

**An Empirical Study of Method Optimization and Productivity  
Improvement in Labor-Intensive Manufacturing Using Historical  
Data**

Karunamoye Paul

Student ID-24272578

A thesis submitted to Auckland University of Technology

In partial fulfilment of the requirements for the degree of

**Master of Engineering**

2026

School of Engineering, Computer and Mathematical Sciences

Auckland University of Technology

Primary Supervisor: Dr Ryan Ip

### **Attestation of Authorship**

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Signed:

Name: Karunamoye Paul

Date: September 21, 2026

## **Acknowledgements**

I would like to express my sincere gratitude to my primary supervisor, Dr Ryan Ip, for his invaluable guidance, insightful feedback, and continuous support throughout this research. His expertise, encouragement, and patience have been instrumental in the successful completion of this thesis.

I would also like to extend my appreciation to the management and staff of Esquire Knit Composite Ltd. for granting access to the production data and for their cooperation, which made this research possible.

Finally, I am deeply grateful to my family for their unwavering love, patience, encouragement, and constant support throughout my academic journey. Their understanding and belief in me have been a source of strength and motivation during the completion of this thesis. Above all, I thank Almighty God for His endless blessings throughout this journey.

## Abstract

This research presents an empirical investigation of production method optimization and productivity improvement in a labor-intensive manufacturing environment using historical production data in the garment industry. In conventional textile manufacturing systems, operational inefficiencies frequently arise from inaccurate estimation of the Standard Minute Value (SMV), suboptimal workflow configuration, excessive manpower deployment, and the absence of systematic analytical evaluation of production performance. These limitations contribute to reduced production output, elevated unit manufacturing cost, and significant financial loss. The present study demonstrates how the enhancement in productivity and profitability of engineering-level process optimization without major capital investment can be evaluated statistically, grounded in real industrial production data.

Historical production records were collected from Esquire Knit Composite Ltd., focusing on matched blanket manufacturing data from two consecutive production years. Comparative statistical and graphical analyses were conducted to evaluate key operational indicators, including SMV, manpower utilization, working hours, daily and total output, production efficiency, and financial performance under fixed Free on Board (FOB) pricing. Root-cause diagnosis of productivity loss in the initial production year was performed through detailed observation of Enterprise Resource Planning (ERP) production records and structured fishbone (cause-and-effect) analysis to identify deficiencies in production method, machine configuration, workflow organization, and technical coordination.

Based on the identified causes, coordinated engineering interventions were implemented, including enhanced pre-production planning, multidisciplinary technical and mechanical consultation, machine layout rearrangement, and refinement of sewing production methodology. Empirical results demonstrate that excessive SMV in the first production year significantly constrained labor productivity and generated substantial operational loss. Following systematic method optimization, SMV was reduced by 52.31%, accompanied by reductions in manpower requirement and working hours, while production output and operational efficiency increased markedly. These improvements transformed a loss-incurring manufacturing system into a profitable production outcome in 2024 without major technological investment.

To validate these findings beyond fixed average values, a Monte Carlo simulation was developed to model operation-level time variability, error-prone conditions, and rework probability under both production methods. Across 10,000 simulated production outcomes per method, the improved 2024 process consistently produced a more favorable distribution of cost and profit per piece than the conventional 2023 process, confirming that the observed productivity gains remain robust under realistic

operational uncertainty rather than holding only under idealized average conditions. Statistical evidence further confirms that productivity recovery in labor-intensive manufacturing is primarily driven by production method refinement and SMV optimization rather than increased labor intensity or overtime extension.

Overall, the study contributes a technically grounded and empirically validated framework for productivity and profitability enhancement through historical data analysis, statistical evaluation, simulation-based validation, and engineering process optimization. The proposed methodology is particularly applicable to labor-intensive manufacturing industries seeking sustainable operational improvement under resource-constrained conditions.

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## Artificial intelligence Declaration Template

### Artificial Intelligence Guidelines:

Artificial Intelligence (AI) tools, including generative AI tools approved for use by AUT ([AI Tool Register](#)), can be used as learning tools when preparing to write your research proposal or research component. AI tools also have capability to assist with data modelling, data analysis and data visualisation. However, the research component you submit for examination must be substantively your own work. AI tools cannot solely be used to generate content when writing or creating an artwork/artefact, as this constitutes plagiarism. The formal guidelines for appropriate use of AI on the [AI Hub](#) must be followed. Also refer to the [Using Artificial Intelligence in your Research: Self-Assessments, Checklists, and Sample Text](#), for examples and sample text.

If you do plan to use AI tools, this declaration should be submitted with the initial research proposal, Confirmation of Candidature, and when you submit your research component for examination. You must complete the template below for each AI output used detailing the following:

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- Purpose of AI Use
- AI Tool(s) Used
- Prompts Used
- Post-AI Processing Methods

|                                                                                                                                                                                                                                                                                                                |                                                                                                                                                                                                                                                                |
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| <b><i>Specify the chapter number(s) in your research proposal/research component where AI was used.</i></b>                                                                                                                                                                                                    |                                                                                                                                                                                                                                                                |
| <b>Chapter number(s):</b>                                                                                                                                                                                                                                                                                      | Chapter 1, 2, 6, & 7 Paraphrasing, Grammar Checking & Synchronising and Chapter 3, 4, & 5 Paraphrasing & Grammar Checking                                                                                                                                      |
| <b><i>Briefly explain why the AI tool was used (e.g., idea generation, summarization, data analysis, image creation, etc.).</i></b>                                                                                                                                                                            |                                                                                                                                                                                                                                                                |
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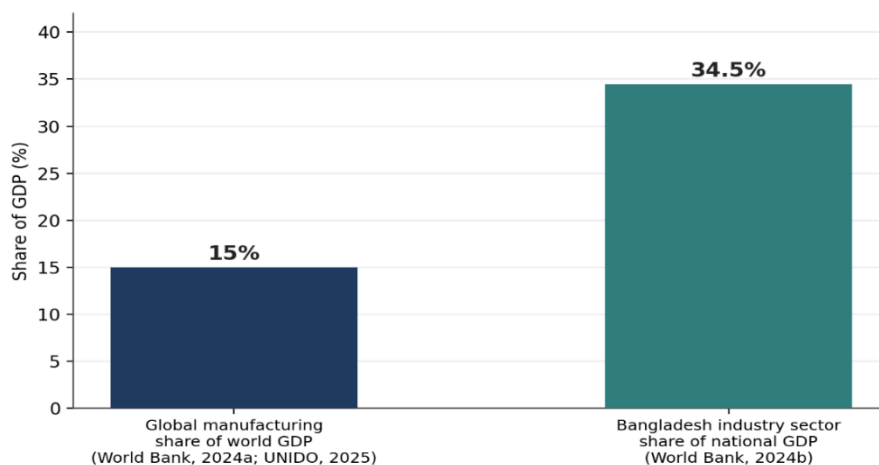
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## CHAPTER 1: INTRODUCTION

### 1.1 Background of the Study

Manufacturing continues to serve as a cornerstone of global economic development, contributing substantially to gross domestic product, employment generation, technological advancement, and international trade. Globally, manufacturing value added reached approximately USD 16.6 trillion in 2024, representing around 15% of total world GDP and supporting millions of jobs across both developed and developing economies (United Nations Industrial Development Organization [UNIDO], 2025; World Bank, 2024a). Within this landscape, labor-intensive manufacturing sectors, particularly textiles and ready-made garments (RMG), remain critical engines of industrialization in developing economies, where they generate large-scale formal employment, absorb surplus labor, and drive export-led growth strategies (Araque González et al., 2022).

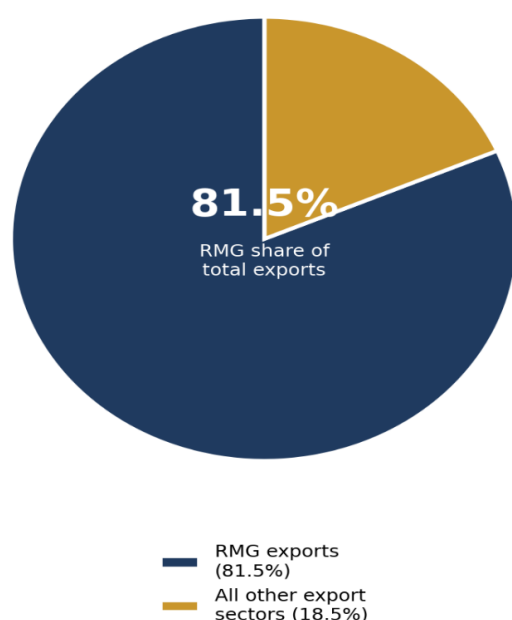
In Bangladesh, the manufacturing sector is a defining structural feature of the national economy. The broader industry sector, comprising manufacturing, construction, and mining, accounted for approximately 34–35% of the country's GDP in 2024, a figure considerably higher than the global manufacturing average (World Bank, 2024b). Figure 1.1 illustrates this gap, situating Bangladesh's industrial intensity against the global benchmark and underscoring the extent to which the national economy is structurally dependent on industrial output relative to the rest of the world.



**Figure 1.1.** Manufacturing/industry sector share of GDP: global average versus Bangladesh.

*Note: Data adapted from World Bank (2024a, 2024b) and UNIDO (2025).*

Within Bangladesh's industry sector, the RMG industry is by far the largest and most influential single contributor, and it is this sub-sector that anchors the country's export economy. In FY2024–25, the RMG industry earned approximately USD 39.35 billion in export revenue, representing about 81.5% of Bangladesh's total merchandise export earnings (Nasrin et al., 2025; Export Promotion Bureau, 2025). Figure 1.2 visualizes this concentration, showing that more than four out of every five export dollars earned by Bangladesh originate from a single manufacturing sub-sector — a degree of economic concentration that makes RMG productivity performance nationally consequential rather than merely firm-level significant.

