. In this context, Posada et al. suggested that it is essential to map the entire value creation from customers' demand to product architecture towards integrating the end-to-end integration strategy [105].

Posada et al. explained that end-to-end digital integration is a comprehensive digital framework that aims to close the gap between product design and development, allowing for a digital engineering perspective throughout the entire product life cycle [105]. The end-to-end integration strategy focuses on the product's entire life cycle and prioritizes value creation. Real-time data access for all associated suppliers is a key feature of this strategy, as it enables them to make informed decisions and add value to the product [1]. The use of digital and virtual communication allows for significant optimization. However, Kagermann et al. point out that connecting the business process with end-to-end integration using CPS is a significant challenge [92]. In this context, Posada et al. suggest that mapping the entire value creation process, from customer demand to product architecture, is essential for integrating the end-to-end integration strategy [105].

According to Wan et al., full digitization and virtualization of the real world are necessary to successfully implement end-to-end integration [103]. This requires CPS support throughout the supply chain, from product design and development to manufacturing and distribution, as highlighted by Koch et al. [81]. According to Kagermann et al., unlike traditional manufacturing systems, this integration allows for direct IT support without relying on multiple interfaces [92]. End-to-end integration enables customization of the production process, allowing customers to choose from a wide range of features and products, as opposed to the limited options offered by traditional manufacturing systems. As noted by Kagermann et al. customers' demands and feedback can also be incorporated at every stage of the production system [92]. Consequently, end-to-end integration empowers customers to combine individual components and functions to create their desired products, rather than having to rely on the manufacturer's predetermined product portfolio, as observed by He and Jin [106].

Overall, I-4.0 allows the creation of horizontal value networks at a strategic level, enables end-to-end integration across the entire value chain of the business process level, including engineering, and enables the vertically integrated and networked design of manufacturing systems [92]. The horizontal integration of corporations and the vertical integration of factories inside are two bases for the end-to-end integration of the engineering process because the product lifecycle comprises several stages that should be performed [95]. These features are the key enablers for manufacturers to achieve a stable position in the face of highly volatile markets whilst flexibly adapting their value creation activities in response to changing market requirements [92].

2.14 Key technologies of industry 4.0

As earlier discussed, the term 'I-4.0' is used to describe the fourth industrial revolution, which is characterized by the integration of advanced technologies such as the IoT, artificial intelligence (AI), robotics, and big data into manufacturing processes [107, 90]. However, the key technologies of I-4.0 can be broadly categorized into nine pillars, as follows [108]:

Cyber-Physical Systems: Cyber-Physical Systems (CPS) integrate physical and cyber components to enable intelligent and autonomous operation. They are a key technology for I-4.0 because they enable machines to communicate with each other and with humans, resulting in increased efficiency and productivity [109]. This enables real-time data collection, analysis, and decision-making, leading to increased efficiency and productivity in manufacturing processes. Additionally, CPS can improve safety by enabling machines to detect and respond to potential hazards [107]. Research on CPS is ongoing, with new developments focused on improving their interoperability, security, and reliability in real-world settings.

Internet of Things: The Internet of Things (IoT) is a key technology for I-4.0, as it enables real-time monitoring and control of machines and processes, leading to improved productivity and reduced costs [107]. Primarily, IoT devices are embedded with sensors, software, and connectivity to enable them to exchange data with other devices and systems over the internet. The objects can include everyday items such as appliances, vehicles, buildings, industrial equipment, and machines. The IoT enables the collection and analysis of data from these objects, which can be used to optimize processes, improve efficiency, and create new products and services [110].

Big Data Analytics: Big data refers to the large volume of data that is generated by machines and devices in manufacturing processes. Big data analytics uses advanced algorithms and tools to extract insights from this data, enabling manufacturers to optimize their operations and improve their products [111].

Artificial Intelligence: Artificial Intelligence (AI) refers to the ability of machines to learn and make decisions based on data. In I-4.0, AI is used to optimize production processes, predict maintenance needs, and improve product quality [84].

Additive Manufacturing (3D printing): Additive Manufacturing (AM) refers to the process of creating three-dimensional objects by adding layers of material. In I-4.0, 3D printing is used to create prototypes, customize products, and reduce waste [112].

Augmented Reality: Augmented Reality (AR) refers to technology that overlays digital information on the physical world. In I-4.0, AR is used to provide workers with real-time information and guidance, improving productivity and safety [113].

Autonomous Systems: It refers to machines and devices that can operate without human intervention. In I-4.0, autonomous systems are used to optimize production processes and reduce labor costs [114].

Cloud Computing: Cloud computing refers to the use of remote servers to store, manage, and process data. In I-4.0, cloud computing is used to enable real-time data analysis and communication between machines [115].

Security: Security refers to the protection of data and systems from unauthorized access or attacks. While the I-4.0 technologies offer many benefits, such as increased efficiency and productivity, they also pose significant security risks [116]. Cybersecurity threats such as hacking, data breaches, and ransomware attacks are more prevalent than ever in I-4.0 [117]. To mitigate these risks, companies must prioritize security measures such as regular software updates, strong password policies, and employee education and training on cybersecurity best practices [118]. It is also essential to have a comprehensive incident response plan to minimize the impact of potential security breaches. Overall, as I-4.0 continues to evolve, it is crucial to prioritize security measures to ensure the protection of valuable data and systems.

2.15 Concept of 'Lean Industry 4.0' ('Lean 4.0')

Lean 4.0 refers to the integration of Lean principles and I-4.0 technologies in manufacturing processes to improve efficiency, productivity, and overall performance [119]. It combines the best practices of Lean production, such as waste reduction and continuous improvement, with advanced digital technologies such as automation, data analytics, and machine learning [116]. Lean I-4.0 aims to create a more agile and flexible production system that can quickly adapt to changing customer demands while maintaining high-quality standards [116]. Manufacturers have been using Lean principles and tools for several decades to improve productivity and reduce operational complexity by empowering workers. Lean practices are based on operational excellence and involve standardizing processes and building a culture of continuous improvement [14, 120]. However, the diffusion of I-4.0 technologies in manufacturing over the last decade has led to a new competitive manufacturing landscape. Lean manufacturers are now experiencing a demand to achieve ever higher level of operational excellence [121]. To attain this higher level of operational excellence, several studies have shown that manufacturers can combine the right technologies and methods of Lean production [122, 14, 123, 124]. This combination of techniques and technologies has resulted in better performance, efficiency, and even self-managing factory operations [31, 122, 14]. When Lean and I-4.0 are implemented together, they are referred to as Lean I-4.0, which can further enhance the benefits of LM.

One study suggested that manufacturing companies could achieve significant synergies by holistically implementing Lean and I-4.0 rather than independently or sequentially [75]. The same study also noted that successful implementation of Lean and I-4.0 together could reduce production costs by 40 percent within five to ten years. Thus, the integration of Lean principles and I-4.0 technologies holds great potential for enhancing manufacturing performance and competitiveness. The integration of Lean and I-4.0 creates new opportunities for achieving operational excellence by encompassing various factors such as safety, quality, productivity, speed, and flexibility [14]. Regarding safety, using I-4.0 technologies, such as sensors in virtual reality, can significantly enhance operators' working conditions. By fitting operators with sensors, they can be alerted to the presence of dangerous gases or the possibility of a collision with nearby forklifts or trucks [125]. Such measures not only reduce the chances of accidents but also increase the confidence and efficiency of operators in performing their tasks. This approach to safety through the application of I-4.0 technologies in LM represents a significant shift towards a safer and more productive working environment.

The production quality can be enhanced by incorporating data-driven control systems in Lean I-4.0, as stated by research [126]. In manufacturing, producing products that do not meet specifications leads to a waste of production capacity. Even worse, it can result in higher costs and damage the reputation of the supplier if poor-quality products are shipped to customers [127]. To reduce errors and improve the rate and speed of error detection, Lean management tools like self-inspection, Poka-yoke, and jidoka have been developed [125]. For instance, self-inspections have been shown to accelerate error detection and reduce the number of defects by 50 to 70 percent by providing feedback to engineers and operators [125]. However, to achieve zero defects, manufacturers must use a data-driven approach to support self-inspections that identify the root causes of errors [126]. I-4.0 technologies provide context data and detailed tracking, which can enhance error analysis through camera-based visual inspection, correlation models, and real-time monitoring of process parameters [125].

The combination of Lean and I-4.0 has enabled manufacturers to improve the speed of production through real-time data monitoring systems [116]. However, increasing the number of product variants while reducing batch sizes has made production planning more complex, and traditional Lean management tools are not sufficient for planning and controlling production in real-time [121]. To overcome this challenge, manufacturers can apply certain algorithms that make use of real-time data. By doing so, line staff and managers can identify the root causes of performance issues, validate improvement measures, and accelerate the continuous improvement process. This allows for a faster rollout of improvement measures throughout the plant.

Lean methods have long been used to boost OEE by minimizing equipment breakdowns and failures using autonomous or preventive maintenance [128]. Companies can assign their operators specific maintenance responsibilities using autonomous maintenance to reduce downtime to fix minor issues [128]. Advanced analytics algorithms and machine-learning techniques can be used to analyze the data collected by sensors in real-time. This allows for predictive insights that identify potential equipment breakdowns before they occur, reducing disruptions, unnecessary downtime, and replacement costs. Predictive algorithms, sensors, and software have enabled efficient changeover and autonomous maintenance, enhancing the effectiveness of Lean methods in many manufacturing industries.

In conclusion, the integration of Lean and I-4.0 can create a powerful combination that can help organizations achieve greater levels of efficiency, flexibility, and profitability [120]. While Lean provides a solid foundation for process improvement and waste reduction, I-4.0

technologies can collect and analyze vast amounts of data in real-time, leading to more informed decision-making and predictive maintenance [32]. By embracing both Lean and I-4.0 principles and technologies, organizations can improve their operational performance, enhance customer satisfaction, and achieve sustainable growth in today's highly competitive business environment. Therefore, companies must consider the benefits of this integration and adopt a holistic approach to their digital transformation journey.

2.16 Integration of industry 4.0 into lean production systems

Over the past decade, there has been a debate in the manufacturing industry about whether I-4.0 can replace LP principles. While some manufacturers assumed that I-4.0 could replace Lean, several studies have shown that there is a significant co-relationship between the two approaches [31, 17, 124, 119, 15]. For example, I-4.0 technologies can provide data to support Lean initiatives, such as identifying waste and inefficiencies in production processes. At the same time, Lean principles can help to ensure that I-4.0 initiatives are focused on creating value for customers and improving overall business performance [129]. In a study, the authors discussed the integration of Lean principles with modern ICT to meet the rapidly changing demands of customers [130]. The authors pointed out that ICT has potential applications in Kanban production. Specifically, they suggested that ICT could be used to identify empty Kanban bins and initiate replenishment. However, the authors did not specify which ICT technologies could be used for this purpose. In a study, the authors mentioned while Lean principles focus on waste reduction and continuous improvement, modern ICT tools such as big data analytics and cloud computing enable real-time monitoring and analysis of customer demand, production processes, and supply chain operations [120]. By combining these two approaches, manufacturers can respond more quickly to changes in customer demand, optimize production processes, and reduce lead times.

According to a recent study, there is potential for Lean tools such as mistake-proofing to be used in conjunction with I-4.0 technologies like actuators and sensors to enhance quality improvement efforts [24]. Although there is potential for Lean tools and I-4.0 technologies to complement each other for quality improvement, there are currently limited examples of their interaction. In many cases, the benefits of combining Lean and I-4.0 are still mostly theoretical rather than being applied at the practical level. For example, the authors of a recent study [4] suggested integrating I-4.0 technology into the LP system to address some of the limitations of Lean. However, they did not specify these limitations, as noted in a previous study [131]. Indeed, several authors have emphasized the complementary nature of Lean and I-4.0 [4, 119, 95].

Although there is a complementary relationship between Lean and I-4.0, some studies have noted that there is still a lack of empirical evidence [130, 132, 133]. Given the current state of knowledge and the potential benefits of combining Lean and I-4.0, further research is needed to fully understand the nature of their relationship, assess the integration framework, and identify key factors for ensuring sustainability. Many manufacturers recognize the need to implement both Lean management and I-4.0, but they often lack a clear understanding of how to combine the two to achieve maximum benefit effectively. According to a study, companies should approach Lean I-4.0 integration by considering use cases and identifying the best combination of Lean tools and digital technologies for a particular situation [4]. They should then carefully select which use cases to implement to address specific pain points effectively.

Overall, the integration of Lean and I-4.0 provides a unique opportunity for companies to create a more efficient, responsive, and competitive business model. By combining the principles of Lean with the advanced technologies of I-4.0, organizations can achieve a seamless flow of information and materials, leading to reduced waste, increased productivity, and improved quality [129]. Additionally, the integration of Lean and I-4.0 enables organizations to leverage the power of data analytics, artificial intelligence, and machine learning to optimize their processes, make data-driven decisions, and continuously improve their operations [126]. As companies face increasing pressure to adapt to changing market conditions and evolving customer demands, the integration of Lean and I-4.0 can provide a strategic advantage that can help them stay ahead of the curve. Therefore, organizations need to embrace this integration and invest in the necessary resources and technologies to drive sustainable growth and success in the long run.

Chapter 3

Integration of Industry 4.0 into Lean Production System: A Conceptual Framework

3.1 Theoretical framework's background

The integration of Lean and I-4.0 has emerged as a popular topic in the fields of operations management, industrial engineering, and business administration. Theoretical frameworks have been developed to guide the integration process and help organizations maximize the benefits of these two approaches [134]. The theoretical framework for the integration of Lean and I-4.0 draws on the principles of LP, which emphasizes the elimination of waste, continuous improvement, and customer focus [124, 24]. At the same time, it also incorporates the key concepts of I-4.0, such as the IoT, CPS, and advanced analytics.

The framework recognizes that the integration of Lean and I-4.0 is not a one-size-fits-all approach and that each organization needs to tailor its integration strategy to its unique needs and circumstances [135]. It emphasizes the importance of creating a culture of innovation and continuous improvement, essential for achieving sustainable change. Moreover, the framework highlights the need for organizations to invest in the right technologies, infrastructure, and human capital to support the integration process [136]. It also stresses the importance of data-driven decision-making and advanced analytics to optimize processes and improve performance.

Overall, the theoretical framework for integrating Lean and I-4.0 provides a road map for organizations to successfully navigate the integration process and reap the benefits of these two approaches [76]. It emphasizes the importance of a holistic approach that encompasses all aspects of the organization and enables companies to achieve long-term success and competitiveness.

3.2 Foundations of the theoretical framework

Over the past few decades, Lean has been a popular method for achieving operational excellence by minimizing waste and continuously improving processes. However, with the advent of I-4.0 technologies, some may believe that Lean will become outdated and replaced by this new paradigm [137, 138]. However, the fusion of Lean principles with I-4.0 technologies creates a powerful synergy, optimizing processes and driving innovation for enhanced efficiency and competitiveness [31, 122, 14]. The principles of Lean can serve as a solid basis for the effective adoption of I-4.0 technologies. The merger of Lean and I-4.0 can assist companies in achieving higher levels of efficiency, productivity, and quality, as well as empower them to adapt to shifting market demands and customer requirements [31, 4]. Therefore, rather than seeing them as competing paradigms, it is more appropriate to view Lean and I-4.0 as complementary approaches that can work together to achieve sustainable success and competitive advantage in the modern business environment.

The inter-dependency between Lean and I-4.0 is supported by a literature review highlighting how LP process orientation, standardization of work and places, and emphasis on visual control and transparency can facilitate the implementation of I-4.0 technologies. The streamlined process orientation of Lean provides a solid foundation for the automation and digitization of processes that are central to I-4.0 [130, 14]. Furthermore, Lean's standardization of work and workplaces fosters a reliable and consistent environment that can be readily assimilated with I-4.0 technologies. The emphasis on visual control and transparency in Lean also provides the necessary data and information for effective decision-making and optimization of processes, which are essential for I-4.0 [130, 139]. On the other hand, several studies have pointed out that I-4.0 technologies can boost LP practices [31]. I-4.0 technologies, such as the IoT, advanced robotics, and big data analytics, can provide real-time data and insights that can be used to optimize processes and reduce waste [125]. By integrating I-4.0 technologies with LP, companies can achieve greater efficiency, productivity, and quality while reducing costs and lead times [32, 138]. For example, IoT sensors can enable companies to track and monitor the performance of machines and equipment, allowing for predictive maintenance and reducing downtime [140]. Similarly, advanced robotics can automate repetitive and labor-intensive tasks, freeing workers to focus on more value-added activities [141]. Big data analytics can provide insights into process performance and identify areas for improvement, allowing for continuous improvement and waste reduction [111]. For example, integrating factory systems, sensors, and IoT technologies can improve LP practices such as Kanban, cycle time, and waste reduction [142]. Furthermore, these technologies enable the instantaneous gathering of information that can enhance the process of value-stream-mapping and accelerate the identification of inefficiencies [143, 132]. Overall, the integration of I-4.0 technologies with LP can enhance the benefits of Lean and enable companies to achieve even greater levels of operational excellence.

Previous studies confirm that the relationship between I-4.0 technologies and LP functions in both directions: (a) I-4.0 affects LP, and (b) LP affects I-4.0 [31, 123, 119]. To provide more detail, LP facilitates the progression of I-4.0 by fostering a culture of innovation and efficiency, laying the groundwork for integrating digital technologies and advanced analytics. By embracing Lean principles, organizations can streamline their processes and enhance their readiness to adopt I-4.0 solutions, ultimately enabling them to operate more agilely and responsively in an increasingly digitized landscape [4, 14, 24]. Conversely, I-4.0 enhances LP by providing tools and capabilities to optimize performance and drive continuous improvement. Integrating AI, IoT, and I-4.0 technologies can enhance Lean methodologies by providing real-time data insights and predictive analytics. This enables organizations to identify inefficiencies more proactively. By leveraging I-4.0, Lean practices can become even more agile, adaptive, and customer-centric, leading to higher operational excellence and competitiveness in the digital age. However, a comprehensive strategy for integrating LP and I-4.0 is yet to be explored. This presents an opportunity for further research and development in this dynamic and evolving field [4, 14, 24].

The integration of I-4.0 technologies with LP systems can enhance the benefits of Lean rather than making it irrelevant. Acknowledging this connection is important for companies to achieve long-term success and stay competitive in today's dynamic business environment. In essence, the process-oriented approach of Lean and the automation, digitization, and data-driven decision-making of I-4.0 complement each other, highlighting the interdependence between the two paradigms.

3.3 Literature review on integration framework of lean and industry 4.0

The integration of Lean and I-4.0 has gained increasing attention in recent years, as both paradigms are aimed at enhancing operational performance and achieving competitive advantage. Several studies have investigated the complementary relationship between the two paradigms and suggested that Lean practices might act as a precursor to I-4.0 implementation [131, 19]. However, there is still a lack of a comprehensive integration framework that considers the link between I-4.0 technologies and Lean practices across the entire value chain [123]. Although researchers concur on the empowering impact of executing LP before I-4.0, this influence has been investigated at a general level without scrutinizing the individual LP methodologies that produce it [31]. Furthermore, there is presently a deficiency of thorough pairwise assessments at a practical and technological level capable of elucidating the functions of both Lean and I-4.0 paradigms in the transformation of LP to I-4.0 [119]. These gaps are also associated with the overall shortage of empirical research on this subject matter [31, 123].

In fact, according to a recent review, only 14 percent of the studies in this field are empirical and examine how these associations take place [123]. These various factors have resulted in the absence of a comprehensive integration framework, particularly one that considers the connection between I-4.0 technologies and LP practices across the entire value chain [31, 123]. Dalenogare et al. proposed that it is advisable to implement I-4.0 technologies after the adoption of Lean tools, as LP reduces the process to essential and uncomplicated work with minimal waste, making it easier to automate [131]. In another study, Tortorella et al. observed that Lean practices can serve as a precursor to the implementation of I-4.0 [19].

In a study by Chiarini and Kumar, it was noted that there is a complementary relationship between Lean Six Sigma and I-4.0, with the author suggesting that it is preferable to implement Lean Six Sigma first, followed by I-4.0 [144]. The findings imply that Lean Six Sigma is a precursor to I-4.0. However, how the integration model should be structured and what performance improvements can be achieved and pursued strategically is unclear. Additionally, there was limited evidence of a connection between the Six Sigma DMAIC methodology and I-4.0 technologies and systems. Furthermore, the compatibility between Lean and I-4.0 is still under investigation, and there is a lack of empirical studies on the topic [123]. In-depth and comprehensive pairwise analysis at a practice-technology level is needed to clarify the roles of both paradigms in an LP-I-4.0 transformation [123].

Overall, it can be concluded that numerous studies have been conducted on integrating I-4.0 technologies into LP systems. However, there is still a lack of research that focuses on understanding the most effective ways to integrate these technologies into the LP framework. Future studies should address this knowledge gap and provide insights into integrating specific I-4.0 technologies into specific LP systems.

3.4 Methodology

The SLR methodology is widely used to review and analyze existing literature on a particular topic. In this case, the SLR reviews the literature on Lean and I-4.0 and their integration framework. The review follows the guidelines provided by Kitchenham and Charters [145] and Dyba and Dingsoyr [146] to ensure the quality and reliability of the results. Kitchenham and Charters provide guidelines for conducting SLRs in software engineering [145]. The guidelines cover various aspects of the review process, including planning, conducting the review, and reporting the results. Dyba and Dingsoyr provide further guidance on conducting SLR in software engineering, specifically focusing on evaluating empirical studies [146].

The SLR methodology is a rigorous and systematic approach to reviewing and analyzing existing literature on a particular topic. It allows for a comprehensive and reliable analysis of the current research on the integration of Lean and I-4.0. We followed an SLR methodology involving a stepwise and sequential approach to define the research protocol, including research questions (RQs), keywords, search strings, databases, data extraction, analysis, and reporting. This approach was guided by the guidelines provided by Kitchenham and Charters and Dyba and Dingsoyr. The review process consisted of three stages: planning, conducting, and reporting. Figure 3.1 shows the process and stages involved. In line with Dyba and Dingsoyr's guidelines, we used Boolean operators 'AND' and 'OR' to define the search strings with the keywords.

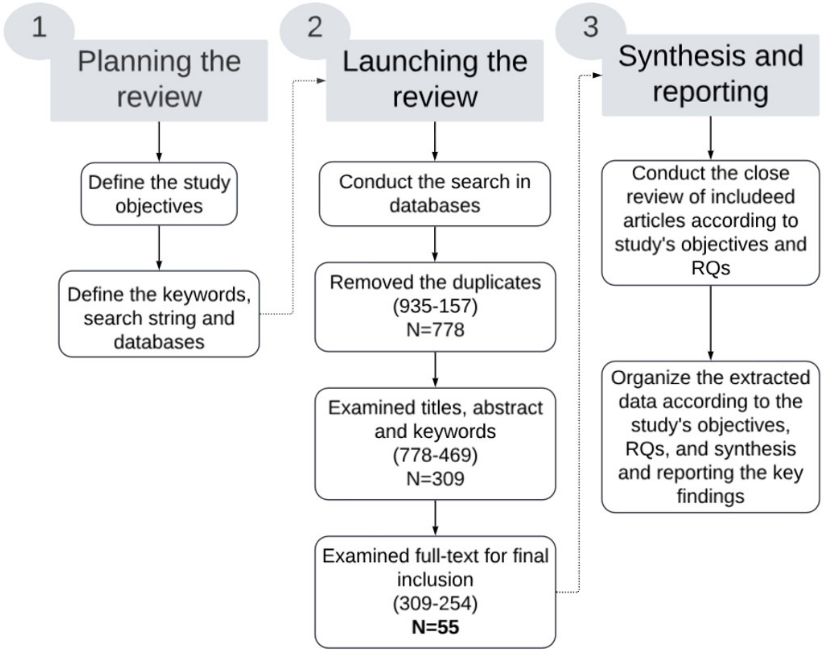


Figure 3.1: Basic steps of SLR

3.4.1 Research questions (RQs)

The SLR study was conducted by defining four RQs. These RQs are stated below. These RQs guided the selection of keywords, search strings, and other essential components of the SLR methodology.

- ***RQ1**:* Is there any synergy between Lean and I-4.0?
- ***RQ2**:* Is there any strategic framework for Lean and I-4.0 integration?
- ***RQ3**:* What key success factors need to be considered for integration?
- ***RQ4**:* What challenges need to be considered for integration?

3.4.2 Keywords and search string

A set of keywords was selected to investigate the articles in the selected database that support the research questions. The chosen keywords were divided into three groups based on the similarity of the referring field, as shown in Table 3.1. The words from the same group were connected using the Boolean, ‘OR,’ while it was ‘AND’ for the different groups, and likewise, the following search string was formulated: ("Industry 4.0" OR "Industrie 4.0" OR "Fourth industrial revolution" OR "Smart manufacturing") AND ("Lean thinking" OR "Lean Manufacturing" OR "Lean Production") AND ("Framework" OR "Model").

Table 3.1: Three groups of keywords

Group A	Group B	Group C
Industry 4.0	Lean Thinking	Framework
Industrie 4.0	Lean manufacturing	Model
Fourth industrial revolution	Lean production	

3.4.3 Inclusion and exclusion criteria

The studies were included based on the predefined set of inclusion criteria, and similarly, the studies were excluded based on the exclusion criteria.

3.4.3.1 ***Inclusion criteria***

- The article must focus on the research questions and be published in a peer-reviewed journal or conference proceedings
- The article must be written in English
- The article must be published between 2011 and October 2023

3.4.3.2 ***Exclusion criteria***

- Articles published before 2011 must be excluded
- Articles not focusing on the research questions must be excluded.
- Articles published as a workshop, newspaper reports, industry reports, and other forms must be excluded
- Non-English articles must be excluded

3.4.4 Data sources and search strategy

To conduct the study, three databases, ScienceDirect, Emerald Insight, and Taylor and Francis were searched based on predefined research questions and the search string. The primary inclusion criteria were each article's title, keywords, and abstract, while the full text was considered for the final inclusion. After the initial search, 55 articles met the predefined criteria for further exploration. Each of these articles was independently reviewed by the authors to determine their suitability for answering the research questions. The methodology for the study is illustrated in Figure 3.1.

3.4.5 Synthesis and reporting

After screening through the SLR process, all included articles were grouped according to the themes derived from the research questions. Both descriptive and thematic analyses were carried out over the included articles. The key identifying information was extracted from the included articles and recorded in Excel sheets for descriptive analysis. The sub-themes were decomposed from the research question to conduct the thematic analysis for evaluating the research questions qualitatively.

3.5 Results

This section outlines the included articles' fundamental characteristics and the complementary relationship between Lean tools and I-4.0 technologies. Different integration roadmaps and frameworks are explored to effectively combine the Lean tools/approaches and I-4.0 technologies. Additionally, the sustainable integration aspects of Lean and I-4.0 are investigated, emphasizing the importance of a long-term perspective in implementing these paradigms together.

3.5.1 Characteristics of included articles

The included articles were categorized into several groups to analyze the essential characteristics based on the year of publication, sources of databases, nature of publication, types of studies, and country where the study was conducted. The overall summary of the included articles in the SLR is documented in Figure 3.2.

The number of publications from 2015 to 2022, as shown in Figure 3.3, follows an overall upward tendency across the years, referring to an emerging research field. Also, this pattern can be perceived from the highest number of articles corresponding to 2018 with 2, 2019 with 3, 2020 with 6, 2021 with 12, 2022 with 18, and 2023 with 9. A significant number of studies (33 out of 55) were published as journal articles, while the rest (22 out of 55) were conference proceedings, as shown in Figure 3.4. Importantly, it is noted that other articles, such as blogs, symposiums, newspapers, scientific reports, and technical reports, were not included in this study.

Among the included articles, 31 were from Science Direct, followed by Emerald Insight with 13, and Taylor and Francis with 11, as shown in Figure 3.5. According to the types of study, in number, 30 studies were conceptual, corresponding to the highest, followed by empirical study with 13, and case study with 12, as shown in Figure 3.6. It appears that most of the articles (48 out of 55) pertain to RQ1, while 13, 17, and 8 are relevant to RQ2, RQ3, and RQ4, respectively, as shown in Figure 3.7

Among the included articles (a total of 55) in the study, the highest number of studies were conducted in Germany with 9, followed by Italy with 7, India with 6, the UK with 5, France and Brazil with 4, respectively. Spain, Morocco, and Australia conducted 2 studies each, while the rest of the studies were conducted only once, as shown in figure 3.8. The major Lean tools and I-4.0 technologies are discussed in the included articles were documented with significant contributions in Table 3.2.

3.5.2 The complementary effect of Lean and industry 4.0

As documented in Figure 3.7, the results reveal that the highest number of studies (48 of 55) were conducted to evaluate the complementary status of Lean and I-4.0. For example, Mrugalska and Wyrwicka demonstrated the complementary relationship between Kanban and CPS [132]. More specifically, multiple studies showed that big data analytics significantly improves

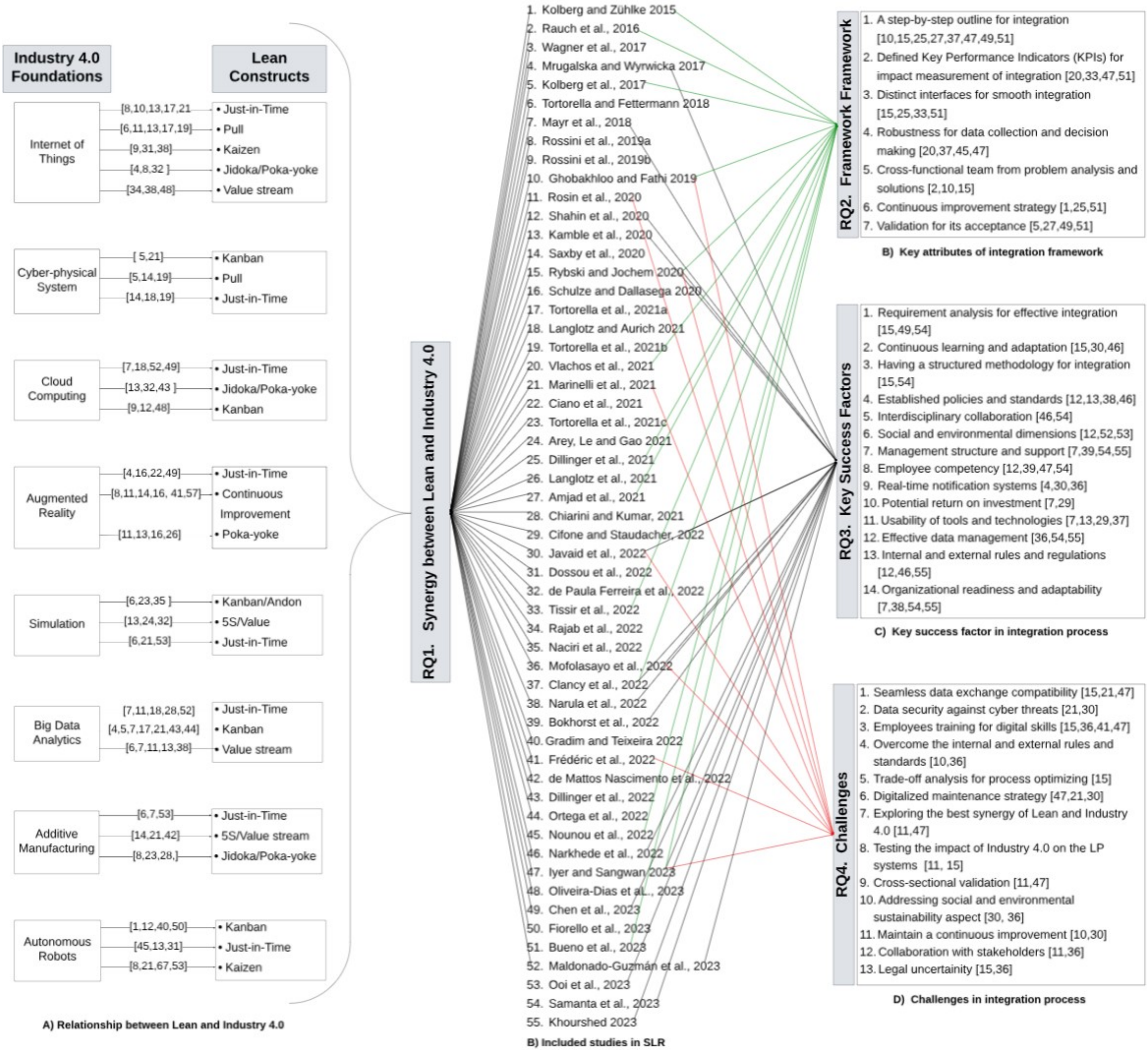


Figure 3.2: Overall summary of the included articles in the SLR

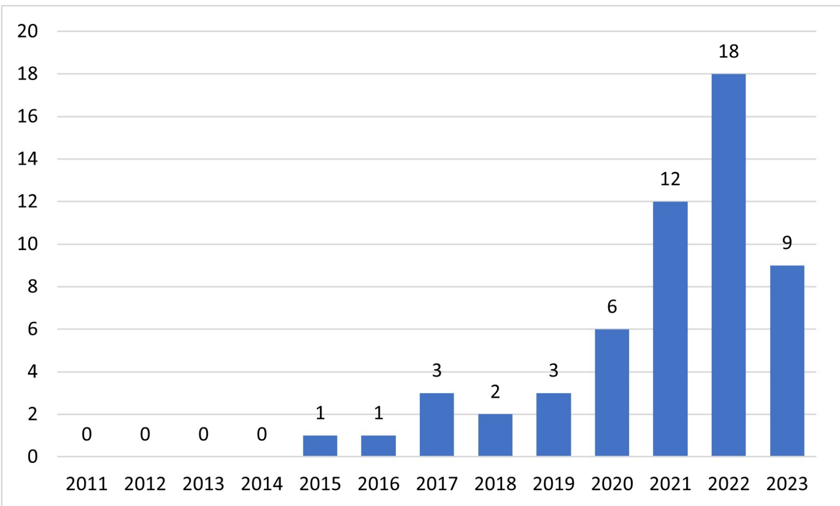


Figure 3.3: Studied articles across the year.

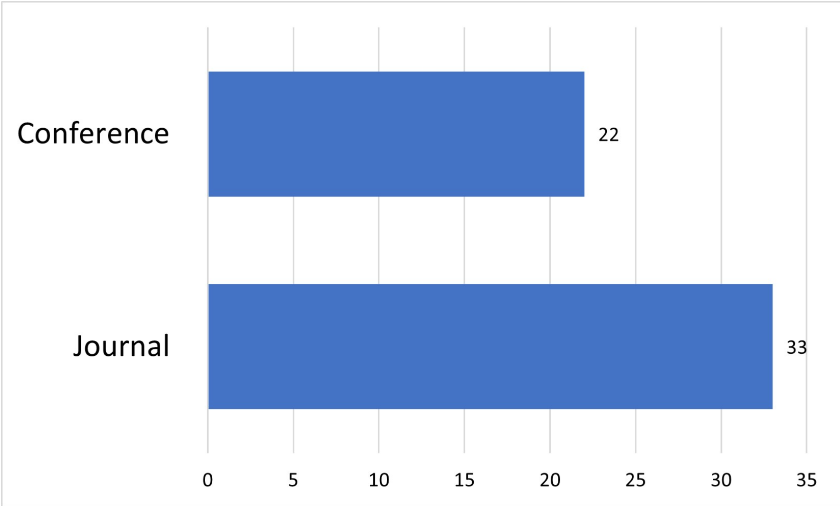


Figure 3.4: Publication types of included articles

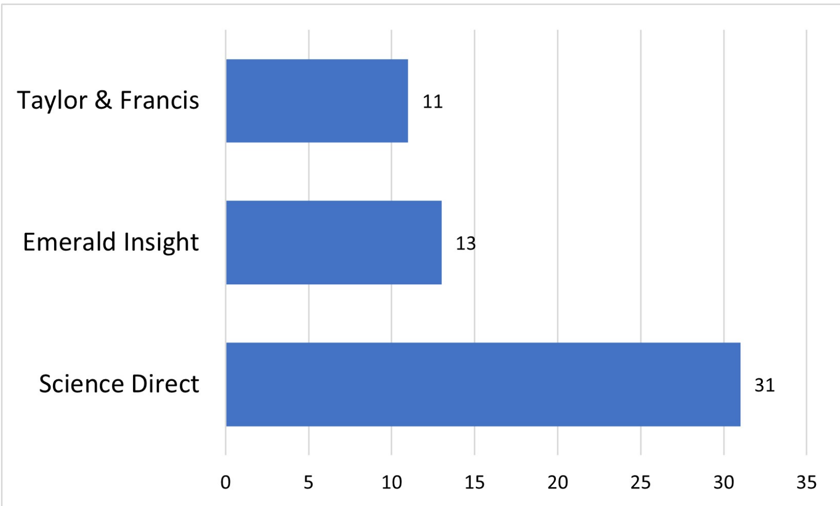


Figure 3.5: Distribution of databases of included articles

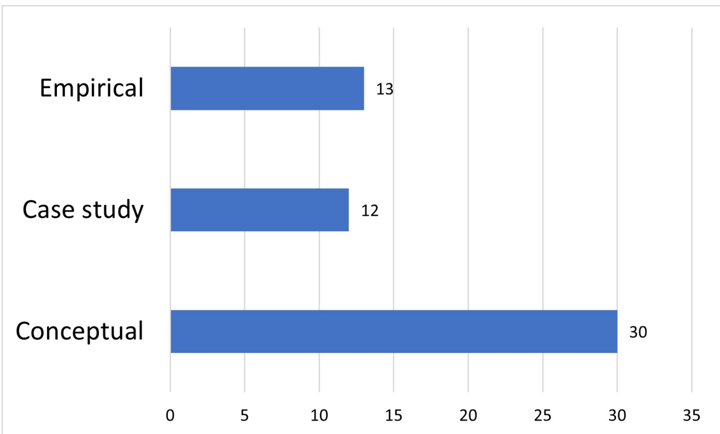


Figure 3.6: Distribution of included articles according to study's types

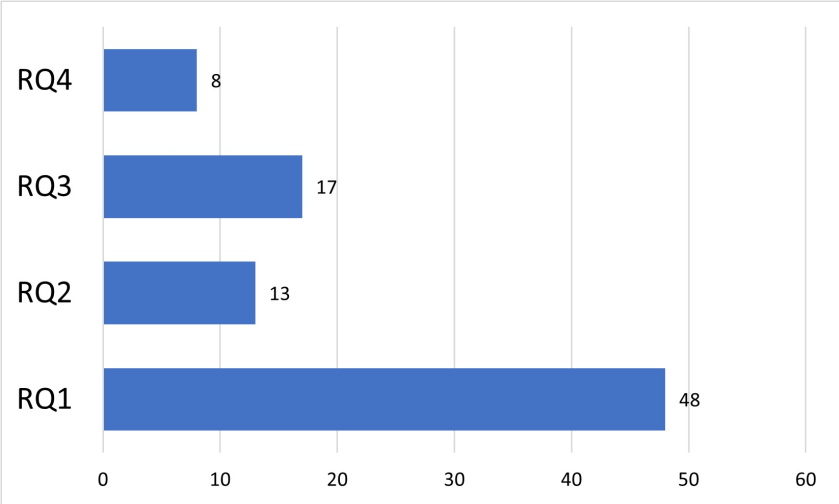


Figure 3.7: Distribution of articles according to RQs. Here, RQ1: Is there any synergy between Lean and I-4.0? RQ2: Is there any strategic framework for Lean and I-4.0 integration? RQ3: What key success factors need to be considered for integration? RQ4: What challenges need to be considered for integration?