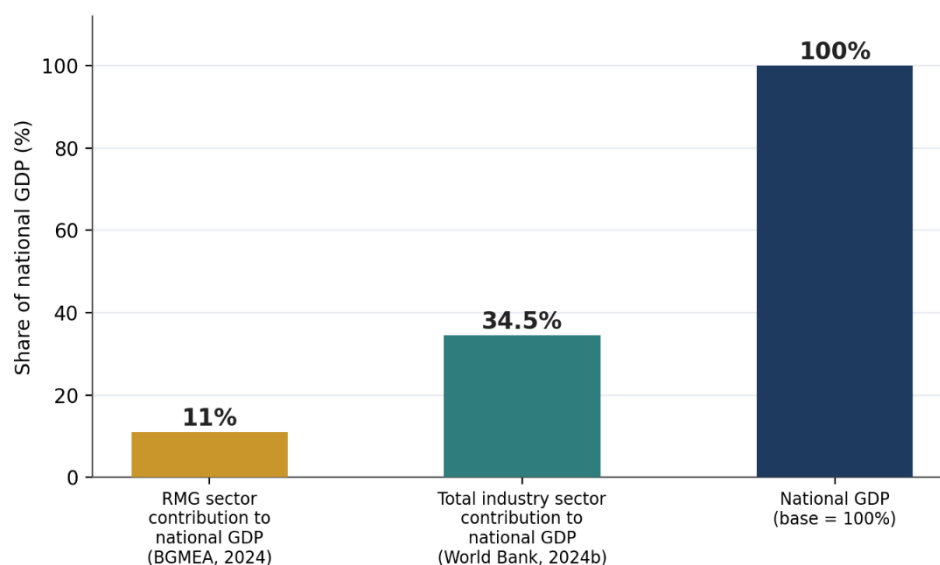


**Figure 1.2.** Composition of Bangladesh's total merchandise exports, FY2024–25, showing the RMG sector's dominant share.

*Note: Data adapted from Nasrin et al. (2025) and Export Promotion Bureau (2025).*

Beyond its export dominance, the RMG sector also carries substantial weight in domestic output and employment. The sector contributes approximately 11% of national GDP directly (Bangladesh Garment Manufacturers and Exporters Association [BGMEA], 2024), a figure that, when set alongside the broader 34–35% industry-sector contribution shown in Figure 1.1, indicates that RMG alone accounts for roughly one-third of Bangladesh's entire industrial output. This relationship is illustrated in Figure 1.3, which situates the RMG sector's GDP contribution against the total industry sector and the national economy as a whole. Bangladesh has, on this foundation, become the world's second-largest garment exporter after

China (Nasrin et al., 2025), and the sector employs millions of workers, with women constituting just over half of the workforce, making it one of the largest sources of formal employment in the country (Sabbir, 2025).



**Figure 1.3.** The RMG sector's economic weight relative to the total industry sector and national GDP.

*Note: Data adapted from BGMEA (2024) and World Bank (2024b).*

Despite its economic significance, the ready-made garment (RMG) industry continues to face persistent productivity challenges associated with its labor-intensive manufacturing environment. Sewing operations remain highly dependent on operators' skills, production methods, workstation layout, and workflow organization, making them particularly vulnerable to inefficiencies such as line imbalance, excessive non-productive time, and inconsistent production output (Moin et al., 2017). Similar challenges have been reported across garment manufacturing industries beyond Bangladesh, where studies have identified production bottlenecks, inefficient workflow, and unbalanced production lines as major constraints to manufacturing performance (Saravanan et al., 2023; Teshome et al., 2024). These findings indicate that productivity losses resulting from inefficient production methods are common across labor-intensive apparel manufacturing rather than being confined to individual factories. Even in more technologically advanced manufacturing environments, organizations continue to face challenges in improving operational efficiency while maintaining cost competitiveness and sustainable production practices (Tsai et al., 2024).

These industry-wide challenges are often reflected in day-to-day production operations. Ineffective production planning, excessive non-productive time, inefficient manpower utilization, poor machine configuration, and inadequate workflow coordination frequently disrupt production continuity, resulting in higher SMV, reduced resource utilization, and lower manufacturing productivity (Taimy & Khan, 2025). Such conditions commonly create bottlenecks, idle labor, and uneven workstation utilization throughout the production line, ultimately reducing operational efficiency (Teshome et al., 2024). Previous studies have demonstrated that systematic work-time study, production planning, and line balancing can effectively eliminate non-value-added activities, improve workflow continuity, optimize resource utilization, and enhance overall manufacturing performance (Erol, 2025). Collectively, these findings indicate that sustainable productivity improvement depends not on increasing labor or production capacity alone, but on systematically optimizing production methods, workflow, and operational coordination through engineering-based interventions.

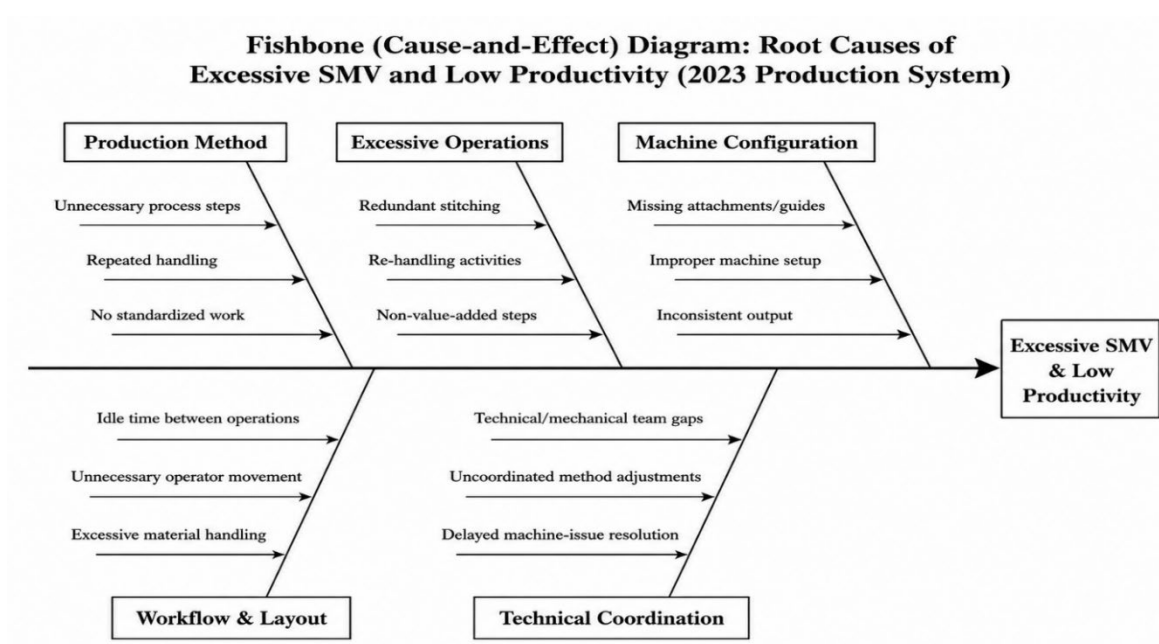
Among the various productivity indicators used in labor-intensive manufacturing systems, SMV is one of the most important parameters for both production planning and performance evaluation. SMV represents the standard time required to complete a particular production operation under defined working conditions. It is widely used for line balancing, manpower allocation, production scheduling, and cost estimation in textile and garment manufacturing. When SMV is inaccurately calculated or production methods are inefficient, it can significantly reduce production output and increase operational costs. Therefore, systematic SMV analysis and production method optimization are essential for improving manufacturing productivity.

In modern manufacturing environments, many organizations have implemented digital production monitoring systems and ERP platforms that continuously record production information such as output levels, manpower allocation, working hours, and operational efficiency. Proper analysis of such historical production data using statistical and graphical techniques can provide valuable insights into productivity patterns and help identify operational bottlenecks. This data-driven approach enables manufacturing companies to make informed decisions regarding production method optimization and resource utilization.

This research focuses on productivity improvement in labor-intensive blanket manufacturing using historical production data collected from Esquire Knit Composite Ltd., a textile manufacturing company in Bangladesh, in 2023 and 2024. Initial analysis of the company's production records revealed that during the first production year, the SMV was excessively high, resulting in low productivity and

significant financial loss for the company. Detailed observation of production data through the ERP system identified several inefficiencies in the production process.

To determine the root causes of these inefficiencies, a structured fishbone (cause-and-effect) analysis was conducted, as illustrated in Figure 1.4.



**Figure 1.4: Fishbone (Cause-and-effect) diagram.**

*Note. Author's own analysis based on production records from Esquire Knit Composite Ltd.*

The fishbone (cause-and-effect) diagram presented in Figure 1.4 was developed as part of a structured root cause analysis conducted to systematically identify the underlying operational factors responsible for the productivity challenges observed during the 2023 production year. The decision to apply this diagnostic tool at this stage of the research reflects a core methodological principle of this study: that effective and lasting production improvement must be grounded in a thorough understanding of why underperformance occurs, rather than simply responding to its observable symptoms. Addressing surface-level indicators without first identifying their root causes risks implementing corrective measures that are misdirected, incomplete, or unsustainable in the long term.

The root cause analysis was conducted using evidence gathered from three complementary sources. First, ERP daily production records were systematically reviewed to identify patterns of underperformance

across key operational indicators. Second, direct shop floor observation was carried out during active production to examine workflow behavior, machine utilization, and operator practices at the process level. Third, structured discussions were held with production engineers, line supervisors, and mechanical personnel who possessed direct operational knowledge of the manufacturing system. By drawing on multiple evidence sources in this way, the analysis ensured that both quantitative production data and practical practitioner insights were incorporated into the diagnostic process, strengthening the reliability and completeness of the findings.

The resulting fishbone diagram organizes the identified contributing factors into five major cause categories — Production Method, Excessive Operations, Machine Configuration, Workflow and Layout, and Technical Coordination — each representing a distinct area of the production system in which operational inefficiencies were found to be contributing to excessive SMV and reduced productivity. The fishbone framework was selected for this purpose because of its well-established effectiveness as a structured diagnostic tool for mapping causal relationships between contributing factors and a defined problem outcome in manufacturing and quality management research (Joy et al., 2024; Vergara et al., 2025). By making these causal relationships explicit and visible, the diagram provided a clear and evidence-based foundation for the production method optimization interventions that were subsequently designed and implemented in the 2024 production cycle.

The detailed examination of each identified root cause category, together with the specific engineering-based corrective interventions developed in response, is presented in Chapter 3 of this thesis.

## **1.2 Problem Statement**

The present study originates from a real industrial productivity challenge observed in Esquire Knit Composite Ltd., a labor-intensive textile manufacturing enterprise. The company operates as a vertically integrated knit composite unit, incorporating knitting, dyeing, finishing, and garment production processes under one roof, and primarily serves international export markets in Europe and North America. As part of the Esquire Group, the organization employs approximately 10,000 employees (workers and staff) across its operations and maintains a large-scale production capacity of approximately 30 million garments per year, contributing to annual export earnings of around USD 100 million (Esquire Group, n.d.).