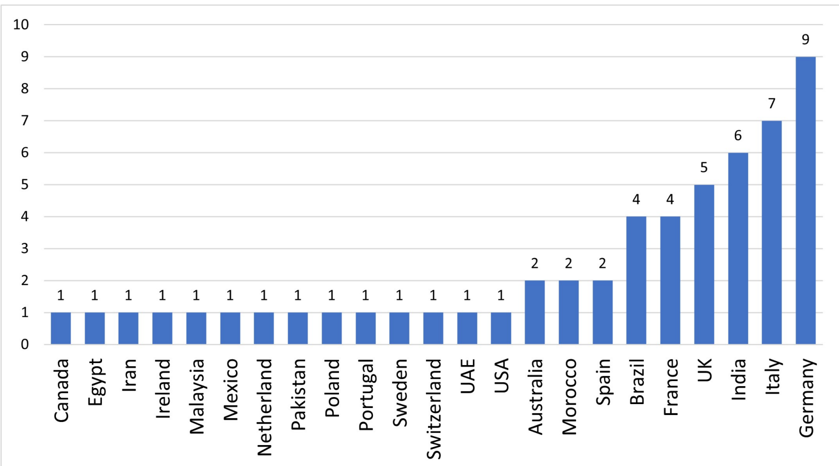


Figure 3.8: Types of included articles.

Table 3.2: Key Lean tools and I-4.0 technologies with their major contributions

Reference	Lean tools	I-4.0 technologies	Major contributions
[130]	Kanban	CPS	Lean automation
[124]	JIT, Pull	IoT, RFID	Integration framework
[95]	Not specified	Not specified	Integration framework
[122]	Not specified	Not specified	Integration framework
[147]	Kanban	CPS	Integration framework
[132]	Kanban	RFID	Relationship framework
[19]	JIT, Pull	IoT, BDA	Integration framework
[14]	TPM	CC	Relationship framework
[27]	Not specified	Not specified	Relationship framework
[119]	Not specified	Not specified	Relationship framework
[148]	JIT, TPM	Sensor, AM	Lean Digitization
[19]	JIT, Pull	Sensor, IoT	Lean automation
[42]	JIT, Jidoka	IoT, CC	Relationship framework
[24]	Poka-yoke	CC, AR	Relationship framework
[17]	JIT, Pull	BDA, AR	Relationship framework
[149]	Pull, Flow	IoT, CC	Integration framework
[150]	SMED	RFID, CC	Integration framework
[151]	DVSM	RFID	Lean digitization
[152]	JIT, TPM	RFID, CC	Integration framework
[153]	Kanban, 5S	AGV, RFID	Relationship framework
[154]	Not specified	Not specified	Relationship framework
[30]	5S	IoT	Lean automation
[155]	Kanban	RFID, CPS	Lean automation
[4]	JIT, 5S	IoT, DT	Relationship framework
[25]	TPM	IoT, BDA	Integration framework
[51]	DVSM	CPS, ICT	Lean digitization
[26]	Not specified	Not specified	Integration framework
[156]	Kanban	AR, DT	Relationship framework
[157]	Jidoka, CI	Not specified	Lean digitization
[144]	5S, Heijunka	AGV, VR	Relationship framework
[158]	JIT, Kaizen	RFID, IoT	Integration framework
[19]	DVSM	CPS	Lean automation
[159]	5S, CI	AR, AM	Lean automation
[160]	DVSM	IoT, BDA	Integration framework
[34]	DVSM	Simulation	Integration framework
[161]	Not specified	IoT, BDA	Not specified
[36]	Kanban	RFID	Relationship framework
[162]	Not specified	Not specified	Relationship framework
[32]	Not specified	Not specified	Relationship framework
[76]	Not specified	Not specified	Integration framework
[133]	JIT, Kaizen	AR, IoT	Integration framework

Note: RQ1:Is there any complementary effect of Lean and I-4.0 on operational performance improvement? RQ2: Is there any strategic roadmap or framework for Lean and I-4.0 integration? RQ3: What critical factors need to be considered for the sustainable integration of Lean and I-4.0?

the efficiency of the pull production system [133, 149, 19, 30]. Some authors discover the significant effect of big data analytics on the synergy of TPM [158, 163, 19]. A substantial number of studies affirm that the I-4.0 enables the Lean tools/principles to increase the productivity of the LP system [144, 32, 151, 150, 15, 95]. On the contrary, less evidence demonstrated that Lean could assist I-4.0 [22, 32, 149].

Integrating Lean and I-4.0 paradigms has become a topic of substantial research interest in recent years. Lean methodologies are generally viewed as facilitators for implementing I-4.0, while I-4.0 is seen as a way to achieve an expanded Lean enterprise [155]. Mayr et al. asserted that the widespread agreement on the compatibility of Lean and I-4.0 can be explained by conceptual similarities in areas such as objectives (e.g., simplifying complexity), the comprehensive approach, and the crucial role of employees, among other factors [14]. Regarding the joint employment of tools, the literature also includes numerous research papers suggesting the combined use of I-4.0 and Lean tools to improve operational efficiency in manufacturing.

Davies et al. refer to using CPS-supported real-time data to generate e-Kanbans, enabling automatic orders and inventory level control [164]. Furthermore, with the help of RFID technology, a CPS-based production system can collect information about inventory, location, networking, and man-machine interface and enable digitized information sharing between shop floors and business departments [165]. This results in a transparent Leaner process since the efficient communication of changes in components and technical drawings reduces errors, increases capacity, and enhances customer satisfaction. Additionally, CPS-based smart devices, e.g., smart watches, allow operators to receive error messages in real-time and act on repair actions required with no delay. In addition, CPS equipped with proper sensors can recognize failures and automatically trigger fault-repair actions on other CPS [130].

Ma et al. suggested a standardized, integrated approach to design and implement a Cyber-Physical System (CPS) based intelligent system that incorporates Cloud and IoT technology. This approach guarantees flexibility in terms of configuration, deployment, and performance [166]. Additionally, Blunck et al. introduced a framework supported by Cyber-Physical Systems (CPS) in which intelligent agents can autonomously decide on their routes [167]. This framework is valuable in decreasing time and offering flexibility and optimal allocation of production capacity. An IoT-based logistics model incorporating Lean Six Sigma elements proposed by Jayaram et al. allows for a fully autonomous global supply chain with an optimized flow and overall efficiency [168]. This IIoT-supported model enables the communication between production and supply chain with real-time data used to optimize processes and reduce costs and resource consumption.

Ferrera proposed an IoT framework achieving easy integration and data exchange between machines, sensors, and end users of software tools at industrial sites [169]. Similarly, Silva et al. developed a cloud-based application that can process real-time inputs from computational systems within the company to create electronic work instructions and standard words [170]. Another study by Ogu et al. presents the integration of cognizant computing and Lean practices to ensure business success [171]. Cognizant computing provides real-time databases supported by cloud computing and powered by IoT technology. The benefits reported include tremendous savings and returns, reduction in lead times, inventory volumes, process wastes, and minimal rework. In a study, authors noted that in the context of the product development process, implementing the cloud substantially contributes to eliminating waste associated with disconnected users or sending wrong information [172]. Additionally, Mayr et al. highlight how cloud computing and machine learning-based condition monitoring enhance product quality and TPM by reducing machine downtime, rework, and scrapping [14]. Furthermore, the cloud can provide maintenance data to the workers and enable the dynamic scheduling of maintenance activities. The use of Big data to facilitate Lean applications has also been widely reported in the literature. The combination of data analytics and cloud technologies for real-time KPI generation has been suggested by Rauch et al. as an improved data processing approach that, based on current information, can promote the project team's motivation and efficiency [172].

Meudt et al. discuss VSM 4.0 as a new VSM approach focused on data collection, storage, handling, and utilization for KPI generation to achieve maximum waste reduction and appreciation of how information flows within the logistic processes [173]. Similarly, Lugert et al. supported the potential use of Big Data technology for improving the VSM [174]. Their main focus was to optimize the value stream with the help of data analytics, simulation, and an RFID-supported user interface that enables real-time results visualization and employee engagement. Mrugalska Wyrwicka agrees that I-4.0 and Lean could support each other and coexist [132]. Sanders et al., in their paper, argue that adopting I-4.0 can help overcome existing barriers to Lean implementation [124].

[37, 31, 147, 19]

In many studies [37, 31, 147, 19], authors have noted the lack of research on integrating I-4.0 into the LP systems. This emphasizes the need for future investigations to explore the synergies and challenges of integrating Lean and I-4.0 frameworks. These studies should use empirical methods and case studies to gain practical insights for organizations. Integrating academia and industry can enhance this discussion, promoting innovation that meets modern manufacturing and business requirements. By closing this research gap, scholars can unlock the transformative potential of aligning Lean principles with the digital capabilities of I-4.0. In this context, Sanders et al. have suggested that there is a need for further research to fully comprehend the relationship between Lean and I-4.0 and the impact they have on operational performance. [124]. Buer et al. also demonstrated a need to understand the compatibility to work together of both Lean and I-4.0 areas [31]. Ana Pereira et al. aim in their research, which includes a literature review, to examine how 12 technologies of I-4.0 can enhance Lean practices and to analyze their implications and advantages for companies orienting toward this new industrial model [175]. Sule satoglu et al. highlighted the relationship between Lean and I-4.0 and suggested a framework that gives guidelines for developing Lean 4.0. In addition, seven technologies for I-4.0 and Lean production-oriented automation applications are also included [176].

In a study, authors mentioned that Lean and I-4.0 are not mutually exclusive, though they are two different paradigms [4]. These two paradigms can be seamlessly integrated. But before integration, ensuring information flows in the right direction is key, as they stressed its importance in production. Getting data to move accurately where it needs to go is crucial for smooth operations. Additionally, they mentioned that I-4.0 could not solve the mismanagement and weakly organized problems.

In their study, Sanders et al. aimed to identify the primary barriers to implementing LM in small and medium-sized enterprises (SMEs) in Germany [124]. They found that communication, integration, and monitoring were the main obstacles to implementing Lean principles in SMEs. To address these challenges, the authors suggested using I-4.0 technologies. Specifically, they recommended using RFID and smart IoT devices to implement just-in-time (JIT) production and e-Kanban for pull production. Sanders et al. also noted that the combination of Lean principles and I-4.0 technologies could increase productivity and reduce waste in manufacturing. However, the authors acknowledged that further research is needed to develop a comprehensive conceptual framework for integrating Lean and I-4.0 [124].

Wang et al. (2016) developed a matrix to show the impact of I-4.0 technology on Lean principles [95]. The researchers surveyed 24 I-4.0 project leaders, out of which 8 had experience in both Lean and I-4.0. The matrix displayed a significant relationship between Lean and I-4.0. For instance, I-4.0 technologies such as cloud computing and big data analytics were rated highly for their potential to improve the Jidoka and standardization principles of Lean production. The researchers also mentioned that augmented reality could enhance the 5S, Kaizen, and standardization. However, the study was limited to the authors' experiences and lacked any field-level experimentation. Therefore, the practical interaction between Lean and I-4.0 still needs further investigation [95].

A review study delved into the connection between Lean and I-4.0 [122], examining 31 articles that met their criteria. Surprisingly, only three articles explored Lean within the context of I-4.0, indicating a lack of focus on their integration until 2016. However, the study did not elaborate on the coexistence of Lean and I-4.0. It underscores the need for future research to concentrate on how to integrate I-4.0 into LP systems [122].

Mrugalska and Wyrwicka were inspired by the lack of research on the complementary relationship between Lean and I-4.0 [132]. They conducted a review of previous studies and found that I-4.0 technologies such as CPS and RFID can be utilized as supporting tools to improve the performance of Andon and Kanban. However, the study did not explore the extent to which these I-4.0 technologies could enhance the performance of the Lean system when applied to Andon or Kanban [132].

Kolberg et al. were motivated by the limited customization capability of the LP system, which led them to explore the integration of CPS into the LP system. However, theA review study investigated the relationship between Lean and I-4.0 [122]. The study selected 31 articles based on their inclusion criteria. The results showed that only three articles considered the Lean concept within the framework of I-4.0, indicating that until 2016, significant research was not focused on integrating Lean and I-4.0. However, the study did not explain how Lean and I-4.0 coexist. The study suggests that future research should focus on integrating I-4.0 within the LP system [122]. y also identified a lack of interface between these two paradigms in the manufacturing sector [147]. As a result, they conducted this study to develop an interface that would bridge the gap between LP and I-4.0, ultimately leading to improved productivity that can better meet customers' flexible demands [147].

Tortorella and Fettermann conducted a survey study to evaluate the relationship between Lean and I-4.0 in 110 Brazilian companies [15]. The authors found a positive association between Lean and I-4.0, but they did not analyze the one-to-one relationship between specific I-4.0 technologies and Lean tools. The study concluded that experience in Lean implementation (more than 2 years) positively impacted the association between Lean and I-4.0, but did not explain the reasons behind this outcome. The study also found that company size did not have any effect on the relationship between Lean and I-4.0 [15].

Mayr et al. noticed a gap in the combination of Lean and I-4.0 practices and decided to investigate whether there is a complementary relationship between the two [14]. After analyzing the existing literature, they found evidence to support such a relationship. Additionally, they conducted a case study to evaluate the use of cloud computing technology and digital twins in improving TPM and VSM. Although their findings suggest a positive relationship between Lean and I-4.0, the study lacks empirical data to accurately measure the extent of this relationship [14].

A study was conducted to investigate the impact of the combination of Lean and I-4.0 on operational performance improvement. The authors surveyed 108 European manufacturing companies and analyzed five driving factors, including company size and technological intensity. They found that while LP implementation is independent of I-4.0 adoption, the adoption of I-4.0 is significantly related to LP implementation. The authors concluded that the combined impact of Lean and I-4.0 is better than LP implementation alone in operation. However, the study's sample size is a weakness that may affect its validity for further use [27].

A literature review examined the complementary relationship between Lean and I-4.0 and the barriers to their integration in manufacturing performance improvement [37]. The authors found a significant relationship between the two paradigms, with Lean implementation often preceding I-4.0 integration. However, they did not comprehensively map specific Lean tools and I-4.0 technologies. The authors identified technological and human factors as barriers to integration but did not consider cost and environmental factors. Some relevant articles were not included, calling for further research to make sustainable decisions in merging Lean and I-4.0 [37].

A survey was conducted by Rossini et al. to investigate the connection between Lean practices and the adoption of I-4.0 technologies over 108 European manufacturing companies [27]. According to their findings, a positive correlation exists between a higher level of Lean implementation and a greater likelihood of adopting I-4.0 technologies. In contrast, companies that do not prioritize Lean principles are less likely to adopt new technologies, regardless of their novelty. This suggests that a comprehensive Lean approach is advantageous for the adoption of I-4.0 technology. However, the authors acknowledge that the study's sample size is limited and that further research is required to validate their findings. Furthermore, the authors did not specify what they meant by a ”higher level” of Lean implementation. Overall, the authors emphasize the significance of Lean practices in facilitating the adoption of I-4.0 technologies in manufacturing companies [27].

A study investigated the role of I-4.0 technology in supporting the implementation of Lean principles in the manufacturing industry [42]. To achieve this, five Lean principles - JIT, Jidoka, waste reduction, people and teamwork, and standardization were examined for their connections with eight I-4.0 technologies, including autonomous robots, simulation, system integration, IoT, cloud computing, augmented reality, big data analytics, and cybersecurity. The study discovered a positive correlation between continuous flow, and the IoT and simulation technologies. The findings indicated IoT had a significant relationship with visual management, continuous flow, pull systems, in-station quality control, and waste reduction. Similarly, simulation was closely related to continuous flow. However, the research did not indicate how these relationships influenced operational improvements. The study was limited in its synergies application; therefore, further research is necessary to validate the proposed links. Moreover, the research did not mention the Key Performance Indicators (KPIs) used for managing these relationships [42].

Shahin et al. conducted a study to explore the connection between Lean and I-4.0 and how they affect operational performance [24]. The study involved a review of the literature to establish the relationship between Lean and I-4.0. The authors concluded that I-4.0 technology could enhance Lean implementation and improve process efficiency. For example, cloud computing can support the Kanban, poka-yoke, and andon Lean approaches, while Big Data analytics can aid the poka-yoke and VSM approaches. Similarly, the VR/AR technology supports the kaizen, and sensor technology enhances the jidoka or quality improvement of the Lean production system. However, the study did not mention the extent to which these relationships can enhance operational efficiency, and there was no mention of the measuring scale used [24].

A study was conducted to evaluate the effectiveness of Lean management in promoting continuous improvement within a company utilizing I-4.0 [149]. The research data were gathered through interviews with five Lean-quality personnel. The study aimed to determine the level of support that Lean provides to the world of I-4.0. The findings revealed that while Lean partly supports I-4.0, it is not entirely supportive. Most of the responses (48 percent) were positive, while 39 percent of the responses were neutral, and a small percentage (8 percent) were negative. The study concluded that a significant percentage of Lean directly supports the implementation of I-4.0 within the organization [149].

Ramadan et al. conducted an exploratory study to enhance the effectiveness of LM by incorporating digital technology [151]. The authors achieved this by utilizing IT-based technologies to digitalize the Lean management process. Specifically, RFID tags were implemented to enable a dynamic flow of value in the value stream mapping of the Lean production system. Additionally, the study proposed and tested a dynamic architecture of VSM. However, more case studies are required to validate this proposed method's effectiveness. The study also identified some challenges, such as overlapping readings of RFID, which need to be addressed by revising and improving the architecture of the dynamic VSM [151].

A study was conducted to investigate the integration of Lean and I-4.0 technologies to decrease manufacturing company losses [152]. A review study was conducted to clarify the nature of the relationship between Lean and I-4.0, and based on previous research, the authors proposed a relationship framework for integrating Lean tools and I-4.0 technologies. While this framework highlighted a positive association between Lean and I-4.0, it was not validated using empirical data. Furthermore, the study did not discover how much this association contributes to reducing losses, nor was any measuring scale established to quantify this impact. Another limitation of this study is that it focused solely on quality parameters in reducing losses without examining other performance metrics [152].

Throughout a study, Cifone and Staudacher concluded that it is important to analyze the company's culture, mission, and vision before implementing Lean 4.0 [154]. Furthermore, they suggested that the production strategy plan should also be considered in the adoption of I-4.0. The authors emphasized the significance of analyzing the production strategy of operations to apply Lean 4.0 effectively cite cifone$_{r}epetitive_{2}021.$

Vlachos et al. conducted a review study to explore the integration of Lean and I-4.0 from a socio-technical system perspective [30]. They revealed that the integration of Lean and I-4.0 integration process is not a straightforward system. Instead, it is a complex system where the ergonomics and socio-technical viewpoints must be considered. However, the study's findings, which suggest the importance of considering socio-technical factors in designing the integration of Lean and I-4.0, were based on a single case study. As such, the validity of the findings may be limited and could benefit from additional validation through multiple case studies [30].

Marinelli et al. conducted a case study in designing Lean automation [155]. In the case study, the authors demonstrated the potential of automating the Kanban-based LP system using CPS and RFID technologies. However, the authors emphasized standardizing each working station in the process line before automation. Additionally, they stated that multiple case studies are required for validation [155].

A study was conducted by Ciano et al. (2021) to explore the relationship between Lean and I-4.0 technology through eight case studies [4]. While the study established a specific relationship between the two, it lacked empirical quantitative data to represent the strength of their correlation and how much it contributes to operational performance. Moreover, the sample case studies were from a single country, which limited their validity. The study also suggested that action research case studies are required to provide clear guidelines for practitioners instead of retrospective longitudinal studies [4].

Tortorella et al. conducted a study to explore the drivers and impediments of integrating I-4.0 technologies in TPM [25]. Four case studies were conducted to answer the research questions. The authors identified management culture, vision, motivation, leadership, and organizational structure as the key drivers for successfully integrating Lean and TPM. Additionally, diverse production systems, employee skill levels, organizational culture, and maintenance competencies were identified as the main impediments. However, the generalizability of the findings is limited due to the small number of case studies conducted. Also, the study did not specify the operational mode of these case studies [25].

Arey et al. aimed to integrate I-4.0 technology into the VSM of operating companies [51]. The study demonstrated the use of CPS in digitalizing the flow of material and information in the VSM. The case study showed a reduction in lead time from 6.5 days to 1 day, indicating the effectiveness of this integration. However, the study's validity is limited due to using a single case study and a single field. Therefore, it is necessary to conduct multiple case studies in various areas to validate the digitalized VSM [51].

A study was conducted to delineate the impact of digital transformation of LP at a different levels [157]. The data were extracted through an SLR to draw an inference from this study. Based on the review analysis, the Lean tools were categorized into five levels, which could benefit practitioners for employing at the root level. However, the relationship between Lean tools and I-4.0 technologies was not depicted. Additionally, their impact on operational performance was not evaluated. Therefore, future research scope is still demanding to find out the one-to-one relationship between Lean and I-4.0 and their effects on Lean production systems [157].

A study was conducted to discover if I-4.0 could impact the operational improvement of the LSS project. The authors interviewed ten experienced managers of ten Italian manufacturing [144] companies. Besides the interview, a holistic literature review was conducted. Based on that, it was postulated that before employing the I-4.0 in any LSS project, it is essential to apply the LSS to make the operation efficient unless it will magnify the inefficiency of the process. Additionally, the I-4.0 technology was analyzed in terms of how it can be used at different phases of LSS. A theoretical framework between I-4.0 and LSS was proposed, but it lacks empirical evidence for validation. Additionally, the small size of interviews reduces its validity for wide acceptance [144].

Tissir et al. conducted a review study to integrate I-4.0 within the Lean Six Sigma approach. The authors stated three stages in integrating LSS and I-4.0: 1) the relationship between LSS and I-4.0, 2) the Implementation of LSS tools and I-4.0 technology, and 3) performance measurement using KPI [120].

To identify the nature of synergistic relationships between Lean tools and I-4.0 technologies, a study was conducted [129]. A bibliometric analysis was conducted over the database, Web of Science, and Google Scholar, to select the most appropriate articles and thus extract the information to analyze the goals. In this context, the authors demonstrated using I-4.0 technologies and Lean tools most in varying manufacturing companies. This relationship between Lean tools and I-4.0 technologies could be helpful to practitioners in selecting and employing the right synergy of Lean and I-4.0. However, the impact of these synergies was not evaluated over the study period, which creates a gap for further study. Furthermore, the limited database considerations limited its validity [129].

A study was conducted to integrate the I-4.0 into the OEE system to reduce waste [161]. A review study was conducted, and came to a decision was that big data analytics, cloud computing, AR, & simulation have significant contributions in reducing the seven Lean waste. However, no empirical evidence or quantitative analysis was presented against their results from the literature review. The specific Lean tools associated with Lean waste management were not delineated with the synergy of I-4.0 technology.

Naciri et al. conducted a study in Mocco to explore the opportunity to integrate the I-4.0 technology in the LM environment to improve operational performance [36]. Throughout a single case study, the authors showed a few combinations of Lean principles and I-4.0 technology that can be applied to LP systems, such as RFID for Lean production flow and the sensor for Kanban & Andon systems. Nonetheless, this conclusion was driven by a single case study [36].

A study was conducted to identify how Lean tools and I-4.0 technology coexist in process performance improvement [163]. In this essence, the authors conducted an SLR. The data extracted from the included articles were described mainly for characterizing the articles according to publication year, database, and country. The authors explored the nature of the association between Lean tools and I-4.0 technology- how they work together for performance improvements. For example, the authors have stated that CPS positively associates with jidoka, Kanban, and WIP (Work in Process). On the other hand, the performance of TPM can be enhanced by the collaboration of robotics and AR. However, it hasn't been determined through any quantitative analysis to what extent their relationship exists. This is a common gap like others, which urges more empirical studies to be conducted [163].

A study by Kolberg and Zühlke aimed to increase the level of automation in the LP system through the use of I-4.0, particularly the CPS [130]. The authors discovered a research gap in Lean automation, specifically that the LP system is typically restricted to fixed cycle times and production sequences, which may not be suitable for individual single-item production. Additionally, any modifications to the LP system require significant effort in adjusting the Kanban cards to achieve balance in buffer stocks or cycle time. As a result, the suitability of LP is limited in the case of shorter product life cycles. To address this gap, the authors proposed a combination framework integrating I-4.0 technologies, such as CPS, with Lean tools like Kanban and Andon. However, they did not provide quantitative analysis to support their proposed relationship [130].

A study was conducted to identify the critical aspects of the relationship between Lean and I-4.0 [162]. The authors launched a SLR to achieve the goals. According to the authors, the concept of integration between Lean and I-4.0 is still in a rudimentary stage. Based on the review study, an LSS culture is recommended to incorporate Lean and I-4.0 successfully. While defining and establishing the manufacturing culture was considered a significant challenge, continuous improvement was suggested as the critical success factor [162].

These studies investigate and analyze how Lean and I-4.0 work together to achieve optimal results despite each having advantages and disadvantages. Although some studies were limited to a single case study or lacked empirical evidence, while others had small sample sizes or did not specify the operational mode of the case studies, they still offer valuable insights for future research on the collaborative relationship between Lean and I-4.0. Additionally, these findings identify research gaps that must be addressed in designing future studies.

3.5.3 Integration framework of lean and industry 4.0

Based on this review study, it is perceived that while many studies discussed the positive association between Lean and I-4.0, the number of research works on their integration framework is still limited. Figure 3.7 shows that in only 13 (out of 55) studies, authors demonstrated the integration framework, leading the strategic paths to incorporate I-4.0 into LP systems. Among them, in [158, 160, 150], authors outlined the integration strategy using five different stages, while in [34, 26], authors defined their integration model with four steps. In [120], the authors depicted the integration roadmap using only three stages: relationship, implementation, and performance. In [133], the authors focused on individual framework characterization of I-4.0 and Lean approaches. In contrast, most studies consider the relationship between Lean and I-4.0 at the beginning stage of the integration model. In [158], the authors proposed their integration model of Lean and I-4.0 for large manufacturing companies, while the rest of the studies do not specifically refer to their model for any company, whether it is small, medium, or large. Also, limited guidelines were presented on the integration framework, which refers to further studies needed for formulating the comprehensive integration framework of Lean and I-4.0.

The power of I-4.0 will not be fully materialized as an industrial revolution if it is not integrated into the LM theoretical framework [177]. The previous studies in I-4.0 were purely theory-oriented; hence, it is not readily adaptable for practical implementation in an organization. There is a lack of a comprehensive framework combining I-4.0 solutions with LM management methods [147, 130]. Thus, there is a need to develop a framework for the successful integration of LM and I-4.0 [124]. I-4.0 and LM utilize decentralized control and aim to increase productivity and flexibility [31]. There have been few studies on the importance of investigating the link between LM and I-4.0 [31, 147, 124, 15]. In a recent study, Buer et al. suggest that the area of LM and I-4.0 is yet immature, which is why no implementation framework for integrating LM and I-4.0 has been published yet [31]. They further suggest a need to understand how these domains interact. This study addresses the research gap by developing a theoretical integration model between LM and I-4.0. This research proposal will be designed to guide future research in this direction. The theoretical background is elucidated in the next section, trailed by the proposed model and research proposition, and this paper presents a subsequent discussion and conclusion.

The authors conducted a study to formulate a strategy to integrate the I-4.0 into the LM system [26]. They proposed a seven-step strategic plan to implement the integration at the field level to obtain the goal. Mainly, the scope, design, and evaluation stages are considered in their conceptual design. However, the proposed strategic plan was not validated through any case study. Moreover, concerning the nature of manufacturing, the proposed strategic plan was neither specific nor generalized, which limited its acceptance [26].

I-4.0 can be classified based on integration principles into vertical, horizontal, and end-to-end integration [95]. The five main principles for LP implementation are the overarching guidelines for implementing LP [2]. Waste must be eliminated before implementing three integration mechanisms; otherwise, one will be automating the waste. With this principle in mind, the model proposes LP principles in all three forms of integration in I-4.0. Therefore, I-4.0 and LP integration model. The vertical, horizontal, and end-to-end engineering integration model and its integration with five principles are elucidated in the model.

A study was conducted to develop a matrix showing the impact of I-4.0 technology on Lean principles. The authors surveyed over 24 I-4.0 project leaders; eight had both Lean and I-4.0 experiences. This relationship matrix shows a significant relationship between Lean and

I-4.0. For example, they rated I-4.0 technology, such as cloud computing and big data analytics, as the highest possibility to keep contributing to improving the Jidoka and standardization principle of LP. Similarly, they also mentioned that augmented reality might have significant power in enhancing the 5S, Kaizen, and Standardization. However, they depicted the relationship between Lean and I-4.0 based on their experience, which was not proven with any field-level experimentation. Hence, a practical interaction between Lean and I-4.0 is still lacking [29].

A survey study was conducted with over 100 Brazilian companies of different sizes and sectors implementing Lean at varying levels. An analytical framework was used to analyze the collected data [15]. In their background study, the authors mentioned that Lean and I-4.0 still demand a deeper investigation to explore whether their association is complementary. Therefore, the authors conducted this survey study to evaluate the relationship between Lean and I-4.0, where both are used, and their effect on the operational performance of the respected company. Theoretically, this study shows a significant association between Lean and I-4.0 if the company has become more experienced in Lean implementation (greater than 2 years). However, they did not show the major reasons behind this outcome. This study found that the size of a company does not affect the relationship between Lean and I-4.0. Overall, the study concludes that there is a positive association between Lean and I-4.0. However, it's worth noting that the authors did not conduct a one-to-one relationship analysis. As a result, for future applications, the practitioners might be confused about which I-4.0 technology will positively and significantly associate with Lean principles/tools. Besides, they did not make the interaction between Lean tools and I-4.0 technology instead of qualitative analysis based on the experience of practitioners in their analysis [15].

A study was conducted by Mofolasayo et al. to explore the way how to integrate the LM system to support the I-4.0 in SMEs for their productivity improvement [32]. The authors conducted a case study in a small electronics manufacturing company to attain their goal. The authors mentioned that for SMEs to adapt the I-4.0 holistically is not possible from the business perspective. Therefore, they suggested that focusing on data management and functional digitization is important before taking the stepwise initiative for the cyber-physical system. However, the root causes behind their statement were unclear in their manuscript, even though they only mentioned that the organizational and culturally flexible mindset is required to integrate Lean and I-4.0. Their case study showed that cloud computing benefits VSM and waste reduction but did not experimentally show their correlation [32].

A study was conducted towards sustainable framework development to integrate I-4.0 into the LP and logistic system to reduce NVA activities. In designing the digital transformation, it was emphasized that the cost, quality, social, and environmental aspects for sustainable incorporation of I-4.0 technology and Lean tools/principles should be considered. In addition, these aspects were emphasized in integration with the strategic digitalization plan. However, the proposed sustainable elements were not decomposed to understand better how these are linked in the integrated framework. Moreover, one case study reduces the validity of the proposed framework [160].

Mayr et al. found a need for a comprehensive conjunction of Lean and I-4.0, which motivated them to conduct this work to explore- whether there is a complementary relationship between these two paradigms [14]. Based on the literature, the authors identified a complementary relationship between Lean and I-4.0. Besides, they conducted a case study to evaluate how cloud computing technology and digital twins help improve the TPM and VSM accordingly. While authors showed a positive relationship between Lean I-4.0, their works lack empirical data to measure the level degree of their association [14].

Rossini et al. conducted a survey study of 108 European manufacturing companies to identify the nature of the relationship between Lean and I-4.0 [119]. They found that a higher level of Lean practice positively correlates with a higher level of I-4.0 implementation opportunity. Conversely, their findings revealed that if the companies are not extensively designed with Lean principles, they are unwilling to adopt any I-4.0 technology. It means a holistic Lean approach is favorable for the adoption of I-4.0 technology. However, to validate their findings, the sample size should be bigger. Additionally, while the authors mentioned the higher level of Lean adoption offers a good environment, what it means by higher level was not defined [119].

A study explored the combined implication of Lean and I-4.0 in operational performance improvement [27]. This is the extended form of article [119]. To evaluate the combined impact on operational performance, the authors surveyed 108 European manufacturing companies. The strength of this article is its convergent analysis of five driving factors discovered in previous studies, such as company size, business operating model, type of ownership, and technological intensity. The authors concluded that LP is a system, and its effective and efficient application of I-4.0 adopting I-4.0 is significantly related to LP implementation, while LP is independent of the I-4.0 adoption. In other words, the authors demonstrated that LP is stronger than I-4.0 regarding operational performance improvement. However, the combined impact is better than implementing LP itself in operation. The authors mentioned that the study's sample size is small, which may lower its validity for further use [27].

A survey study examined the pairwise relationship between Lean and I-4.0 [25]. The authors surveyed 147 manufacturers adopting Lean principles and the I-4.0 technology to evaluate this relationship. Based on their finding's authors proposed a relationship framework between Lean and I-4.0. The most important point in this study is that authors used a large set of Lean tools (31) derived from Shah and Ward [49], and 8 I-4.0 technologies from Tortorella et al. [15] were considered in their proposed Lean automation framework, which enhances its scope of acceptance. However, this pairwise framework of Lean and I-4.0 was proposed based on the survey, which means it was not derived from pairwise empirical interaction. As a result, further research is required for validation through the practical interaction between Lean tools/principles and I-4.0 technology [25].

A study was conducted to improve the efficiency of LM through integrating digital technology [151]. To do this, IT-based technologies were used to digitalize the LM. In this context, the authors used the RFID tags to make the dynamic value flow in the value stream mapping of the Lean production system. A dynamic VSM architecture was proposed and verified. However, to validate the proposed study, more case studies are needed. Moreover, some challenges, such as the overlapping reading of RFID, should be solved by revising & improving the architecture of dynamic VSM [151].

Schulze and Dallasega conducted a review study to delineate the nature of synergy of Lean and I-4.0 [152]. Based on the data from the previous studies, a Lean and I-4.0 framework architecture was proposed. This framework shows a positive association between Lean tools and I-4.0 technologies. However, the proposed framework was not validated by using any empirical data. Additionally, the association between Lean and I-4.0, which contributes to reducing the loss, was not discovered in terms of any measuring scale. Another critical lack in this study focused only on quality parameters by reducing loss, not on others like performance [152].

Marinelli et al. conducted a study to design a Lean automation system by integrating the I-4.0 technology into the LP system [155]. The study uncovers a lack of framework in designing Lean automation. The case study demonstrated that the Kanban Lean production system could be automated through the CPS and RRID technologies. However, the authors stated that each working station of the respective process line should be standardized before automation. For validation, multiple case studies are required [155].

This study explored the one-to-one relationship between Lean and I-4.0 technology [4]. Eight case studies were conducted for the empirical evidence behind the one-to-one relationship between Lean tools and I-4.0 technologies. While the specific relationship was delineated, the empirical quantitative data, representing the strength of their correlation or how much these relationships contribute to operational performances, was missing. The sample case studies were considered from a single country, limiting their validity. In addition, the action research case studies are demanded to represent clear guidelines for practitioners instead of retrospective longitudinal for broad acceptance [4].

Arey et al. conducted a study to integrate the I-4.0 technology in operating companies' VSM [51]. The authors demonstrated the use of CPS in the VSM for digitalizing material and information flow. Consequently, a case study showed that the lead time was reduced from 6.5 days to 1 day. Nonetheless, the validity of this study is limited to a single case study. Additionally, the case study was limited to a single field. Thus, multiple case studies are required in diverse areas to validate digitalized VSM [51].

Dossou et al. conducted a study towards sustainable framework development to integrate I-4.0 into the LM and logistic system to reduce NVD activities [160]. In designing the digital transformation, it was emphasized that the cost, quality, social, and environmental aspects should be considered for sustainable incorporation of I-4.0 technology and Lean tools/principles. In addition, these aspects were emphasized in integration with the strategic digitalization plan. However, the proposed sustainable elements were not decomposed to understand better how these are linked in the integrated framework. Moreover, a single case study reduces the validity of the proposed framework [160].

A study proposed an integrated framework to integrate the VSM in the hybrid simulation modeling [34]. A holistic conceptual framework was designed by considering the functional principles of VSM and hybrid simulation to reduce manufacturing waste. Later, the proposed framework was employed in the case of manufacturing companies for validation. However, a single case study limits its validation. The study was a case study conducted in an SME; thus, for its validation, multiple manufacturing cultures may demand employing the proposed framework [34].

Rajab et al. conducted a study to integrate the I-4.0 into the LP system to reduce waste [161]. A review study was conducted, and came to the decision was that big data analytics, cloud computing, AR, & simulation have significant contributions in reducing the seven Lean waste. However, no empirical evidence or quantitative analysis was presented against their results from the literature review. The specific Lean tools associated with Lean waste management were not delineated with the synergy of I-4.0 technology. Hence, a future empirical study was required to develop a holistic framework to obtain the research objectives [161].

Mrugalska & Wyrwicka conducted a study investigating the literature to explore the relationship between Lean and I-4.0. They reviewed previous studies and determined that I-4.0 technologies like CPS and RFID can be supporting tools for Andon and Kanban to enhance their performance. However, the study does not demonstrate to what extent these I-4.0 technologies can enhance the performance of Lean systems that employ Andon or Kanban [132].

Vlachos et al. conducted a study to explore how the socio and technical factors can be integrated into the integration of Lean and I-4.0 [30]. To achieve this, the authors conducted a review study to investigate the significance of socio and technical factors in designing Lean automation. The authors revealed that integrating Lean and I-4.0 is a complex system that requires considering issues such as design and ergonomics from a socio-technical perspective. However, the empirical evidence for this study was based on a single case study, so further validation through multiple case studies is required [30].

A study examined the critical drivers and impediments to integrating I-4.0 into TPM. To achieve this, the authors conducted four case studies. The study found that management culture, structure, vision, motivation, and leadership patterns were the driving factors in integrating Lean and TPM. Conversely, various production systems, employee skill levels, organizational culture, and maintenance competencies were identified as impedance factors. However, due to the limited number of case studies, the study's generalizability may be limited, and the operational mode of the case studies was not specified [25].

Chiarini & Kumar conducted an interview study to investigate the impact of I-4.0 on the operational improvement of Lean Six Sigma projects [144]. Over the study, ten experienced managers from ten Italian manufacturing companies were interviewed. Additionally regarding literature was investigated. The study concluded that, before introducing I-4.0 into any LSS project, it is essential to first apply LSS to make the operation efficient. The study also analyzed the use of I-4.0 technology in different phases of LSS and proposed a theoretical framework for integrating I-4.0 and LSS. However, the lack of empirical evidence to validate the proposed framework and the small sample size of interviews limit the validity and generalizability of the study's findings [144].

Mofolasayo et al. conducted a study to investigate the integration of LM systems to support I-4.0 in SMEs and improve their productivity [32]. They conducted a case study in a small electronics manufacturing company to achieve their goal. The authors suggested that holistically adapting I-4.0 is not feasible for SMEs from a business perspective, and instead, they proposed focusing on data management and functional digitization before taking any steps toward a cyber-physical system. However, the reasons behind this recommendation were unclear in their manuscript, although they stated that an organizational and culturally flexible mindset is required for integrating Lean and I-4.0. The authors' case study demonstrated that cloud computing could be beneficial for VSM and waste reduction, but they did not provide experimental evidence to support their correlation [32].

To summarize, the studies reviewed in this analysis aimed to explore integrating Lean and I-4.0 technologies, each with its strengths and limitations. Some studies lacked empirical evidence or were limited to a single case study, while others had a small sample size or did not mention the operational mode of the case studies. Despite these limitations, these studies provide valuable insights for future research on integrating Lean and I-4.0 technologies.

3.5.4 Driving factors on the integration of Lean and Industry 4.0

It is crucial to consider several important factors when integrating or adopting new and advanced technologies to achieve competitiveness and sustainability [178, 116, 112]. Organizations need to consider various factors before making technology investments. These factors include cost, quality, and socio-economic considerations. By taking into account these factors, organizations can ensure that their technology investments are not only efficient and effective but also have a positive impact on the broader economic and social aspects of society [178, 116, 112, 72]. Also, organizational culture and a flexible mindset need to be considered to sustain in the competitive manufacturing world [14, 32, 19, 69]. Accordingly, Lean can be regarded as best suited for integrating and sustaining in the manufacturing world [144]. LP has been considered a sustainable production system for the last four decades [120]. In LP, the feedback of the directly involved people on the production floor is essential for identifying areas of improvement and implementing solutions. By involving front-line workers in the improvement process, LP recognizes their expertise and empowers them to take ownership of their work processes [144]. By involving employees in the improvement process, LP acknowledges the role of human creativity and expertise in identifying opportunities for improvement and implementing solutions. This approach emphasizes the importance of creating a culture of continuous improvement that values the contributions of all employees [44].

Therefore, in Lean Thinking, socio-economic factors are significantly considered. Alternatively, the concept of I-4.0 primarily considers the technological factors, slightly ignoring the socio-economic factors [147, 30]. In this context, if both Lean and I-4.0 are combined, the synergistic approach would be sustainable for a considerable period. However, towards the successful unification of Lean and I-4.0, the potential driving factors should be considered and prioritized, which creates an urge to review the driving factors for the sustainable integration of these two paradigms. This inquiry led to the third research question to examine the articles, as shown in Table 3. The result shows that only the seven studies [25, 17, 179, 132, 30, 160, 32] focused on driving factors of sustainability. More specifically, among these eight, only in [180] and [181] the authors considered the three basic dimensions of sustainability, such as societal, economic, and environmental, while others evaluated only the cost drivers. It implies that the sustainability aspect was not significantly considered in the research design of included studies.

Although Lean and I-4.0 focus on similar goals, such as improving productivity and production quality, these two paradigms have distinct similarities in their philosophy and functionalities [31]. In a study, the authors mentioned that Lean primarily focuses on the human-driven production system while I-4.0 concentrates on technology. In academia and industry, there is a debate on whether Lean is an inhibitor or enabler to integrate the I-4.0. Additionally, the researchers and practitioners want to know if a contradictory relationship exists in which the environment supports this contradiction. Similarly, if there is a complementary relationship between Lean and I-4.0, in which environment does it support the complementary effects of integration? It is important to delineate.

Lean focuses on people thinking in its continuous improvement philosophy, similar to the principle of I-4.0 with the distributed autonomy of production management. In this context, Ciano et al. [4] suggested that LM could be seen as a forerunner to applying I-4.0. This is because LM and I-4.0 share similar goals, such as improving efficiency and reducing waste in manufacturing processes [4]. To adopt and effectively use any technology, it is necessary to provide a suitable setting. It is believed that the environment for LP is favorable for adopting and implementing I-4.0 technology [95]. Likewise, several studies have regarded the LP setting as a favorable factor in successfully implementing I-4.0 technology [139, 130, 25]. According to a study, the degree of LP adoption is strongly linked to the successful implementation of I-4.0 technology [15].

Satoglu et al. argued that implementing I-4.0 technologies solely cannot address the issues rooted in mismanagement or disorganization [176]. These technologies should be applied to Lean activities performed successfully before automatization. They also emphasize the importance of an adequate information flow before and after implementing these technologies [24]. A study mentioned that the big data and actuator/sensor could help improve the efficiency of mistake-proofing for quality improvement [24]. Mayer et al. confirmed the importance of LP, suggesting its adoption as a fundamental strategy in a roadmap for I-4.0 implementation [14]. Erol et al. pointed out that LP as an essential competence should also be transferred to the technical level [182]. Mayr et al. added that LP enables I-4.0 even because of the competencies that an LP decisionmaker has in considering customer value and avoiding waste [14]. They also highlighted the potential of LP reduction of product and process complexity to enable the efficient and economical use of I-4.0 technologies. The study was also supported by Rossini et al. [27].

According to a study conducted by Westgard in 2016, technological advancements, typically associated with automation or the implementation of quality systems, have a positive effect on analytical quality [183]. However, the impact is modest; sometimes, it may even be negative for certain analytes. These findings are similar to what has been observed in the automotive industry, where automation has improved quality, but not to the extent expected, as noted in Hinckley's 2007 study [74]. Further investigation is necessary to confirm the correlation between I-4.0 and Lean practice, as proposed by Ciano et al. [4].

Therefore, the literature considers LP a prerequisite to the I-4.0 implementation [4]. Nevertheless, Buer et al. identified a lack of investigation into the facilitating effect of LP on I-4.0 [31]. Indeed, even if scholars agree on the general enabling effect of I-4.0 on LP, the knowledge of how it happens is still immature [31, 27, 95]. The line represents the least-squares linear fit to the data. Although automation improves quality, the line is surprisingly horizontal, and the correlation is exceptionally poor (r2 = 0.014). The figure shows that automation can contribute to quality but does not assure good quality. Many other vital factors are essential for success [74].

3.5.5 Challenges in integrating industry 4.0 into lean production systems

Integrating I-4.0 into the LP systems represents a transformative journey with substantial potential for manufacturing organizations. Although this integration is not without its challenges, a small subset of included studies (8 out of 55) considered this issue during their integration process. These challenges encompass a wide spectrum, ranging from ensuring seamless data exchange compatibility [184, 71, 150] and safeguarding against cyber threats [159] to the continuous training of employees in digital skills [32, 150] and navigating complex regulatory landscapes [148]. Integrating I-4.0 into the LP systems should be aligned with sustainable practices and eco-friendly initiatives, which is another big challenge [159, 32]. Collaborative efforts with stakeholders, both internal and external [159, 71] are paramount to ensure a smooth and effective integration process as legal uncertainties continue to evolve [32, 150], staying informed about legal frameworks and seeking legal guidance is essential to maintain compliance and minimize risks.

Hence, to effectively integrate I-4.0 in LP, organizations need to overcome several challenges. These challenges include ensuring seamless data exchange compatibility and cybersecurity, providing continuous employee training in digital skills, navigating complex regulatory landscapes, and aligning with sustainable practices. Collaboration with both internal and external stakeholders is of utmost importance. Legal uncertainties and the need for proactive risk management further complicate matters. It is crucial to address these challenges strategically to ensure successful integration. This emphasizes the necessity for comprehensive risk management plans, which are currently lacking in the literature. Overall, the multifaceted nature of these challenges underscores the intricate landscape organizations must navigate to harness the transformative potential of I-4.0 in LP.

3.6 Discussion

This review study sheds light on the interdependent relationship between Lean and I-4.0, their integration model, and the crucial factors that influence the longevity of the proposed model.

The findings suggest that most current research has primarily focused on the harmonious features of Lean and I-4.0 rather than on the integration model and its sustainability aspects. However, there is still a scarcity of research investigating the collaborative features, integration model, and prospective sustainability of integrating I-4.0 technology into the LP system, as elaborated in the subsequent discussions.

3.6.1 Discussion on synergistic characteristics of Lean & I-4.0

In several studies, the authors conceptually envisioned the complementary association of Lean and I-4.0 [4, 27, 120, 25], regardless of considering the strength level of that relationship in their analysis. Several authors examined the depth of the relationship between Lean and I-4.0 in this context. For example, qualitatively, Langlotz et al. [156], and Leyh et al. [122] attempted to categorize the depth of the relationship between Lean and I-4.0 at different levels, such as low, medium, and high. However, the authors did not consider the measuring scale to quantify the relationship in their analysis. It is also worth noting that the key performance indicator (KPI) was lacking in the current literature in evaluating the impact of the synergistic association of Lean and I-4.0 on operational performance, leading us to formulate the following proposition:

Proposition 1*: A specific key performance indicator (KPI) is necessary to evaluate the impact of the relationship between Lean tools and I-4.0 technologies on the respective operational performance.*

3.6.2 Discussion on the integration framework of 'Lean & Industry 4.0'

Regardless of the companies' size and culture, an argument can be derived from this study referring to a positive inclination of manufacturers to integrate I-4.0 into the LP systems. This claim also endorses the propositions postulated by others [144, 25]. While the relationship between Lean and I-4.0 was discussed in many references, their integration framework is limited in breadth and depth. For example, the individual characteristics of two paradigms, Lean and I-4.0, were not accounted in the proposed integration model [76, 147, 157, 19]. Additionally, the interfaces at different levels of integration were not considered adequately in most of the studies. Moreover, the necessary trade-off analyses were not conducted to verify whether the proposed frameworks work according to the expected goals, leading to the formulation of the following proposition:

***Proposition 2**: Designing a comprehensive framework for incorporating I-4.0 into the LP system by identifying its different stages and interfaces is still an emerging need for the effective and efficient digital transformation of LP systems.*

In the literature, the authors agreed that Lean and I-4.0 could mutually assist each other in improving operational performance [76, 17, 161]. Additionally, the contradiction between Lean and I-4.0 was rejected by several authors [22, 19]. Instead, they argued that adopting I-4.0 could remove the potential barriers to implementing Lean. In turn, it was stated that practitioners should not be treated the same when they try to implement Lean and I-4.0 simultaneously, as both approaches have been developed based on different principles [19]. In this context, it is noted that integrating two different paradigms, the impact of the specific combination of Lean tools and I-4.0 technology is lacking from the literature, leading to the following proposition:

***Proposition 3**: To examine the impact of integrating two paradigms, Lean and I-4.0, one-to-one interaction between specific Lean tools and the I-4.0 technology is required.*

The sustainability of I-4.0 integration into the LP system Lean is a human-centric approach where human creativity is highly regarded for continuous improvement. Thus, it significantly values the different components of sustainability, such as socio-economic, technological, and environmental aspects. On the other hand, I-4.0 is a technology-driven approach widely used in agile manufacturing. However, when these two approaches are proposed in an integrated model, the question could arise as to whether the sociocultural aspect of Lean is sustained or not. This review result reveals minimal research on the sociocultural sustainability aspect of the integration approach of Lean and I-4.0. Specifically, no comprehensive study was recorded to evaluate the sociocultural factors of Lean and I-4.0 integration. Instead, some authors emphasized the cost-effectiveness of synergistic implementation. For example, a lack of sufficient infrastructure and logistics support may hamper the digital transformation of the LP system

[159, 129, 19]. In more detail, it may require retrofitting machines, tools, equipment, workforce, and others, thus increasing the investment of companies. Furthermore, these requirements may vary from country to country and manufacturer to manufacturer, as mentioned by Tortorella et al. [19], leading to formulate our final proposition:

Proposition 4*: Current literature reveals a significant gap in successfully considering the operational settings for integrating I-4.0 into LP systems. Companies' internal, such as culture, and external environment, such as the governmental rules & regulations, should be characterized while formulating the integration framework.*

3.6.3 Discussion on driving factors of integrating industry 4.0 into lean production systems

The available literature indicates that integrating I-4.0 and LP has potential but is a complex process. Both Lean and I-4.0 aim to improve efficiency and reduce waste, which makes them compatible for integration. LP is widely recognized as a favorable environment for adopting I-4.0 technology. However, certain challenges need to be addressed, such as the need for successful Lean activities before automation and the importance of effective information flow.

Since Lean is a prerequisite for I-4.0 implementation, a research proposition aims to understand how Lean practices facilitate the incorporation of Industry 4.0 technologies. Although scholars agree that I-4.0 enables LP, a gap exists in understanding how Lean practices enhance this integration. To fill this gap, it is necessary to conduct a comprehensive investigation into how Lean augments and eases the incorporation of I-4.0.

This research is essential to develop targeted strategies and frameworks that can bridge the gap in understanding and capitalize on the synergies between Lean and I-4.0. Ultimately, this research aims to contribute to creating informed and effective approaches that can lead to successful and sustainable transformations within manufacturing environments.

Based on the above discussion, it is perceived that the literature lacks a discussion on the impact of key role-playing factors in integrating I-4.0 technologies into the LP systems. This leads to the following proposition:

Proposition 5: *To ensure the successful integration of I-4.0 into the LP system, it is crucial to identify key success factors and create a framework for conducting trade-off analyses among them to select the most optimized combinations.*

3.6.4 Discussion on the challenges of integrating industry 4.0 into lean production systems

The integration of I-4.0 into LP systems has enormous potential for manufacturing organizations. However, several challenges need to be addressed for successful integration. Unfortunately, only a few studies have addressed these challenges while proposing integration processes. These challenges range from technical complexities like ensuring seamless data exchange compatibility and bolstering defenses against cyber threats to human-centric concerns like ongoing employee training in digital skills and navigating intricate regulatory landscapes.

Successful integration also requires alignment with sustainable practices and eco-friendly initiatives, which poses another challenge. Collaboration with internal and external stakeholders is crucial to ensure a seamless and effective integration process. As legal uncertainties evolve, staying well-informed about legal frameworks and seeking legal guidance becomes indispensable for maintaining compliance and mitigating risks.

To navigate this complex landscape, organizations must proactively and strategically address these challenges to pave the way for successful I-4.0 integration into LP systems. It is crucial to recognize that inherent risks accompany these challenges. Overcoming these hurdles requires formulating and implementing a comprehensive risk management plan, which is currently lacking in the literature.

In essence, while the integration of I-4.0 into LP systems holds tremendous promise, a nuanced understanding of challenges and the implementation of meticulous risk management are imperative for a successful integration. This refined discussion underscores the strategic importance of addressing challenges to unlock the full potential of Industry 4.0 within the realm of Lean Production systems. By addressing these challenges the following proposition is proposed.

Proposition 6: *It is imperative to define and incorporate a risk management plan for each challenge for the successful digital transformation of the LP systems through the integration of I-4.0 technologies.*

3.7 Conceptual integration framework

A conceptual framework for technology integration into the production system can be defined as a model that outlines the key concepts, relationships, and assumptions that underpin the use of technology in the production process [185]. It provides a theoretical foundation for understanding how technology can be effectively integrated into productivity improvement and helps to guide the designing and implementation of technology-enhanced production practices [180]. In this study, a six-step integration model is proposed to integrate the I-4.0 technology into the LP system. These six steps are defining, measuring, interacting, controlling, analyzing, and validating, as shown in. A brief description of these steps is depicted below.

3.7.1 Rationale beyond the integration framework

Based on the SLR results, it was discovered that only 13 out of 55 included studies (23.6%) discussed the impact of integrating I-4.0 into the LP system to improve productivity. This suggests that there is a lack of research on navigating the digital transformation of LP systems. During our investigation, we discovered various aspects of the proposed conceptual framework. However, we could not find any studies that confirm all these attributes. Therefore, there is a need for a framework that aligns with its holistic views. During our investigation into these frameworks, we delved into their theoretical foundations but found them lacking. Additionally, the proposed framework lacked content validity. These gaps must be addressed in a comprehensive manner, which motivated us to conduct this study.

3.7.2 Theoretical foundation of proposed framework

Our framework is based on General System Theory (GST), initially developed by biologist Ludwig von Bertalanffy in the mid-20th century. GST offers a unified and abstract perspective

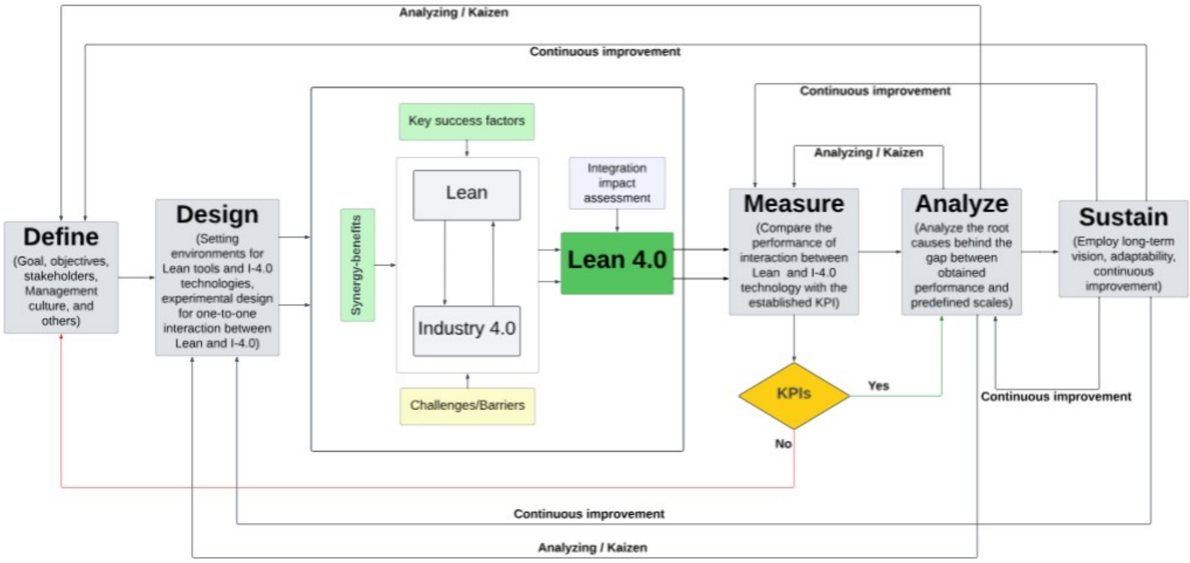


Figure 3.9: A conceptual framework for the integration of Lean tools and I-4.0 technology

that helps integrate different paradigms harmoniously. It allows us to identify common principles and patterns that go beyond specific details, emphasizing the idea that 'the whole is greater than the sum of its parts,' as Friedrich Hegel advocated [186]. Our approach involves integrating nine principles derived from the GST. These principles are (GST-1) understanding system dynamics, (GST-2) embracing holism, (GST-3) fostering interdisciplinary approaches, (GST-4) delineating system boundaries, (GST-5) recognizing hierarchical structures, (GST-6) acknowledging emergent properties, (GST-7) incorporating feedback mechanisms, (GST-8) considering equifinality, and (GST-9) maintaining a long-term vision. These principles are seamlessly integrated into the step-by-step creation of our conceptual framework. In addition, we considered the Axiomatic design perspective in designing this integration framework. Axiomatic Design, developed by [187], offers key principles for effective design. Its core principles focus on the independence of design parameters and minimization of information content to simplify and optimize the integration framework.

3.7.3 Phase-1: Defining the dynamics of 'Lean 4.0' framework (GST principles 1, 2 & 3)

In the framework's initial development, we placed a strong emphasis on grasping the overall dynamics of Lean 4.0, with a focus on input and output dynamics [188], aligning framework objectives with the organization's ultimate goals. These objectives were then refined into specific, time-bound targets to cater to diverse customer demands. Within the context of Lean 4.0, our approach centered on capturing the dynamics of both paradigms, embracing a holistic perspective, and accommodating multidisciplinary viewpoints. During the requirement analysis, we adopted a holistic outlook, establishing the boundaries of Lean 4.0 while preserving the individualistic nature of Lean and I-4.0 through Axiomatic Design thinking.

3.7.4 Phase-2: Designing the boundary and hierarchical structure of 'Lean 4.0' (GST principles 4 & 5)

In the design phase, we delved into the hierarchical dynamics of the system and defined the boundaries of Lean 4.0 from the GST principles. We focused on utilizing the hierarchical dynamics in specifying the synergy of Lean principles with I-4.0 technologies. To validate this synergy and ensure it aligns with predefined objectives, we propose designing and conducting a pilot study. Our recommendation for ensuring a direct and meaningful interaction between Lean tools and I-4.0 technologies is to create an experimental setup on a prototyping scale. By promoting this seamless one-to-one interaction between Lean and I-4.0, organizations can harness the full potential of both methodologies, leading to increased productivity, flexibility, and innovation [189]. This collaborative approach serves as a pathway to successful integration, empowering organizations to thrive in the ever-evolving landscape of modern manufacturing and beyond. In the context of Lean and I-4.0 integration, one-to-one interaction denotes the harmonious and synergetic collaboration and communication between Lean tools and various I-4.0 components [190], resulting in the maximization of their combined benefits and the attainment of operational excellence.

3.7.5 Phase-3: Measuring the impact of 'Lean 4.0' (GST principle 6)

In our measurement approach, we focused on the interaction between a specific Lean tool/principle within a specific I-4.0 technology. Here, the Lean tool/principle is the organizational internal input while I-4.0 technology is an external input. To measure the impact of this interaction we proposed to define a specific and appropriate KPI. While conventional Lean KPIs, such as cycle time, TP, and defect rates, gauge efficiency, and waste reduction, I-4.0 introduces novel KPIs encompassing areas like equipment uptime, predictive maintenance accuracy, real-time data analysis, and OEE, exemplifying data-driven insights and smart manufacturing capabilities. To elucidate the dynamic interplay of Lean and I-4.0, we leverage the concept of emergence from the GST. Emergence involves the emergence of properties, behaviors, or patterns in a complex system that cannot be straightforwardly deduced from its components. Instead, these emergent qualities arise from the interactions and relationships among these components. This phenomenon is similar to what occurs when Lean and I-4.0 converge [120, 75]. Furthermore, our approach emphasizes trade-off analysis, encompassing key success factors, challenges, barriers, and the synergistic benefits of both paradigms. Given the complexity of this scenario, effective measurement becomes integral to the success of Lean 4.0.

3.7.6 Phase-4: Analyzing the performance of 'Lean 4.0' (GST principle 7)

To assess whether Lean 4.0 is delivering its best outcomes, we focused on establishing a robust analysis process incorporating dynamic feedback loops inspired by the GST principle. This feedback mechanism, illustrated in Figure 3.9, is aligned with the KPI developed in the previous phase (Phase 3). It is a data-driven approach that can collect data from various sources, including production systems, sensors, and quality control processes. Through data analysis and visualization techniques, organizations gain insights into performance trends and areas that require further improvement. This iterative approach, driven by real-time feedback, enables organizations to optimize Lean 4.0 outcomes, enhance productivity, and achieve sustainable success. For example, [151, 191] showed how real-time data can be employed in real-time decisions towards improvement. We also focused on real-time data analysis ineffective decisions on time for obtaining the best outcomes from the Lean 4.0 framework.

3.7.7 Phase-5: Sustaining synergy of 'Lean 4.0' (GST principle 8 & 9)

Sustaining Lean 4.0 is a dynamic process where we draw inspiration from the principles of equifinality and long-term vision inherent in the GST principles. Equifinality, as per GST, suggests that there are multiple paths to achieving the same goal. In the context of Lean 4.0, organizations have the flexibility to adopt various strategies, processes, and technologies to achieve their desired outcomes. For instance, in some studies [192, 127], authors recommended the establishment and utilization of cross-functional collaboration as a means to effectively and efficiently solve problems and achieve the best outcomes. Additionally, we emphasize the importance of incorporating a long-term vision to sustain the outcomes derived from Lean 4.0. Utilizing a long-term vision in Lean 4.0 involves setting clear goals, strategic planning [30], continuous improvement [80], resource allocation [178], risk management [193], fostering communication [107], measuring performance [194], and celebrating milestones [184]. This approach ensures that Lean 4.0 initiatives remain aligned with the organization's overarching objectives, driving sustained success.

3.8 Summary & limitations

This study aimed to discover the previous research findings on the relationship between Lean tools/principles and I-4.0 technologies, the key strategy of their integration frameworks, and the drivers leading to the sustainable integration of I-4.0 technologies into the LP system. In this context, this study reviews the synergistic relationship between Lean and I-4.0, their integration framework, and the key factors affecting the sustainability of the integration framework. Subsequently, the capability level of the relationship delineated in the existing literature was analyzed comparatively. Additionally, the results uncovered that the included studies were either narrow in scope with the limited trade-off analysis or conceptually envisioned without validation. Thus, the identified limitations regarding the relationship between Lean and I-4.0 and their framework led the authors to formulate four propositions. The proposed propositions unveil a clear need for further study to mitigate the limitations of successfully integrating Lean and I-4.0. To conclude, it is important to discuss the major limitations of this conceptual study.

First, the study was limited to three databases, as mentioned in the Methodology section, which has narrowed down its scope. Second, only journal articles and conference proceedings were included in the full review. Consequently, essential book chapters, symposiums, educational talks, blog writings, and industrial reports were excluded, limiting its broad validation. Third, the sample size of the articles included on the topic is very small, which is another lack of this study. The identified gap and limitations create future research opportunities on this emerging topic. In this essence, in the future, the authors plan to revise the study by considering the uncovered research propositions, accounting for 4-5 sources of databases, including the scientific and industrial reports, along with the journal articles and conference proceedings.

Chapter 4

Interaction between Lean and Industry 4.0: A Case Study for Overall Equipment Effectiveness

4.1 Background study

LP has been applied in manufacturing because of its effectiveness on quality and performance [4]. Primarily, LP focuses on standardizing the works, reducing the non-value-adding activities, shifting the production systems from capacity to demand-oriented, and installing a distributed production improvement system with closed loops between workstations [6, 4, 7]. Lean principles originated in the 1950s in the Toyota Motor Corporation, which took a long process to establish an improved and efficient production system [8]. There is a rule of thumb for most technologies; after a particular time, either the technology needs to be replaced by a new one, or it needs improvement to maintain growth [195]. Several patterns are used to review the successive growth stages of technology. The Sigmoid-curve is one of them, which refers to the technology reaching its saturation stage after a particular time [11]. At this stage, improving or incorporating a new technological dimension is essential to remain competitive. Additionally, in the last decade, I-4.0 has emerged in manufacturing, creating pressure on the feet of the manufacturer to speed up and be more competitive. I-4.0 refers to a cyber-physical system where the physical World is connected to the virtual World, and the total controlling system is distributed [87]. I-4.0 is considered a new paradigm for connecting man, machine, and process within the changing operative framework conditions and distributed management systems [12]. On the other hand, human beings' socio-economic and political views have changed significantly [196], making customer choices and demands more volatile. Consequently, some scholars consider meeting the customers' demands to incorporate I-4.0 in the LP.

The current literature reveals limited research on the impact of Lean methodology and I-4.0 technology when used together. To fill this gap, a study was conducted with two main objectives.

1. Conducting an interaction between a specific Lean tool and I-4.0 technology

2. Measuring the combined impact of Lean and I-4.0 on the production performance

4.2 Interaction between lean and industry 4.0

In recent times, in the manufacturing world, there has been an inquiry into the compatibility of Lean and I-4.0, exploring the feasibility of their seamless integration. Furthermore, the investigation delves into the potential complementary impact of I-4.0 on enhancing the performance of LP systems and aims to identify optimal pairings between Lean tools and I-4.0 technology. Before the case study, we conducted a comprehensive literature review to provide insights and answers to these relevant questions.

In the last decade, with the diffusion of I-4.0, manufacturers might think the necessity of LP can end. However, in several studies, authors reviewed that the broad range utility of I-4.0 does not refer to the end use of LP. Instead, they recognize a significant co-relationship between Lean & I-4.0 [31, 17, 42, 119, 124, 19]. In a study, the authors mentioned that LP could be integrated with modern ICT to meet the customers' rapid changeable demand [147]. For instance, they noted that ICT could be used in Kanban production, where the empty Kanban bin can be identified and replenished using ICT, even though they did not mention which ICT technology can be used. A study unveiled that Lean tools, like mistake-proofing, and the I-4.0 technology, like big data and actuators/sensors, could be applied together for quality improvement [24]. However, like this, the pairwise example of interaction between Lean and I-4.0 is minimal. In most cases, the complementary effects of Lean and I-4.0 are still thinking in conceptual frameworks. For instance, the authors suggested integrating I-4.0 technology in the LP system to overcome some limitations of Lean [4], while they did not specify them [131]. It is stated that LP can be considered a pre-requisite for the I-4.0 application [19], but it is not demonstrated how Lean and I-4.0 co-exist together. Several authors also acknowledge that the knowledge and comprehensive direction on how Lean and I-4.0 work together is still immature [4, 27, 95].

In several other studies, researchers emphasized the complementary impact of I-4.0 alongside LP. However, these discussions largely remained at the conceptual level without practical interactions between Lean and I-4.0 being explored [4, 116, 156, 122, 119]. This conceptual nature of investigations is further supported by a study indicating that only 14% of the research conducted at the field level has verified the relationship between Lean and I-4.0 [123, 4]. Consequently, a notable research gap exists, and it is imperative to undertake further studies to validate the relationship framework between Lean and I-4.0. Motivated by this research gap, we embarked on this field-level case study to investigate the practical interaction between Lean Practices and Industry 4.0.

4.3 Working methodology

This section outlines a step-by-step methodology for integrating I-4.0 into the LP system. The objectives are defined through a research hypothesis and strategy. To help the reader understand the experimental environment, we provide a brief description of the one-to-one interaction between the Lean tool and I-4.0 technology, including the operation mode, operation stations, Lean tools, and I-4.0 technologies used. Additionally, we present an experimental design in this section.

4.4 Development of the research hypothesis

Our investigation is based on three postulated null hypotheses to set the foundation for our objectives. To test each null hypothesis, corresponding alternative hypotheses are developed, offering alternative perspectives for consideration. The next step in our research involves collecting and analyzing comprehensive data to systematically support or refute the initially proposed null hypotheses. This process aims to provide evidence, guide our conclusions, and contribute to the field's knowledge.

4.4.1 First hypothesis

Null Hypothesis: *There is no significant impact of Lean tools on operational performance improvement*

Alternative Hypothesis: *There is a significant impact of Lean tools on operational efficiency improvement*

4.4.2 Second hypothesis

Null Hypothesis: *There is no significant impact of I-4.0 technology on operational performance improvement*

Alternative Hypothesis: *There is a significant impact of I-4.0 technology on operational performance improvement*

4.4.3 Third hypothesis

Null Hypothesis: *There is no significant impact of integration between mistake-proof device and vision technology on operational performance improvement*

Alternative Hypothesis: *There is a significant impact of Integration between mistake-proof devices and vision technology on operational performance improvement.*

4.5 Research questions

- ***Research Question 1****:* Does a mistake-proof device improve the OEE of the LP system significantly?
- ***Research Question 2****:* Does a vision/sensor technology improve the OEE of the LP system significantly?
- ***Research Question 3****:* Does the interaction between mistake-proof devices and vision/sensor technology improve the OEE of the LP system significantly?

4.6 Research strategy

This study aimed to explore the relationship between Lean tools (such as Mistake-proof) and I-4.0 technologies (like sensor technology). As we previously mentioned, the study established a null and an alternative hypothesis to accomplish this objective. An experimental setup was designed to test the null hypothesis, and the relevant tools and technologies were identified and installed on the production floor. The treatments or experimental conditions were defined and randomly selected before conducting a one-to-one interaction between Lean tools and I-4.0

technology. Data were collected using predefined sheets, and both descriptive and statistical analyses were carried out to investigate the proof of the null hypothesis. Finally, the decision was made based on the results of hypothesis testing.

4.7 Experimental environment

We conducted an experimental interaction between Lean and I-4.0 at the Lean Education Laboratory in Auburn University's Department of Industrial and Systems Engineering. The laboratory has developed an LP over the years that involves the assembly of cars using Lego parts. Two types of cars, SUVs, and Speedsters, are assembled over the assembly line, divided into 15 stations. The LP production line is divided into three cells, each with five working stations. Each cell has a cell leader responsible for communication between the cells and assisting workers in fixing problems that may arise during production. Additionally, each cell has a material handler to replenish the empty parts bins from the supermarket storage. At station 5, one person is responsible for changing the die whenever a different car model is assembled. A stopwatch is present at each station to calculate the cycle time, simulated to be 60 seconds for each station. In this study, to interact with Lean and I-4.0, we used station 10, where the camera is installed for the in-station quality check. We used the SUV for building at station 10. To eliminate the defects, we used the check-piece of the SUV as a mistake-proof device. Four treatments were designed to evaluate the impact of interaction between Lean tools and I-4.0 technology, as described in the following sections.

4.8 Experimental setups

The purpose of this section is to describe how the experiment was designed to make the interaction between I-4.0 and the Lean tools. Several major components, such as a Lean tool, I-4.0 technology, and operation modes, are described to obtain the purpose. The input and output variables were defined. Controllable and uncontrollable factors were considered during the experiments.

Figure 4.1: Lean education lab at Department of Industrial and System Engineering, Auburn University

Figure 4.2: Cell-1 of the Lean education lab. It is one of the three cells of the Lean Manufacturing Lab. Production stations from 1 to 5 are designed & established in this cell.

Figure 4.3: Cell-2 of the Lean education lab. The production stations from 6 to 10 are designed & assembled in this cell.

Figure 4.4: Cell-3 of the Lean education lab. The production stations from 11 to 15 are designed & assembled in this cell.

Figure 4.5: The production station 10 of the Lean education lab. The interaction between Lean (mistake-proof) and I-4.0 (vision technology) was performed at this station.

4.9 Defining the lean tool

Our study emphasized the importance of using mistake-proof devices as a key Lean tool. These devices effectively prevent human errors and align with Lean principles. The concept of mistake-proof devices was developed by Shigeo Shingo in 1986 and has since become a foundational concept in Lean methodology [28]. We have implemented a systematic protocol to define mistake-proof devices in our study. This step-by-step process ensures a comprehensive and methodical approach to incorporating Lean tools into our investigation. Below, we outline each step in this protocol, shedding light on the procedures undertaken to enhance error reduction and optimize operational efficiency within the context of our research.

- ***Step-1:*** *Develop a flowchart of the production process. Review & investigate the process and discover where and when human errors are likely to occur.*

- ***Step-2:*** *Whenever an error is discovered, it is important to find out the source of the error by reviewing the process line.*

- ***Step-3:*** *To think and develop ways to make it impossible for the error to occur. This can be done by considering elimination (eliminating the step that causes the errors),* *replacement (replacing the step with an error-proof one), and facilitation (making the correct action far easier than the error).*

- ***Step-4:*** *If it is impossible to prevent the error, consider ways to detect it and minimize its effects. It can be done by considering inspection methods and setting functions expanded on below.*

- ***Step-5:*** *Choose the best mistake-proofing method or device for each error. Test it, then implement it.*

4.10 Defect inspection

Defect inspection is a crucial process in quality control, which involves systematically examining and assessing products or processes to identify and categorize defects or imperfections. It is vital in ensuring the quality and reliability of manufactured goods or executed processes. Defect inspection is essential in defect elimination experiments as it is a diagnostic tool to pinpoint areas of weakness or inefficiency in production or operational processes. By systematically identifying and categorizing defects, organizations can gain valuable insights into the root causes of issues, enabling targeted interventions for process improvement. This proactive approach not only helps enhance the quality of the final product but also contributes to the optimization of production processes, minimizing waste and ultimately improving customer satisfaction and trust in the product or service.

In defect inspection, five distinct inspection methods can be used to quickly provide feedback [59, 28]. These methods are outlined below:

- ***Successive inspection:*** *Successive inspection is done at the next step of the process by the next worker.*

- ***Self-inspection:*** *Self-inspection means workers check their work immediately after doing it. Before the process step takes place, source inspection checks that conditions are correct. Often, it is automatic and keeps the process from proceeding until conditions* *are right. Setting functions are the methods by which a process parameter or product attribute is inspected for errors.*

- ***Contact inspection:*** *The contact or physical method checks a physical characteristic such as diameter or temperature, often using a sensor.*
- ***Motion-step inspection:*** *The motion-step or sequencing method checks the process sequence to make sure steps are done in order.*
- ***Fixed-value inspection:*** *The fixed-value or grouping and counting method counts repetitions or parts, or it weighs an item to ensure completeness.*

4.11 Defining the Industry 4.0 technology

In this study, we have considered smart sensor technology as a part of I-4.0 technology. The sensor technology is used to inspect the produced cars for defects. It is mounted at the end of Station 10, where the assembly of the car is completed. The operator then checks the car under the vision technology to identify any defects associated with the car. A data window view provides the operator with information about the defect and its location. To improve the performance and quality of the operation, a mistake-proof device is used as a Lean tool.

4.12 Design of the treatment

To measure the impact of the interaction between Lean tools and I-4.0 technology, four different treatments have been considered under the defined production environments. These treatments include control, check-piece, vision technology, and the combination of check-piece and vision technology. Each treatment is briefly described in the following sections.

4.12.1 Control

The term ‘Control’ refers to a particular operational situation where conventional paperwork instructions (PWI) are implemented rather than a Lean tool or I-4.0 technology. In this instance, PWI is being employed at station 10 in the Lean Education Lab facility, as shown in a diagram

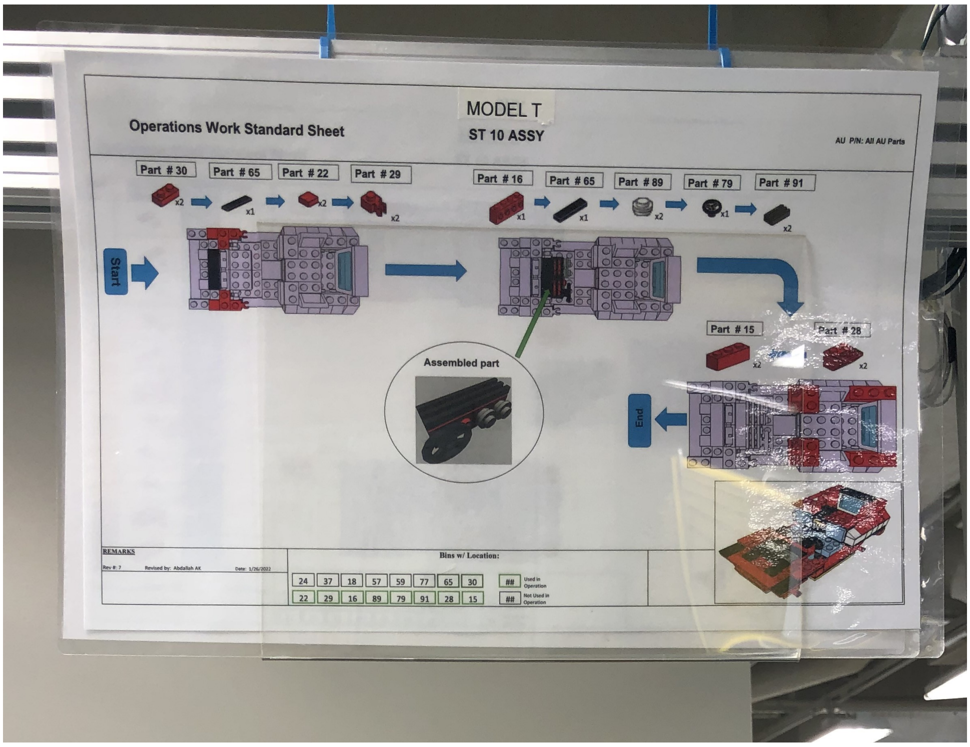


Figure 4.6: Paper-work instruction/control. These instructions are used in assembling the studied SUV model cars.

of the assembly layout (Figure 4.6). The PWI provides instructions for the assembly process, specifically detailing the sequence in which Lego parts should be picked from designated bins. The location of these bins is indicated at the bottom of the PWI, and the research associate is available to show the exact location of each bin.

4.12.2 Vision technology

It is the sensor technology/smart camera installed in station 10, as shown in Figure 4.7. It is installed using the PLC programming, and the parts' locations are programmed to check for defects. After assembling, the operator needs to place the car under the camera. It is important to make sure that the car is correctly put on the die under the smart camera, as shown in Figure 4.8. After that, the operator can see the report on the screen as NG (not good) or OK (good). If it is NG, the operator needs to track the defect location and fix it. Thus, the system helps to prevent defective production.