Despite its advanced infrastructure, skilled workforce, strong export presence, and an established ERP-based production monitoring system, the company experienced significant and persistent operational inefficiencies during a specific production period. These inefficiencies were characterized by excessively

high SMV, inefficient manpower and resource utilization, suboptimal machine configuration, and workflow imbalances, which collectively increased production time and manufacturing cost while constraining output and reducing overall profitability. Although extensive operational data were available through the ERP system, they had not been systematically analyzed to support systematic engineering analysis and evidence-based production improvement, leaving a substantial gap between the data the company already collected and the decisions that data could have informed.

These challenges highlight the need for an empirical investigation into whether production method optimization, supported by historical production data and statistical analysis, can improve productivity and financial performance without requiring major capital investment. Accordingly, this study evaluates whether engineering-based production method optimization can significantly improve productivity and profitability by comparing manufacturing performance before and after implementation of the optimized production method using historical production data and statistical analysis.

### **1.3 Rationale and Need for the Study**

Modern manufacturing systems continuously generate substantial volumes of operational data through ERP, production monitoring sheets, and efficiency tracking records. Within Bangladesh's ready-made garment sector in particular, such data resources are frequently collected but remain underutilized for rigorous statistical evaluation and evidence-based engineering decision-making (Hossain & Sani, 2025; Iqbal et al., 2024). This gap between data availability and data utilization represents both a limitation in current industrial practice and an opportunity for empirical research capable of demonstrating how existing records can be converted into actionable engineering insight.

Systematic analysis of historical production data, using statistical, graphical, and comparative techniques, offers several distinct advantages over conventional, experience-based approaches to production management. It enables the evidence-based identification of productivity bottlenecks that might otherwise remain undetected through routine supervision; it allows quantitative validation of SMV reduction and efficiency improvement rather than reliance on anecdotal assessment; it reveals the underlying relationships among manpower, working hours, output, and cost that jointly determine manufacturing performance; and it provides practical, data-grounded guidance for sustainable method optimization that does not depend on capital-intensive investment.

This data-driven approach is particularly valuable for labor-intensive manufacturing enterprises, where productivity enhancement must often be achieved through the refinement of existing production methods rather than through the acquisition of new technology, which frequently carries substantial capital cost

and implementation risk. In such contexts, the ability to extract engineering value from data that organizations already collect represents a low-cost, high-impact avenue for performance improvement.

The dataset available for this study, comprising real production records from 2023 and 2024, with process improvement actions implemented during 2024, therefore presents a valuable and relatively uncommon opportunity. It allows the effects of a genuine industrial intervention to be examined empirically, using verified operational data rather than simulated or hypothetical scenarios, and provides the basis for establishing a reliable, generalizable framework for productivity and profitability improvement in comparable manufacturing environments.

#### **1.4 Purpose of the Study**

The primary purpose of this research is to empirically evaluate the effects of production method optimization and SMV reduction on productivity and profitability in a labor-intensive manufacturing environment using statistically analyzed historical production data from matched blanket manufacturing during two consecutive production periods (2023 and 2024). The study integrates statistical, graphical, comparative, and simulation-based analyses to evaluate operational and financial performance before and after the implementation of engineering-based production method improvements. The specific research questions and objectives that operationalize this purpose are presented in Sections 1.5 and 1.6.

#### **1.5 Research Questions**

The following research questions were developed to operationalize the purpose stated in Section 1.4, addressing the operational, statistical, and simulation-based dimensions of production method optimization in a labor-intensive blanket manufacturing environment:

1. How does SMV influence production output, efficiency, and production cost in labor-intensive manufacturing?
2. What operational factors contribute to increased SMV and reduced productivity within the blanket manufacturing process?
3. How does production method optimization influence manpower utilization, working hours, and overall operational performance?
4. Are the observed differences in productivity, efficiency, cost, and earnings between the 2023 and 2024 production periods statistically significant?

5. How does operational variability and error-prone production behavior influence total Simulated Processing Time (SPT) under different manufacturing conditions?
6. Can simulation-based modeling provide additional insight into manufacturing uncertainty and process variability within labor-intensive production systems?

## **1.6 Research Objectives**

To achieve the stated purpose, the study pursues the following objectives:

1. To analyze historical production performance in terms of SMV, manpower utilization, working hours, and output.
2. To identify root causes of productivity inefficiency using ERP-based observation and fishbone analysis.
3. To implement and evaluate production method optimization through engineering-level corrective interventions.
4. To statistically compare productivity and financial outcomes between two consecutive production years.
5. To develop and apply a Monte Carlo simulation model evaluating the influence of operational variability on SMV, thereby testing whether the observed productivity gains remain robust under realistic manufacturing uncertainty.
6. To develop an empirical framework for productivity and profitability improvement applicable to labor-intensive manufacturing industries.

These research questions were formulated to address a specific gap identified in the preceding review: while prior studies have examined SMV estimation (Kamruzzaman et al., 2024; Shen & Ji, 2024) or ERP-based production monitoring in isolation (Hossain & Sani, 2025), few have combined verified industrial ERP data, root-cause diagnosis, and simulation-based validation within a single empirical framework. RQ1–RQ4 target the operational and statistical dimensions of this gap, while RQ5–RQ6 extend the inquiry beyond fixed average performance to test whether observed gains persist under realistic operational uncertainty.

## **1.7 Significance of the Study**

The significance of this study is reflected in its contributions to both industrial practice and academic research. By integrating historical production data with engineering analysis, statistical evaluation, and simulation-based modeling, the research provides practical insights for manufacturing improvement while extending current knowledge on productivity optimization in labor-intensive manufacturing systems (Kanakana-Katumba et al., 2024).

### **1.7.1 Industrial Significance**

From an industrial perspective, this study addresses one of the major challenges faced by labor-intensive manufacturing industries: improving productivity and profitability under increasing global competition and resource constraints. Previous studies have shown that production methods of optimization, work measurement, and continuous process improvement can significantly enhance manufacturing performance without necessarily requiring major investment in automation or advanced technologies. Building on these principles, this research demonstrates how engineering-based process improvement can be implemented using historical production data obtained from an ERP system.

The study further demonstrates the value of ERP production data as a decision-support tool for engineering improvement. Although many manufacturing organizations routinely collect operational data through ERP systems, these records are often underutilized for systematic production analysis and continuous improvement (Deepthi & Bansal, 2024). This research illustrates how historical ERP production records can be analyzed to identify productivity bottlenecks, evaluate operational performance, and quantify the impact of engineering interventions on manufacturing efficiency and financial performance. Consequently, the proposed analytical framework provides manufacturing practitioners with a practical and evidence-based approach for supporting engineering decision-making and sustainable process improvement.

Furthermore, the improvement framework developed in this research integrates root-cause analysis, operation-level process evaluation, machine layout optimization, pre-production planning, and ERP-based performance monitoring. Because these approaches rely primarily on systematic engineering analysis rather than substantial capital investment, the framework has potential applicability to other labor-intensive textile and apparel manufacturing organizations seeking sustainable productivity improvement (Arafat et al., 2026; Begum et al., 2024).

### 1.7.2 Academic Significance

From an academic perspective, this study contributes to the growing body of knowledge on production method optimization, SMV management, and manufacturing productivity by providing empirical evidence derived from a real industrial production environment. Unlike many previous studies that rely primarily on laboratory experiments, theoretical models, or short-term production observations, this research is based on matched historical production records collected over two consecutive production years. The use of actual ERP production data strengthens the practical relevance of the findings and enables manufacturing performance to be evaluated under real operating conditions (Kanakana-Katumba et al., 2024).

A further contribution of this study is its examination of the relationship between production method optimization, operational efficiency, manufacturing cost, and profitability. Previous research has predominantly focused on operational indicators such as production output, efficiency, and SMV improvement, while comparatively fewer studies have investigated how these operational improvements translate into measurable financial outcomes under fixed FOB pricing conditions (Joy et al., 2024; Tsai et al., 2024). By integrating operational and financial performance evaluation, this study provides a broader understanding of the economic implications of engineering-based production improvement.

Methodologically, this research adopts an integrated analytical framework that combines graphical analysis, descriptive statistics, inferential statistical analysis, financial evaluation, and Monte Carlo simulation. The integration of empirical production data with simulation-based validation provides a comprehensive approach for evaluating manufacturing performance under both observed and uncertain production conditions, thereby extending existing methodological approaches commonly reported in manufacturing productivity research (Jung et al., 2022; Shen & Ji, 2024).

Finally, the study establishes a transparent and replicable methodological framework that can be adapted by future researchers investigating productivity improvement in labor-intensive manufacturing systems. The integration of historical production data, engineering analysis, statistical evaluation, and simulation-based modeling contributes to the growing field of data-driven manufacturing and supports the broader application of evidence-based decision-making within industrial engineering research (Hossain & Sani, 2025; Iqbal et al., 2024). Overall, this research contributes both practical guidance for manufacturing practitioners and a robust analytical framework for future research. By demonstrating how historical production data can be transformed into actionable engineering knowledge, the study supports continuous manufacturing improvement and contributes to the advancement of data-driven production management in labor-intensive manufacturing environments.

## **1.8 Alignment of Research Aim, Objectives, Questions, and Methodology**

These research questions require data that reflects real, sustained production behaviour rather than laboratory or short-term conditions, since the improvements under investigation depend on cumulative operational patterns across full production periods. The ERP-derived production records used in this study therefore provide the matched, day-by-day operational and financial data across the 2023 and 2024 periods needed to answer RQ1–RQ4 empirically, while the same historical variability observed in these records is used in Chapter 5 to parameterise the Monte Carlo simulation addressing RQ5 and RQ6.

The remaining chapters of this thesis are structured to answer these research questions in turn. Chapter 2 reviews literature relevant to each research question, establishing the conceptual and statistical foundations for the analysis. Chapter 3 presents the methodology used to collect, clean, and analyse the ERP-derived production data, including the root-cause analysis addressing RQ2 and the statistical procedures addressing RQ4. Chapter 4 presents the findings addressing RQ1, RQ3, and RQ4, while Chapter 5 presents the Monte Carlo simulation addressing RQ5 and RQ6. Chapter 6 discusses these findings in relation to the existing literature and the study's limitations, and Chapter 7 concludes by directly answering each research question and evaluating the achievement of the six research objectives stated above.

## CHAPTER 2: LITERATURE REVIEW

### 2.1 Manufacturing Productivity in Textile and Garment Industries

Productivity improvement remains one of the most critical and persistent challenges in textile and garment manufacturing, where operational performance is fundamentally determined by work measurement accuracy, production method design, and workflow organization (Kamruzzaman et al., 2024; Vergara et al., 2025). Labor-intensive manufacturing environments are particularly susceptible to productivity losses arising from inaccurate standard time estimation, imbalanced production lines, and inefficient task sequencing, all of which increase unit manufacturing costs and reduce production capacity. Empirical evidence demonstrates that structured line balancing, supported by stopwatch-based work measurement, standard time determination, and simulation-assisted workstation allocation, can significantly improve sewing-line efficiency and capacity utilization, thereby enhancing productivity in labor-intensive apparel manufacturing (Teshome et al., 2024).