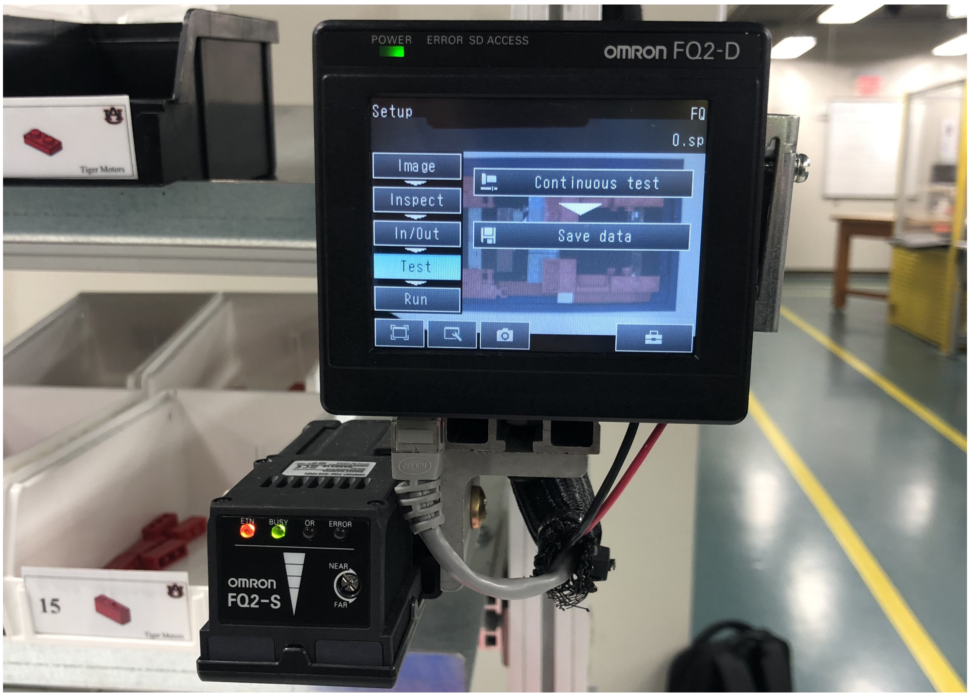


Figure 4.7: The vision technology/smart camera, which is used as the I-4.0 to inspect the defects on assembled studied SUV model cars.

In our research, we have utilized vision technology to prevent errors. Error-proofing is a systematic approach that helps to minimize or eliminate mistakes by implementing mechanisms, devices, or systems that ensure consistent task execution. This approach helps to improve quality, efficiency, and reliability in various industries. By using error-proof devices, organizations can avoid costly rework or corrections and optimize their operations. Error-proofing fosters a culture of accuracy and dependability, which ultimately leads to greater customer satisfaction.

4.12.3 Check-piece

In our experiment, we use a check-piece, a fully assembled car known as the SUV Model. It is located within the Lean Education Lab of the Department of Industrial & System Engineering at Auburn University, as shown in Figure 4.9. The SUV Model serves as a fundamental device to prevent mistakes. In the experiment, participants (subjects) are instructed to use a check-piece to help them place the correct components in their designated positions. This check-piece is a visual aid that helps prevent errors and reduces defects in the assembly process. It also streamlines the assembly operations, potentially reducing the assembly time. This integration

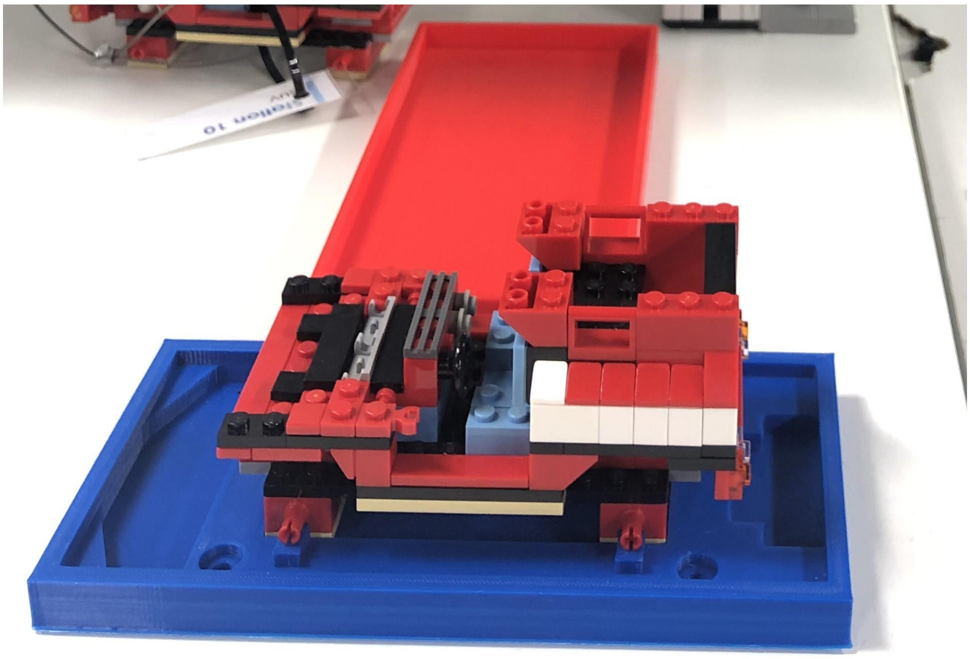


Figure 4.8: Vision technology/smart camera' Fixture. It is used to properly position the car under the smart camera for its digital inspection.

aligns with Lean principles, emphasizing the importance of mistake-proofing techniques to enhance efficiency and overall product quality.

4.12.4 Check-piece and vision technology

In this treatment, the subject or the operator uses both a Mistake-proof device (check piece of the SUV) along with the vision technology. Both the check piece and vision technology are used to identify defects in assembled cars. The prime objective of using these two tools is to evaluate the integration impact on quality by reducing the defects. Since quality is one of the most essential parameters of the OEE, this synergy might have a significant impact on the OEE improvement of the LP.

4.13 Defining the key performance indicators

The OEE is defined as the key performance indicator (KPI) of the study's impact. The OEE can be defined as the multiplicative function of Availability, Quality, and Performance [197, 21], as shown in equation 4.1. During the planned production time, any events that cause the operation

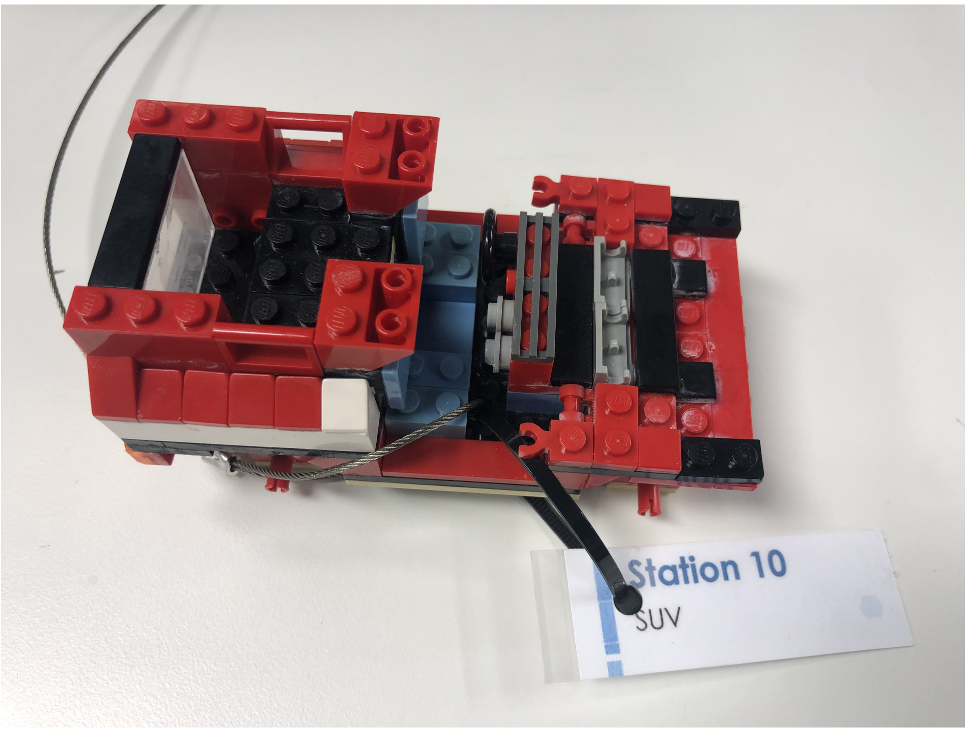


Figure 4.9: The check-piece, which is used as a mistake-proof device - a Lean tool.

to stop are included in the calculation of availability. This is determined by the ratio of actual run time to total planned production time, as shown in Equation 4.2. Quality, on the other hand, is concerned with manufacturing products that meet customer demands and the standards required. It also takes into account any necessary rework to ensure that these standards are met [198]. Simply put, quality can be defined as the ratio of the total number of good parts produced to the total number of parts produced, including both good and bad ones. This can be represented by Equation 4.3. The performance metrics are controlled by two important parameters: total count and planned count. The actual output count divided by the total planned count is the ratio used for these metrics, as shown in Equation 4.4. It is worth noting that our experimental interaction between lean and I-4.0 was conducted in a prototype lab without any machine breakdowns. Therefore, we assumed our availability to be 1 for each production run at station 10.

$$OEE = Availability * Performance * Quality \tag{4.1}$$

$$Availability = \frac{Actual\ run\ ime}{Total\ planned\ time} * 100\% \tag{4.2}$$

$$Quality = \frac{Total\ count\ of\ good\ parts}{Total\ count\ of\ produced\ parts\ including\ good\ \&\ bad\ parts} * 100\% \tag{4.3}$$

$$Performance = \frac{Actual\ output\ count}{Total\ planned\ count} * 100\% \tag{4.4}$$

4.14 Data collection

The synergy between Lean practices and I-4.0 represents a dynamic human-machine interaction, a pivotal aspect explored in this study. To capture and analyze this interaction in detail, we created four different treatments that were then randomly assigned to participants. Subjects were invited following the approved research protocol sanctioned by the Institutional Review Board of Auburn University (Protocol 22-538-EP-2301), and all procedures adhered strictly to this protocol. We carefully recorded and documented the performance data of each subject for every treatment. Under each treatment, each subject was allowed a designated 10-minute timeframe for assembling SUV cars using Lego parts, as previously outlined. The quality and performance data, corresponding to equations 4.3 and 4.4, were documented to estimate efficiency, measured by OEE. Throughout the experiments, we emphasized the critical importance of effective data collection in human-machine interaction studies, ensuring a comprehensive understanding of the nuances in the manufacturing processes under investigation.

4.15 Data analysis

We used our collected data for subsequent analysis, constituting a step in evaluating the postulated hypothesis. Performance and quality data are leveraged to calculate OEE, providing a comprehensive measure of efficiency. Analysis of variance (ANOVA) serves as a robust statistical tool to compare variance among the treatments, drawing on established methodologies

[199, 200]. For hypothesis testing, the paired t-test is employed to discern evidence against the null hypothesis, relying on well-established principles in statistical analysis [199, 200]. In addition to these analyses, the study delves into defect analysis through the application of control charts, offering valuable insights into different types of defects and their variations throughout the experimental treatments.

4.16 Results

As mentioned earlier, our study aims to investigate three specific hypotheses. To accurately test these hypotheses, we have collected experimental data and conducted a series of descriptive analyses. treatments were randomly assigned, which ensures that the data collection process is independent. Before testing the hypotheses, we performed two crucial tests - normality and equal variance - to determine the most appropriate statistical analysis methods, following the established guidelines in statistical literature [201]. This approach emphasizes our commitment to maintaining the integrity of our research methodology and laying a foundation for meaningful statistical analyses.

4.16.1 Normality of treatment data

A normality check is a statistical procedure used to determine whether a given dataset follows a normal distribution. A normal distribution is a theoretical probability distribution that is symmetric, bell-shaped, and characterized by its mean and standard deviation [202, 203]. Normality checks are important because many statistical tests, such as t-tests and ANOVA, assume that the data follows a normal distribution. If the data are not normally distributed, these tests may not be valid or may provide misleading results. There are several methods to check for normality, including graphical methods such as histograms, probability plots, and box plots, as well as statistical tests such as the Shapiro-Wilk test, the Anderson-Darling test, and the Kolmogorov-Smirnov test [204]. These methods can help researchers determine if their data is normally distributed and if they need to use alternative statistical methods that are appropriate

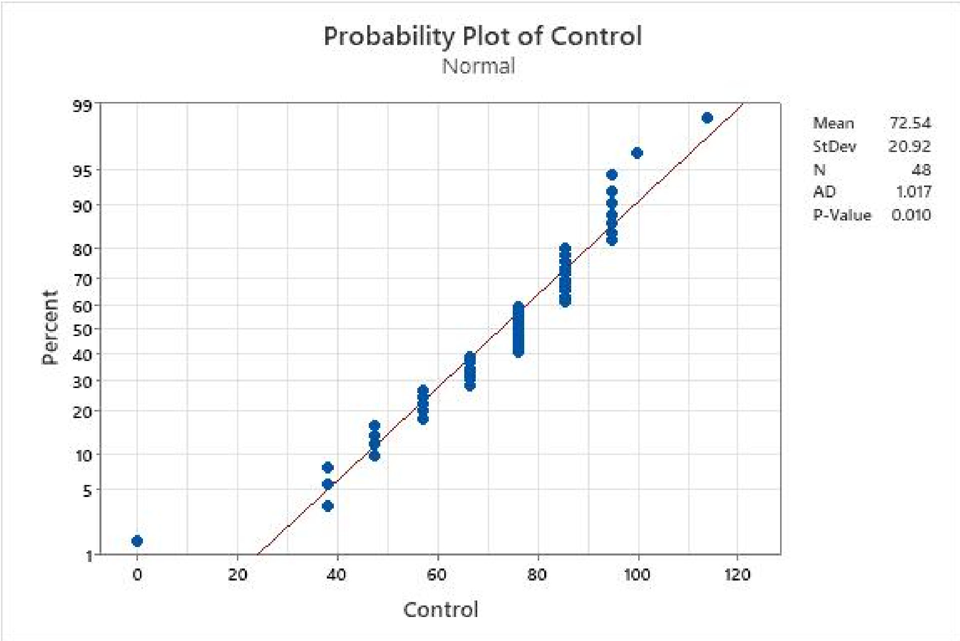


Figure 4.10: Normality check for treatment - 'Control'

for non-normal data. In this study, we used histograms and probability plots to check for normality. Based on these plots, it was determined that the data collected from the four treatments (Control, Lean, I-4.0, and 'Lean & I-4.0') are normally distributed.

The Figures 4.10 and 4.11, serve as representations of the normality check conducted for the treatment labeled 'Control.' Likewise, Figures 4.12 and 4.13 are indicative of the treatment labeled 'Lean.' Furthermore, Figures 4.14 and 4.15 pertain to the 'Industry 4.0' treatment, while Figures 4.16 and 4.17 are associated with the treatment 'Lean Industry 4.0.' These visual representations are integral to our analytical approach, providing insights into the distribution and characteristics of the data for each treatment. The normality checks are crucial in ensuring that the data conforms to the assumptions required for subsequent statistical analyses, reinforcing the reliability and validity of our findings.

4.16.2 Descriptive analysis of treatment's outcomes

We conducted a variance analysis on four different treatments to identify any significant variations and potential outliers in the data. To achieve this, we recorded the mean, standard deviation, and confidence interval of the OEE scores for each of the four treatments, as depicted in Table 4.1. We recorded 48 run scores (N) for each treatment and calculated the standard

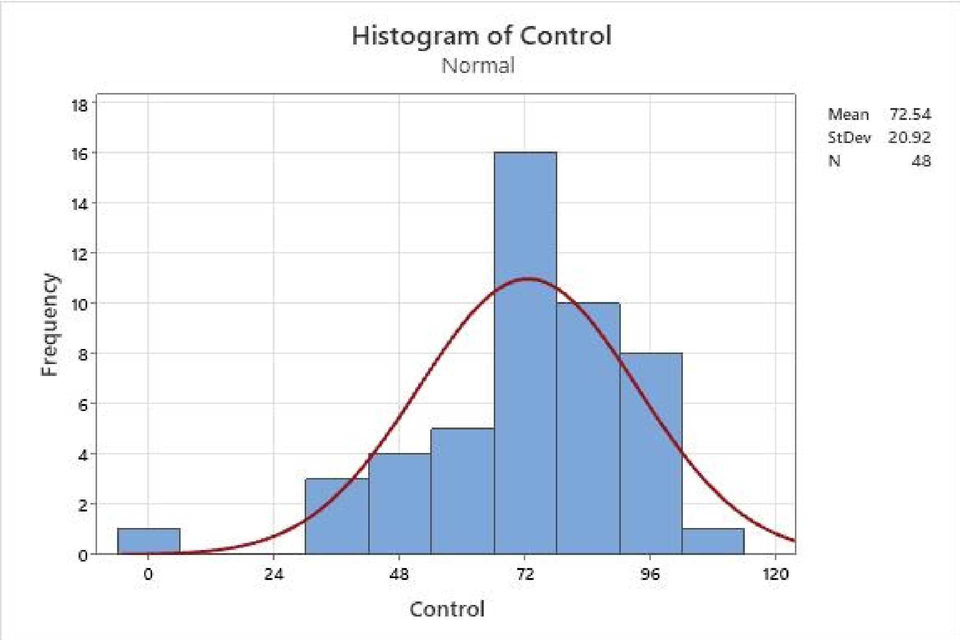


Figure 4.11: Distribution fit for treatment - 'Control'

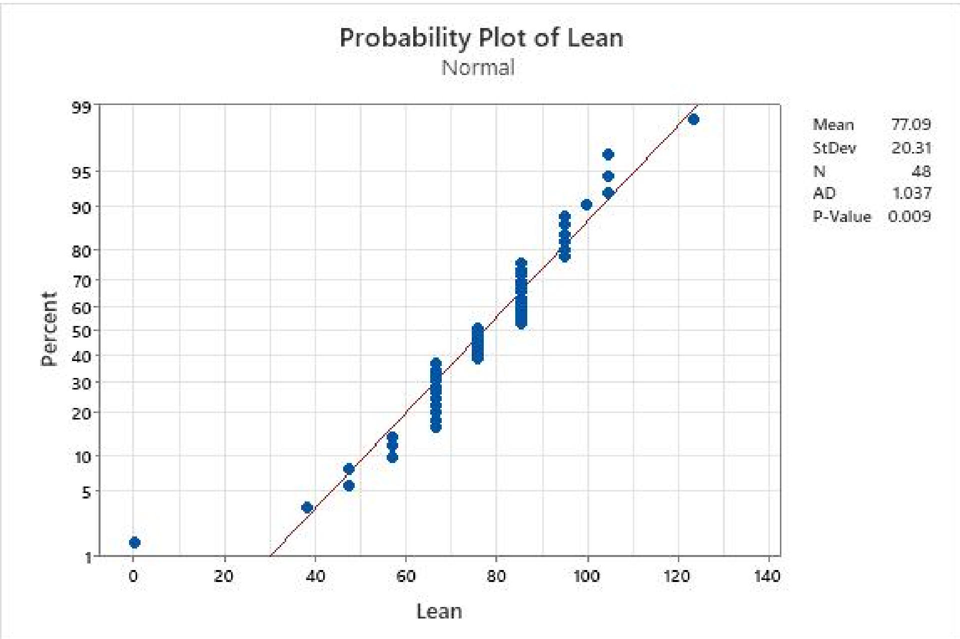


Figure 4.12: Normality check for treatment - 'Lean'

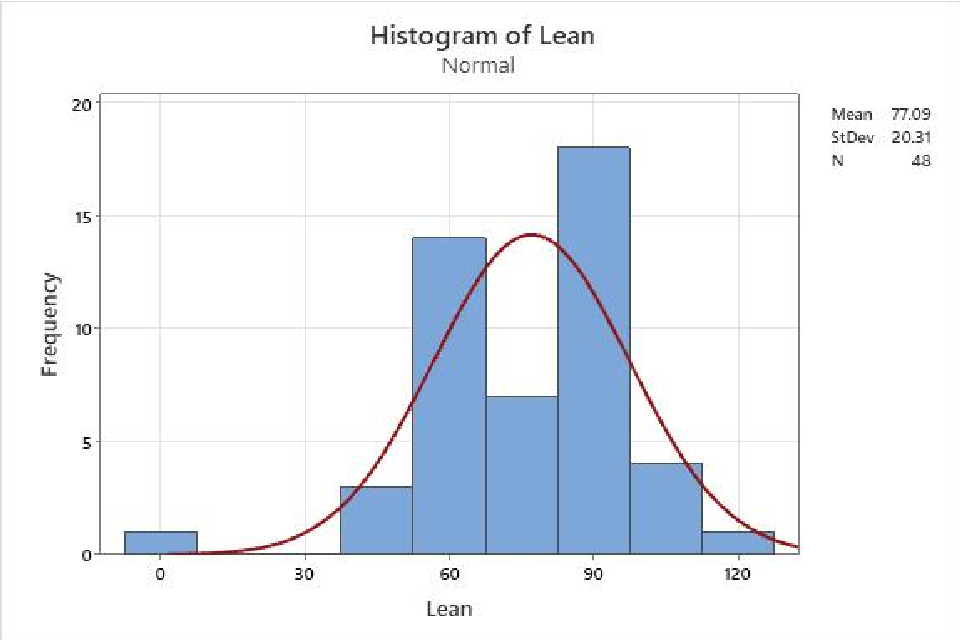


Figure 4.13: Distribution fit for treatment - ‘Lean’

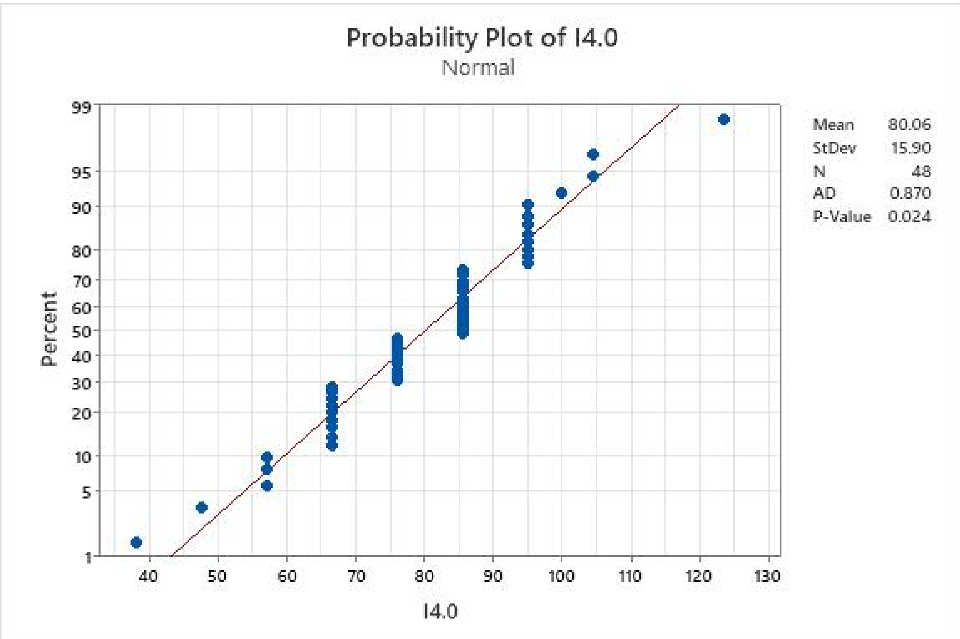


Figure 4.14: Normality check for treatment - ‘Industry 4.0’

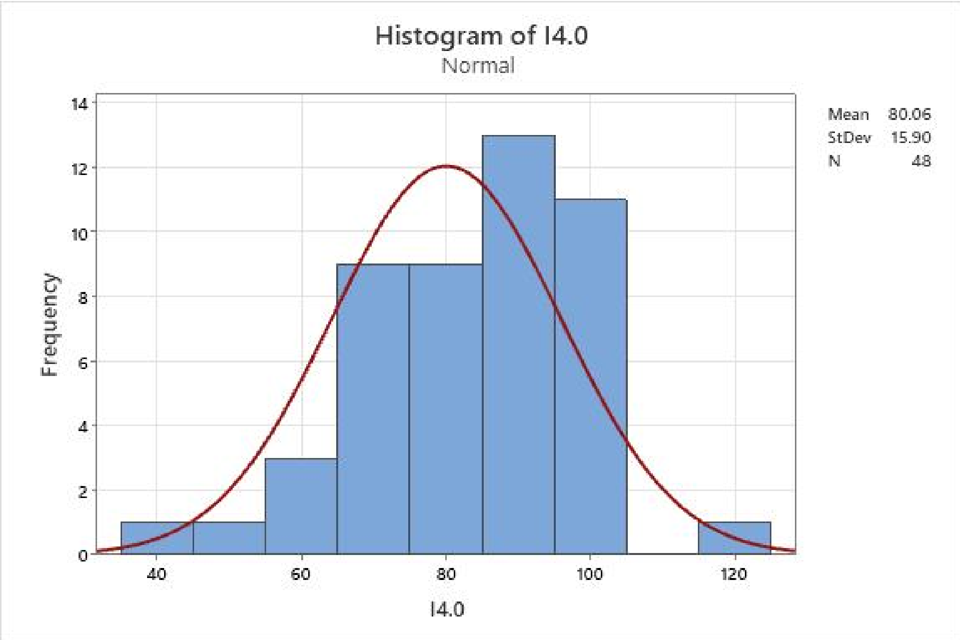


Figure 4.15: Distribution fit for treatment - ‘Industry 4.0’

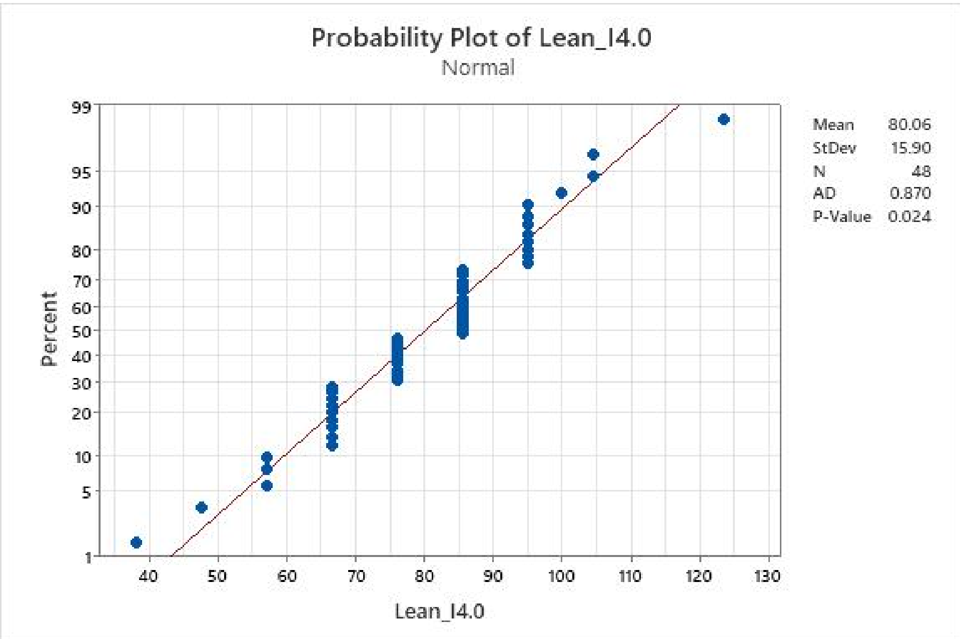


Figure 4.16: Normality check for treatment - ‘Lean & Industry 4.0’

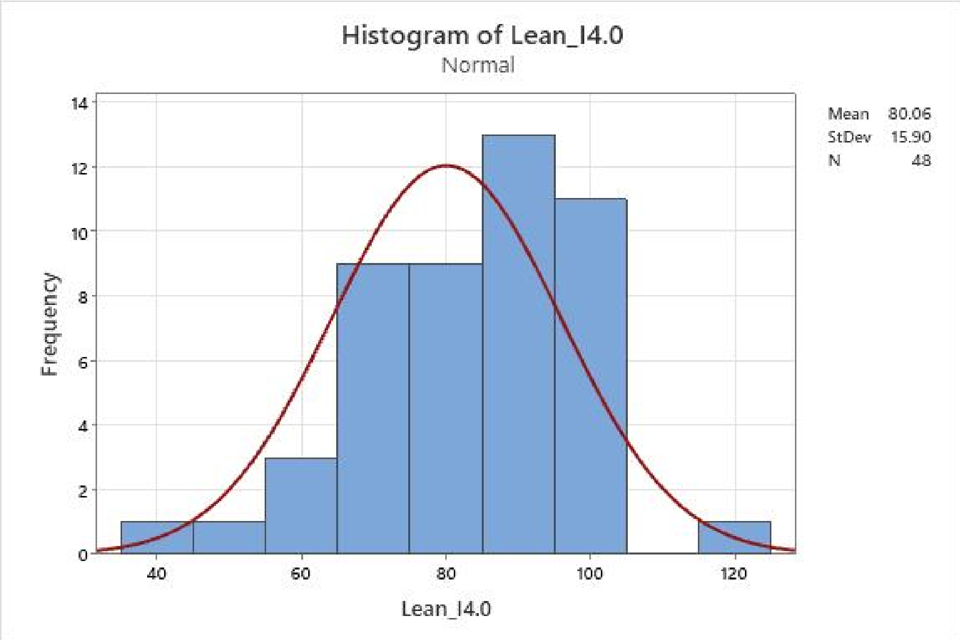


Figure 4.17: Distribution fit for treatment - 'Lean & Industry 4.0'

deviation to determine the variability of the scores. To evaluate the central tendency of the scores, we reported the mean scores and confidence intervals of the OEE metrics. In addition, we created a boxplot of the OEE scores for each treatment to visually identify any differences, as depicted in Figure 4.18.

Table 4.1: Analysis of variance of the studied treatments

Treatments	N	Mean	SD	C.I.
'Control'	48	72.54	20.92	(66.47, 78.62)
'Lean'	48	77.09	20.31	(71.20, 82.99)
'Industry 4.0'	48	80.06	15.73	(75.45, 84.68)
'Lean and Industry 4.0'	48	77.64	17.76	(71.71, 82.33)

4.16.3 Analysis of variance of four treatments

We aimed to conduct this analysis to investigate whether there were any significant differences among these four treatments. We conducted a one-way ANOVA. The results of the ANOVA showed that the p-value (0.286) was greater than the predetermined significance level of 0.05, as shown in Table 4.2, indicating that there were no significant differences among treatments.

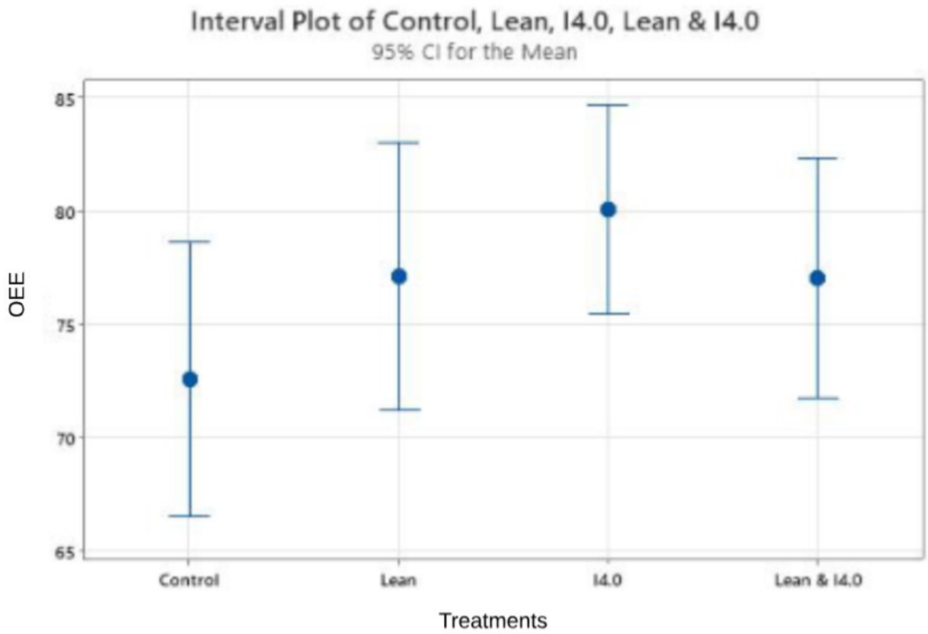


Figure 4.18: Box plot of studied four treatments. It is noted that individual standard deviation is used to calculate the intervals.

This suggests that none of the treatments had a statistically significant impact on the outcome variable compared to the control group.

Table 4.2: One-way ANOVA for four treatments

Sources	DF	Sum of SS	Mean Sq.	F-Value	P-value
Level	3	1382.00	460.81	1.27	0.286
Error	188	68247.00	363.01		
Total	191	69629.00			

The ANOVA results show no statistical significance, indicating that we do not need any further comparison tests. This means that none of the treatments are significantly different from each other. Moving forward, we will focus on the next phase of our analysis, which involves testing our initial hypothesis. In the upcoming subsection, we will gather critical statistical information that will form the basis of our hypothesis testing and enhance our understanding of the underlying dynamics.

4.16.4 Equal variance

It is important to ensure equal variances when conducting statistical tests that compare data between two groups. To assess equal variance, an equal variance test is conducted. This step is crucial in determining whether the variances of two treatments are statistically equivalent [205]. This test holds particular significance in statistical analyses, such as t-tests and ANOVA, where the assumption of equal variances is fundamental to the validity of results.

Additionally, the process of decision-making based on the equal variance result is crucial for accurate statistical inferences. If the variances are found to be equal, it provides a strong foundation for confidently applying parametric tests like t-tests and ANOVA while assuming their validity. However, if the variances are significantly different, alternative non-parametric tests may be considered. This nuanced approach ensures that the chosen statistical tests align with the underlying characteristics of the data, ultimately facilitating more reliable and informed decision-making based on the outcomes of the equal variance assessment.

4.16.5 Equal variance tests for treatments -'Control' & 'Lean'

After analyzing the bar plot and probability distribution graph, it has become apparent that both the 'Control' and 'Lean' treatments exhibit a normal distribution. To corroborate this observation, Bonett and Levene's tests were executed for the aforementioned treatments.

The outcomes for treatments 'Control' and 'Lean' are presented in Table 4.3, illustrating that both Bonett (p=0.891) and Levene (p=0.835) p-values comfortably exceed the 0.05 threshold. This consistency is visually evident in Figure 4.19.

The higher p-values signify that a two-sample t-test is warranted to rigorously evaluate the significance between these treatments. This approach ensures a robust and statistically sound assessment of their respective impacts, contributing valuable insights into the comparative effectiveness of the 'Control' and 'Lean' treatments.

Table 4.3: Equal variance tests ('Control' Vs. 'Lean')

Test	Treatments	n	df	Mean	SD	Test statistics	P-value
Bonett	Control	48	47	72.54	20.92	0.02	0.891
	Lean	48	47	77.09	20.31		
Levene	Control	48	47	72.54	20.92	0.04	0.835
	Lean	48	47	77.09	20.31		

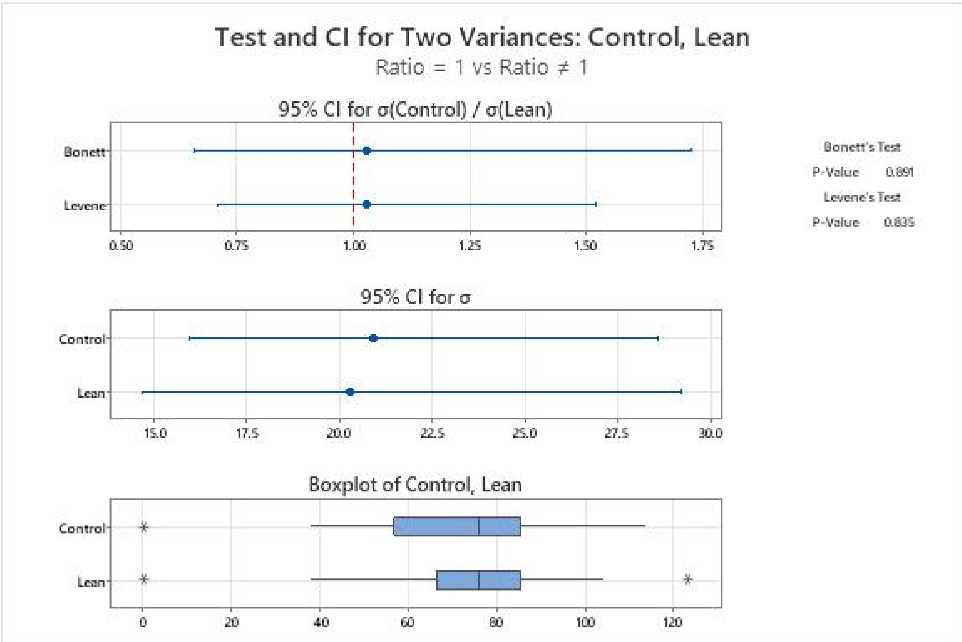


Figure 4.19: Equal variance test (Bonnet & Levene) for treatments- 'Control' & 'Lean'

4.16.6 Equal variance test for treatments-'Control' & 'Industry 4.0'

To determine whether there was equal variability between the 'Control' and 'Industry 4.0' treatments, we conducted Bonett and Levene's tests, and we present the results concisely in Table 4.4. Notably, both Bonett (p=0.173) and Levene (p=0.230) p-values exceed the 0.05 threshold, as visually corroborated in Figure 4.20.

The high p-values suggest that there is not a significant difference in variability between the 'Control' and 'Industry 4.0' treatments. This indicates that we can use a two-sample t-test to thoroughly examine and distinguish their respective significant impacts on each other. This will provide useful insights into how effective each treatment is compared to the other.

Table 4.4: Equal variance tests (‘Control’ Vs. ‘Industry 4.0’)

Test	Treatments	n	df	Mean	SD	P-value	
Bonett	Control	48	47	72.54	20.92	1.86	0.173
	Industry 4.0	48	47	80.06	15.73		
Levene	Control	48	47	72.54	20.92	1.46	0.230
	Industry 4.0	48	47	80.06	15.73		

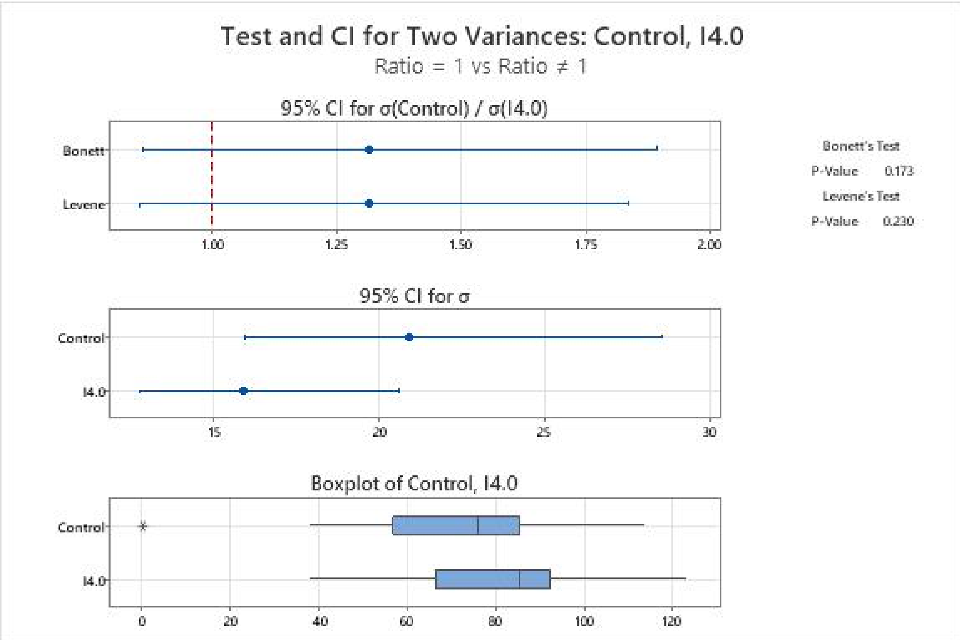


Figure 4.20: Equal variance test (Bonnet & Levene) for treatments- ‘Control’ & ‘Industry 4.0’

4.16.7 Equal variance tests for treatments-‘Control’ & ‘Lean & Industry 4.0’

To assess the equality of variance between the two treatments, Control and Lean & Industry 4.0, we conducted both Bonett and Levene’s tests. The test results are presented in Table 4.5. The results indicate that both Bonett (p=0.464) and Levene (p=0.776) exceed the significance level of 0.05. These findings are visually reinforced in Figure 4.21.