Similarly, Erol (2025) demonstrated that the integration of work-time study, production line balancing, and systematic workflow optimization can effectively reduce operational inefficiencies, eliminate idle activities, and improve resource utilization within garment manufacturing. The study showed that engineering-based production planning and workload balancing significantly enhanced labor productivity, line efficiency, and overall manufacturing performance, highlighting the importance of method engineering and work measurement as fundamental approaches for improving productivity in labor-intensive manufacturing industries.

In the context of Bangladesh's garment manufacturing sector, lean manufacturing tools including 5S, cellular manufacturing, and line balancing have been shown to increase production output by up to 17.8%, improve efficiency by 12.46%, and reduce defect rates significantly (Arafat et al., 2026). These results highlight the transformative potential of systematic production engineering interventions in export-oriented textile manufacturing environments.

Recent research has demonstrated that applying heuristic line balancing techniques can substantially improve production efficiency in garment manufacturing. By implementing the Ranked Positional Weight method, the Largest Candidate Rule, and the Kilbridge and Wester method in a Bangladeshi garment hemming unit, the number of workstations was reduced from forty-two to twenty-three, increasing line efficiency from 43.70% to 79.80%. These findings demonstrate that systematic workstation reallocation and cycle time analysis can significantly enhance sewing line performance without requiring additional

capital investment. They further support the view that engineering-based method redesign, rather than increasing labor or machinery, is the primary driver of productivity improvement in labor intensive apparel manufacturing (Ara et al., 2025).

## **2.2 Standard Minute Value (SMV) and Operational Efficiency**

This section addresses RQ1 by examining how SMV influences production output, efficiency, and production cost.

Standard Minute Value (SMV), also referred to as Standard Allowed Minute (SAM), is one of the most fundamental work measurement parameters in garment manufacturing. It represents the standard time required for a qualified operator to complete a specific operation under prescribed working conditions using the standard production method and appropriate allowances. SMV provides the foundation for production planning, manpower allocation, capacity planning, line balancing, cost estimation, and performance evaluation. Accurate determination of SMV enables manufacturers to establish realistic production targets, allocate resources efficiently, estimate manufacturing costs, and benchmark labor productivity, making it a critical component of production management in labor-intensive manufacturing environments (Nchalala et al., 2023).

Recent studies have demonstrated that effective SMV management contributes directly to improvements in manufacturing performance. Rather than relying solely on engineers' experience or conventional time-study practices, researchers have increasingly adopted data-driven approaches to improve the accuracy and consistency of SMV estimation. Shen and Ji (2024) developed an Improved Particle Swarm Optimization–Back Propagation (IPSO-BP) neural network model that incorporates multiple production variables, including fabric characteristics, stitching length, sewing technology, and auxiliary materials, to predict SMV more accurately for garment sewing operations. Similarly, Hemal et al. (2025) applied machine learning regression models using historical production data collected from a ready-made garment factory and demonstrated that accurate SMV prediction can support production planning, reduce manufacturing costs, minimize manpower requirements, and improve productivity by reducing dependence on subjective manual estimation (Hemal et al., 2025).

Beyond its role in production planning and productivity improvement, SMV also influences broader manufacturing performance. Previous research has shown that SMV affects labor utilization, operational efficiency, production cost, and even environmental performance because longer sewing times are associated with increased energy consumption and carbon emissions during manufacturing (Shen & Ji, 2024). Consequently, effective SMV management should be viewed not merely as a work measurement

metric but as a strategic engineering parameter that supports operational efficiency, cost control, resource optimization, and sustainable manufacturing performance.

Overall, the existing literature demonstrates that accurate SMV estimation and systematic production method optimization are essential for improving productivity in labor-intensive manufacturing.

### **2.3 Data-Driven and Lean Approaches to Productivity Improvement**

This section supports RQ2 and RQ4 by reviewing data-driven and lean approaches to identifying productivity constraints and by establishing the evidence base for validating improvement outcomes statistically.

Contemporary manufacturing literature increasingly emphasizes the integration of lean principles with data-driven analytical frameworks as a practical pathway for productivity enhancement in labor-intensive textile manufacturing. This convergence enables organizations to identify waste, standardize processes, and improve operational decision-making using existing production data rather than relying on ad hoc, experience-based judgment alone.

Begum et al. (2024) conducted a systematic literature review encompassing sixty research papers and empirical analyses involving case studies, interviews, and surveys with industry practitioners to evaluate lean manufacturing implementation in the textile sector. Their research identified substantial efficiency gains, waste reduction, and quality improvements among textile companies adopting lean practices including Just-in-Time production, Kanban systems, value stream mapping, 5S workplace organization, and Kaizen continuous improvement. The study revealed that lean implementation remains relatively underexplored in textile manufacturing compared to automotive and electronics industries, indicating significant potential for further adoption.

Saravanan et al. (2023) proposed a structured lean implementation model for a textile company in south India, focusing on waste reduction through lean techniques applied following thorough process analysis. Their research demonstrated that sequenced lean implementation addressing multiple waste categories simultaneously yielded measurable improvements in throughput, resource utilization, and operational efficiency, supporting the argument that a comprehensive rather than isolated lean approach is necessary for sustainable productivity improvement.

Extending this data-driven direction, Tsai et al. (2024) proposed an integrated framework combining Industry 4.0 technologies, activity-based costing, and the theory of constraints to guide production and investment decisions in textile manufacturing. Their findings demonstrated that linking real-time

production data with cost and constraint analysis allows manufacturers to identify which process improvements yield the greatest financial return, illustrating how data-driven decision-making can convert operational-level efficiency gains into measurable profitability outcomes at the organizational level.

Furthermore, Vergara et al. (2025) proposed a productivity improvement model combining standardized work principles with Poka-Yoke defect prevention using artificial vision technology in a garment manufacturing case study in Peru. Validation against historical production data from 2023 and 2024 demonstrated transformative results, including a dramatic reduction in sewing rework rates and substantial productivity growth exceeding 170%, confirming that combining standardized work with automated error-proofing can deliver major improvements in labor-intensive garment operations.

## **2.4 Engineering Method Optimization and Process Redesign**

This section addresses RQ3 by reviewing how engineering method optimization and process redesign influence manpower utilisation, working hours, and overall operational performance.

Engineering-based method optimization encompasses a range of systematic interventions including process redesign, machine layout rearrangement, pre-production planning, and technical consultation, all of which target improvements in workflow efficiency, cycle time, and labor productivity. These approaches are particularly relevant in labor-intensive manufacturing where productivity recovery is achievable through method improvement rather than major capital investment.

Root cause analysis tools play a central role in identifying operational bottlenecks prior to method improvement implementation. The fishbone diagram, originally developed by Ishikawa, provides a structured visual framework for categorizing potential causes of production problems across dimensions such as manpower, machines, methods, materials, and environment. The fishbone (cause-and-effect) analysis is widely recognized as an effective quality management tool for systematically identifying the underlying causes of operational problems and supporting targeted process improvement. Its structured approach enables organizations to categorize and analyze multiple contributing factors, facilitating evidence-based decision-making and continuous improvement. In a manufacturing context, systematic fishbone-based root cause analysis has been shown to identify actionable deficiencies related to personnel, materials, methods, and the working environment that may not be evident through descriptive problem analysis alone (Fatmaria Tantri et al., 2024). This confirms that structured cause-and-effect diagramming enables systematic identification of underlying inefficiencies and informs targeted corrective interventions in industrial settings comparable to the present study.

ERP systems provide a critical data infrastructure for evidence-based production method optimization in modern manufacturing. The digital production records generated by ERP platforms, including production output, manpower allocation, working hours, and operational efficiency, enable comparative analysis of performance across different production periods and support engineering diagnosis of productivity problems (Surjit et al., 2016, as cited in Deepthi & Bansal, 2024).

Recent empirical studies have further demonstrated the effectiveness of Lean Six Sigma (LSS) methodologies in improving manufacturing performance within the textile and garment industry. Khan et al. (2025) integrated the Define–Measure–Analyze–Improve–Control (DMAIC) framework with the Ranked Positional Weight (RPW) method to optimize sewing line balancing, increasing line balancing efficiency from 53.0% to 70.3%, reducing the defect rate from 8.34% to 4.6%, and improving the process sigma level from 2.90 to 3.19. Similarly, Subramaniam et al. (2026) applied Lean Six Sigma techniques supported by Value Stream Mapping (VSM), Measurement System Analysis (MSA), and statistical process control to reduce production cycle time from 62.5 to 53.1 minutes (15.0%), decrease defect rates from 19.43% to 12.38% (36.3%), and improve overall process capability and reliability. Collectively, these studies demonstrate that structured engineering methodologies, supported by statistical analysis and continuous process improvement tools, can significantly enhance productivity, product quality, and operational efficiency in labor-intensive textile manufacturing (Khan et al., 2025; Subramaniam et al., 2026).

## **2.5 Simulation-Based Approaches to SMV Estimation and Production Planning**

This section establishes the foundation for RQ5 and RQ6 by reviewing simulation-based approaches to modelling production variability and uncertainty.

Simulation-based methods have emerged as a powerful complement to traditional time-study approaches for SMV estimation and production planning in garment manufacturing. By integrating computational modeling with real production data, simulation frameworks enable more accurate prediction of standard times, identification of line bottlenecks, and evaluation of alternative production configurations before physical implementation, thereby reducing the cost and risk associated with trial-and-error method changes.

Shao et al. (2022) proposed a machine learning approach for predicting sewing process standard time using a Support Vector Machine (SVM) optimized with Particle Swarm Optimization (PSO). Recognizing that standard time is a key indicator for measuring production efficiency in the sewing department and plays a vital role in production forecasting, their model was trained on multiple influencing factors

including fabric characteristics, sewing complexity, operator skill, and production conditions. The SVM-PSO model achieved significantly improved prediction accuracy compared to conventional manual time-study methods, demonstrating that data-driven standard time prediction can enhance SMV estimation reliability in labor-intensive sewing environments.

Building on this computational approach, Shen and Ji (2024) extended SMV prediction methodology by developing an Improved Particle Swarm Optimization–Back Propagation neural network (IPSO-BP) model that incorporated ten influencing factors in garment sewing operations, including fabric weight, fabric density, stitching length, stitching shape, number of cut pieces, sewing technologies, machine type, and auxiliary accessories. The IPSO-BP model achieved a prediction accuracy coefficient of  $R = 0.9818$ , outperforming standard BP neural networks and demonstrating the feasibility of high-precision computational SMV prediction as a substitute or supplement to direct time-study observation in complex garment operations.

Beyond SMV prediction, discrete-event simulation (DES) has been applied to model garment production lines and evaluate the impact of alternative time and workflow configurations on overall productivity. Jung et al. (2022) introduced a real-time data-driven DES framework for garment production lines, using ICT-based power monitoring data from sewing machines to extract individual workers' task times. These real-time task time data were used as simulation inputs to measure overall productivity, individual operator productivity, and other key performance indices. Their simulation results were 18.8% more accurate than conventional approaches, demonstrating the substantial potential of data-driven simulation in improving the accuracy of production performance evaluation in labor-intensive manufacturing environments.

Collectively, these simulation-based studies illustrate a progressive shift from manual stopwatch-based SMV measurement toward data-driven computational and simulation-supported approaches. While these advanced methods offer improved accuracy and predictive capability, they require significant digital infrastructure investment. For resource-constrained manufacturers, accurate empirical SMV measurement through systematic production data analysis and method observation remains a practical and accessible foundation for productivity improvement, as demonstrated in the present study.

## **2.6 Industry 4.0 and Sustainable Textile Manufacturing**

The progressive adoption of Industry 4.0 technologies is increasingly influencing production system design and operational management in textile manufacturing. Digital transformation initiatives encompassing the Internet of Things (IoT), artificial intelligence, cyber-physical systems, cloud

computing, and advanced analytics are enabling textile manufacturers to modernize operations, improve planning accuracy, and support sustainable production goals.

Tsai et al. (2024) proposed a comprehensive green production planning and control model integrating Industry 4.0 concepts, activity-based costing (ABC), and the Theory of Constraints (TOC) for the textile industry. The model utilizes real-time sensing technologies and ERP systems to optimize product mix, maximize profitability, and minimize environmental impact through carbon emission management. Their findings demonstrate the potential of integrated digital-analytical frameworks to simultaneously achieve operational efficiency and environmental sustainability in textile manufacturing.

At the sector level, Deepthi and Bansal (2024) conducted a systematic literature review and bibliometric analysis of Industry 4.0 research in the textile and apparel industry, evaluating the adoption trajectories and implementation challenges of key technologies. Their analysis confirmed that while cyber-physical systems, IoT, RFID, blockchain, and digital twins are increasingly incorporated into textile production and fashion retailing, the apparel and textile manufacturing sector continues to lag behind automotive and electronics industries in I4.0 adoption maturity.

A comprehensive global review further confirmed that Industry 4.0 national strategies and manufacturing initiatives in countries including Germany, France, Italy, Indonesia, Malaysia, Thailand, Vietnam, and Bangladesh are progressively incorporating I4.0 technologies into textile and apparel manufacturing (Haq et al., 2025). However, the review also identified persistent implementation barriers including high investment costs, skills gaps, and the absence of standardized digital infrastructure, particularly in developing-country export manufacturers.

These developments indicate that while data utilization and intelligent optimization are becoming core drivers of manufacturing productivity and sustainability, significant opportunities remain for labor-intensive manufacturers to improve performance through lower-cost, data-supported engineering interventions prior to full-scale digital transformation.

## **2.7 Research Gap**

Despite extensive research on lean manufacturing, SMV optimization, line balancing, engineering method redesign, and Industry 4.0 applications, a significant gap remains in empirical studies that comprehensively evaluate productivity improvement using real historical production data from labor intensive textile manufacturing. Although previous research has demonstrated the effectiveness of individual approaches such as lean implementation, work study, production line balancing, simulation, and digital technologies, these approaches have largely been investigated independently or within

controlled experimental settings. Consequently, limited evidence exists on how an integrated production method optimization strategy influences operational, financial, and productivity performance over successive production periods within an actual manufacturing environment.

Furthermore, existing studies have primarily concentrated on operational performance indicators, including SMV reduction, production output, line efficiency, and machine utilization. Comparatively few studies have examined the broader organizational impact of production method optimization by evaluating its influence on manpower utilization, manufacturing cost, profitability, and overall business performance using actual industrial production records collected over multiple production cycles.

This gap is particularly important for labor intensive textile and apparel manufacturers operating in highly competitive global markets, where continuous productivity improvement and cost reduction are essential for maintaining long term competitiveness and profitability. While advanced digital technologies and Industry 4.0 solutions offer considerable opportunities for manufacturing improvement, many organizations continue to face financial, technical, and organizational barriers to their implementation. Consequently, there remains a need for empirical research that demonstrates how systematic engineering process optimization, supported by historical production data, can achieve sustainable productivity improvement under real manufacturing conditions.

## **2.8 Contribution of the Present Study**

To address the identified research gap, this study presents an empirical investigation of production method optimization using historical production data from Esquire Knit Composite Ltd., a large-scale textile manufacturer in Bangladesh. By evaluating production performance before and after engineering interventions under actual manufacturing conditions, the study provides practical evidence of how systematic process improvement can enhance both operational and financial performance.

Specifically, this study:

- presents a longitudinal comparison of matched production records from two consecutive production years within the same manufacturing organization, enabling a rigorous evaluation of production method optimization;
- quantifies the effects of engineering interventions on SMV, manpower utilization, working hours, production output, efficiency, manufacturing cost, and profitability;

- identifies the root causes of productivity loss through ERP supported production analysis and structured fishbone analysis, providing an evidence-based foundation for production improvement;
- demonstrates the effectiveness of coordinated engineering interventions, including production method redesign, workflow improvement, machine layout optimization, pre-production planning, technical consultation, and sewing method refinement, in improving productivity without substantial capital investment;
- provides industrial evidence demonstrating how engineering-based production optimization can transform inefficient manufacturing processes into more productive and financially sustainable operations; and
- offers a practical framework that can support continuous productivity improvement and evidence-based decision making in labor intensive textile and apparel manufacturing.

Accordingly, this study contributes to the manufacturing productivity literature by providing robust empirical evidence from a large-scale industrial case study. It demonstrates the practical value of integrating engineering analysis, production management, and historical operational data to support sustainable productivity improvement, cost reduction, and long-term profitability in labor intensive manufacturing environments. This contribution is empirical in that it provides verified, matched operational and financial evidence from a real manufacturing setting; methodological in that it integrates ERP-based root-cause analysis, statistical comparison, and Monte Carlo simulation within a single evaluation framework; and managerial in that it offers manufacturing organizations a practical, replicable framework for diagnosing and addressing productivity loss without requiring capital investment.

## CHAPTER 3: RESEARCH METHODOLOGY

### 3.1 Research Approach

This study adopts a quantitative empirical research methodology to examine the impact of production method optimization on productivity and profitability in a labor-intensive manufacturing environment. A quantitative approach was selected because the study seeks to measure objective changes in production performance indicators, including SMV, manpower utilization, working hours, production output, efficiency, manufacturing cost, and profitability, and to statistically evaluate differences before and after engineering interventions. The research is empirical because it is based on observed industrial production records rather than theoretical assumptions, laboratory experiments, or simulated datasets alone.

A within-case, before-and-after comparative design was selected instead of a cross-sectional multi-company design because it holds the product type, workforce, production facility, and organizational context constant across the two observation periods, thereby reducing the influence of inter-company differences in equipment, management practices, and labor conditions. This design strengthens the internal validity of the study by allowing observed changes in production performance to be more confidently attributed to production method optimization. A randomized experimental design was not feasible because the engineering interventions were implemented as part of routine industrial operations rather than under controlled experimental conditions.

The methodology is based on historical production data collected over two consecutive years (2023 and 2024), providing an objective basis for evaluating operational changes over time under real manufacturing conditions. Actual industrial production data, rather than laboratory time studies or simulated datasets alone, were prioritized to ensure that the findings reflect real-world manufacturing operations rather than idealized conditions. The methodology integrates descriptive statistics, inferential statistical analysis, graphical evaluation, and before-and-after comparative techniques to systematically evaluate operational performance, productivity, and financial outcomes associated with production method optimization.

To complement the empirical analysis, Monte Carlo simulation (Chapter 5) was used to evaluate whether the observed improvements remain robust under realistic operational variability rather than relying solely on average values. While the within-case design provides strong internal validity, its primary limitation is reduced generalizability to other manufacturing organizations. This limitation is discussed in Section 6.9 and is identified as an opportunity for future multi-company research in Sections 6.10 and 7.6.

### 3.2 Data Source and Industrial Context

The empirical data used in this study were obtained from Esquire Knit Composite Ltd., one of Bangladesh's leading vertically integrated textile and garment manufacturing companies. The company was selected because it provided an appropriate industrial setting for investigating the impact of production method optimization on productivity and profitability using real historical production data. As a large export-oriented manufacturer, the company operates an integrated production system supported by an ERP platform that systematically records detailed operational information throughout the manufacturing process. The availability of comprehensive and reliable production records made the company an appropriate case for conducting an empirical evaluation of production method optimization under real industrial conditions.

A key reason for selecting Esquire Knit Composite Ltd. was the availability of comparable historical production data from two consecutive production periods (2023 and 2024), during which engineering-based production method improvements were implemented. This provided a unique opportunity to conduct a within-case, before-and-after comparative analysis under consistent manufacturing conditions. Because the product type, production facility, organizational environment, and general manufacturing processes remained largely unchanged between the two production periods, the study was able to evaluate the effects of production method optimization while reducing the influence of external factors, such as differences in equipment, management practices, workforce characteristics, and organizational structure, that commonly affect comparisons across multiple organizations.

The production data were extracted from the company's ERP system and supporting production records. The dataset included key operational and financial variables required for the analysis, including SMV, manpower utilization, working hours, production output, production efficiency, manufacturing cost, and profitability. These data provided objective measurements of manufacturing performance before and after the implementation of the optimized production method, enabling a comprehensive evaluation of the engineering interventions through descriptive statistics, inferential statistical analysis, graphical evaluation, comparative analysis, and Monte Carlo simulation.

Formal permission to access and use the historical production data for this research was obtained from the authorized management of Esquire Knit Composite Ltd. The data were provided exclusively for academic research purposes and were handled in accordance with ethical research principles. To protect organizational confidentiality, commercially sensitive information and personally identifiable employee information were excluded from the dataset. All analyses were conducted using archived production

records and objective statistical methods to ensure the reliability, transparency, and integrity of the research findings.