Based on the higher p-values that exceed the significance level, we can confidently conclude that the variability in both treatments is not significantly different. This finding supports the feasibility of conducting a two-sample t-test to evaluate the impact of both treatments. The test will determine whether one treatment significantly outperforms the other in terms of OEE improvement at Station 10, where the study took place.

Table 4.5: Equal variance tests (‘Control’ Vs. ‘Lean & Industry 4.0’)

Test	Treatments	n	df	Mean	SD	P-value	
Bonett	Control	48	47	72.54	20.92	0.56	0.464
	Lean & Industry 4.0	48	47	77.76	17.76		
Levene	Control	48	47	72.54	20.92	0.08	0.776
	Lean & Industry 4.0	48	47	77.76	17.76		

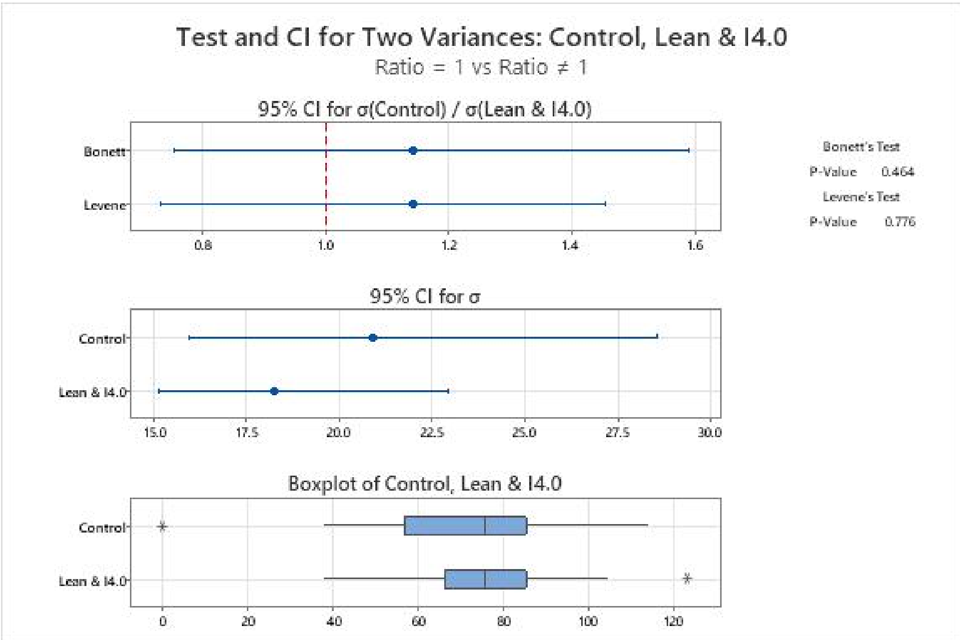


Figure 4.21: Equal variance test (Bonnet & Levene) for treatments- ‘Control’ & ‘Lean & Industry 4.0’

4.16.8 Evidence for hypothesis-1

In order to evaluate the hypothesis, we performed a Welch t-test to compare the mean scores of the ‘Control’ group and the ‘Industry 4.0’ group for the outcome variable, OEE. The t-value we obtained was -1.08, calculated with 47 degrees of freedom, resulting in a p-value of 0.282, as shown in the table 4.6.

The obtained p-value is higher than the significance level of 0.05 that was set earlier, indicating that there is no significant difference between the treatments. Therefore, we cannot reject the null hypothesis, and it can be concluded that the ‘Lean’ treatment does not lead to a statistically significant increase in operational OEE compared to the ‘Control’ group.

Table 4.6: Two sample t-test ('Control' Vs. 'Lean')

Treatments	n	df	Mean	SD	T-value	P-value
Control	48	47	72.54	20.40	-1.08	0.282
Lean	48	47	77.76	17.76		

4.16.9 Evidence for hypothesis-2

A Welch t-test was conducted to compare the mean scores of the control treatment (M = 72.54, SD = 20.92) and I-4.0 treatment (M = 80.06, SD = 15.73) on the outcome variable, the OEE. The t-value was -2.11 with 47 degrees of freedom, and the p-value was 0.038, as shown in Table 4.7, which is less than the significance level of 0.05. These results indicate a statistically significant difference between the treatments. According to our test results, we fail to reject our null hypothesis ('*There is no significant impact of Lean tools on operational performance improvement*'). This means that there is a significant difference between the control and I-4.0 treatments in terms of improving operational OEE at station 10. After analyzing the data, we can conclude that the I-4.0 treatment resulted in a statistically significant increase in operational OEE when compared to the control group.

Table 4.7: Two sample t-test ('Control' Vs. 'Industry 4.0')

Treatments	n	df	Mean	SD	T-value	P-value
Control	48	47	72.54	20.40	-2.11	0.038*
Lean	48	47	80.20	15.73		

4.16.10 Evidence for hypothesis-3

We used a two-sample t-test to compare the mean scores of the treatments, 'Control' (M = 72.54, SD = 20.4) and 'Lean & Industry 4.0' (M = 77.64, SD = 17.76) for the outcome variable, OEE. The t-value obtained was -1.12 with 47 degrees of freedom and a p-value of 0.267, shown in Table 4.8, which is higher than the significance level of 0.05.

With the higher p-value, we fail to reject the null hypothesis, suggesting no significant difference between 'Lean & Industry 4.0' and 'Control' treatments in improving operational OEE at station 10. In conclusion, it can be inferred that the 'Lean & Industry 4.0' treatment did not result in a statistically significant improvement in operational OEE compared to the Control treatment.

Table 4.8: Two sample t-test ('Control' Vs. 'Lean & 'Industry 4.0')

Treatments	n	df	Mean	SD	T-value	P-value
Control	48	47	72.54	20.40	-1.12	0.267
Lean	48	47	77.64	17.76		

4.16.11 Analysis of variance of order levels of treatment -'Industry 4.0'

The study found that the 'Lean' and 'Lean & Industry 4.0' treatments have no significant impact over the 'Control' in terms of OEE. We found only the 'Industry 4.0' treatment significantly improves OEE over the control. However, each treatment has four levels (first, second, third, and fourth). Now, the question is, is there any significant difference among these order levels? To respond to this question, we conducted a one-way ANOVA to determine if order level significantly impacted the OEE improvement. Since other treatments do not significantly improve OEE, we excluded those from this analysis.

A one-way ANOVA was performed on the control treatment to investigate whether different order levels significantly impacted OEE improvement. The results, as shown in Table 4.9, indicate that the p-value (0.240) exceeds the 95 percent confidence level of 0.05. This suggests no significant impact of the order level of the control treatment on OEE improvement.

Table 4.9: Analysis of variance for order level of treatment-'Industry 4.0

Sources	DF	Sum of SS	Mean Sq.	F-Value	P-value
Level	3	1089.00	362.90	1.45	0.240
Error	44	10988.00	249.70		
Total	47	12077.00			

For further investigation, we conducted a Tukey post hoc test to see if there is any significant difference between order levels. For this, we conducted the Tukey LSD grouping comparison analysis, and the results are documented in Table 4.10 and 4.11. The results reveal that between the order levels, there is no significant difference in keeping over the OEE improvement.

For a more detailed analysis, we conducted a Tukey post hoc test to identify any significant differences among the order levels. Using the Tukey LSD grouping comparison analysis, the results are presented in the tables 4.10 and 4.11. According to the findings, there is no statistically significant difference observed between the various order levels when considering OEE improvement. This analysis provides valuable insights into the consistency of OEE enhancements across different order levels within the 'Industry 4.0' treatment. It contributes to a more nuanced understanding of the impact of order levels on OEE improvement.

Table 4.10: A Tukey LSD model summary for order-levels of'Industry 4.0'

Order level	N	Mean	SE	95 % C.I.
1st	12	76.79	13.10	(67.60, 85.99)
2nd	12	74.42	19.36	(65.22, 83.61)
3rd	12	83.13	18.62	(73.93, 92.32)
4th	12	86.29	10.29	(77.10, 95.49)

Table 4.11: A Tukey LSD comparison for order-levels of 'Industry 4.0'

Order level	N	Mean	Grouping
1st	12	76.79	A
2nd	12	74.42	A
3rd	12	83.13	A
4th	12	86.29	A

4.16.12 Demographic impact on subject's performance

We invited 48 subjects to participate in our study and categorized them based on their age, gender, education, geographic location, and experience with lego parts. We conducted a statistical analysis to determine if these demographic factors affect the subject's performance. To evaluate these factors, we used multiple regression analysis. All the factors we studied are categorical variables, while our target variable is the OEE, which is a quantitative variable.

The results, presented in Table 4.12, indicate that Gender, age, education level, and experience with Lego parts did not significantly influence performance. However, the subjects' geographic origin exhibited a noteworthy impact. Specifically, participants from the USA demonstrated significantly superior performance compared to their Asian and European counterparts ($p < 0.05$). This implies that the location of origin is a factor influencing performance in Lego-related tasks. The findings highlight the nuanced interplay between demographic factors and task performance, underscoring the importance of considering geographical distinctions in future analyses. In conclusion, while certain demographic variables show no discernible effect, geographic origin emerges as a key determinant, emphasizing the need for a more nuanced understanding of diverse influences on task performance.

Table 4.12: Demographic impact on subject's performance

Terms	Coefficient	SE	t-value	p-value
Gender (Reference level: Female)				
Male	0.052	0.054	0.95	0.348
Age (Reference level: 19-29 years)				
30-39 years	-0.095	0.08	-1.17	0.251
40-49 years	-0.117	0.118	-0.99	0.333
50-60 years	-0.280	0.153	-1.83	0.077
Country (Reference level: Asia)				
USA	0.112	0.054	2.06	0.048*
Europe	0.031	0.090	0.34	0.737
Education (Reference level: Associate)				
Bachelor	-0.196	0.101	-1.94	0.061
Graduate	-0.190	0.116	-1.65	0.110
High school	-0.041	0.099	-0.41	0.684
Master	-0.038	0.104	-0.37	0.713
PhD	-0.080	0.174	-0.46	0.650
Experience with lego (Reference level: Expert)				
Some	-0.125	0.065	-1.91	0.064
None	-0.125	0.050	-2.49	0.018*

4.17 Discussion

During our discussion, we aimed to answer some important questions related to the manufacturing community. One of the areas we explored was the role of Lean tools in improving instructional paperwork. We also examined whether I-4.0 is more effective on its own or when combined with Lean in improving performance. Based on our research findings, the following subsections provide detailed answers to these questions.

4.17.1 Which is more efficient, the mistake-proof (Lean) device or the control (paperwork instruction)?

To explore the efficiency comparison between the mistake-proof (Lean) device and the control (paperwork instruction), we conducted a hypothesis test by comparing the mean scores of the 'Control' group and the 'Industry 4.0' group for the outcome variable, OEE.

As indicated in Table 4.6, the results suggest that Lean does not significantly impact the subject's performance. In the context of our research, this implies that the mistake-proof device, representing Lean in this scenario, does not lead to a statistically significant increase in operational OEE compared to the 'Control' group, which relied on paperwork instructions. Based on our statistical analysis, there is no clear evidence to suggest that the mistake-proof (Lean) device is more efficient than the control (paperwork instruction) in influencing operational OEE. However, a closer look at the analysis of variance, presented in Table 4.3, reveals that subjects using the Lean tool experienced an increase in their average performance.

Our findings highlight the complexity of real-life assembly lines or manufacturing floors, which vary in modes and designs. The effectiveness of tools and technology is contingent on these parameters, which were not accounted for in our research. Therefore, we recommend conducting a pilot-scale analysis of tool and technology performance before their final installation. This approach ensures a more accurate understanding of their impact in diverse operational settings.

4.17.2 Does the implementation of 'Industry 4.0' have a significant impact on enhancing worker's performance?

Our analysis examined the relationship between Lean and I-4.0 and how they contribute to worker performance. At first, we thought that Lean tools would not have a significant impact, but our findings were more complex than we initially expected.

After examining the data, we discovered that combining I-4.0 with Lean resulted in a notable improvement in operational OEE at station 10. This suggests that using Lean principles alongside advanced I-4.0 technologies can positively affect worker performance. Our research highlights how important it is to explore the interaction between different methodologies and technologies in a manufacturing context. While in this study using Lean alone may not have a statistically significant impact, combining it with Industry 4.0 can lead to better overall efficiency.

In summary, our study demonstrates that integrating Lean and I-4.0 can significantly improve worker performance, especially in complex manufacturing environments. This knowledge can help refine strategies and tailor approaches for optimal performance.

4.17.3 To what extent does the synergy between 'Lean' and 'Industry 4.0' lead to a significant improvement in worker performance?

In our case study, we aimed to gather valuable information by conducting a hypothesis test, specifically exploring the impact of the synergy between Lean and Industry 4.0 on Overall Equipment Efficiency (OEE). Our hypothesis posited that the combination of Lean and Industry 4.0 would lead to higher OEE.

However, our analysis presented a higher p-value, which led us to fail to reject the null hypothesis. This indicates that there is no statistically significant difference between the 'Lean Industry 4.0' treatment and the 'Control' treatment in terms of improving operational OEE at station 10. In simpler terms, our statistical results do not provide enough evidence to support the idea that the collaborative approach of Lean and Industry 4.0 resulted in a significant improvement in OEE compared to the Control treatment.

This finding highlights the importance of critically examining the synergy between Lean and Industry 4.0 within the specific context of Station 10. While the combined treatment may have potential benefits, our analysis suggests that, in this instance, it did not lead to a statistically significant enhancement in operational OEE.

It's crucial to note that the absence of statistical significance in this particular case does not discount the potential effectiveness of the 'Lean Industry 4.0' approach in other contexts or scenarios. Manufacturing environments are diverse, and the impact of different strategies can vary based on factors such as processes, infrastructure, and workforce dynamics.

In conclusion, our study results suggest that, for station 10 in this specific case, the 'Lean & Industry 4.0' treatment did not yield a statistically significant improvement in operational OEE compared to the Control treatment. This emphasizes the need for careful consideration of the unique characteristics of each manufacturing scenario when implementing strategies aimed at enhancing operational efficiency. Further research and context-specific analysis may uncover additional insights into the potential benefits of synergizing Lean and Industry 4.0 methodologies.

4.17.4 Does a person's demographic background have an impact on their performance?

Demographic factors are often evaluated in studies that involve human subjects. In our analysis, we also took into account the impact of these factors. To do this, we conducted a survey of our 48 participants, where we collected information about their gender, age, country of origin, education, and experience with lego. Finally, we performed a multiple regression analysis to assess how these factors influenced the participants' performance, which we measured using OEE.

According to the statistical analysis conducted, most demographic factors did not significantly affect task performance. The results, as presented in Table 4.12, refer that gender, age, education level, and experience with lego parts were non-significant contributors to variations in OEE. This means that these factors do not play a discernible role in predicting or explaining the subjects' performance in the LEGO task.

The study found that apart from gender, age, education level, and experience, the geographical origin of the participants also affects task performance. The research revealed that participants from the United States performed significantly better than their Asian and European counterparts, with a significance level of p ¡ 0.05. Hence, the study suggests that the regional location of origin plays a crucial role in determining performance in Lego-related tasks. Therefore, it is essential to consider regional differences while analyzing and interpreting task performance data.

To sum up, the study found that certain demographic factors, such as gender, age, education, and Lego experience, did not have a significant impact on task performance. However, the study identified geographic origin as a factor affecting performance. This highlights the need for a more nuanced understanding of the various factors that influence task performance. The study's findings suggest that future analyses should consider geographic distinctions, emphasizing a context-specific approach when evaluating performance in Lego-related tasks.

4.18 Summary of the study

This study aimed to address the research gap in the current literature regarding the lack of one-to-one interaction between Lean and I-4.0. It was designed to evaluate the impact of a specific Lean tool and a specific I-4.0 technology, both individually and combined, on OEE improvement. Statistical analysis was carried out to test the significance of the individual and combined impact of Lean and I-4.0 on OEE. The results showed that I-4.0 had a significant impact on OEE, while Lean and Lean & I-4.0 did not.

However, the study is limited by certain constraints, which should be taken into account by researchers in similar fields in their future research. For example, the study analyzed variance to examine the impact of the order of treatments assigned to the subject on performance. It was found that the third and fourth orders had a significantly higher impact on OEE. The subject's experience can influence this effect. We assumed that as the subjects gained experience in assembling the cars during the first and second orders, their performance would be enhanced in the fourth order. However, to validate this assumption, we require experimental data, which calls for additional research. This study is limited to the subject recruitment process. We invited a total of 48 subjects while the first 24 were without offering any motivation. In the second half, we invited 24 subjects with motivation. However, we did not find any statistically significant difference in the performance of the subjects who were motivated compared to those who were not motivated.

Although the study has certain limitations, its findings are significant in understanding the relationship between Lean and I-4.0 and their impact on OEE. The results offer valuable insights to industries and organizations striving to optimize their operations and enhance efficiency. In conclusion, exploring the one-to-one interaction between Lean and I-4.0 and its implication for OEE improvement provides valuable knowledge to increase operational efficiency and productivity across different industries.

Chapter 5

Impact of a balanced workflow in productivity and efficiency improvement

5.1 Introduction

The manufacturing industry is constantly changing and requires a strategic response to keep up with the dynamic nature of processes, technologies, and market demands [112, 161, 163]. Organizations need to adapt and thrive amidst this dynamism. Two crucial considerations emerge in this context: efficiency and productivity of processes. Efficiency is a measure of how well a system or activity converts inputs into valuable outputs while minimizing waste and maximizing productivity. Efficient processes are characterized by optimal use of resources, reduced costs, minimal errors, and timely completion of tasks. Manufacturers are always aiming to obtain higher efficiency. The literature says that higher efficiency can be achieved through Lean methodologies [158, 160]. Lean is a structured approach that focuses on eliminating waste, improving efficiency, and enhancing overall process performance. It enables organizations to adapt quickly to changes, ensuring that their processes are not only efficient but also agile enough to respond to evolving market demands. Lean's emphasis on continuous improvement aligns seamlessly with the dynamic nature of modern manufacturing, making it a fundamental strategy for process optimization in dynamic environments [9, 181].

On the other hand, productivity refers to the measure of the efficiency with which resources are utilized to generate output or achieve specific goals. It is often expressed as the ratio of output to input in a given time period. Productivity is a crucial metric for evaluating the efficiency and effectiveness of processes, systems, or individuals [206, 207]. While Lean focuses on streamlining and optimizing processes, I-4.0 introduces advanced technologies like Simulation, IoT, AI, and real-time data analytics to improve efficiency. These technologies automate tasks, provide predictive analytics, and enable intelligent decision-making, thus improving process efficiency. Combining Lean and I-4.0 technologies becomes a strategic imperative as Lean creates a foundation for efficient processes, and I-4.0 technologies provide the tools for digitalization and smart manufacturing practices to amplify this efficiency [208, 209]. This collaborative approach ensures that organizations optimize their processes with Lean while also future-proofing their operations by leveraging the transformative capabilities of I-4.0 in the manufacturing landscape.

Technological advancement offers multiple alternatives for similar purposes. Among these options, manufacturers need to choose the best alternative. In this essence, simulation emerges as a valuable tool to conduct trade-off analyses among different combinations of options in a virtual environment rather than through physical installations [178, 209]. This approach is advantageous as it facilitates cost-effective decision-making while minimizing potential financial risks associated with direct implementation [208, 210]. Simulation, in the context of industrial processes or manufacturing, involves the creation of a computer-based model that mimics the behavior of a system [211, 210]. This model enables manufacturers to analyze and evaluate the performance of various alternatives under simulated conditions. By employing simulation, manufacturers can assess factors such as production efficiency, resource utilization, and overall system performance without the need for costly physical prototypes or installations.

The dynamic nature of simulation modeling permits organizations to adapt integration strategies to changing conditions and evolving requirements. Simulation not only provides a cost-effective and controlled environment for experimentation but also serves as a strategic decision-support tool for mitigating risks and fine-tuning the integrated system before its real-world implementation [208, 210]. In essence, it becomes a catalyst for refining and optimizing the integration strategy to align seamlessly with the intricacies of dynamic industrial landscapes.

In the literature, several authors demonstrated the application of simulation modeling in trade-off analysis of different production strategies within the manufacturing floors, allowing visual representation of complex systems [212, 213]. Simulation modeling can be effectively used to explore the intricacies of workflows, enabling a shared perspective on the current state of operations and potential areas for improvement. The authors demonstrated how organizations can use simulation models to validate and refine constant improvement initiatives, ensuring that changes positively impact efficiency without causing unintended consequences elsewhere in the system [210, 214]. Thus, simulation allows stakeholders to observe the virtual manufacturing environment, offering insights into the alignment and potential modifications required for the coexistence of different strategic paradigms [210, 209]. It identifies interdependencies, enabling decision-makers to foresee challenges, mitigate risks, and optimize the overall system's performance. Through this visual and dynamic representation, simulation serves as a catalyst for informed decision-making [210, 213], ensuring a strategic and harmonious integration of different paradigms [76, 215].

In order to address the limitations of physical experimentation and bridge the gap between theoretical concepts and real-world industrial applications, the study has turned to simulation or computer modeling. By simulating extensive production scenarios virtually, it is possible to emulate the intricacies of a production environment on a scale that mirrors real-world complexities. This approach provides a versatile platform for testing and iteratively refining the integration framework. The simulation model is instrumental in validating the conceptual framework in a virtual setting, offering a cost-effective and efficient means to simulate the interactions between I-4.0 and LP within the expansive scope of large-scale industrial operations.

We drew motivation from literature, which highlights simulation's efficacy in closely replicating system performance. The focus remains on exploring efficient and balanced workflows that can enhance productivity. Our goal with DES is to thoroughly analyze workflow dynamics and provide insights for optimizing productivity through an efficient operational framework.

This contribution is the extended case study of the previous two studies, as we demonstrated in Chapters 3 & 4, respectively. In short, in Chapter 3, we proposed a conceptual framework to integrate Lean and I-4.0. In Chapter 4, we demonstrated validation of the proposed framework by implementing it in the Lean Education Automotive Lab. However, the validation process was limited to a small number of subjects. Therefore, in this study, we aimed to extend the validation process to increase the number of replications under different scenarios. More specifically, the study aims to validate the proposed integration framework of 'Lean 4.0' by examining the variability of its performance under a large number of replications and different scenarios using DES. Additionally, it aims to conduct a comparative analysis of eight different layouts of workflow and to identify the most efficient one followed by the subject.

5.2 Literature review

In this section, we will discuss the successful application of DES in the context of Lean digitization. Our focus will be on examining empirical evidence regarding the effectiveness of DES in improving manufacturing processes. The literature consistently highlights DES as a powerful and influential tool for enhancing various aspects of manufacturing operations. For instance, separate studies have demonstrated that DES modeling can be used to evaluate and improve the productivity of manufacturing floors by optimizing the use of resources [216, 217]. One important application of DES modeling in manufacturing is process optimization. By utilizing DES, the entire production process can be modeled to identify bottlenecks, inefficiencies, and opportunities for improvement. Manufacturers can optimize workflows, reduce cycle times, and enhance overall productivity by evaluating different Lean methodologies and scenarios, such as VSM or Kanban [17, 129].

DES plays a vital role in the field of Lean layout design, enabling proactive identification of issues and optimization of performance. Its efficient implementation can significantly enhance the overall productivity and efficiency of the process [218]. Through meticulous DES of real-world scenarios and nuanced analysis of variable interactions, DES serves as an indispensable tool for refining the intricacies of Lean layout design [218, 211]. Effective utilization of DES provides a competitive edge in manufacturing production, distinguished by insights derived from a comprehensive evaluation of dynamic factors, leading to a higher level of operational effectiveness within Lean methodologies [126, 219].

Manufacturers can visualize and test various layout configurations in a virtual environment. They can observe the impact on material flow, operator movement, and workstation utilization by simulating different layouts. This allows for designing a Lean layout that minimizes waste and maximizes operational efficiency. Inventory management is another crucial aspect where DES comes into play. By simulating various inventory management strategies, such as JIT inventory or Kanban systems, manufacturers can analyze the effects of inventory levels on production, inventory holding costs, and stock-outs [220, 221]. This enables them to find the right balance between inventory and production needs.

Workforce optimization is also enhanced through DES modeling. Manufacturers can assess workforce productivity and efficiency by incorporating workforce behaviors and capabilities into the DES. It helps to identify skill gaps, training requirements, and workforce allocation to optimize human resources within the Lean digitized environment. DES is instrumental in managing change during Lean digitization initiatives. Manufacturers can assess the impact on various departments, processes, and stakeholders by simulating the effects of implementing these changes across the organization [222, 223]. This allows for a smoother transition and effective change management. In addition, DES can analyze equipment utilization within the Lean digitized environment. By simulating different scenarios, manufacturers can identify underutilized resources and optimize equipment allocation to minimize idle time and maximize production output. DES models also facilitate performance measurement by collecting real-time data during manufacturing. Manufacturers can monitor KPIs related to Lean digitization efforts, enabling data-driven decision-making and continuous improvement [224, 225].

In the realm of manufacturing, the integration of robotics is another area where DES plays a significant role. Simulation models validate frameworks that introduce robots into LP systems [210, 221]. These simulations provide insights into how robotic automation affects tasks like material handling, assembly processes, and quality control. These frameworks can be optimized before implementation by evaluating the impact on efficiency and waste reduction. Integration frameworks involving automation and conveyor systems also benefit from DES validation. These frameworks strive to integrate automated material handling systems seamlessly with Lean principles to minimize waste and optimize production flow. Simulation models allow for a thorough evaluation of how these systems impact overall efficiency, identifying potential bottlenecks or areas of improvement. Another vital aspect is integrating digital Kanban systems, which are validated using DES. Kanban systems are crucial to LP for managing inventory and ensuring a smooth production process [226, 181]. Through simulations, integration frameworks that digitize these systems can be tested to guarantee that signals for inventory replenishment remain synchronized with production needs. When considering incorporating predictive maintenance technologies into LP, DES plays a key role in validating the integration frameworks. By modeling the impact of predictive maintenance on production schedules and equipment uptime, simulations help assess how these technologies can be seamlessly integrated without disrupting the efficiency gains achieved through Lean practices. Furthermore, DES is applied to validate integration frameworks that enable data-driven decision-making within Lean environments [227, 228]. By simulating real-time data analytics and their impact on production planning, waste reduction, and overall process optimization, these frameworks can be fine-tuned for optimal outcomes [229, 230].

In LP, integrating technologies that offer real-time monitoring and visualization is becoming increasingly important. Integration frameworks that align LP with agile manufacturing principles are also subject to DES validation. Simulations evaluate how these frameworks manage dynamic changes in production demand while adhering to Lean ideals of waste reduction and continuous improvement [210, 231]. Quality management is a critical aspect of LP, and integration frameworks involving Lean principles and quality management systems are validated using DES [229, 210]. These frameworks can be evaluated through simulations to ensure that quality control processes seamlessly complement production flow. DES finds application in validating integration frameworks that target energy efficiency within LP. These frameworks integrate energy-saving technologies while maintaining Lean efficiency. Simulations provide insights into how these measures impact production processes and energy consumption.

On the manufacturing floor, workflow standardization is a challenging task. Inappropriate workflow can lead to waste and decreased productivity and quality. However, the use of DES can help by virtually simulating various workflows, without the need for investments in time and money. By modeling and analyzing complex processes with a focus on dynamic events, DES is a useful tool for improving workflow balancing. It considers various factors such as processing times, delays, and resource constraints. This helps identify inefficiencies in workflow structure, which can be proactively optimized for a more balanced workflow. DES also optimizes resource allocation by simulating different scenarios to determine the optimal distribution of tasks among resources. This minimizes idle time and enhances overall resource utilization for a more efficient workflow. DES is also adaptable to changes in workflow conditions dynamically, allowing stakeholders to examine how the workflow responds to changes and ensuring the system remains balanced under varying conditions. DES provides a visual representation of workflow dynamics, enabling stakeholders to observe the flow of tasks, identify bottlenecks, and comprehend the overall balance of the system. This contributes to informed decision-making for workflow improvement and facilitates ongoing efforts for workflow enhancement and efficiency through continuous scenario analysis. For example, in a study [232], authors endeavored to assess the efficiency of various strategies to optimize the operations of a body shop system while keeping costs under control using DES modeling. The authors analyzed the current system and identified areas of concern that led to suggested solutions. Upon implementing the proposed changes, the body shop TP increased by 2.6 percent, while uptime rose by 79.5 percent, and scrap was reduced by 0.3 percent. These improvements resulted in an impressive return on investment of 497 percent. The study aimed to address the facility manager's needs and priorities, with the primary objective of improving the body shop's efficiency. In a case study [233], authors applied the DES model to overcome shortcomings in planning construction processes while using each technique alone or with Building Information Modeling (BIM). This approach results in a more efficient integration with BIM models, providing a comprehensive framework for planning that takes into account constraints on equipment and labor. The use of DES in conjunction with takt time optimizes supply chain management, enabling JIT implementation based on optimal time, equipment, and labor. The results, demonstrated in a small building context, suggest wider applicability across diverse construction processes, promising reductions in time, cost, waste, and energy consumption while optimizing resources.

In all these cases, DES proves invaluable by providing a virtual environment for exploring balanced workflow and testing integration frameworks of technology and LP principles. Having a balanced workflow is essential for businesses to remain competitive and productive. On the other hand, an effective and efficient integration framework is essential to allow new and emerging technologies into the production floors. In our case study, we observed eight different workflow layouts that had varying cycle times. However, we noticed that our sample size was very small (n=12). As a result, we needed to replicate the subject's behavior and extend it to a larger set of data. To do this, we used the DES model to explore a balanced workflow and determine whether such a workflow could significantly improve productivity and efficiency.

5.3 Research questions and hypotheses

We conducted this study with two research questions, as defined below.

RQ1: How does the implementation of a balanced workflow impact throughput?

RQ2: How does implementing a balanced workflow impact cycle time reduction?

To explore the answers to the above-mentioned research questions in a scientific way, we develop two hypotheses. Then, we gathered data to prove whether these hypotheses were true or false and made our decision.

Hypothesis-1: The implementation of a balanced workflow does not have a significant impact on the throughput improvement.

Hypothesis-2:The implementation of a balanced workflow does not have a significant impact on cycle time reduction.

5.4 Methodology

In this section section, we outline the basic steps that we followed in constructing the DES model. We break down the various components of the entire working procedure into steps to provide a comprehensive view of the system. Additionally, we highlight the assumptions underpinning our model, offering insights into its foundational principles. In the following subsections, we demonstrated how we executed our study toward obtaining a balanced and efficient workflow by applying the DES model.

5.4.1 Working procedures

In Chapter 3, we proposed an integration framework. Consequently, we tested the proposed framework in the Lean Education Lab in Chapter 4. We defined the Lab manufacturing environment as a manufacturing organization. Primarily, we validated the ‘Control’ phase of the framework, where the invited subject assembled the SUV cars using Lego parts. The subjects followed a paperwork instruction in picking and placing the Lego parts during the assembly. There were 18 Lego parts showing the picking and placing sequence in the paperwork instructions. Their picking and placing sequences were recorded. In this study, we watched the recorded videos and calculated the time each subject took to pick and place Lego during their assembling process.

The study was driven by the research question - does the sequence of workflow impact the subject’s performance? To respond to this question, we were motivated to conduct this study. The required data were pulled from the study as demonstrated in Chapter 4. We invited 48 subjects to perform in assembling SUV cars under four different treatments (described in Chapter 4). Using ‘Industry 4.0’ was one of the four treatments. However, in this study, we only used the data from the treatment - ‘Industry 4.0’. We randomly used 12 (out of 48) subjects’ performance data, which information was used to mimic their performance using the DES model. The employed steps are depicted in Figure 5.1, providing a visual representation of the working procedures.

Model Development: Build a detailed DES model in Simio that represents the integration framework and its processes. Define the entities, resources, and logic of how Lean and I-4.0 components interact and work together.

Input Data Collection: Gather relevant data on process times, equipment capabilities, and other parameters required for the DES model. This data will be used to replicate real-world scenarios accurately.

Input Data Collection: Scenario Definition: Define the scenarios to be simulated, representing different operating conditions and integration strategies. This may include workload variations, machine breakdowns, or different integration framework configurations.

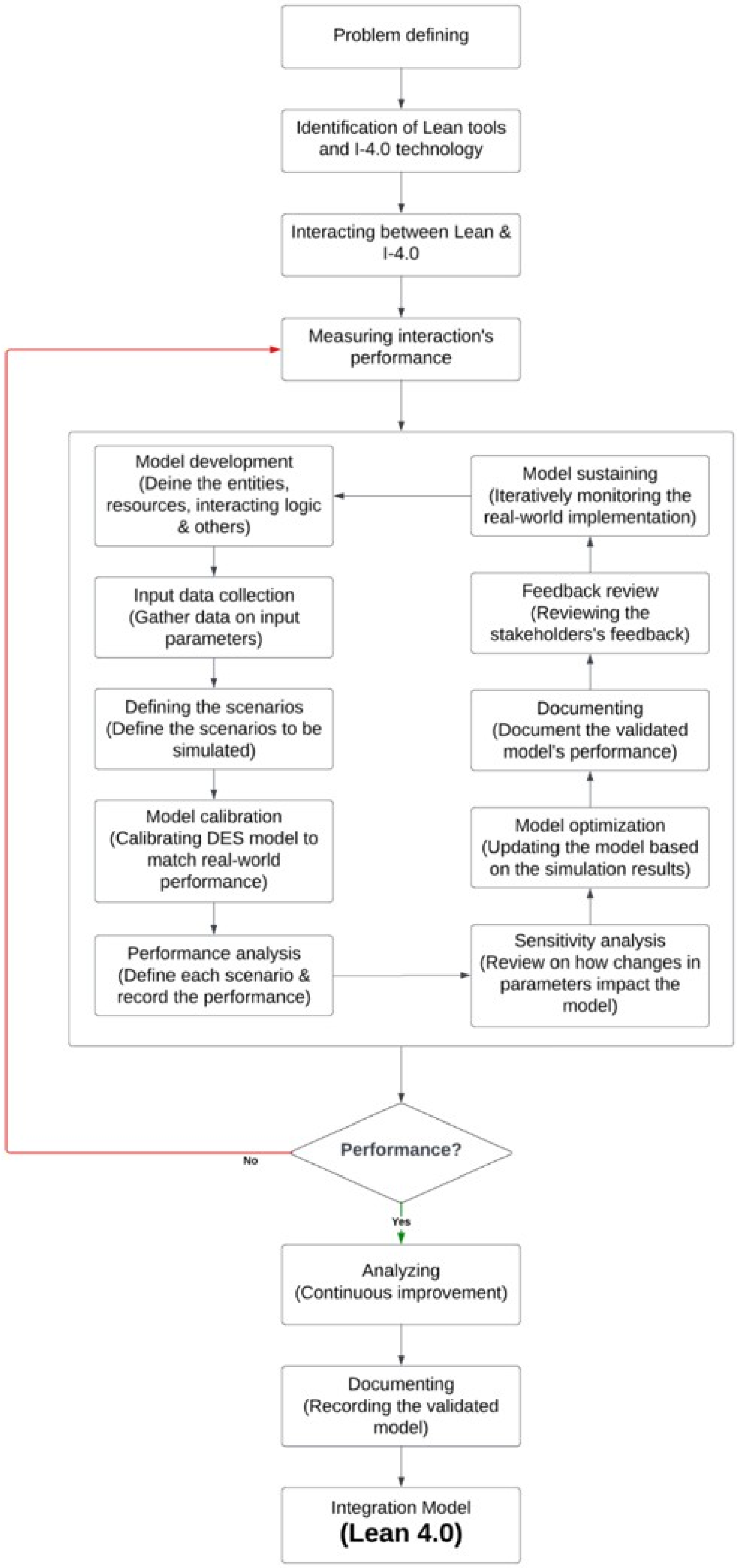


Figure 5.1: Basic steps of DES modeling

Input Data Collection: Model Calibration: Calibrate the DES model to match real-world performance by adjusting parameters and validating against historical data or observed behavior.

Performance Analysis: Simulate each defined scenario and collect performance data. Analyze the results to assess the integration framework's effectiveness in achieving desired objectives, such as efficiency gains, waste reduction, or quality improvements.

Sensitivity Analysis: Conduct sensitivity analysis to understand how parameter changes impact the integration framework's performance. Identify critical factors and potential bottlenecks.

Optimization and Improvement: Use the insights gained from the DES to identify areas for optimization and improvement. Make changes to the integration framework based on DES results to enhance performance.

Validation Report: Document the entire performance validation process, including the DES model, input data, scenarios, results, and improvement recommendations, in a comprehensive validation report.

Feedback and Stakeholder Review: Present the validation report to stakeholders for feedback and review. If necessary, incorporate their input into further refining the integration framework and DES model.

Continued Monitoring and Iterative Validation: Continuously monitor the real-world implementation of the integration framework and iteratively validate the DES model as changes or updates are made to ensure its accuracy and relevance.

5.4.2 Discrete event simulation modeling

Although we introduced the DES in the previous section, we will now outline its basic features. DES modeling is a powerful technique used to represent and analyze complex systems, operations, or processes dynamically [229, 212]. It involves modeling systems as they change over time due to discrete events, which occur at specific points in time and trigger state changes or interactions. Unlike continuous DES, which uses continuous variables for time representation, DES focuses on event-driven modeling, advancing the DES to the next relevant event when an occurrence takes place. This approach optimizes computational resources and allows decision-makers to explore various scenarios and understand system behavior under different conditions.

The roots of DES can be traced back to the early 20th century when early applications were seen in the military for tactical scenario analysis [212, 234]. However, its widespread adoption came with the development of digital computers during the mid-20th century, making it feasible to perform complex DES in a relatively short time. Over the years, DES has found applications in diverse fields such as manufacturing, logistics, healthcare, finance, and telecommunications, proving particularly useful in studying complex systems where analytical solutions are impractical. Developing a DES model involves formulating a conceptual model of the system, specifying entities, events, resources, and their interactions [9, 235]. This conceptual model is then translated into a computer program using specialized DES software or programming languages. The DES model allows for experimentation by varying input parameters or system configurations to analyze the impact of different scenarios and optimize system performance. By using DES, decision-makers can make informed choices based on the DES results.

As technology advances, the accuracy and performance of DES models are expected to improve further, making them an indispensable tool for solving real-world problems and gaining insights into the behavior of complex systems. Its versatility and ability to handle dynamic, event-based systems continue to ensure its relevance and importance across various industries and domains.

5.4.3 Simio software for DES modeling

Simio is a simulation software developed in 2005, offering powerful tools for DES and agent-based modeling (ABM) [236, 237]. Its unique combination of DES and ABM allows users to create comprehensive models of complex systems. Simio uses an object-oriented approach, simplifying model development and promoting re-usability. Its intuitive drag-and-drop interface and 3D animation enhance the visualization of models, aiding in better understanding and analysis. The software offers optimization and analysis tools, enabling users to evaluate scenarios and make data-driven decisions for system improvement. Simio supports integration with external data sources and cloud-based collaboration, making it a versatile tool used in various industries and academia for teaching DES concepts. Its popularity stems from its user-friendliness and ability to tackle intricate real-world problems.