### **3.3 Data Preparation and Processing**

The production dataset was extracted from the company's ERP system and initially consisted of large, unstructured files containing multiple product records, operational variables, and financial information. Since the dataset included both relevant and irrelevant information for this study, a systematic data preparation process was carried out to extract, clean, and organize only the required data.

#### **3.3.1 Data Selection and Filtering**

The initial dataset contained production records for various styles and file numbers. As this study focuses on specific blanket production cases, the first step involved sorting and filtering the required file numbers from the complete dataset. Only the selected files relevant to the study (i.e., 931, 931A, 1031, and 1033) were retained, while all unrelated records were removed.

In addition, the dataset included several variables that were not required for this research, such as detailed quality inspection data and additional financial information. These variables were excluded through sorting and filtering in Microsoft Excel to ensure that the dataset remained focused, relevant, and manageable.

#### **3.3.2 Data Cleaning and Correction**

After filtering the required data, a detailed cleaning process was performed to ensure accuracy and consistency. Within the same production file, inconsistencies were observed in the recorded SMV, arising primarily from manual entry variation across shifts. These discrepancies were corrected by verifying and assigning the appropriate SMV based on the actual production method applied. Any incorrect or abnormal entries identified through logical checks, such as unrealistic production output or time values, were corrected or removed using ERP records. Furthermore, all variables were reviewed to ensure consistency in units and formatting across the dataset. While this cleaning process resolved identifiable recording inconsistencies, ERP-derived production data carries inherent limitations for research purposes. The records capture standard operational fields but do not log some contextual information, such as informal line changes, minor unplanned stoppages, or operator reassignments, that may influence day-to-day performance. These unmeasured operational variables should be considered when interpreting the statistical and simulation-based findings presented in later chapters.

### **3.3.3 Data Alignment**

To enable accurate comparison between 2023 and 2024, the data were aligned based on production running days rather than calendar dates, since the two years contained a different number of actual working days due to holidays and non-production periods. This ensured that production performance was compared under equivalent operational stages and conditions, rather than being distorted by calendar-driven differences in the number of days available for production.

### **3.3.4 Derived Variable Calculation**

In addition to the raw data obtained from the ERP system, key performance indicators were derived to support the analysis. Production efficiency was calculated using SMV, manpower, working hours, and output data to measure how effectively labor resources were utilized.

Similarly, production cost was derived using FOB values and Cost of Making (CM), where CM represents the cost associated with manufacturing operations. These calculated variables enabled a comprehensive evaluation of both operational and financial performance.

### **3.3.5 Data Standardization**

The study utilized actual operational values, such as SMV in minutes, output in pieces, and efficiency in percentage form. Therefore, statistical normalization methods were not applied. Instead, consistency was ensured by maintaining uniform units and measurement scales across all variables, allowing direct and meaningful comparison between the two production years.

### **3.3.6 Dataset Integration**

After completing the cleaning, correction, and calculation processes, the data from both production years were combined into a single structured dataset. Additional variables, such as Year of Production and File Number, were included to facilitate grouping, comparison, and statistical analysis.

### **3.3.7 Tools Used**

Microsoft Excel was used for data filtering, sorting, cleaning, and initial structuring, while R programming (using packages such as dplyr and ggplot2) was used for data transformation, visualization, and statistical analysis.

### **3.4 Production Method Optimization and Implementation**

Production method optimization was carried out based on detailed analysis of ERP production data and systematic root cause identification using fishbone (cause-and-effect) analysis. The initial production system in 2023 exhibited several operational inefficiencies, including excessively high SMV, inefficient manpower utilization, suboptimal workflow arrangement, and improper machine configuration.

To address these issues, a structured and engineering-based improvement process was implemented in the subsequent production period (2024). The method optimization was conducted through the following step-by-step approach:

#### **Step 3.4.1: Problem Identification**

Production data obtained from the ERP system were analyzed to identify key performance issues. The analysis revealed that the production system was characterized by high SMV (28.62 minutes), low output, excessive manpower usage, and extended working hours. These factors collectively indicate inefficiencies in production methods and workflow design.

#### **Step 3.4.2: Root Cause Analysis**

To ensure that the production method optimization implemented in the 2024 production cycle was directed at verified operational causes rather than observable symptoms, a structured root cause analysis (RCA) was conducted using the fishbone (cause-and-effect) framework. This approach was selected because of its established effectiveness in systematically decomposing complex manufacturing performance problems into discrete, investigable cause categories, enabling targeted and evidence-based corrective intervention (Joy et al., 2024). The analysis was conducted through the triangulation of three complementary evidence sources: systematic review of ERP daily production records, direct shop floor observation during active production, and structured discussions with production engineers, line supervisors, and mechanical personnel with direct operational knowledge of the manufacturing system. The triangulation of these sources was methodologically important because it ensured that both quantitative production data and qualitative practitioner insight were incorporated into the diagnostic process, reducing the risk of incomplete or biased causal identification that can arise from reliance on a single evidence source alone.

The analysis identified five principal cause categories as material contributors to the excessive SMV, and reduced production efficiency observed during the 2023 production year. Each category is discussed in turn below.

**Inefficient production method design** was identified as the primary cause of performance loss. The existing sewing method incorporated unnecessary process steps, repeated component handling between operations, and non-optimized operation sequences that collectively increased cycle time and reduced operator efficiency. Critically, the absence of standardized work instructions meant that operation performance varied substantially between individual operators and across production shifts, introducing systematic variability into the production system that further inflated the effective SMV beyond its theoretical value. The lack of standardization also made it difficult to identify and address individual performance deviations through supervision alone, as there was no defined baseline against which actual performance could be objectively compared.

**Excessive non-value-adding operations** constituted a closely related and independently significant cause category. The 2023 production method contained multiple operations that consumed productive labor time without contributing to the functional integrity or aesthetic quality of the finished product. These included redundant stitching activities arising from a multi-step component joining sequence that could be consolidated, and re-handling operations that required operators to reposition or reorient components between workstations without advancing the production process. Each such operation added directly to the total SMV while generating no corresponding product value, representing a structurally embedded source of inefficiency within the method design itself (Kanakana-Katumba et al., 2024).

**Improper machine configuration** was observed as a significant contributing factor across several operations. A number of machines were not appropriately equipped for their assigned tasks, with missing attachments and guides requiring operators to perform positioning and alignment functions manually that would otherwise be handled mechanically. This increased both the skill dependency of individual operations and their effective cycle time. Suboptimal machine settings further resulted in inconsistent stitching quality, necessitating periodic manual correction and contributing to output variability. Collectively, these configuration deficiencies increased processing time, elevated operator workload, and introduced quality-related interruptions into the production flow.

**Workflow imbalance and unnecessary operator movement** were identified as structural layout related inefficiencies. The physical arrangement of machines on the production floor did not correspond to the logical sequence of sewing operations, requiring operators and supervisors to transport work in process bundles between non adjacent workstations. This increased material handling time, created idle time while operators waited for incoming work, and disrupted the continuity of production flow across the sewing line. Similar challenges have been widely reported in labor intensive garment manufacturing, where inefficient machine layout, poor workstation allocation, and unbalanced production lines contribute

to excessive work in process movement, higher SMV, and reduced production efficiency (Ara et al., 2025; Teshome et al., 2024).

**Insufficient coordination between technical and mechanical teams** represented the fifth identified cause category. In the 2023 production system, there was no structured protocol for the timely escalation and resolution of machine-related problems, method adjustment requirements, or process improvement proposals. As a consequence, operational issues that arose during production were frequently left unresolved for extended periods, disrupting production continuity and preventing the correction of avoidable inefficiencies. The absence of coordinated inter-team communication also meant that method changes identified as necessary during production were not implemented consistently across operators and shifts, further contributing to performance variability and elevated SMV.

The systematic identification of these five root cause categories through the fishbone analysis provided a transparent, evidence-based foundation for the targeted production method optimization interventions designed and implemented in the 2024 production cycle. Each subsequent corrective action undertaken in Steps 3.4.3 through 3.4.7 was directly traceable to one or more of the root causes identified at this stage, ensuring that the improvement process was both methodologically grounded and operationally focused.

### **Step 3.4.3: Operation-Level Process Analysis**

A detailed operation-level process analysis was conducted to examine each sewing operation involved in the blanket manufacturing process and identify opportunities for production method improvement. The objective was to determine whether every operation contributed value to the final product or unnecessarily increased production time and cost. The analysis focused on the sequence of operations, processing time, operator movement, machine utilization, and material handling activities. Particular attention was given to identifying operations that could be simplified, combined, or eliminated without affecting product quality.

The existing production method consisted of approximately 11 sewing operations, depending on the blanket style and customer requirements. Each operation was evaluated using video-based time-study observations, ERP production records, and technical discussions with the Industrial Engineering (IE), Production, Mechanical, and Quality Assurance teams. The time required for each operation was measured and compared to determine its contribution to the overall manufacturing process.

Table 3.1 summarizes the major operational issues identified during the analysis and the corresponding improvement actions implemented.

**Table 3.1: Key Operation-Level Improvements Implemented During Production Method Optimization**

| <b>Identified Issue</b>         | <b>Existing Production Method</b>                                            | <b>Improvement Implemented</b>          | <b>Expected Impact</b>                                      |
|---------------------------------|------------------------------------------------------------------------------|-----------------------------------------|-------------------------------------------------------------|
| <b>Blanket assembly</b>         | Blanket layers were joined using two separate sewing operations              | Replaced with a single sewing operation | Reduced processing time and SMV                             |
| <b>Temporary stitch removal</b> | Temporary stitches were removed before the final finishing operation         | Eliminated the stitch removal operation | Reduced SMV by 8.90 minutes per unit                        |
| <b>Workflow</b>                 | Several unnecessary handling and movement steps were required                | Simplified the production sequence      | Improved workflow and reduced idle time                     |
| <b>Machine layout</b>           | Machine arrangement required unnecessary movement of materials and operators | Rearranged machine layout               | Improved line balancing and operator efficiency             |
| <b>Technical coordination</b>   | Limited communication between production and technical departments           | Improved cross-functional collaboration | Increased process consistency and implementation efficiency |

One of the most significant inefficiencies was identified during the blanket assembly process. In the original production method, the upper and lower fabric layers of the blanket were first joined using an **overlock stitch**, which is a sewing technique primarily used to secure fabric edges and prevent fraying. After this operation, the blanket was turned inside out so that the seam was positioned correctly. A second sewing operation, known as a **lock stitch**, was then performed to complete the assembly and provide the required seam strength.