In the context of our study, we have chosen Simio as the simulation software due to its unique advantages over other platforms. Simio has a user-friendly interface and robust modeling capabilities, which allows for a seamless integration of object-oriented programming and simulation modeling. It is highly flexible and efficient, making it the perfect fit for our specific needs and providing a comprehensive representation of complex systems. Furthermore, Simio's extensive support for integration with other technologies and its ability to conduct detailed analysis make it the ideal choice for our research objectives, making it a preferred option over alternative simulation software platforms.

5.4.4 Current workflow

The study was conducted at the Lean Education Laboratory, which follows a standard workflow shown in Figure 5.2. The workflow involves using 18 Lego parts to build an SUV car at station 10. Across 15 stations, a total of 237 Lego parts are used to build a single car. Our study was conducted at station 10, where the 18 Lego parts are identified with part numbers, as shown in Figure 5.2. A flow of parts is also shown in the work instructions. It is assumed that the subject will follow the given workflow layout according to paperwork instructions. However, in our investigation, we found that the subject naturally followed their consumed instruction, although the given paperwork guided them. In this essence, we were motivated to explore how many workflow layouts are followed by subjects. Also, we intended to estimate the efficiency of the following workflows in terms of TP and efficient cycle time/TIS. Based on these, we postulated two hypotheses as we demonstrated in the previous 'Research and Hypotheses' section.

We conducted an investigation assuming that the participant would carefully follow the given instructions. Our aim was to examine whether the subject adhered to the prescribed directions outlined in the workflow or deviated from them during the Lego assembly. If any deviations are identified, we will analyze whether there is a better competitive balance workflow

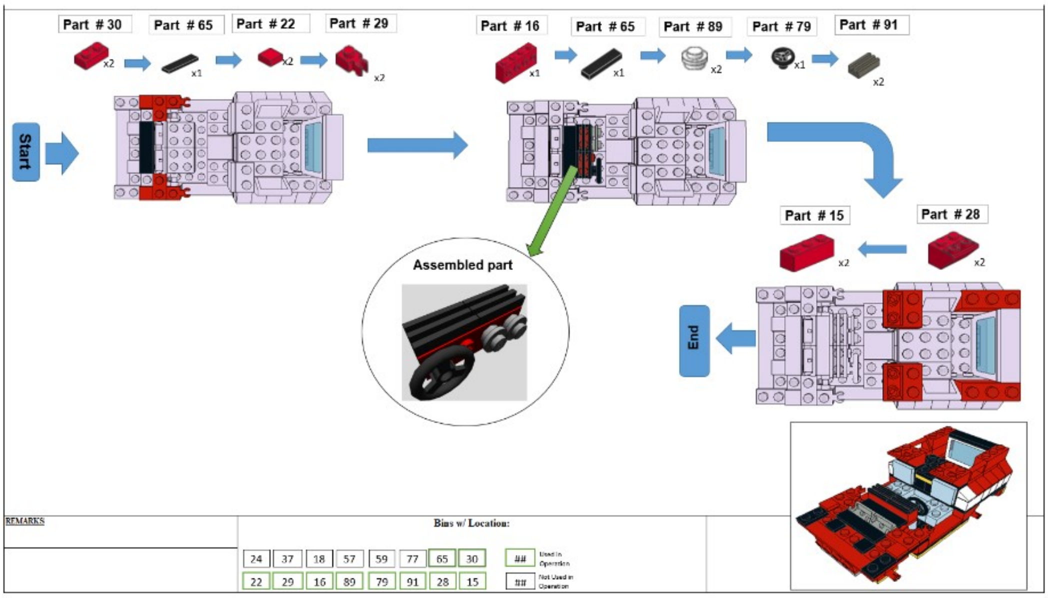


Figure 5.2: Current workflow instructions of 'Lean Education Laboratory'

that maximizes the TP while minimizing the cycle time or time in the system (TIS). This investigation will help us evaluate the practical adherence and procedural efficacy of the established workflow at station 10 within the Lean Education Laboratory.

5.4.5 Strategy followed by subjects in assembling

In our study, we aimed to uncover the overall strategy followed by the subjects. We discovered that the subjects initially followed the given workflow instructions. They were provided with four car buildings in their practice demonstration session and were later given 10 cars to build for each treatment, resulting in a total of 40 cars over the four treatments. However, as they progressed, they deviated from the given workflow instructions and started following a sequence that they found comfortable. Despite this, they were able to complete the car-building process, which we represented as an entity in the Simio model, at station 10. Once the assembly was completed, they checked the car under the smart camera instruction and corrected any missing or misplaced parts before placing them in the completion tray. This ensured that all parts were good, which was another assumption we demonstrated in building our DES model. The strategy followed by the subjects is illustrated in Figure 5.3.

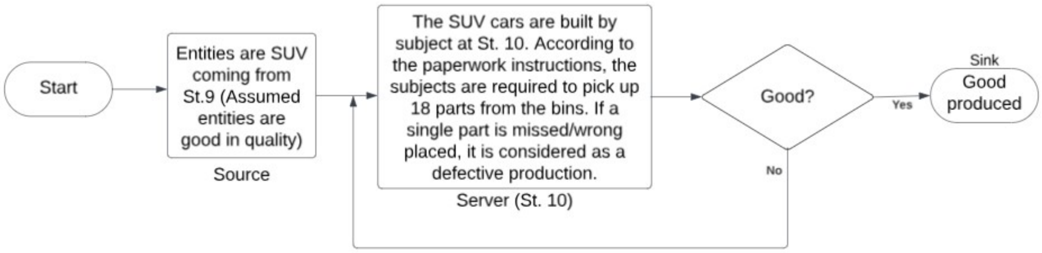


Figure 5.3: The strategy followed by subjects in assembling the cars of SUV model

5.4.6 Subjects' adherence to uncovered workflows

We recorded the subjects' performance in assembling the cars and restricted among the researchers according to the research protocol of the Internal Review Board of Auburn University. We watched the recorded videos and observed the workflow of each subject in assembling the cars. Among a total of 48, we watched and observed 12 subjects' performance randomly under the treatment of 'Industry 4.0'. We have observed eight different sequences, each assigned with a unique number from S1 to S8. These sequences vary in the order of picking and placing Lego parts. The workflows are depicted in individual figures. Specifically, Figure 5.4 corresponds to S1, Figure 5.5 corresponds to S2, Figure 5.6 corresponds to S3, Figure 5.7 corresponds to S4, Figure 5.9 corresponds to S5, Figure 5.8 corresponds to S6, Figure 5.10 corresponds to S7, and Figure 8 corresponds to S8.

5.4.7 Balanced workflow investigation

In the current workflow layouts, we explored eight different layouts that are widely used by research subjects. Now, the aim is to evaluate the efficiency of eight different workflow layouts to identify the most effective one. To achieve this, we engaged a small group of research subjects who actively participated in assembling SUV cars using Lego, as detailed in Chapter 4, under four distinct treatments. For the purposes of this study, we specifically drew upon the performance data from the 'Industry 4.0' treatment. The decision to focus on the 'Industry 4.0' treatment was rooted in the assumption that it was found to be significantly more efficient when compared to the other three treatments. Also, it is capable of ensuring zero-defect operation, which means whatever it produces is good in terms of quality. This capability is attributed to the

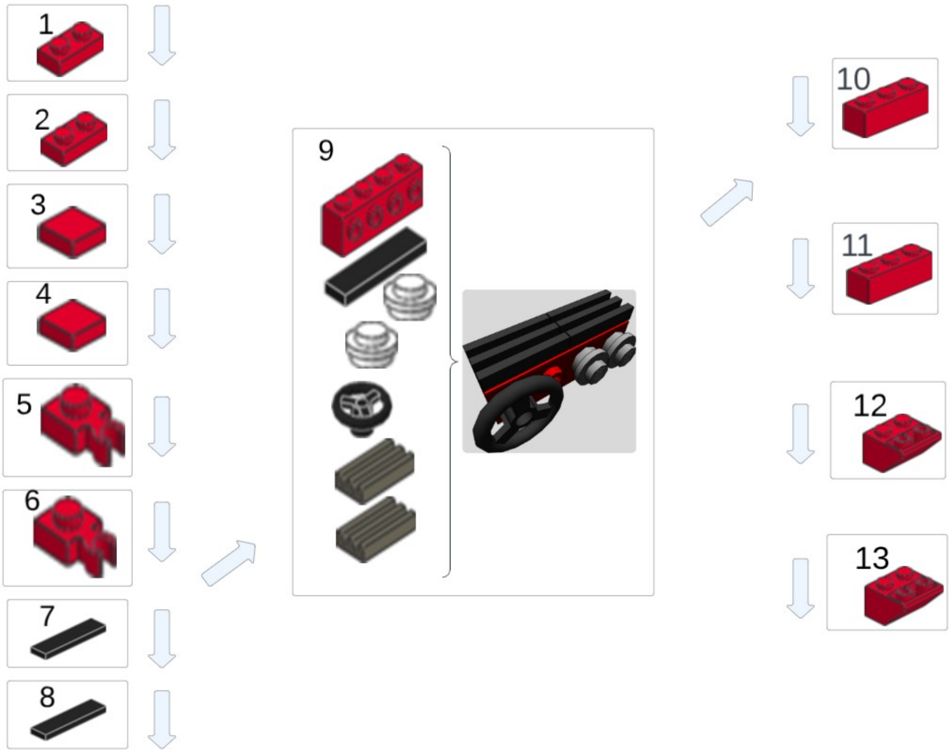


Figure 5.4: Observed workflow, S1. The number represents the sequence of picking and placing the Lego parts during the assembly.

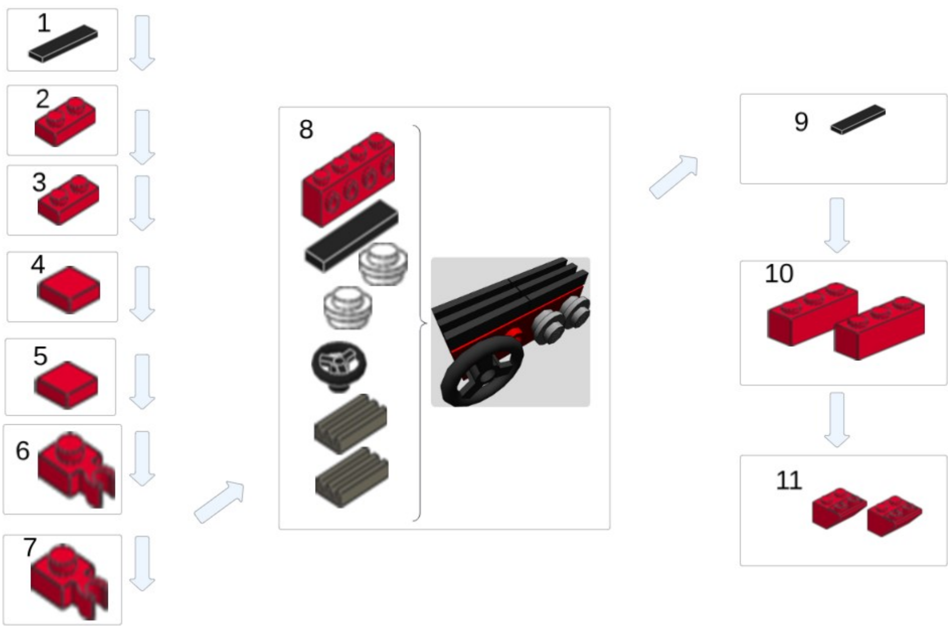


Figure 5.5: Observed workflow, S2. The number represents the sequence of picking and placing the Lego parts during the assembly.

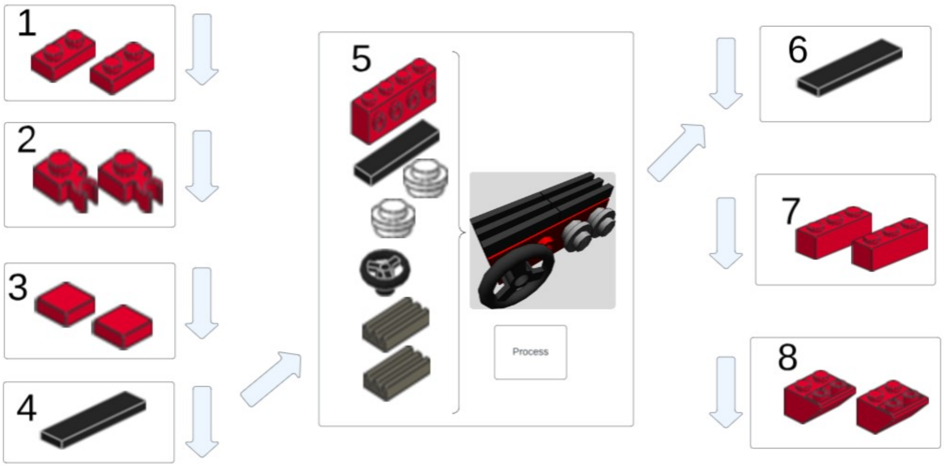


Figure 5.6: Observed workflow, S3. The number represents the sequence of picking and placing the Lego parts during the assembly.

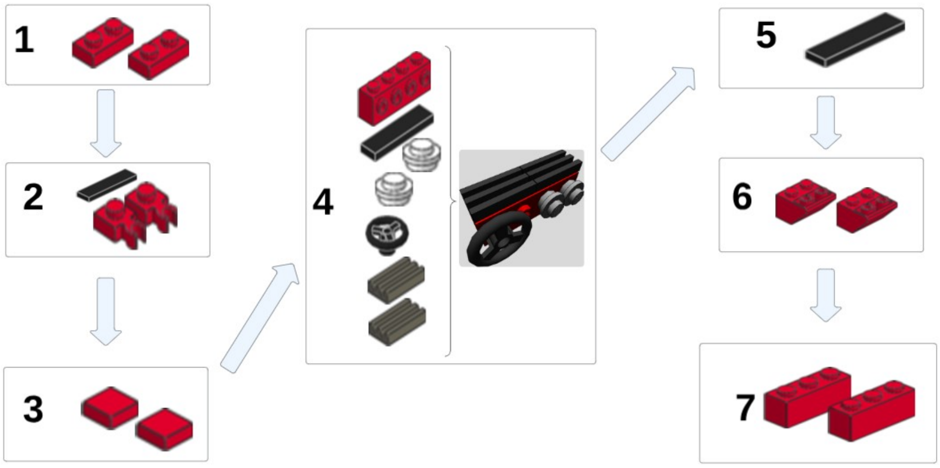


Figure 5.7: Observed workflow, S4. The number represents the sequence of picking and placing the Lego parts during the assembly.

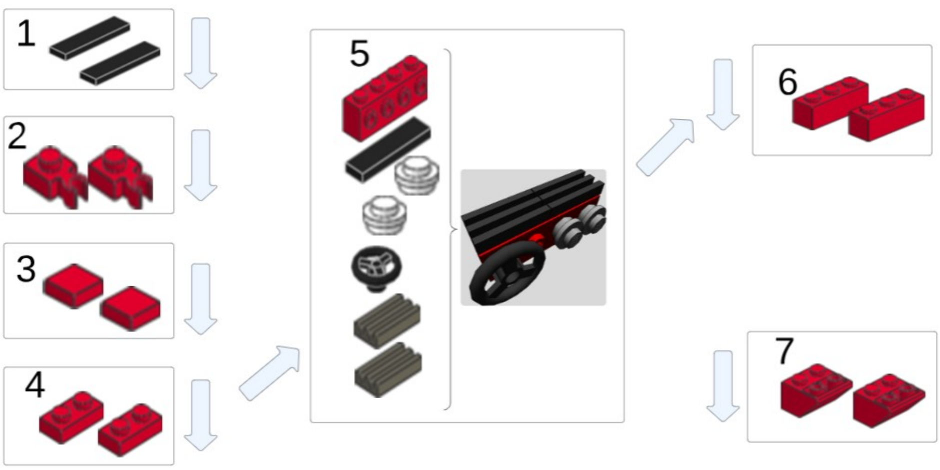


Figure 5.8: Observed workflow, S5. The number represents the sequence of picking and placing the Lego parts during the assembly.

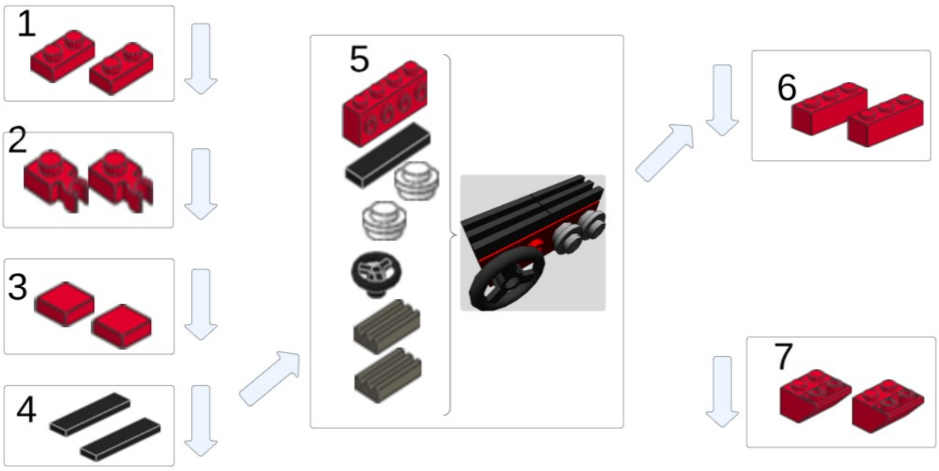


Figure 5.9: Observed workflow, S6. The number represents the sequence of picking and placing the Lego parts during the assembly.

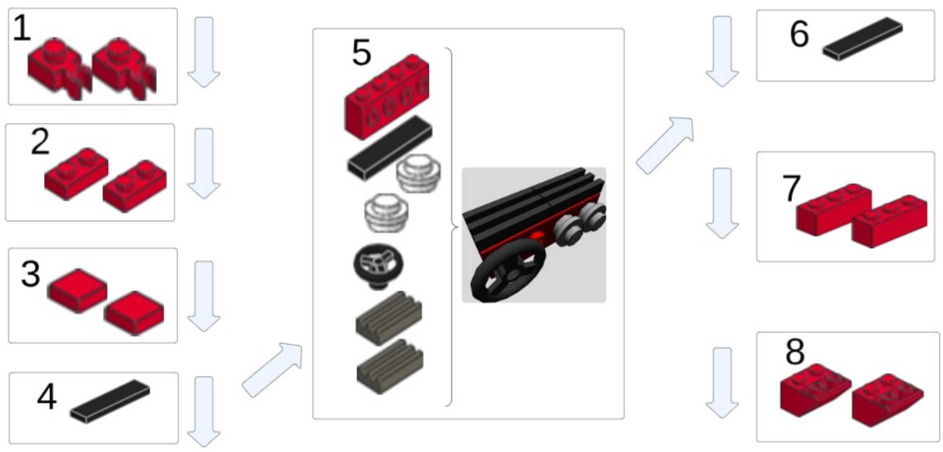


Figure 5.10: Observed workflow, S7. The number represents the sequence of picking and placing the Lego parts during the assembly.

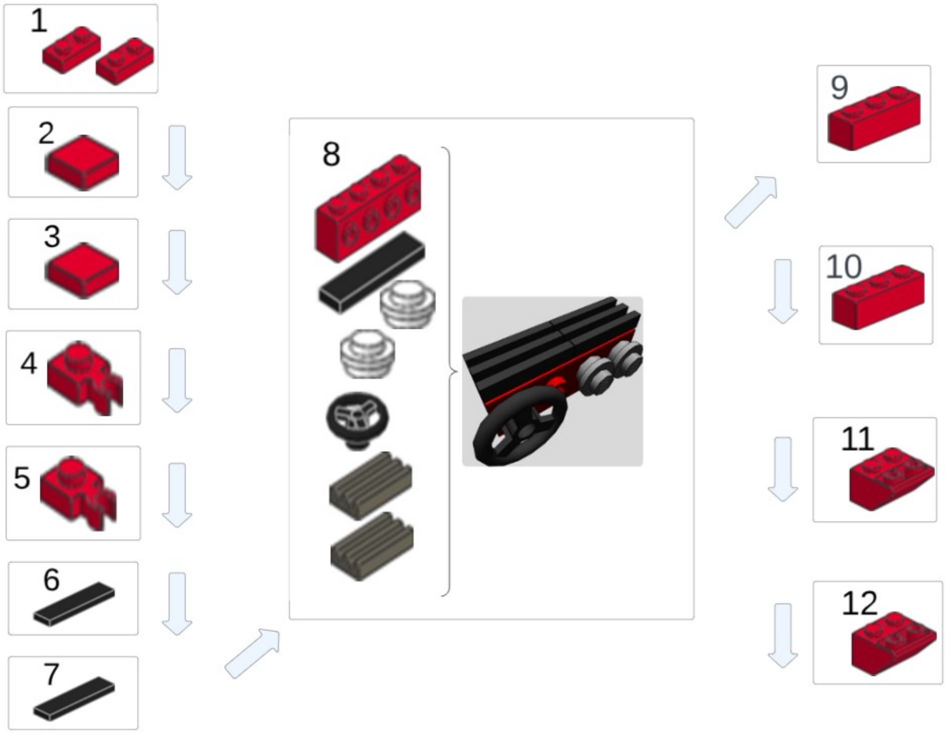


Figure 5.11: Observed workflow, S8. The number represents the sequence of picking and placing the Lego parts during the assembly.

integration of smart vision technology, enabling the detection of defects during the production process.

Since we operate with a single station where each worker can build one car at a time, we created eight different simulation models to represent eight different workflows. Under the given setup with a single working station, it is essential to note that each worker or subject is capable of assembling one car at a time. Upon completion, the subject proceeds to pull another car from the preceding station. In light of this operational context, we developed eight distinct DES models, each corresponding to a unique workflow (S1-S8). Our evaluation criteria focused on assessing their efficiency in terms of TP and Total TIS. Subsequently, we conducted a thorough analysis of their performance, employing these metrics to identify the most efficient and balanced workflow. The ensuing subsections delve into a detailed demonstration of the performance characteristics inherent in the defined workflows.

5.4.8 Measuring scales/measurements in simulation modeling

We measured three metrics to assess the DES outcomes in exploring the most efficient workflow. These metrics are analysis of variance, Throughput (TP), and Cycle time (CT), provide valuable insights into the performance and dynamics of the simulated system.

5.4.9 Aalysis of variance

For the analysis of variance, we employed one-way Analysis of Variance (ANOVA). This statistical method is utilized to evaluate whether statistically significant differences exist among the means of eight independent layouts within the workflow. One-way ANOVA enables us to assess variations between multiple groups and determine if these differences are beyond what could be expected by random chance.

In the context of our study, this technique serves as a robust tool to examine the efficiency and performance disparities among distinct workflow layouts. By statistically evaluating the mean differences, we gain valuable insights into the impact of layout variations on the outcomes, contributing to a more comprehensive understanding of the system's dynamics and aiding in the identification of optimal workflow configurations.

5.4.10 Throughput (TP)

Throughput, a key performance metric in DES modeling, plays a pivotal role in evaluating the effectiveness of the Simio model. TP represents the rate at which a system can produce its desired output, reflecting the efficiency and productivity of the modeled processes. It is an essential parameter as it directly impacts resource utilization, system capacity, and overall performance. The valid TP equation 5.1 is often defined as:

$$Throughput(TP) = \frac{Total\ Output}{Simulation\ Time} \tag{5.1}$$

This equation quantifies the efficiency of the system by calculating the ratio of total output to the simulation time. Evaluating TP allows us to gain insights into how well the simulated workflows are functioning, identifying potential bottlenecks, resource constraints, or areas for improvement. By incorporating TP analysis into our evaluation of the Simio model, we can make informed decisions aimed at optimizing system performance and ensuring that the simulated processes align with real-world expectations.

5.4.11 Time in System (TIS)

The TIS refers to the total time an entity spends within the simulation model from the moment it enters the system until it exits. In the steady state, the TIS is the average queue time and the service time. Mathematically, the TIS can be estimated by employing Little Law's equation [238]:

$$W = W_q + E(S) \tag{5.2}$$

Here, in the steady state, *W: The average time in the system (TIS);* W_q*: The average queue time in the system; E(S): The average service time for entities;*

As indicated by Equation 5.2, during a steady-state scenario, the Total TIS is determined by the average time entities spend in the system. This includes both service times and waiting times at each station, whether examined individually or collectively across the entire system. Nevertheless, in our specific case study, the entity experiences no queue time; thus, W_q is effectively zero for our investigation.

5.4.12 Cycle time (CT)

CT represents the average time that an entity takes for a system or process to complete one full cycle or iteration. It is a broader measure, including processing time, wait time and other delays. In other words, CT is the average TIS, which can be estimated the CT by employing the following equation.

$$CT = \frac{Total\ time\ spent\ by\ all\ entities}{Number\ of\ completed\ cycles} \tag{5.3}$$

The analysis, as per Equation 5.3, suggests that the average TIS for the entity aligns with the CT, representing the duration required for a full cycle. In the context of our specific case study, this complete cycle entails the entire assembly process of an SUV car, using Lego parts.

5.4.13 Model assumptions

A set of assumptions has been defined that serve as foundational premises, shaping and influencing the anticipated outcomes of the model. These assumptions encapsulate the fundamental conditions and parameters considered during the modeling process and provide a framework for understanding and interpreting the subsequent predictions and analyses. In essence, the following set of assumptions are defined.

- We assumed an infinite availability of materials during the simulation runs to ensure no shortages occurred in the production process.
- We assumed that the production station has only one worker, which means the server capacity is one. Therefore, as soon as one entity is assembled, another one will be assembled.
- We assumed the model entities entering into the queue by following the 'first in, first out' ranking rule
- We assumed that the processing time used in the model derived from the distribution of the subject's performance.
- We assumed that manufacturing production would be uninterrupted by equipment breakdowns or maintenance during the simulation.
- We defined the warm-up period as 100 minutes.
- The run time for the experiment was determined to be 550 minutes.
- The experiment for all workflow models was run for 1000 replications under a single scenario.

5.5 Model developments

This section outlines the process of developing the DES model by using data from an empirical study, as presented in Chapter 4. The objective was to verify whether the DES model replicated the behavior of subjects during the assembly of an SUV using Lego parts. Model testing is crucial to evaluate the extent to which the observed outcomes supported or contradicted the real performance of subjects. Our next step was to conduct experiments with more replications and assess if the results were consistent with our proposed hypothesis - '*A balanced workflow has no impact on cycle time reduction of a manufacturing floor.*' The Simio environment was used to develop the DES model through several steps, which are demonstrated below.

First, in the simio software, we created a data table using object instance and object type properties. We utilized the 'object type property' column to refer to particular instances of objects. Additionally, for each object instance's specific location in the facility, we employed two real properties - one denoting the x location and the other representing the z location, as illustrated in Figure 5.12. We used object instance properties to depict the model entity, resource, source, servers, and sink, as depicted in Figure 5.13. Each server represents a specific Lego assembly station and its processing time is the time to pick and place a part.

Second, we created a data table for the model entity called 'Part', referring to the DES model (Figure 5.14). Two columns were created under this table. The first column is for the entity and is denoted as 'Parts'. The second column is for the real property and is denoted as 'Mix', which denotes the probability of source referencing. The entity property column was made as a key column for proper identification.

Third, another table was created, named 'Seq,' representing the part movement in the DES model, as shown in Figure 5.15. This table consists of three columns. The first column is named 'Entity A' and belongs to the 'Foreign Key Property'. It is connected to the 'Parts' column of the 'Part' table. The second column is named 'Sequence' and belongs to the 'Sequence Destination Property'. It refers to the destination of each entity, for example, 'Part A'. The third column is named 'AssembleTime' and belongs to the 'Expression Property'. It represents the processing time of each server.

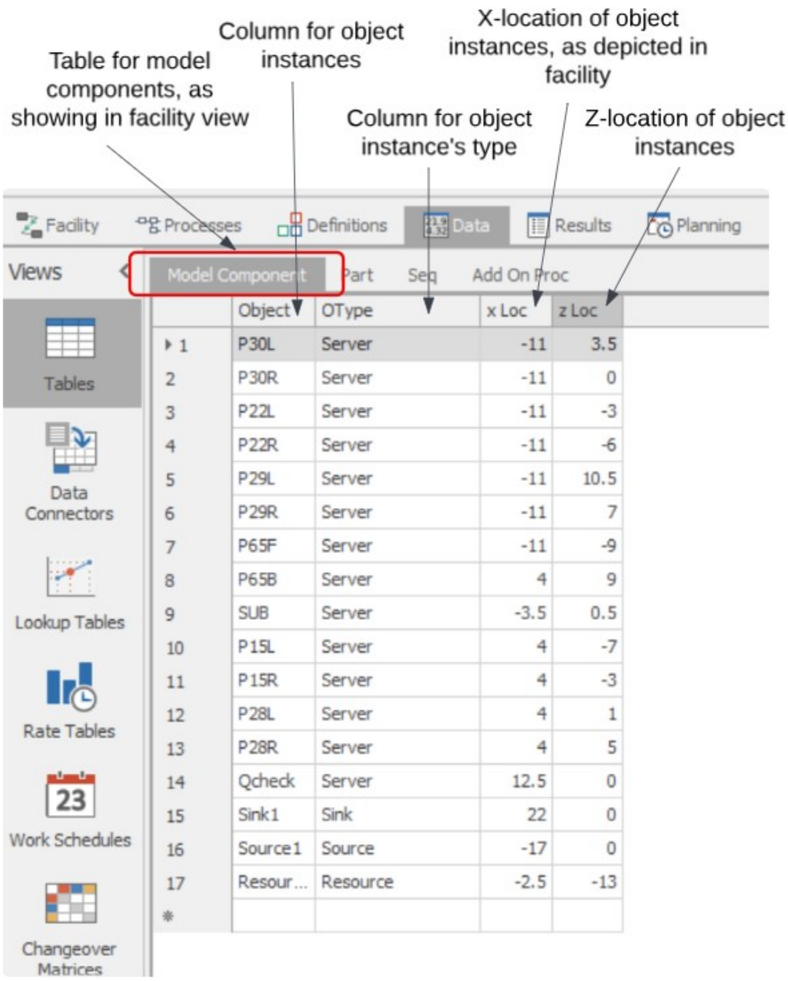


Figure 5.12: DES model component are defined in a structured way

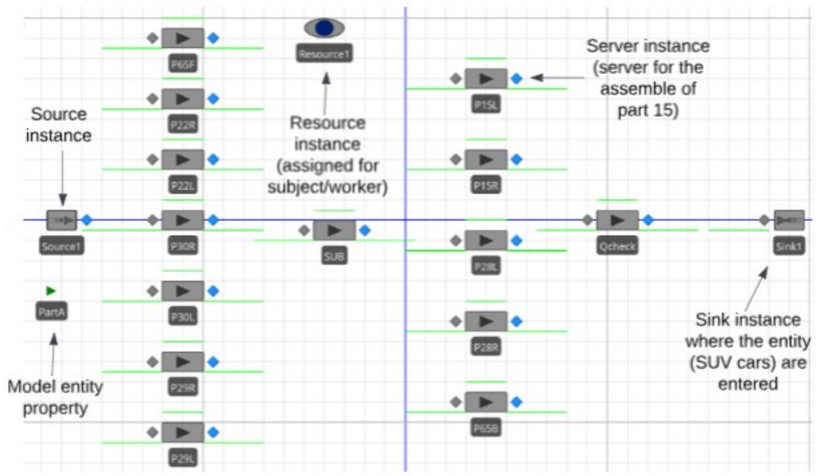


Figure 5.13: DES model facility view (workflow sequence - S1)

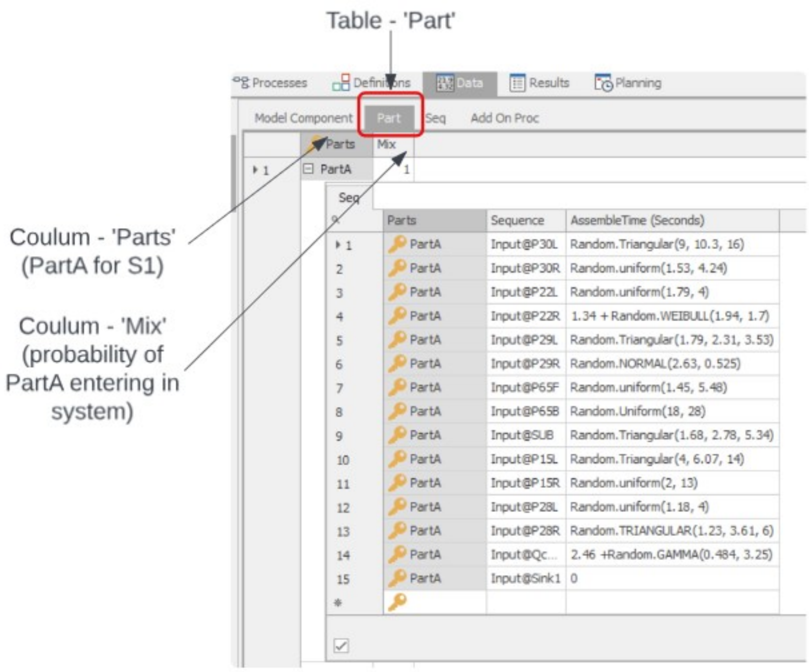


Figure 5.14: The ’Part’ table generation for model entity (PartA) entering into the DES model (workflow sequence - S1)

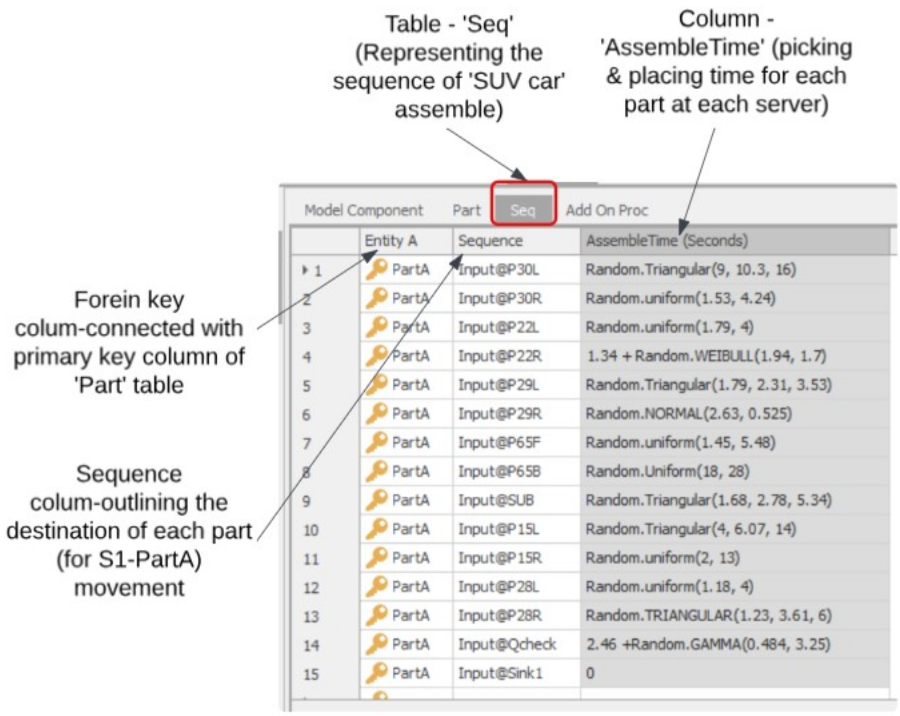


Figure 5.15: The ’Seq’ table generated in DES model facility for model entity (PartA) entering into the assemble line (workflow sequence - S1)

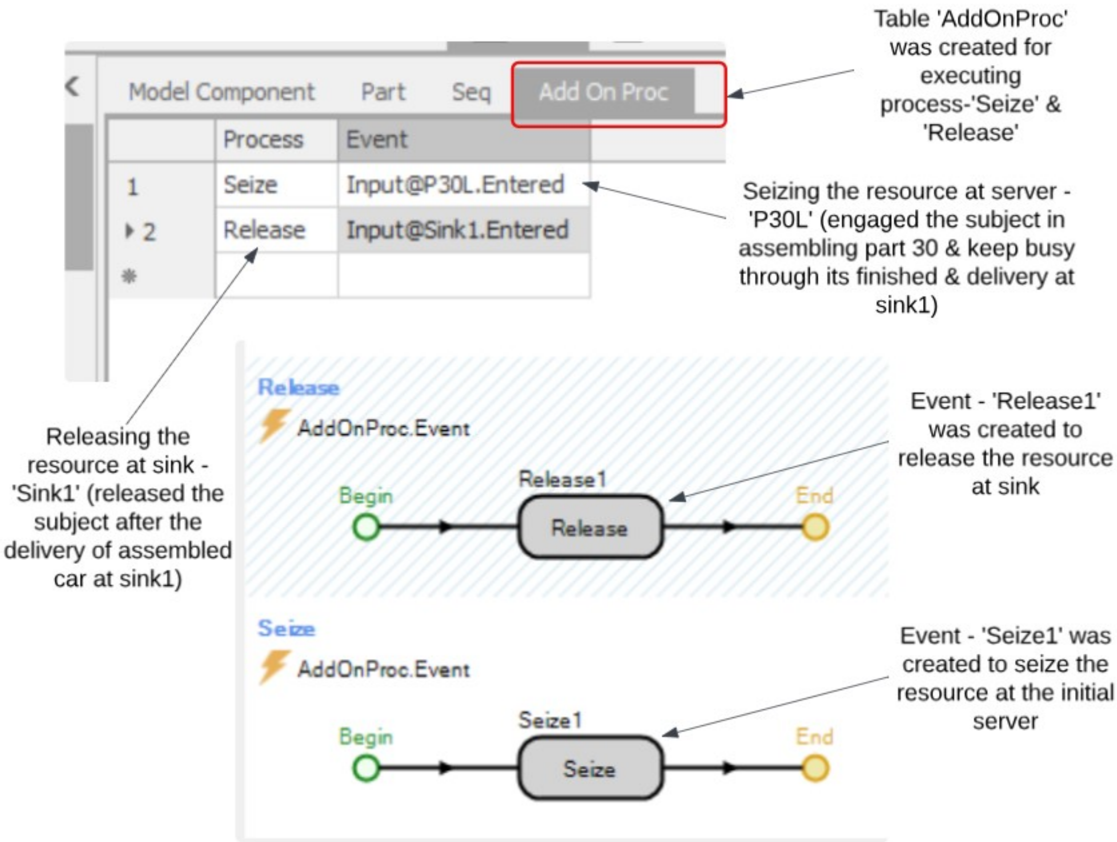


Figure 5.16: Resource seizing and releasing execution through 'Seize1' & 'Release1' event processes (workflow sequence - S1)

Fourth, as part of our work on the DES model, we introduced two new processes. The first process, depicted as 'Seize1' in Figure 5.16, requires the worker to select a part and place it onto the assembled SUV car as it enters the initial server ('P30L'). This event is linked to 'Resource1', which represents the resource instance in the facility. Once the car has been assembled, it is released into the sink1 (Figure 5.16), which is executed in the model by creating and employing the event - 'Release1'. Likewise, it is also connected with a 'resource' instance. These seize and release events are mutually worked on in resource seizing and releasing throughout the assembly process.

Fifth, we set the properties of DES model's instances in the facility, as shown in Figure 5.17. For example, the speed property of model entity 'PartA' was infinite according to the manufacturing process characteristics 5.17 (A). To outline the movement of the entity (PartA), the sequence property was assigned to the output node of each server instance, as illustrated

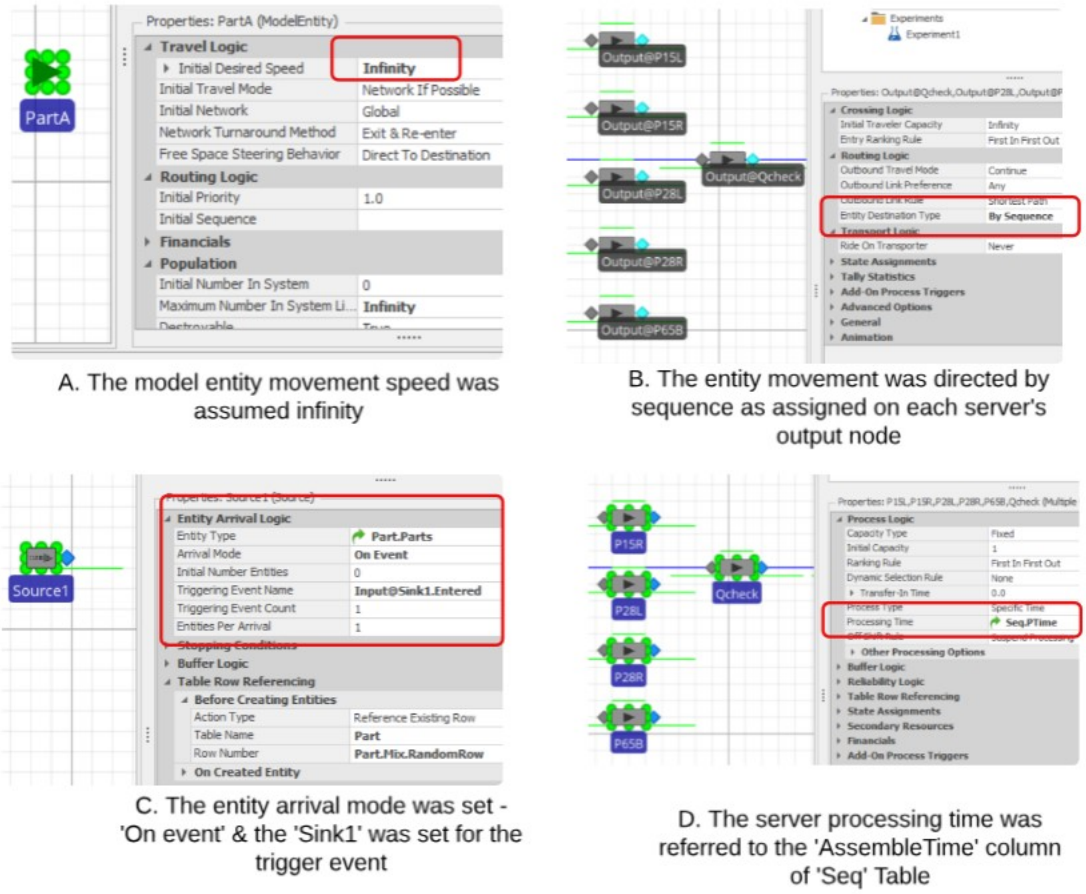


Figure 5.17: Setting the DES model's object instance properties (workflow sequence - S1)

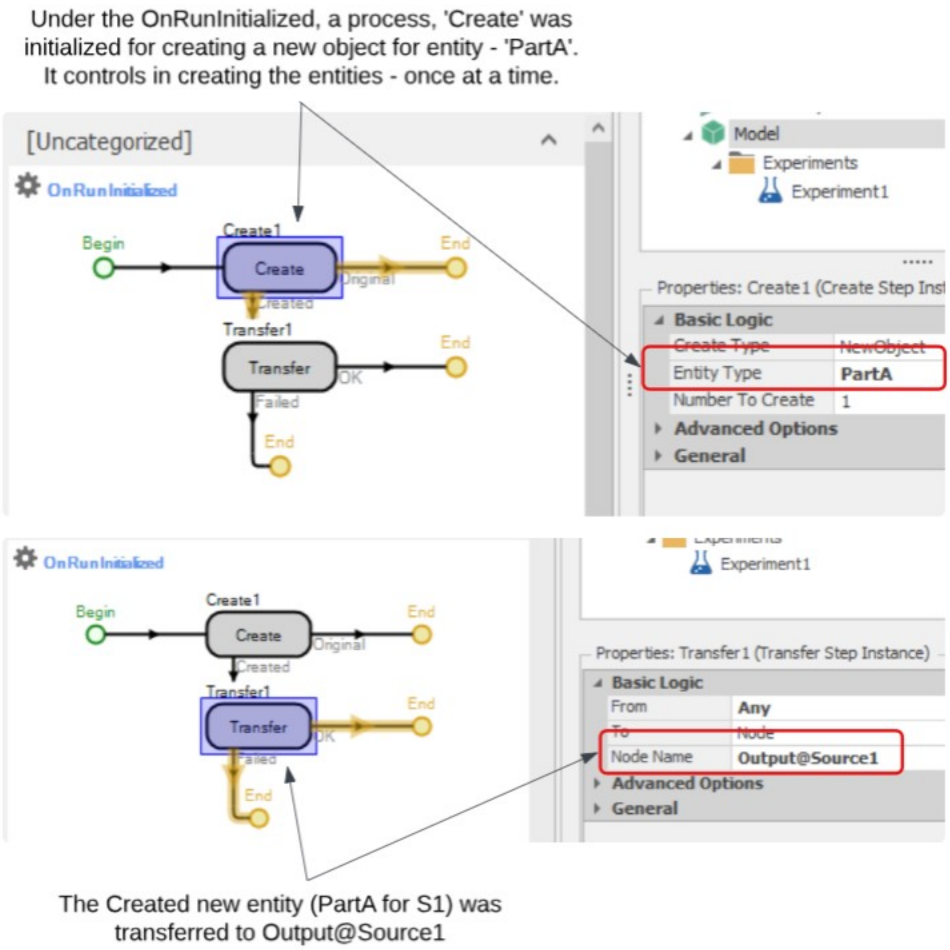


Figure 5.18: Initialized a process to create the entities once at a time (workflow sequence - S1)

in Figure 5.17 (A). We have specified the arrival mode of the entity as ‘On Event’ based on the characteristics of the assembly, as shown in Figure 5.17 (C). The triggering event (Input@Sink1.Entered) has already been defined and is represented in Figure 5.17 (C). To ensure accuracy, we have fixed the table row reference to indicate the specific row number in the Table before introducing entities into the system. This is also reflected in Figure 5.17 (C). The server processing properties were adjusted using the reference Table column, as shown in Figure 5.17 (D).

Finally, a control process is initialized to create the entities one at a time, as shown in Figure. 5.18. It means a source can not create more than one entity at a time, with production characteristics maintained. After incorporating all these properties and features into the DES model, we tested and validated the model in the following subsections.

5.5.1 Model testing for its functionality

In this section, we will demonstrate how we tested the DES model to ensure its proper functionality. We followed a few simple steps to accomplish this goal.

First, we started the model to see if it runs without any issues. Second, we used the step function to check if it goes through the process step by step as it should. Third, to test how entities move based on the steps they follow in assembling, we set the initial speed to 0.4 and observed that the objects moved correctly.

Next, we added a status label to see how many entities are in the system at the same time. It always showed 1, which means the model is functioning accordingly as we set the arrival mode - 'On Event'. Finally, we ran the model and checked its actions using the trace, following its progress in real-time. This helped us ensure that the model functions as intended.

5.5.2 Model testing for its initial bias

The primary purpose of testing the model's initial bias is to avoid the misleading and biased data from the final analysis in making a decision against the postulated hypothesis. We conducted this by exploring the correct warm-up period.

To find the warm-up time, we let the model run for 8.5 hours, adding a changing label to the average TIS (in seconds) shown in Figure 5.19. Watching the TIS line graph, we noticed that the model's behavior becomes steady at around one and a half hours. So, we set our model's warm-up time to 100 minutes based on this observation.

This 100-minute warm-up period allows the model to stabilize and reach a consistent performance level before the actual data collection or analysis phase begins. Discarding the data collected during the warm-up period ensures that the subsequent statistics are based on a stable and unbiased representation of the model's behavior. This practice enhances the reliability of our results, as it accounts for any transitional phases in the model's operation and helps to produce more accurate and meaningful insights. Additionally, the dynamic plot used during the warm-up exploration provides a visual guide for identifying the point of stabilization,

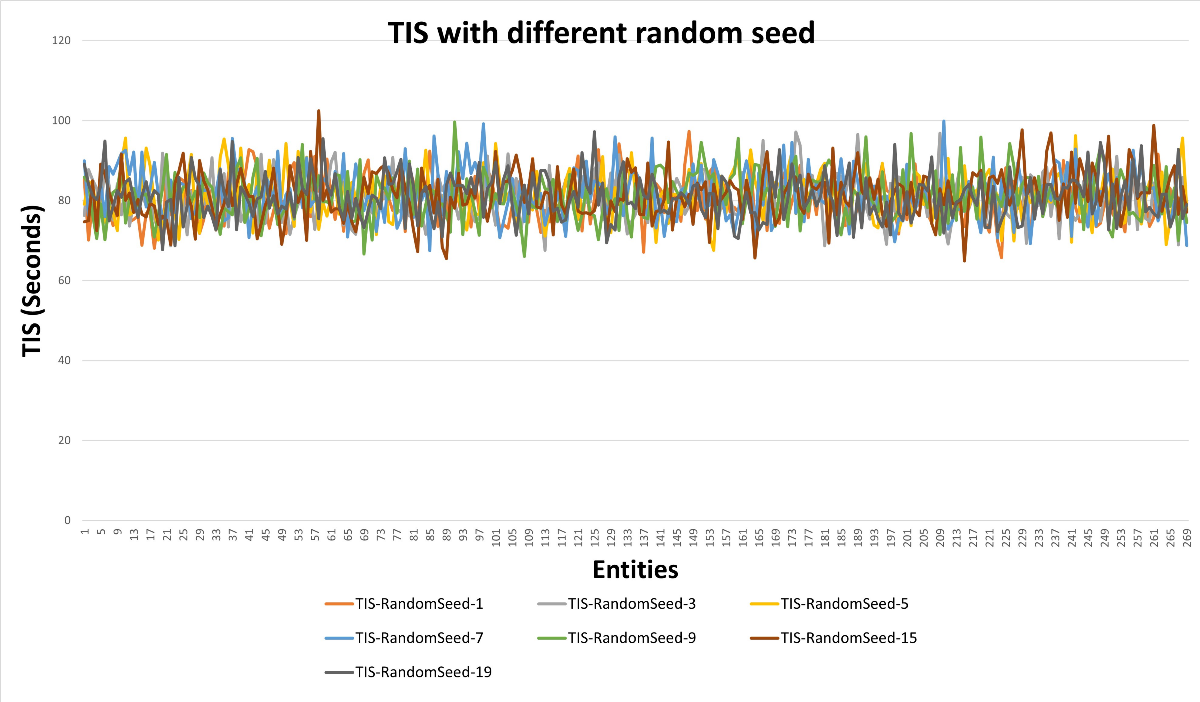


Figure 5.19: Initial bias region of run time of the testing DES model

facilitating an informed decision on the appropriate warm-up time for our specific modeling scenario.

Mathematically, we can predict the appropriate number of replication (n) from the Equation 5.4, where n_0 refers to the applied number of replications, h_0 means the obtained half width and h refers to the expected confidence interval (95%).

$$Replication(n) \approx n_0 \left(\frac{h_0^2}{h^2} \right) \tag{5.4}$$

5.5.3 Model testing for its ideal replications

In this section, we aimed to outline the process that we followed to create an acceptable and validated replication scenario. Having such a scenario is crucial to running our eight different models with unique workflow sequences and exploring the most efficient one with validity. To create this scenario, we selected a model (for workflow S1) and ran it multiple times while varying the number of replications. We used two response statistics, TP and TIS, to measure the performance of each run and recorded the half-width for both TP and TIS. In total, we ran

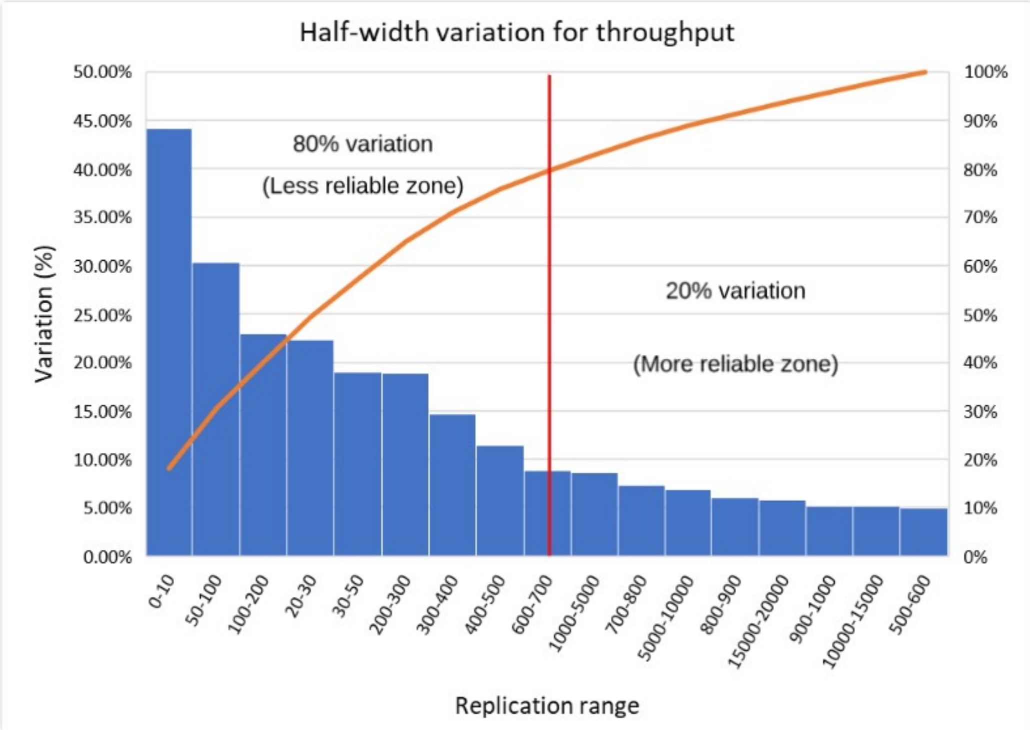


Figure 5.20: Half-Width variation of Throughput (TP) presented through Pareto Analysis across replication ranges

the model for 17 scenarios with replications of 10, 30, 50, 100, 200, 300, 400, 500, 600, 700, 800, 900, 1000, 5000, 10000, 15000, and 20000.

We documented the model outcomes, specifically focusing on TP (Table 5.2) and TIS (Table 5.1), including their respective half-width values. Upon careful examination, we noticed consistent outcomes for TP and TIS across varying replication numbers, indicating no significant differences. Subsequently, we calculated the half-widths and their percentage changes across different replication ranges, as documented in Table 5.3. Interestingly, as the number of replications increased, we observed a notable decrease in the percentage of variation.

To provide a clearer representation, we created Pareto charts for both TP and TIS, visualizing the findings in Figure 5.20 and Figure 5.21. These charts provide a visual representation of how changes in replication range affect the half-width variations for TP and TIS. According to Pareto analysis, the variation decreases significantly at the initial stage but eventually stabilizes after a certain point. Based on both TP and TIS, it appears that replication levels between 800 and 1200 are more reliable.

Table 5.1: TP and its HW across different scenarios

Scenarios	Run time (secs)	TP	Half-width(TP)
10	6.10	7.40000	1.16810
20	10.00	7.39090	0.65310
30	13.30	7.39030	0.50700
50	22.70	7.39382	0.41060
100	45.40	7.39364	0.28620
200	91.10	7.39200	0.22040
300	140.10	7.39164	0.17880
400	185.00	7.39050	0.15260
500	231.70	7.39098	0.13510
600	280.30	7.39127	0.12840
700	335.90	7.39156	0.11710
800	398.70	7.39130	0.10850
900	463.20	7.39109	0.10200
1000	515.00	7.39100	0.09670
5000	4107.70	7.39238	0.08840
10000	6,272.90	7.39266	0.08230
15000	7725.00	7.39275	0.07810
20000	11955.50	7.39280	0.07360

Table 5.2: TIS and its HW across different scenarios

Scenarios	Run time (secs)	TIS	Half-width(TP)
10	6.10	81.00580	0.24530
20	10.00	81.10120	0.13210
30	13.30	81.09780	0.09840
50	22.70	81.05580	0.08190
100	45.40	81.05920	0.05710
200	91.10	81.07190	0.04330
300	140.10	81.07340	0.03480
400	185.00	81.08670	0.02990
500	231.70	81.08200	0.02640
600	280.30	81.07750	0.02500
700	335.90	81.07530	0.02280
800	398.70	81.07770	0.02100
900	463.20	81.08030	0.01980
1000	515.00	81.08120	0.01880
5000	4107.70	81.06670	0.01760
10000	6,272.90	81.06300	0.01640
15000	7725.00	81.06150	0.01520
20000	11955.50	81.06110	0.01410

Table 5.3: Half-width variation for TIS & TP

Replication-range	TP-HW	TIS-HW
0-10	44.09%	46.15%
20-30	22.37%	25.51%
30-50	19.01%	16.77%
50-100	30.30%	30.28%
100-200	22.99%	24.17%
200-300	18.87%	19.63%
300-400	14.65%	14.08%
400-500	11.47%	11.71%
500-600	4.96%	5.30%
600-700	8.80%	8.80%
700-800	7.34%	7.89%
800-900	5.99%	5.71%
900-1000	5.20%	5.05%
1000-5000	8.58%	6.38%
5000-10000	6.90%	6.82%
10000-15000	5.10%	7.32%
15000-20000	5.76%	7.24%

5.5.4 Model testing for its accuracy and verification

After observing the performance of the subjects, it became clear that not everyone followed the same assembly sequence despite receiving the same paperwork instructions. As a result, we conducted an investigation to determine how many different assembly sequences were followed by the subjects. We chose performance data from a subset of 12 subjects from our dataset of 24. We made this selection randomly, taking into account the natural performance of the participants in the first half of the dataset. We excluded the second half of the participants because they were motivated to improve their performance. The performance of the subjects was measured by the number of cars they assembled in ten minutes (Equation 4.4). After recording the videos, we analyzed the workflow sequences and identified 17 distinct sequences used by the subjects while picking and placing parts. Out of the 17, only 8 sequences were

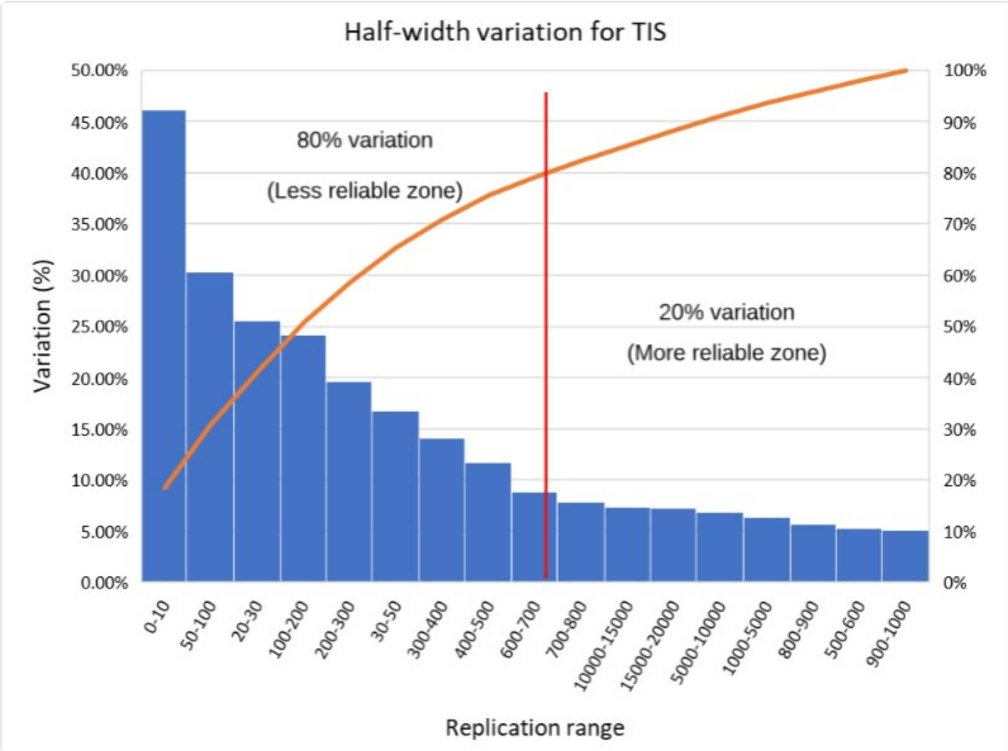
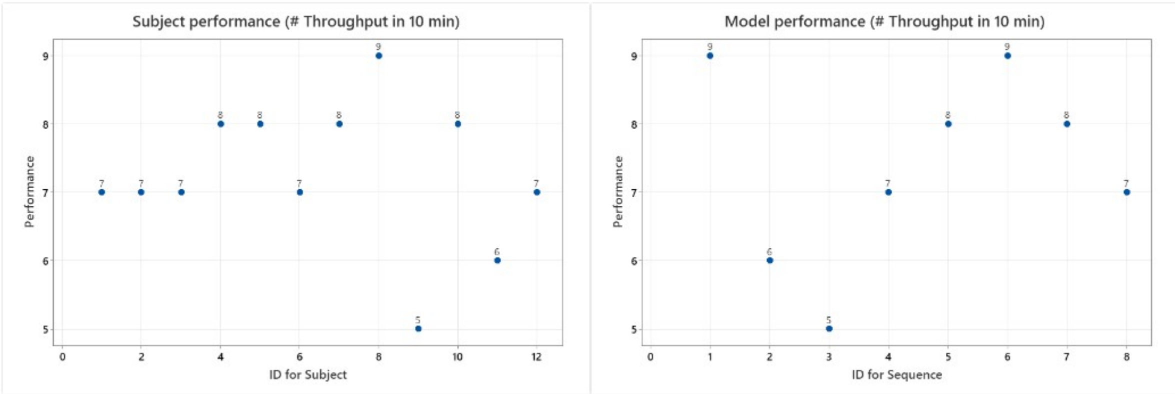


Figure 5.21: Half-Width variation of Time in System (TIS) presented through Pareto Analysis across replication ranges

recurrent and were observed at least 24 times. The remaining sequences were not recurrent more than three times.

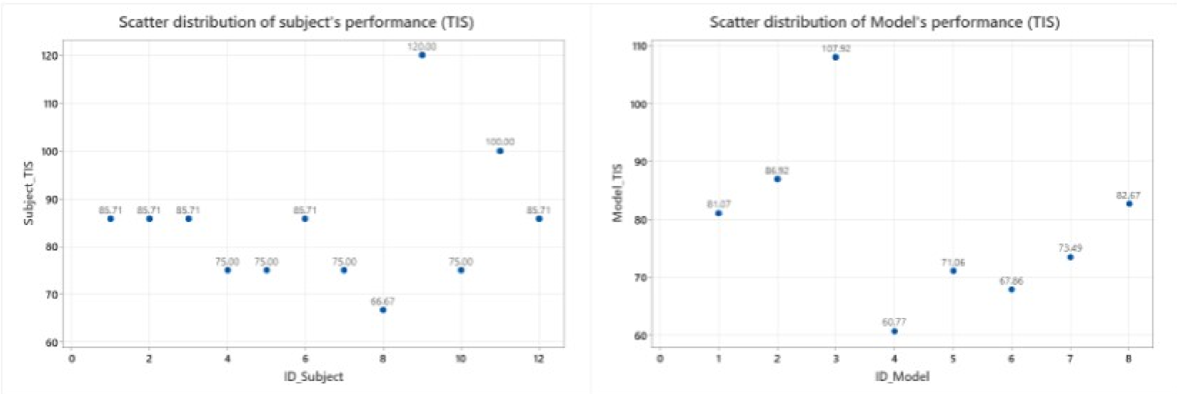
We recorded the time it took to pick up and place each Lego part during the assembly process. As an example, when assembling a car, the subject picked up and placed 18 Lego parts. We assigned these times to each respective part. In DES modeling, each part functions as an individual server. Using the recorded picking and placing times, we constructed a DES model in the Simio environment.

Once the subject's performance has been incorporated into the DES model, it becomes imperative to verify whether the model output significantly differs from the subject or not. This verification is necessary to ensure that the model is accurately mimicking the subject's behavior, which is a key feature of simulation modeling. To accomplish this, we took two steps. First, we constructed scatter plots for easy comparison. The results for TP and TIS were displayed in Figures 5.22 & 5.23. We also observed the mean differences between the outcomes of the model and the actual, as shown in Figure 5.24 & 5.25.



Scatter plots of 12 subject's performance   Scatter plots of 8 model's performance (S1-S8)

Figure 5.22: Distribution plot of model and subject outcomes



A. Subject's performance (TIS)   B. Model's performance (TIS)

Figure 5.23: Performance distribution of model and subject in TIS

After conducting paired t-tests for both TP and TIS, we found p-values higher than the significance level of 0.05, as presented in the tables 5.4 & 5.5.

Table 5.4: Paired comparison with respect to TP

Sample	N	Mean	SE	T-Value	P-value
Subject	8	7.63	0.45	0.26	0.668
Model	8	7.38	0.50		

Table 5.5: Paired comparison with respect to TIS

Sample	N	Mean	SE	T-Value	P-value
Subject	8	79.32	2.60	-0.77	0.466
Model	8	84.35	6.44		

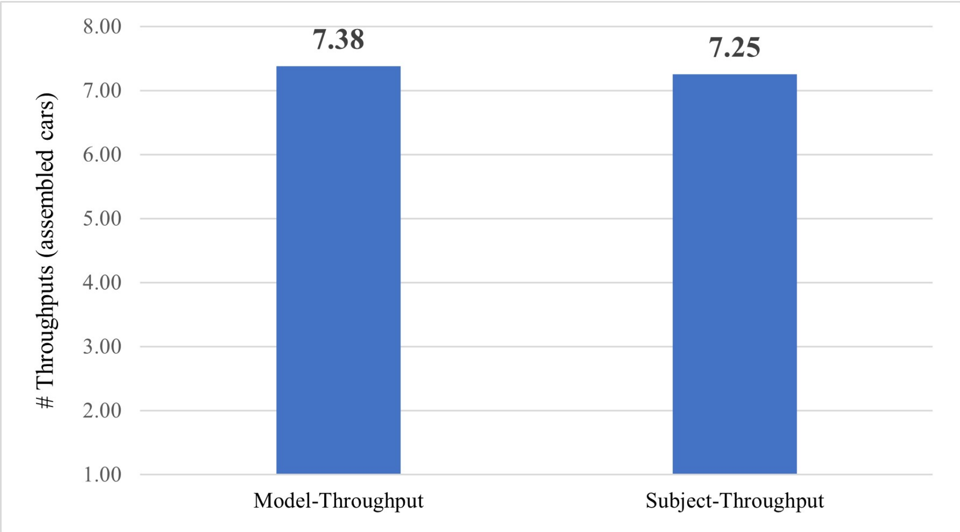


Figure 5.24: Mean difference of model and subject outcomes for TP

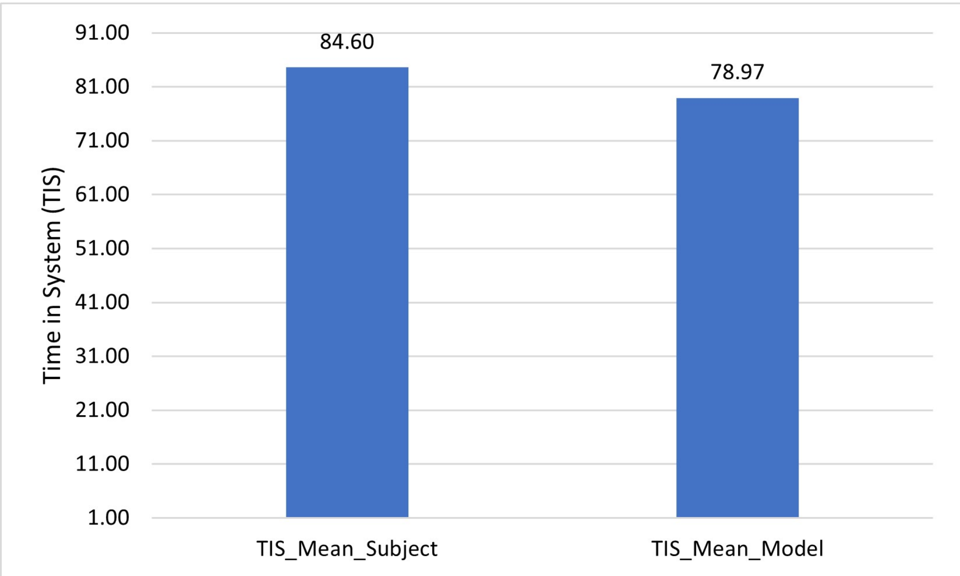


Figure 5.25: Mean difference of model and subject outcomes for TIS

The iterative verification process is important in building trustworthiness and robustness in DES models, ultimately contributing to their effectiveness in various scientific, engineering, and decision-making contexts [233, 239]. In this essence, we aimed to systematically and thoroughly validate the DES model in order to collect enough empirical evidence to instill confidence in the model's accuracy.

We have successfully verified and obtained reliable mimic response of our DES model through both visual and statistical analyses. As a result, we have decided to utilize this DES model to conduct experiments with 1000 replications to gather more information to support our proposed hypothesis. The details of our results are described in the following section.

5.5.5 Determining the processing time distribution of object server instances

The choice of server processing time distributions is a crucial aspect in the accuracy and realism of DES simulations. The selection of a specific distribution, such as triangular, is guided by the need to replicate the inherent variability and unpredictability in real-world processes. Different distributions model varying degrees of uncertainty and variability, and this is why it is essential to choose the appropriate one. To achieve this, we adopt a meticulous approach by scrutinizing historical data, making direct observations, and seeking input from subject matter experts.

This analysis serves as an essential guide, facilitating our comprehensive understanding of the intricate variability in processing times within the system. The workflow and corresponding attributes are documented in Tables 5.6 through 5.13, each corresponding to the distinctive server processing distribution of S1 through S8. These distributions are derived from empirical observations. Each processing distribution refers to each Lego part picking and placing time during the assembling. This expression critically helps to run the model even for thousands of times.

5.6 Results

In this case study, we aimed to improve the process performance by maximizing TP and minimizing cycle time as stated in the equations 5.5 and 5.6, respectively. Several factors might

Table 5.6: Server processing time (sec) for S1

Workflow	Server	Process time
S1	Input@P30L	Random.Triangular(9, 10.3, 16)
S1	Input@P30R	Random.uniform(1.53, 4.24)
S1	Input@P22L	Random.uniform(1.79, 4)
S1	Input@P22R	1.34 + Random.Weibull(1.94, 1.7)
S1	Input@P29L	Random.Triangular(1.79, 2.31, 3.53)
S1	Input@P29R	Random.Normal(2.63, 0.525)
S1	Input@P65F	Random.uniform(1.45, 5.48)
S1	Input@P65B	Random.Uniform(18, 28)
S1	Input@SUB	Random.Triangular(1.68, 2.78, 5.34)
S1	Input@P15L	Random.Triangular(4, 6.07, 14)
S1	Input@P15R	Random.uniform(2, 13)
S1	Input@P28L	Random.uniform(1.18, 4)
S1	Input@P28R	Random.Triangular(1.23, 3.61, 6)
S1	Input@Qcheck	2.46+Random.Gamma(0.484, 3.25)
S1	Input@Sink1	0.00

Table 5.7: Server processing time (sec) for S2

Workflow	Server	Process time
S2	Input@P65F	Random.Triangular(7.38, 9.31, 12)
S2	Input@P30L	Random.Uniform(1.46, 7.64)
S2	Input@P30R	Random.Uniform(8, 19)
S2	Input@P22L	Random.Uniform(1.16, 6)
S2	Input@P22R	Random.Triangular(1.19,2.33,5.98)
S2	Input@P29L	Random.Triangular(1, 2.56, 14)
S2	Input@P29R	Random.Triangular(1.65,2.87,5.72)
S2	Input@SUB	18 + 9 * Random.Beta(0.776, 0.878)
S2	Input@P65B	Random.Triangular(3, 3.75, 8)
S2	Input@P15LR	Random.Triangular(5.77, 6.44, 8)
S2	Input@P28LR	Random.Triangular(3, 5.8, 7)
S2	Input@QCheck	2.46 +Random.Gamma(0.484, 3.25)
S2	Input@Sink1	0.00

effect in improving the performance. However, in this case, we examined the effect of workflow design on increasing TP and reducing TIS, as stated in equations 5.7 and 5.8.

Table 5.8: Server processing time (sec) for S3

Workflow	Server	Process time
S3	Input@P30LR	Random.Triangular(6, 10, 16)
S3	Input@P29LR	Random.Triangular(4, 4.79, 11.9)
S3	Input@P22LR	Random.Uniform(2, 14)
S3	Input@P65F	Random.Triangular(2, 6.5, 11)
S3	Input@SUB	Random.Triangular(13, 15.5, 31)
S3	Input@P65B	Random.Normal(7.03, 2.56)
S3	Input@P15LR	4 + Random.Exponential(3.88)
S3	Input@P28LR	2.47 + Random.Erlang(0.245, 6)
S3	Input@Qcheck	Random.Uniform(4, 11)
S3	Input@Sink1	0.00

Table 5.9: Server processing time (sec) for S4

Workflow	Server	Process time
S4	Input@P30LR	4 + 5.67 * Random.Beta(0.998,1.14)
S4	Input@P29LR65F	Random.Uniform(3.31, 11)
S4	Input@P22LR	Random.Uniform(3.33, 9.61)
S4	Input@SUB	Random.Triangular(14,16.1,35)
S4	Input@P65B	2 + 3.29 * Random.Beta(1.5,2.01)
S4	Input@P28LR	3.28 + 2.72*Random.Beta(1.73,1.24)
S4	Input@P15LR	Random.Triangular(3,5.5,11)
S4	Input@QCheck	Random.Triangular(2,3.41,6.75)
S4	Input@Sink1	0.00

$$TP_{max} = f(Q) \tag{5.5}$$

In the equation: *TP: Throughput; Q: Number of assembled SUV cars*

$$CT_{min} = f(TIS) \tag{5.6}$$

In the equation, *CT: Cycle Time; TIS: Time in System*

$$Q_{max} = f(WL) \tag{5.7}$$

Table 5.10: Server processing time (sec) for S5

Workflow	Server	Process time
S5	Input@P65FB	Random.Triangular(6.24,7.91,11.8)
S5	Input@P29LR	Random.Triangular(3,5.21,9)
S5	Input@P22LR	Random.Uniform(4.06, 9)
S5	Input@P30LR	5 + 5.49 * Random.Beta(1.54,1.91)
S5	Input@SUB	Random.Uniform(19, 33)
S5	Input@P15LR	Random.Triangular(3.24,6.17,10.9)
S5	Input@P28LR	Random.Triangular(3.11,5.55,8)
S5	Input@QCheck	Random.Triangular(2.31,2.95,7.91)
S5	Input@Sink1	0.00

Table 5.11: Server processing time (sec) for S6

Workflow	Server	Process time
S6	Input@P30LR	Random.Triangular(5,6.26,10.5)
S6	Input@P29LR	Random.Uniform(5, 8.96)
S6	Input@P22LR	4.06 + Random.Weibull(2.64,1.93)
S6	Input@P65FB	Random.Uniform(6.24,11.8)
S6	Input@SUB	Random.Triangular(19,21.3,28)
S6	Input@P15LR	Random.Uniform(3.24, 10.9)
S6	Input@P28LR	Random.Uniform(3.14, 7.89)
S6	Input@QCheck	Random.Uniform(2.63, 4.38)
S6	Input@Sink1	0.00

$$TIS_{min} = f(WL) \tag{5.8}$$

In the equation, *WL: Workflow layout*

We employed DES in the investigation to determine whether workflow layout has a significant impact on worker performance. The results of our analysis, presented in the following sections, demonstrate the complex relationship between workflow design, worker performance, and the goals of increasing TP and minimizing cycle time. Our findings provide valuable insights for optimizing processes and refining workflow strategies to achieve greater operational efficiency.

Table 5.12: Server processing time (sec) for S7

Workflow	Server	Process time
S7	Input@P29LR	Random.Triangular(6,10.1,11.5)
S7	Input@P30LR	Random.Triangular(4.77,4.98,7.34)
S7	Input@P22LR	Random.Triangular(4.67,5.79,8.39)
S7	Input@P65F	Random.Triangular(4, 6.1, 7)
S7	Input@SUB	Random.Uniform(19.2, 27.8)
S7	Input@P65B	Random.Triangular(4.87,5.22,6.24)
S7	Input@P15LR	Random.Uniform(5, 9.48)
S7	Input@P28LR	3.22 + 5.33 * Random.Beta(2.56, 1.77)
S7	Input@Qcheck	Random.Triangular(3, 3.3, 6)
S7	Input@Sink1	0.00

Table 5.13: Server processing time (sec) for S8

Workflow	Server	Process time
S8	Input@P30LR	Random.Uniform(8, 19)
S8	Input@P29L	Random.Uniform(1.46, 7.64)
S8	Input@P29R	Random.Triangular(2, 2.21, 4)
S8	Input@P22L	2 + 2.87 * Random.Beta(1.11, 1.66)
S8	Input@P22R	Random.Uniform(2, 4)
S8	Input@P65F	Random.Uniform(2, 9)
S8	Input@P65B	Random.Uniform(2, 9)
S8	Input@SUB	22 + Random.Weibull(6.13, 2.18)
S8	Input@P15L	Random.Triangular(1, 3.93, 11)
S8	Input@P15R	Random.Uniform(1.01, 8.8)
S8	Input@P28L	1.27 + Random.Weibull(1.67, 1.9)
S8	Input@P28R	Random.Triangular(1.23, 3.61, 6)
S8	Input@Qcheck	2.46 +Random.Gamma(0.484, 3.25)
S8	Input@Sink1	0.00

5.6.1 Visual analysis of DES model outcomes

In our study, we have developed eight DES models corresponding to distinct workflows (S1-S8). Employing trade-off analysis, we identified several robust scenarios. From these, we specifically selected scenarios for which we conducted 1000 replications. The DES models

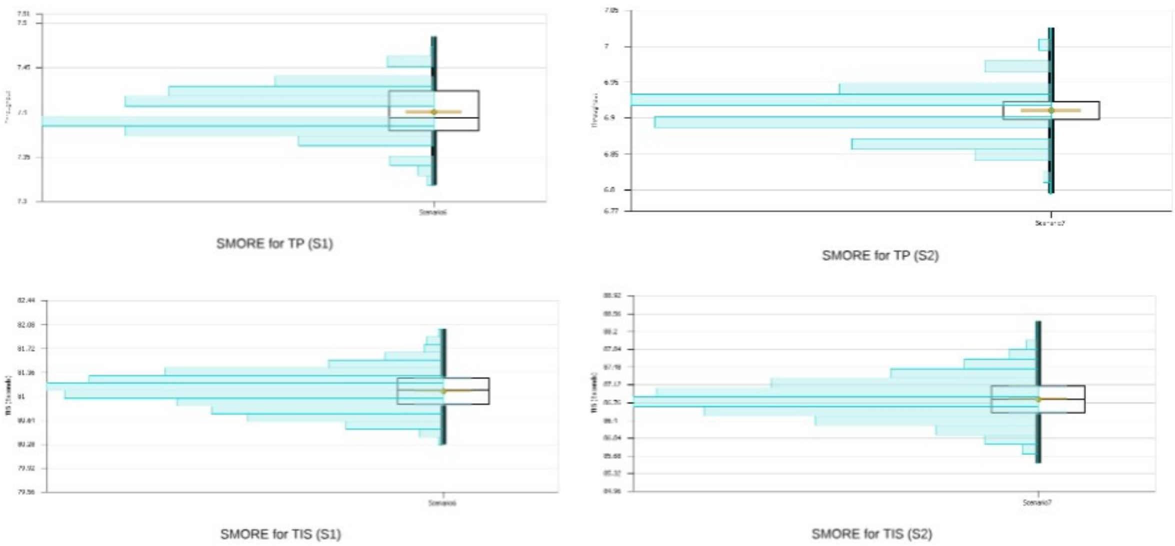


Figure 5.26: SMORE visual for half-width inspection of Throughput (TP) and Time in System (TIS) (S1 & S2)

were executed, generating results in two response variables: TP and TIS. This section focuses on scrutinizing the mean difference observed in both TP and TIS across the selected scenarios.