This two-step assembly process increased production time because the product had to be handled multiple times, transferred between operations, and repositioned by the operator before the second sewing operation could be completed. A detailed technical review found that the initial overlock stitch did not provide any additional functional or quality benefit, as the required seam strength and product appearance could be achieved using only the final lock stitch. Consequently, the overlock operation was removed, and the blanket assembly was completed using a single lock stitch operation. This simplified the production method, reduced operator handling, and lowered the overall SMV.

Another major inefficiency was associated with the temporary stitch removal process. During the original production method, temporary stitches were inserted to hold the blanket layers together before the final finishing operation. These temporary stitches were later removed manually, requiring 8.90 minutes of additional processing time for each blanket. Detailed examination of the finished product showed that these temporary stitches would be completely covered by the final decorative **cover stitch**, meaning they were not visible in the finished product when a matching thread color was used. Therefore, removing the temporary stitches did not improve either the appearance or the functional quality of the blanket. After consultation with the technical team and buyer representatives, this operation was eliminated without affecting customer quality requirements.

The analysis also identified additional opportunities to improve production efficiency by reducing unnecessary material handling, minimizing operator movement between machines, and improving the sequence of operations. The machine layout was reorganized to establish a smoother production flow and reduce transportation distance between workstations. At the same time, closer collaboration between the Industrial Engineering, Production, Mechanical, and Quality Assurance departments ensured that the revised production method was technically feasible, met quality standards, and could be implemented successfully on the production line.

Overall, the operation-level process analysis provided a systematic understanding of the factors contributing to excessive SMV and reduced productivity. The elimination of redundant operations, together with improvements in workflow organization, machine layout, and technical coordination,

formed the basis of the production method optimization implemented in this study. The impact of these improvements on productivity, manufacturing cost, and profitability is evaluated in Chapters 4, 5, and 6.

#### **Step 3.4.4: Technical Evaluation and Buyer Collaboration**

To ensure the feasibility and acceptability of the proposed production method improvements, a structured technical evaluation was conducted involving internal production engineers, the mechanical team, and the buyer's technical representatives. During this stage, all proposed process modifications, including the elimination of non-value-added operations, simplification of sewing methods, and changes in stitching techniques, were thoroughly discussed and reviewed from both manufacturing and quality perspectives.

Particular attention was given to the removal of the false stitching (temporary stitch removal) operation and the modification of the attachment method for the upper and lower blanket components. The technical team demonstrated that the false stitch would remain concealed beneath the cover stitch and would not be visible in the final product if appropriate matching thread color was used. Additionally, the revised method of directly attaching the components using a lock stitch was presented as a more efficient alternative to the previous multi-step process.

Following these discussions, **mock samples (trial production samples)** were developed using the improved production method. These samples incorporated all proposed changes, including operation reduction, method simplification, and improved stitching techniques. The mock samples were then submitted to the buyer for detailed evaluation and quality inspection.

The buyer conducted a thorough review of the samples, including internal assessment and technical validation. After confirming that the revised method met all quality, functional, and aesthetic requirements, the buyer formally approved the improved production method. This approval was a critical milestone, as it validated that the elimination of certain operations and modification of sewing techniques did not negatively impact product quality.

The approved method was subsequently implemented in the production process, enabling the factory to adopt a more efficient and streamlined production workflow.

#### **Step 3.4.5: Process and Machine Optimization**

Following the elimination of unnecessary operations, additional engineering interventions were implemented to optimize the production process. These interventions focused on improving workflow organization, enhancing process consistency, and reducing non-value-added activities within the sewing

line. The optimization measures included the rearrangement of machine layouts to align workstations with the revised operation sequence, thereby minimizing unnecessary material handling, operator movement, and workflow interruptions. Appropriate machine guides and attachments were installed on selected sewing machines to improve stitching consistency, facilitate material handling, and support standardized production operations. In addition, sewing techniques were standardized by establishing uniform work procedures and operational methods for critical sewing processes to reduce operator-dependent variation and improve process consistency. Workstations were also reorganized to eliminate unnecessary movements and idle time through improved tool placement, material flow, and workstation layout.

Collectively, these engineering interventions formed the optimized production method implemented during the 2024 production period. The effectiveness of these interventions was subsequently evaluated through the comparative, statistical, and graphical analyses presented in Chapter 4, and further validated through the simulation-based analysis presented in Chapter 5.

#### **Step 3.4.6: Pre-Production Planning Improvement**

To support the implementation of the optimized production method and address the planning-related coordination gaps identified in the root-cause analysis, several improvements were introduced during the pre-production planning stage. These interventions focused on ensuring that production resources, operational sequences, and workflow arrangements were properly prepared before the start of manufacturing. The pre-production planning improvements included a detailed review and refinement of the operation breakdown, improved line balancing based on the revised SMV and operation sequence, systematic manpower allocation according to workstation requirements, and enhanced coordination among the Industrial Engineering, Production, and Mechanical departments to ensure machine readiness for the revised layout described in Section 3.4.5 and timely production line setup. Production planning activities were also reviewed to confirm that the required machines, attachments, materials, and technical resources were available before production commenced.

These pre-production planning interventions established the operational conditions necessary for implementing the optimized production method during the 2024 production period. Their effectiveness was subsequently evaluated through the comparative, statistical, and graphical analyses presented in Chapter 4, and further validated through the simulation-based analysis presented in Chapter 5.

#### **Step 3.4.7: Implementation and Monitoring**

The optimized production method was implemented during the 2024 production cycle following validation and approval from the buyer. The implementation involved integrating the revised operation

sequence, optimized sewing techniques, and updated machine layout described in Section 3.4.5, together with the revised pre-production planning arrangements presented in Section 3.4.6, into the existing production line.

To support consistent implementation, operators received instruction on the optimized production method, while line supervisors monitored adherence to the revised production procedures. Pre-production setup and line balancing were adjusted to align with the updated operation breakdown. Particular attention was given to maintaining consistency in sewing techniques, machine settings, and workflow sequence throughout the production process.

Performance monitoring was conducted using ERP-based production data. Key operational indicators, including SMV, production output, manpower utilization, and production efficiency, were regularly tracked to verify that the optimized production method was being implemented as intended. Any deviations from the established procedures were identified through routine production monitoring and addressed through continuous coordination among the Production, Industrial Engineering, and Mechanical departments.

This implementation and monitoring approach was designed to support the consistent application of the optimized production method under actual manufacturing conditions and to provide a reliable basis for the comparative, statistical, and graphical analyses presented in Chapter 4, as well as the simulation-based validation presented in Chapter 5.

### **Summary of the Production Method Optimization Process**

Overall, the production method optimization methodology described in Section 3.4 followed a structured sequence of process analysis, root-cause identification, engineering intervention, technical validation, and controlled implementation. The methodology emphasized eliminating non-value-added operations, optimizing workflow and machine layout, strengthening pre-production planning, and improving coordination among the Industrial Engineering, Production, and Mechanical departments. Together, these engineering interventions established a systematic framework for production method optimization under real manufacturing conditions. The effectiveness of the optimized production method was subsequently evaluated through the comparative, statistical, and graphical analyses presented in Chapter 4 and further validated through the simulation-based analysis presented in Chapter 5.

### **3.5 Financial Analysis**

Financial analysis was conducted to evaluate the economic impact of production method optimization under a fixed FOB pricing structure. Manufacturing cost, FOB value, contribution margin, and profitability were calculated and compared between the 2023 and 2024 production periods to assess how changes in SMV and production efficiency influenced financial performance. Because the FOB value remained constant across both production periods, any observed changes in profitability could be attributed primarily to improvements in production efficiency and manufacturing cost resulting from the optimized production method.

### **3.6 Empirical Validation**

Empirical validation was conducted to evaluate the effectiveness of the optimized production method using observed industrial production data collected from the 2023 and 2024 production periods. Rather than relying solely on theoretical assumptions or simulated scenarios, the study validated the engineering interventions through direct comparison of actual production performance before and after implementation. The validation incorporated descriptive statistics, inferential statistical analysis, financial evaluation, and graphical comparison to determine whether the observed operational and financial improvements were supported by empirical evidence.

### **3.7 Inferential Statistical Analysis**

Inferential statistical analysis was conducted to determine whether the observed differences between the 2023 and 2024 production periods were statistically significant rather than resulting from random variation. Depending on the distributional characteristics of the data, appropriate statistical tests were selected to compare matched production observations. These analyses evaluated changes in SMV, manpower utilization, working hours, production output, production efficiency, manufacturing cost, and profitability following the implementation of the optimized production method. Statistical significance was assessed using a significance level of  $\alpha = 0.05$ . The specific test applied and the matched-pair sample construction are detailed in Section 4.5, immediately preceding the presentation of results.

### **3.8 Descriptive Statistical Analysis**

Descriptive statistical analysis was performed to summarize and compare the characteristics of the production data collected during the 2023 and 2024 production periods. Summary measures, including the mean, median, standard deviation, minimum, maximum, and range, were calculated for key production variables such as SMV, manpower utilization, working hours, production output, production efficiency,

manufacturing cost, and profitability. These descriptive statistics provided an overview of production performance, supported the identification of operational trends, and established the basis for the subsequent inferential statistical analyses.

### 3.9 Simulation-Based Validation Method

The statistical analyses presented earlier in this study were based on observed production data and deterministic SMV values derived from individual sewing operations. Although these analyses provide valuable insight into production performance, they do not fully capture the operational variability inherent in real manufacturing environments. In practice, operation times may vary because of differences in operator performance, worker fatigue, machine condition, material handling delays, production interruptions, and occasional defects requiring rework. Consequently, a simulation-based approach was adopted to account for these sources of uncertainty and provide a more realistic evaluation of production performance.

To represent operational variability, a Monte Carlo simulation framework was developed in which the time required for each sewing operation was treated as a random variable rather than a fixed value. The total simulated processing time (SPT) for each product was calculated as the sum of the simulated operation times across all sewing operations. This probabilistic approach enabled the production process to be evaluated over a range of possible operating conditions rather than relying on a single deterministic estimate.

The operation times used in the simulation were derived from video-based time studies conducted by the Industrial Engineering (IE) department for the selected blanket production processes. Each operation time was modeled using a truncated normal distribution bounded by the minimum and maximum values observed during the time-study analysis. This distribution was selected because it represents natural variation around the observed operating time while preventing the generation of unrealistic values outside the measured production range. Consequently, the simulated operation times closely reflected the variability observed under actual manufacturing conditions.

The simulation model was executed for **10,000 iterations** for both the conventional production method used in **2023** and the optimized production method implemented in **2024**. This number of iterations was selected to ensure that the simulated probability distributions remained stable and were no longer materially affected by additional simulation runs. The simulation generated probability distributions for total SPT and key production performance indicators under both production methods. To further represent operational uncertainty, selected error-prone sewing operations were assigned defect probabilities based

on observed production behavior. Whenever a simulated defect occurred, additional rework time was incorporated into the corresponding operation, allowing the model to account for the effects of production errors and process interruptions on overall manufacturing performance.