We examined the central tendency of TP and TIS by using the Simio Measure of Risk and Error (SMORE) plots developed by Barry Nelson [240]. A SMORE plot displays the central tendency of run results using its mean and half-width, as shown in Figures 5.26, 5.27, 5.28, & 5.29 for this study. From this visual, it is apparent that with 1000 iterations data shows a consistence results both for TP and TIS.

We have created bar diagrams to display Total Processing (TP) and Time in System (TIS) for each workflow. The diagrams are shown in Figure 5.30 & 5.31. We observed that Workflow-S4 has lower TIS and higher TP compared to the other workflows. This finding indicates that Workflow-S4 may have more efficient processing times and productivity, which demonstrates its potential advantages in the context of our study. However, the performance of S4 needs to be verified through statistical analysis conducted in the following subsections on hypothesis testing.

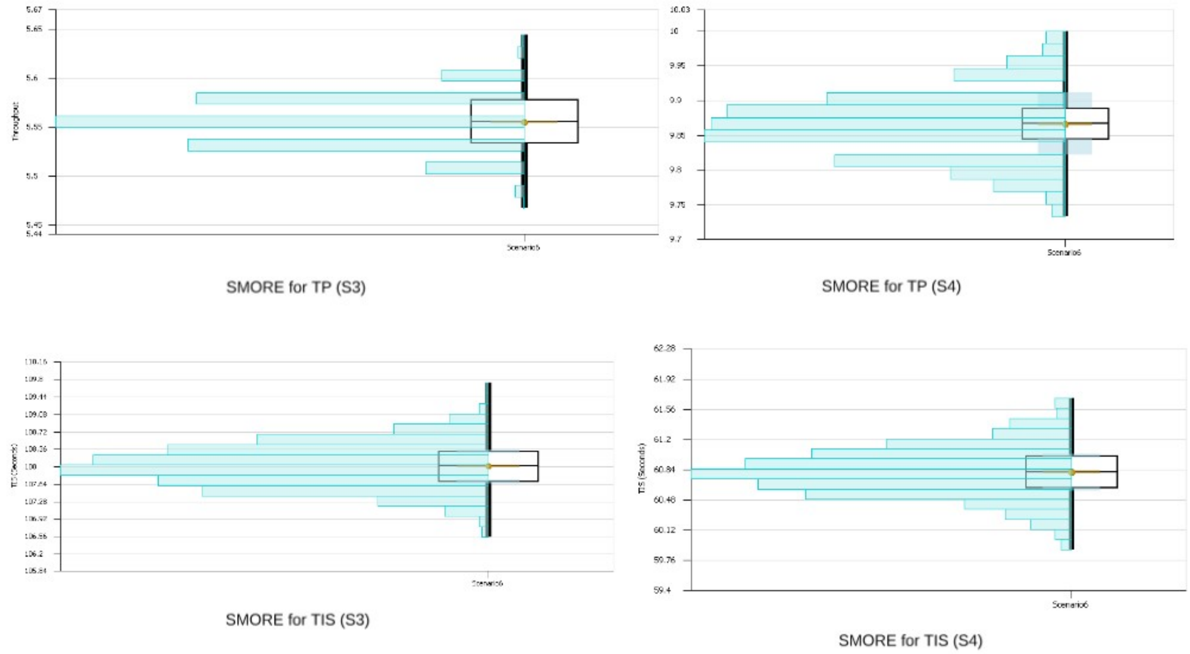


Figure 5.27: SMORE visual for half-width inspection of Throughput (TP) and Time in System (TIS) (S3 & S4)

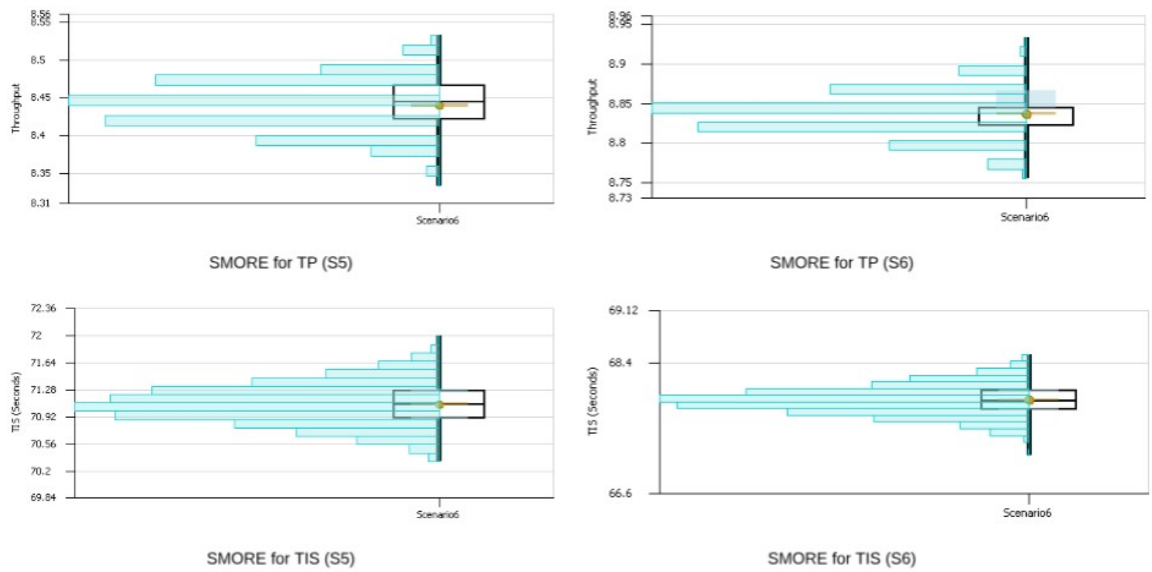


Figure 5.28: SMORE visual for half-width inspection of Throughput (TP) and Time in System (TIS) (S5 & S6)

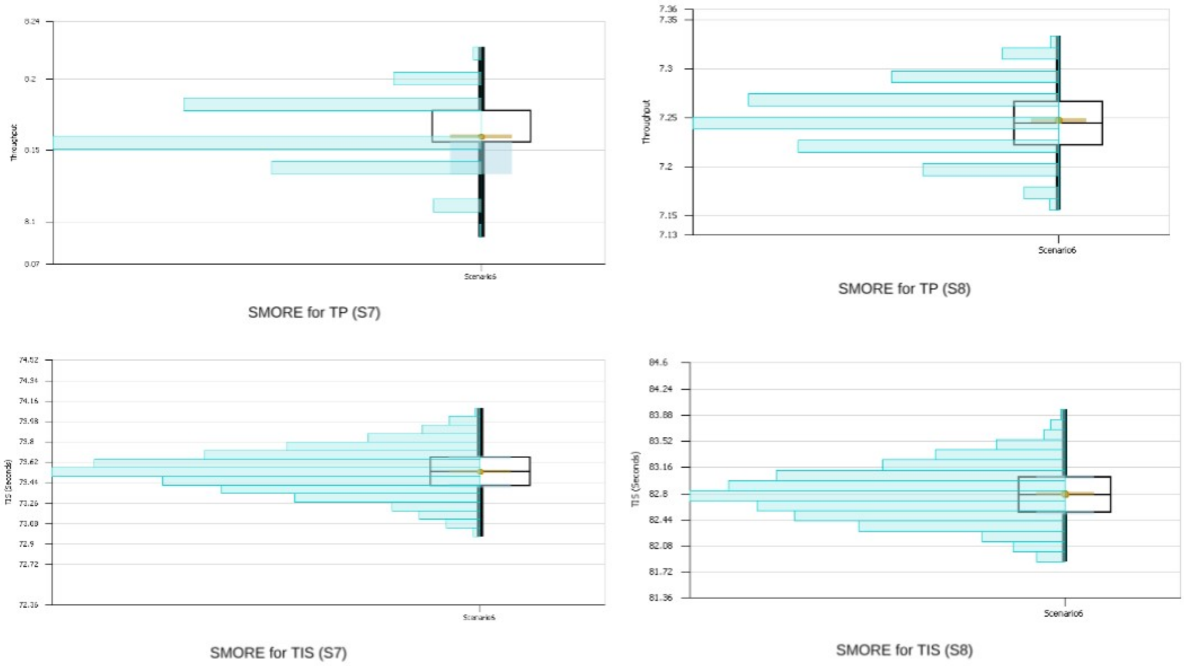


Figure 5.29: SMORE visual for half-width inspection of Throughput (TP) and Time in System (TIS) (S7 & S8)

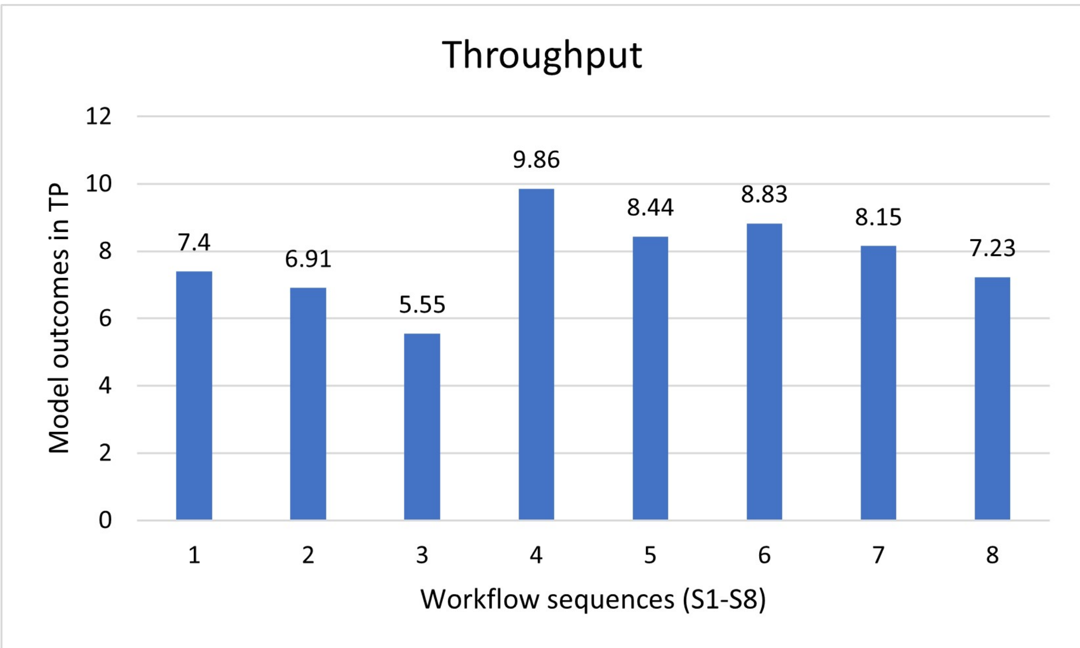


Figure 5.30: Average model outcomes in Throughput (TP) for eight workflows (S1-S8)

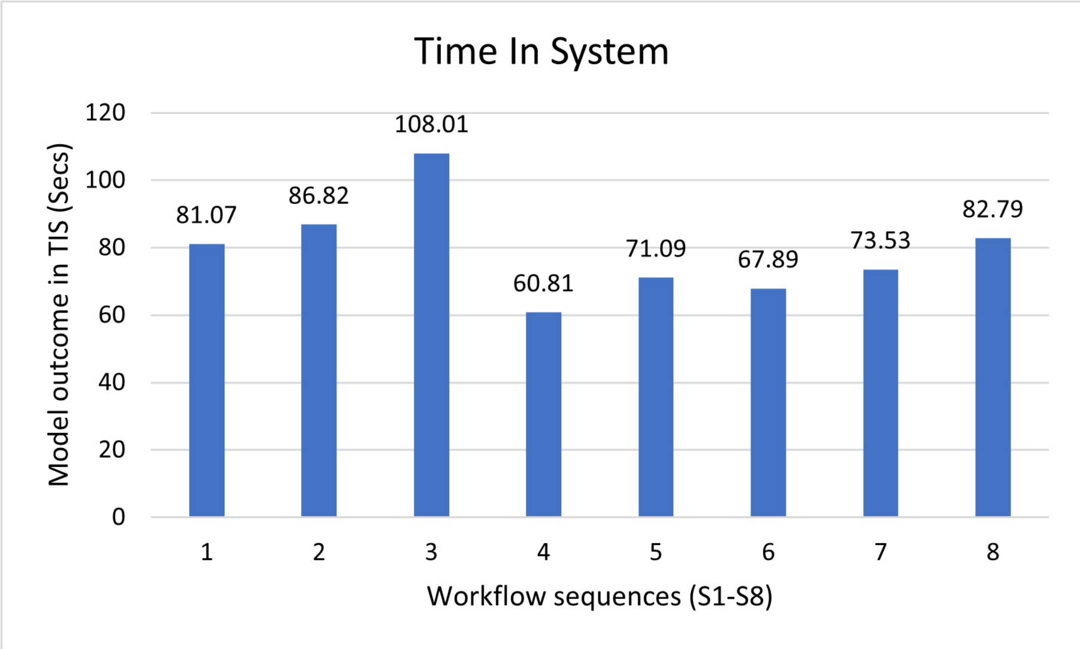


Figure 5.31: Average model outcomes in Time In System (TIS) for eight workflows (S1-S8)

5.6.2 Testing hypothesis-1

This section aims to demonstrate the evidence of whether we could fail to reject our null first hypothesis or not. Our first null hypothesis was - *'The implementation of a balanced workflow does not have a significant impact on the maximization of throughput in a manufacturing setting.'* For this, we conducted the one-way ANOVA for both TP, as shown in Table 5.14.

The results show that for TP, the obtained p-value is higher than the significance level ($\alpha = 0.05$).

Table 5.14: ANOVA for Throughput (1000 Iterations)

Sources	DF	Sum of SS	Mean Sq.	F-Value	P-value
Workflow level	7	12181.2	1740.17	173.24	0.001*
Error	7992	8.00	0.00		
Total	7992	12189.20			

The Table 5.15 documents mean results of 1000 iterations for eight workflows' TP performance, including a 95% confidence interval.From both Tables 5.15 & 5.14, the tabulated results show that there is a significant difference among the workflows' performance. However, we need to determine which workflow layouts are significantly dissimilar from one another, considering that we conducted the Tukey pairwise comparison test. The Tukey grouping information is depicted in Figure 5.32, which reveals that the performance of each workflow is significantly different from the others. Specifically, to know which workflow is significantly higher than others, we conducted the Tukey comparison test. The grouping information using the Tukey method with 95% confidence interval as shown in Figure 5.32. The different letters in grouping information indicate that each workflow is significantly different from the others. In particular, S4 has a significantly higher value than the others.

After a thorough analysis of the statistical data, we reject the null hypothesis. Our findings lead us to conclude that the sequences of workflow significantly contribute to the improvement in productivity on the manufacturing floor.

Table 5.15: Analysis of variance of TP

Workflow level	N	Mean	95 % C.I.
S1	1000	7.403	(7.391, 7.405)
S2	1000	6.910	(6.896, 6.911)
S3	1000	5.554	(5.549, 5.563)
S4	1000	9.866	(9.864, 9.879)
S5	1000	8.439	(8.446, 8.461)
S6	1000	8.837	(8.833, 8.848)
S7	1000	8.159	(8.157, 8.171)
S8	1000	7.247	(7.246, 7.261)

5.6.3 Testing hypothesis-2

This section aims to provide evidence of whether we can or cannot reject our second null hypothesis - *The implementation of a balanced workflow does not have a significant impact on the minimization of cycle time in a manufacturing setting.* We performed a one-way ANOVA analysis for TIS and the results are displayed in the table 5.16. It is noted that TIS was defined as the cycle time of our experimental manufacturing system.

From both Tables 5.16 & 5.17, the tabulated results show that there is a significant difference among the workflows' performance. However, we need to determine which workflow

Grouping Information Using the Tukey Method and 95% Confidence

Model_ID	N	Mean	Grouping
4	1000	9.86647	A
6	1000	8.83711	B
5	1000	8.43980	C
7	1000	8.15936	D
1	1000	7.40039	E
8	1000	7.24727	F
2	1000	6.91064	G
3	1000	5.55484	H

Means that do not share a letter are significantly different.

Figure 5.32: Grouping information using the Tukey method for TP

layouts are significantly dissimilar from one another, considering that we conducted the Tukey pairwise comparison test.

The Tukey grouping information, as illustrated in Figure 5.33, indicates that each workflow is significantly different, as each group belongs to a unique letter. Nonetheless, of all the workflows, S4 had the lowest TIS in comparison to others.

After analyzing the statistical data, we reject the null hypothesis and conclude that workflow sequences significantly impact cycle time reduction in manufacturing.

Table 5.16: ANOVA for Time In System (1000 Iterations)

Sources	DF	Sum of SS	Mean Sq.	F-Value	P-value
Workflow (S1-S8)	7	1468197.00	209742.00	213.65	0.001*
Error	7992	785.00	0.00		
Total	7992	1468982.00			

5.7 Discussion

In this section, we have discussed two main topics. First, we have presented the overall findings of the study conducted in the Lean Manufacturing Lab. Second, we have explained how our study represents real-life scenarios and how it could be beneficial to the manufacturing community, especially in terms of integrating DES model in a balanced workflow design.

Table 5.17: Analysis of variance of TIS

Workflow (S1-S8)	N	Mean (hrs)	95 % C.I.
S1	1000	81.08	(81.05, 81.09)
S2	1000	86.82	(86.81, 86.85)
S3	1000	108.01	(107.99, 108.03)
S4	1000	60.79	(60.79, 60.83)
S5	1000	71.09	(71.07, 71.11)
S6	1000	67.89	(67.87, 67.91)
S7	1000	73.55	(73.51, 73.55)
S8	1000	82.79	(82.77, 82.81)

Grouping Information Using the Tukey Method and 95% Confidence

Model_ID	N	Mean	Grouping
3	1000	0.030004	A
2	1000	0.024118	B
8	1000	0.022998	C
1	1000	0.022522	D
7	1000	0.020427	E
5	1000	0.019748	F
6	1000	0.018859	G
4	1000	0.016893	H

Means that do not share a letter are significantly different.

Figure 5.33: Grouping information using the Tukey method for TIS

5.7.1 The impact of a balanced workflow on productivity and cycle time

Efficient workflows are crucial in the manufacturing industry for achieving productivity and efficiency. The literature also emphasizes the importance of optimizing workflows [211, 214, 210]. In our study, we demonstrated how to use the DES model to achieve a balanced workflow in assembly. We identified eight different workflows used by research subjects who were employed for assembling the SUV cars using Lego parts. Then, we used their performance data in the DES modeling to replicate the subject's behavior under different scenarios. Our study helped us obtain the most efficient workflows, as we demonstrated in the previous result sections. TP, a key performance indicator that reflects the rate of output production within a given time frame, was the primary metric we considered. Also, we measured the TIS metric to identify the efficient workflow.

The identified eight workflows were run 1000 times in a virtual environment using a tested and validated DES model. Then, their performances were evaluated with two measuring metrics - TP and TIS. After conducting a thorough analysis, it has become apparent that each workflow is significantly different than others in terms of their performance metrics (TP & TIS). However, among them, the workflow denoted with S4 was the most efficient, with its higher TP (9.87 SUV cars in 10 mins) and lowest TIS (60.77 secs), as evident in Table 5.15 and 5.17.

The analysis of SMORE plots helped to understand the performance of the models better. These plots visually represent critical statistical measures such as mean, median, and half-width. This aids in a more intuitive understanding of the variability and distribution of DES model outcomes. We also enhanced the accuracy of the analysis by examining the variance of outcomes. Analyzing variance is essential as it helps to understand the variability within the data, which is crucial in assessing the reliability and consistency of DES model outcomes. By considering the mean values and confidence intervals together, we can gain a nuanced perspective of the precision of each workflow's performance in different scenarios. This examination of variance strengthens the findings and provides a strong foundation for decision-making in DES modeling.

The comparison of performance metrics involved an analysis of variance, revealing a significant difference among the eight workflows (S1-S8). However, a more detailed comparison analysis was necessary to identify which workflow is superior. The Tukey pairwise comparison method was employed for this purpose. The Tukey grouping comparison results reveal that a specific workflow denoted with S4 gives the most efficient layout for maximizing the TP and minimizing the TIS or the cycle time.

This study shows that a balanced workflow layout plays a crucial role in enhancing productivity and achieving an efficient cycle time. The literature has extensively explored the relationship between workflow and productivity improvement, shedding light on various factors influencing organizational efficiency [241, 242, 243]. However, despite the existing body of knowledge, there is still a noticeable gap in the research, particularly in the application of DES to comprehensively investigate the balanced workflow by employing necessary trade-off analysis.

While previous studies have delved into the broad implications of workflow on productivity, the utilization of DES remains relatively unexplored in the context of achieving a balanced workflow. As a powerful analytical tool, DES can provide a dynamic simulation environment to model intricate manufacturing processes and assess the impact of different layout configurations on productivity, identifying potential trade-offs between competing factors such as cost, time, and resource utilization.

In this essence, our study aims to fill this research gap by employing DES to explore the nuances of a balanced workflow and conducting a thorough trade-off analysis. By doing so, we seek to contribute valuable insights to the manufacturing community, offering a practical example of how DES can be applied to enhance workflow efficiency. Through examining various layout configurations and their associated trade-offs, our findings aim to provide actionable recommendations for organizations striving to optimize their workflow and achieve a harmonious balance between priorities.

This study adds to the theoretical understanding of workflow dynamics and offers practical implications for manufacturing practitioners. As industries continue to evolve and adapt to changing market demands, the insights derived from this research can guide decision-makers in making informed choices when designing and optimizing their workflow layouts. Ultimately, integrating DES in studying balanced workflows contributes to advancing the field, providing a foundation for future research endeavors, and fostering continuous improvement in manufacturing practices.

5.7.2 The implication of the DES modeling in exploring an efficient balance workflow

Although our study was conducted in a laboratory setting, it closely mirrors the challenges encountered in automotive manufacturing. Similar problems are common in manufacturing, which is becoming increasingly competitive and demanding. The industry now requires enhanced efficiency and zero-defect production. To achieve this goal, our study aimed to showcase a case study that illustrates the application of I-4.0 technology. In particular, we demonstrated how DES can be utilized to design an efficient production process with a balanced workflow in manufacturing. This exploration aligns with the industry's pursuit of cutting-edge technologies to optimize processes and meet the demands of modern manufacturing standards.

Many authors have highlighted the importance of maintaining a balanced workflow in literature. In a study [244], it was revealed that a well-balanced workflow plays a crucial role in reducing workers' workload and stress levels. The study also pointed out that workers employed in assembly lines are at a higher risk of developing work-related musculoskeletal disorders and ergonomics issues.

In another study [245], it is explained that when workloads are not distributed properly, it can lead to decreased performance in assembly lines and cause injuries to workers, resulting in high costs for workers' compensation and absenteeism. In addition, ergonomics problems and musculoskeletal disorders can negatively impact product quality and productivity [246].

Several studies support that implementing balanced workflow practices can increase job satisfaction and improve a company's profitability and brand value. For example, in a study conducted by authors Thun, Lehr, and Bier-wirth [247], they surveyed over 55 automotive industries in Germany to investigate the correlation between a balanced workflow that considers ergonomic aspects and a company's economic and social performance. The study found that a higher implementation of work-oriented ergonomic practices is linked to better economic and social performance in manufacturing. This emphasizes the importance of technology in analyzing ergonomic factors.

DES is instrumental in designing a balanced workflow and introducing dynamism into the value stream production. As highlighted in a study by Samant et al. [248], value stream mapping, a traditional approach, is inherently static, which may not effectively capture the dynamic nature of modern manufacturing systems. The manufacturing landscape is evolving towards increased dynamism, with varying demand, resource fluctuations, and changing production requirements. In response to these dynamic challenges, DES become essential for their ability to model and simulate complex, real-time scenarios. Manufacturers can dynamically assess and optimize their processes by employing DES in workflow design and value stream production. This allows for a more responsive and adaptive production system, aligning with the evolving demands of the contemporary manufacturing environment.

In the real world, money often comes down to testing out different options and determining the best one. However, through the advancement of I-4.0 and thus the DES, it is now easier to replicate the real world virtually and test various scenarios to determine the best option. In this case study, we have demonstrated how DES can be utilized to manage a balanced workflow on the production floor. The critical message to the scientific and manufacturing communities is to incorporate DES to enhance the existing production process and create a new one. A balanced workflow can lead to an optimized production process with reduced idle time and efficient utilization of resources.

Although the literature contains several examples of similar cases, they are still limited. In automotive manufacturing, where precision and timing are critical, a balanced workflow has a direct impact on production output and overall operational efficiency. A balanced workflow helps avoid delays, reduces the risk of mistakes, and ultimately enhances the competitiveness of the manufacturing process [247]. A well-balanced workflow leads to improved resource optimization and cost-effectiveness.

This research significantly contributes to the optimization of SUV car assembly processes, offering practical implications for the automotive manufacturing industry. By highlighting the importance of a balanced workflow, our findings underscore the critical role it plays in achieving heightened efficiency and productivity. As the automotive sector continues to evolve, embracing these insights can guide industry practitioners in making informed decisions to enhance their assembly processes and ultimately contribute to the overall advancement of automotive manufacturing practices.

In conclusion, our in-depth analysis of eight distinct workflows involved in SUV car assembly has yielded valuable insights into their performance across various scenarios. Through meticulous examination and employing advanced statistical methods for variance and comparative analyses, we have successfully pinpointed the most efficient workflow among the options considered.

5.8 Summary

In this comprehensive study, our primary objective was to assess the performance of eight distinct workflows integral to the assembly of SUV cars, with a specific focus on two critical metrics: TP and TIS. To accomplish this, we developed a DES model within a controlled laboratory environment, incorporating the same eight workflows utilized by students.

The validation of our DES model involved leveraging performance data obtained from the second phase of this dissertation. In that phase, 12 randomly selected participants actively engaged in the assembly of cars, allowing us to record precise assembly times at various stages within each workflow. These recorded times served as the basis for the model's server processing time, creating a representative and dynamic simulation environment.

Subsequently, we utilized the Simio DES model to generalize the assembly processes, ensuring their accurate representation within our simulation. Rigorous testing was then conducted to align the model with the actual performance of the subjects, providing a crucial verification step. The model underwent simulation for a diverse array of scenarios, spanning 10 to 20,000 replications in 17 intervals. Notably, the analysis demonstrated reliable performance, as evidenced by the limited half-width, reinforcing the credibility of our findings.

In the final phase, we designed and executed experiments encompassing 1,000 replications for each of the eight workflows. This meticulous approach facilitated a comprehensive evaluation of their performance, allowing us to identify and highlight the most efficient workflow among the options under consideration.

We conducted both visual and quantitative statistical analyses to determine the best performance among eight workflows labeled S1 through S8. Through the analysis, we found that the performances of the studied workflow layouts were significantly different from each other. Among these, the workflow labeled S4 was found to be the most efficient, with a throughput of 9 units every 10 minutes and an average TIS of 60.77 seconds across five different scenarios.

This highlights the importance of considering workflow layout design for achieving the most efficient process design.

The study highlights the significance of a well-balanced workflow in automotive manufacturing, emphasizing how it leads to streamlined production, minimized idle time, and efficient resource utilization. The research findings not only optimize the assembly processes of SUV cars but also underscore the importance of a balanced workflow in achieving productivity and efficiency in automotive manufacturing.

To sum up, this comprehensive analysis provides valuable insights into the optimal workflow for SUV car assembly, enhancing overall efficiency and productivity. The study contributes not only to the specific field of automotive manufacturing but also highlights the broader importance of a balanced workflow in achieving operational excellence in complex manufacturing processes.

Chapter 6

Conclusion

This section aims to highlight the three key contributions of the doctoral research study. In the following subsections, the contributions, limitations, and plans for future works of the three studies were outlined.

6.1 Contributions

In the first study, we introduced a novel conceptual framework aimed at integrating I-4.0 technologies into LP systems. In the current literature, there is a limited number of studies on integrating I-4.0 technologies into LP systems. The existing studies on this topic lack direction on how I-4.0 can be integrated into the LP effectively and efficiently. Also, we discovered the proposed framework's lack of validation. In this essence, we attempted to address these gaps, propose a contextual integration framework, and validate it through prototype and DES modeling. Our study fills this gap. This delineation provides practitioners with valuable insights for selecting tools and technologies that mutually enhance the performance of manufacturing floors.

The first study, as we demonstrated in Chapter 3, proposed a conceptual framework delineating how I-4.0 can be effectively integrated with the LP system. In Chapter 3, we depicted the six distinct phases encompassed by this framework, ranging from the initial planning stages to the seamless integration of I-4.0 into the LP system. This comprehensive framework is anticipated to serve as a practical blueprint for industry practitioners seeking to embrace the synergies between I-4.0 and LP, providing a structured guide for implementation. Moreover, the study delved into identifying and integrating key driving factors essential for successfully incorporating I-4.0 technologies into production processes. Additionally, we addressed potential challenges that may arise during this integration, offering insights into mitigating strategies. By integrating theoretical foundations with practical considerations, the study contributes to the growing body of knowledge on efficiently integrating I-4.0 principles into existing production floor systems, fostering adaptability, efficiency, and innovation in manufacturing settings.

In the second study, we attempted to apply the proposed integration framework. We defined the Lean Education Automotive Lab of the Industrial and System Engineering Department of Auburn University as a small manufacturing floor to do this. Theoretically, we outlined the Automotive Lab as a small manufacturing organization and implemented the proposed framework. We defined four treatments, namely 'Control,' 'Lean,' 'Industry 4.0', and 'Lean & Industry 4.0'. We conducted the interaction between 'Lean' and 'Industry 4.0' and measured their combined interaction. By offering a practical strategy and demonstrating its effectiveness within an educational manufacturing setting, our study serves as a robust validation for professionals and researchers involved in similar fields. This empirical evidence underscores the efficacy of our proposed integration approach, contributing to the body of knowledge in integrating I-4.0 into LP systems in a real-world manufacturing environment. More specifically, our demonstration showed how Lean's mistake-proofing and I-4.0's vision technology can be integrated to improve manufacturing productivity and efficiency.

In our third study, we aimed to determine how a balanced workflow can enhance productivity and improve cycle time efficiency. By utilizing DES modeling, we discovered that a balanced workflow layout has a significant impact on productivity, which we measured in TP. We also found that a balanced workflow contributes significantly to achieving efficient cycle time. In conclusion, we want to send a message to the manufacturing community that a balanced workflow layout is essential to remain competitive in the global manufacturing industry, and this can be achieved through the successful integration of DES modeling.

6.2 Limitations

In our first study, we investigated the incorporation of I-4.0 technologies into LP systems. We primarily concentrated on three databases and analyzed journal articles and conference proceedings. However, valuable insights were unintentionally excluded from diverse sources such as books, blogs, and industrial reports. The small sample size of articles on this emerging topic suggests the need for broader exploration and more robust validation. Furthermore, the content validity of our proposed conceptual framework has yet to be evaluated without incorporating expert opinions, indicating the possibility for future refinement.

In our second study, we validated our conceptual framework by examining a sample of 48 subjects. However, it is important to note that the sample size was relatively small, so the findings must be interpreted cautiously before generalization. The study found an interesting relationship between the order of treatment and OEE, with the third and fourth orders particularly prominent. This suggests that the subjects' experience may play a significant role in determining treatment effectiveness. This proposition needs further investigation to understand better the complex relationship between subject expertise and treatment outcomes. During our experiment, the participant was required to pick up and place 18 Lego parts. Although they were provided with similar paperwork instructions, they followed different sequences when assembling the parts. However, we did not explore whether the order of the workflow has an impact on enhancing productivity and efficiency. Finally, we want to mention that this study was limited to laboratory settings and not real-world manufacturing applications.

In our third study, we utilized Discrete Event Simulation (DES) to improve the assembly process of Lego parts for SUVs. This allowed us to gain valuable insights into creating a balanced workflow in automotive manufacturing. However, we must acknowledge that our study has certain limitations. Firstly, we conducted the DES experiments based on a small sample size, which may affect the generalizability of our findings. Therefore, it would be beneficial to verify our model with a larger dataset to improve the validity of our results. Secondly, we did not consider the movements of the worker's hands, even though they did not walk or move. This means that we may have underestimated the physical demands of the task. Furthermore, we did not gather any data on the subject's workload through surveys or interviews, which may have provided us with additional insights.

6.3 Future work

We are advocating for a comprehensive and multifaceted approach to address the limitations identified in our studies. In our initial investigation into integrating I-4.0 technologies into LP systems, we recognized the significance of diversifying data sources as a crucial step. Our proposed strategy involves incorporating insights from a range of channels, including books, blogs, and industrial reports. This deliberate diversification aims to capture a more holistic understanding of the intricate integration process. By drawing from various sources, we seek to avoid inadvertent constraints on our analysis and ensure that our exploration benefits from a broader spectrum of literature. This multifaceted approach is integral to enhancing the robustness and inclusivity of our research, allowing us to derive insights that encapsulate the richness and complexity inherent in integrating I-4.0 technologies into LP systems.

In our second study, we validated our conceptual framework by analyzing a sample comprising 48 participants. However, the identified limitation of a relatively small sample size prompts a critical consideration for future research endeavors. It is imperative to prioritize the recruitment of a more extensive sample to enhance the statistical reliability of our findings. This expansion in sample size is crucial for robust and generalized conclusions. Furthermore, our future research direction involves delving into the nuanced influence of subject experience on treatment effectiveness. To comprehensively understand this intricate relationship, larger sample sizes, and longitudinal designs may be necessary. Such an approach is essential for thoroughly exploring how treatment order interacts with operational OEE over time, adding depth and context to our insights. We plan to extend our work to explore the impact of workflow layout on productivity and efficiency improvements and implement this lab setting in real-life manufacturing environments.

For the third study, we utilized DES to improve the assembly of Lego parts for SUV cars. However, we discovered that due to the limited distribution of data in our DES modeling, it may not be as applicable in real-world scenarios. To make our findings more practical, we have planned to expand our dataset by collecting more diverse and extensive data. This expansion will help us better understand the optimal sequence for Lego assembly and address the identified limitations. We have planned to provide a more robust and practical application of our DES model findings in real-world scenarios. Our ultimate objective is to refine and extend our DES model findings to offer a more robust and practically applicable solution for real-world scenarios. This expansion of data and subsequent refinement will contribute to the continued evolution of DES in optimizing assembly for automotive manufacturing. Besides, we plan to extend our research to other manufacturing industries that use similar processes for assembly or process improvement by incorporating DES model.

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Appendices

Appendix A

Random Treatments Assign to Subjects

Treatment design for subject assignment-first slot

# Subjects	First treatment	Second treatment	Third treatment	Fourth treatment
1	I4T+LT	PWI	I4T	LT
2	LT	PWI	I4T+LT	I4T
3	I4T	I4T+LT	LT	PWI
4	I4T+LT	PWI	LT	I4T
5	I4T+LT	I4T	LT	PWI
6	PWI	LT	I4T	I4T+LT
7	I4T	PWI	I4T+LT	LT
8	I4T	PWI	LT	I4T+LT
9	I4T+LT	LT	I4T	PWI
10	I4T	LT	I4T+LT	PWI
11	PWI	LT	I4T+LT	I4T
12	I4T+LT	LT	PWI	I4T
13	PWI	I4T+LT	I4T	LT
14	LT	I4T+LT	I4T	PWI
15	PWI	I4T+LT	LT	I4T
16	LT	I4T+LT	PWI	I4T
17	LT	I4T	PWI	I4T+LT
18	LT	I4T	I4T+LT	PWI
19	PWI	I4T	I4T+LT	LT
20	LT	PWI	I4T	I4T+LT
21	I4T	LT	PWI	I4T+LT
22	PWI	I4T	LT	I4T+LT
23	I4T	I4T+LT	PWI	LT
24	I4T+LT	I4T	PWI	LT

Note: In the table, four letter codes are used representing four study's parameters.
PWI: Paper work instructions
LT: Lean Tool
I4T: Industry 4.0 Technology
I4T+LT: Industry 4.0 Technology and Lean Tool

Figure A.1: Random treatments assigned to subjects-first slot

Treatment design for subject assignment-second slot

# Subjects	First treatment	Second treatment	Third treatment	Fourth treatment
25	I4T+LT	PWI	I4T	LT
26	LT	PWI	I4T+LT	I4T
27	I4T	I4T+LT	LT	PWI
28	I4T+LT	PWI	LT	I4T
29	I4T+LT	I4T	LT	PWI
30	PWI	LT	I4T	I4T+LT
31	I4T	PWI	I4T+LT	LT
32	I4T	PWI	LT	I4T+LT
33	I4T+LT	LT	I4T	PWI
34	I4T	LT	I4T+LT	PWI
35	PWI	LT	I4T+LT	I4T
36	I4T+LT	LT	PWI	I4T
37	PWI	I4T+LT	I4T	LT
38	LT	I4T+LT	I4T	PWI
30	PWI	I4T+LT	LT	I4T
40	LT	I4T+LT	PWI	I4T
41	LT	I4T	PWI	I4T+LT
42	LT	I4T	I4T+LT	PWI
43	PWI	I4T	I4T+LT	LT
44	LT	PWI	I4T	I4T+LT
45	I4T	LT	PWI	I4T+LT
46	PWI	I4T	LT	I4T+LT
47	I4T	I4T+LT	PWI	LT
48	I4T+LT	I4T	PWI	LT

Note: In the table, four letter codes are used representing four study's parameters.
PWI: Paper work instructions
LT: Lean Tool
I4T: Industry 4.0 Technology
I4T+LT: Industry 4.0 Technology and Lean Tool

Figure A.2: Random treatments assigned to subjects-second slot

Appendix B

Code sheet

Code Sheet

Part. #	Date	Name	Email	Phone	Assigned	Notes
					1 2	
					1 2	
					1 2	
					1 2	
					1 2	
					1 2	
					1 2	
					1 2	
					1 2	
					1 2	
					1 2	
					1 2	
					1 2	
					1 2	
					1 2	
					1 2	
					1 2	

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Figure B.1: Code number for subject recruitment

Appendix C

Data collection sheet

Data Collection Sheet #1

Participant #: __________ **Date:** __________

First Investigation
Circle Training Treatment:
PWI / PAR / HMDAR / HMDMR

Second Investigation	
Treatment Number	**Treatment**
1 / 2 / 3 / 4	Control / Lean / I4.0 / Lean+I4.0

Car #	TCT	Errors Made		Uncorrected Error Types			PWI Ref Count	Trial Notes
		Corrected	Uncorrected	Sel	Pos	Rot		
1								
2								
3								
4								
5								
6								
7								
8								
9								
10								

Observer Initials: ________

Figure C.1: Data collection sheet