To improve the realism of the simulation, actual ERP-derived production efficiency values were incorporated into the model so that simulated production performance reflected observed factory conditions rather than idealized assumptions. The simulation was implemented using the **R** statistical programming environment and was used to evaluate production variability, operational stability, manufacturing cost per piece, and profit per piece under the two production methods. By integrating stochastic simulation with empirical production data, the model complemented the statistical analyses presented earlier in this study and provided additional validation of the effectiveness and robustness of the optimized production method under realistic manufacturing conditions. The detailed simulation procedure, model assumptions, parameter settings, and simulation results are presented in **Chapter 5**.

### **3.10 Summary**

This chapter presented the research methodology adopted to investigate the impact of production method optimization on productivity and profitability in a labor-intensive blanket manufacturing environment. A structured empirical research approach was employed, combining real industrial production data with statistical, analytical, and engineering-based evaluation techniques.

The chapter described the processes of data collection, selection, cleaning, alignment, and integration to ensure the reliability and comparability of the 2023 and 2024 production datasets. Historical production records extracted from the ERP system, together with operational information and video-based time-study observations, served as the primary data sources. Key performance indicators, including SMV, manpower utilization, working hours, production output, efficiency, production cost, earnings, and profit per piece, were prepared for detailed analysis.

The methodology further outlined the systematic procedure used to evaluate and optimize the production method. This included operational assessment, root cause analysis, operation-level process evaluation, workflow analysis, machine configuration assessment, technical consultation, and implementation of corrective actions. Methods for data visualization, descriptive analysis, inferential statistical testing, and comparative performance evaluation were also discussed.

To account for production uncertainty and operational variability, a Monte Carlo simulation framework was incorporated into the study. Individual sewing operations were modeled using truncated normal distributions derived from video-based time-study observations. The simulation considered variations in

operation times, production efficiency, and potential rework caused by operational errors. In addition to evaluating production performance, the simulation was used to generate cost-per-piece and profit-per-piece distributions under different manufacturing scenarios. This enabled a probabilistic assessment of profitability and provided a more realistic understanding of the financial impact of production method optimization.

Overall, this chapter established the methodological foundation for evaluating the effectiveness of production method optimization. The findings obtained through descriptive analysis, statistical testing, financial evaluation, profit-per-piece distribution analysis, and simulation modeling are presented and discussed in the following chapter.

## **CHAPTER 4: DATA ANALYSIS AND RESULTS**

### **4.1: Introduction**

This chapter presents the empirical analysis of historical blanket production data collected during the **2023** and **2024** production periods. The analysis evaluates the impact of production method optimization on productivity, operational efficiency, and financial performance within a labor-intensive manufacturing environment.

A structured comparative approach was adopted to examine production performance before and after the implementation of the optimized production method. The analysis incorporates graphical analysis, descriptive statistics, inferential statistical analysis, relationship analysis, and financial evaluation to provide a comprehensive assessment of changes in key operational and financial performance indicators.

Particular attention is given to the relationships among key production variables, including SMV, production output, production efficiency, manpower utilization, working hours, and manufacturing cost, to examine how changes in production methods are associated with manufacturing performance. Financial analysis is also conducted to evaluate the economic implications of the observed operational changes under a fixed FOB pricing structure.

The findings presented in this chapter provide the empirical foundation for evaluating the effectiveness of the optimized production method. A complementary simulation-based validation of these findings is presented in Chapter 5, while their implications are discussed in Chapter 6.

### **4.2: Overview of the Dataset**

The dataset consists of matched daily production records from comparable blanket production files collected during the 2023 and 2024 production periods. These records were extracted from the company's ERP system and organized to facilitate a consistent comparison of production performance before and after the implementation of production method optimization.

The dataset includes both operational and financial variables representing key aspects of the manufacturing process. Operational variables include SMV, manpower utilization, working hours, production running days, daily production output, and production efficiency, which collectively describe production activities, resource utilization, and overall operational performance.

Financial variables include production cost, CM, and FOB earnings. These variables were included to evaluate the financial implications of production method optimization and to complement the operational performance analysis.

The dataset preparation process, comprising file selection, exclusion of unrelated variables, correction of inconsistent records, and alignment by production running days, followed the procedure described in Section 3.3, thereby ensuring analytical consistency and comparability across the two production periods.

Overall, the dataset provides a comprehensive empirical foundation for the graphical, descriptive, inferential, relationship, and financial analyses presented in this chapter, as well as the simulation-based validation presented in Chapter 5.

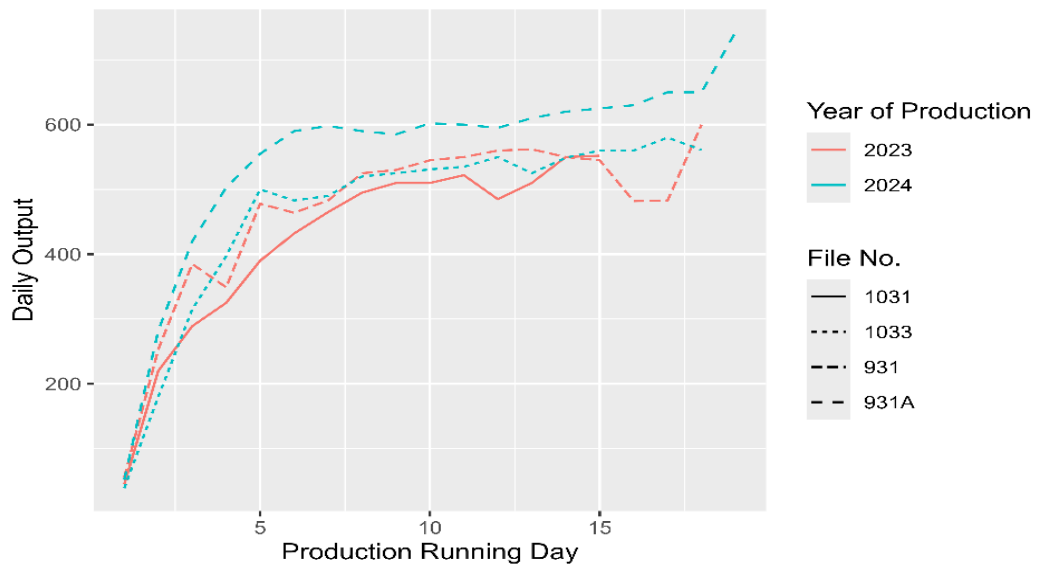
### **4.3: Graphical and Exploratory Analysis**

Graphical analysis was conducted to visually examine production performance and identify trends across the 2023 and 2024 production periods. Visual exploration of the production data provides an initial understanding of variations in key operational and financial performance indicators and complements the subsequent descriptive and inferential statistical analyses

#### **4.3.1: Daily Production Output Analysis**

Figure 4.1 presents the variation in daily production output across the production running days for the 2023 and 2024 production periods. As shown in the figure, daily production output was generally higher during 2024 than during 2023 for most of the production period. In addition, the 2024 production profile exhibits fewer fluctuations and a more consistent trend, indicating greater stability in daily production performance.

The higher production output achieved in 2024 occurred despite reductions in manpower utilization and working hours observed during the same production period. These observations are consistent with the implementation of the optimized production method and suggest improved utilization of available production resources. These graphical observations provide preliminary evidence of improved operational performance and are examined further through the descriptive and inferential statistical analyses presented in the following sections.



**Figure 4.1:** Daily Production Output Comparison (2023 vs 2024)

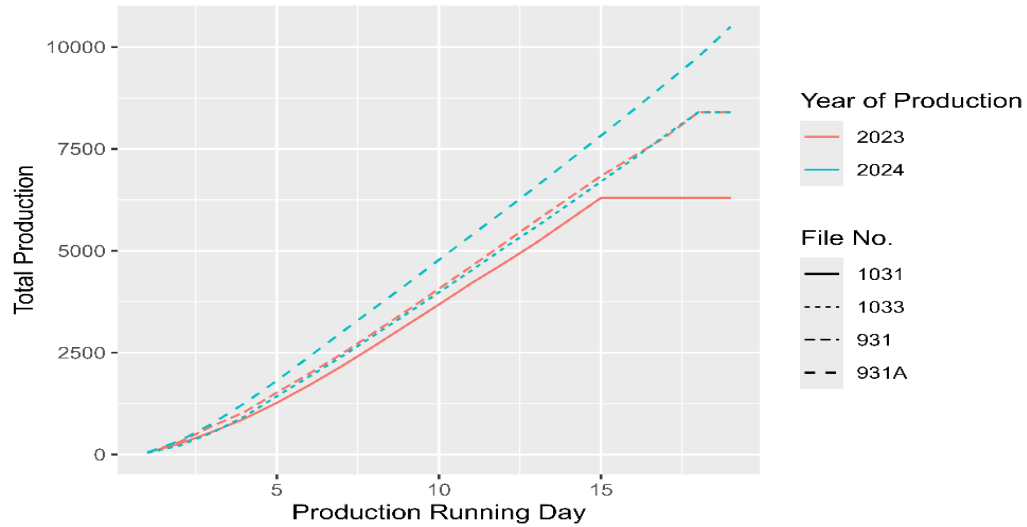
#### 4.3.2: Total Production Trend

Figure 4.2 presents the cumulative production output across the production running days for the selected blanket production files during the 2023 and 2024 production periods. The cumulative production increased steadily in both years as production progressed. However, the production curves for 2024 consistently remained above those for 2023, indicating that a greater number of blankets were produced within the same production period.

During the initial production days, the cumulative output for both years followed a similar upward trend. As production progressed, the difference between the two production periods became increasingly pronounced, with the 2024 production lines accumulating output at a faster rate. This pattern is consistent with the implementation of the optimized production method during the 2024 production period.

A further observation is that some of the selected production files in 2023 showed little or no further increase in cumulative production during the later production days, whereas the corresponding production files in 2024 continued to accumulate output and achieved higher total production volumes by the end of the production period. The higher cumulative production observed in 2024 coincided with reductions in SMV and improvements in production efficiency reported in Section 4.4, despite reductions in manpower utilization and working hours.

The widening gap over the course of the production period indicates that the differences in cumulative production were maintained throughout the production cycle rather than being confined to isolated production days. The statistical significance of these observed differences is examined in Section 4.5.



**Figure 4.2: Total Production Comparison**

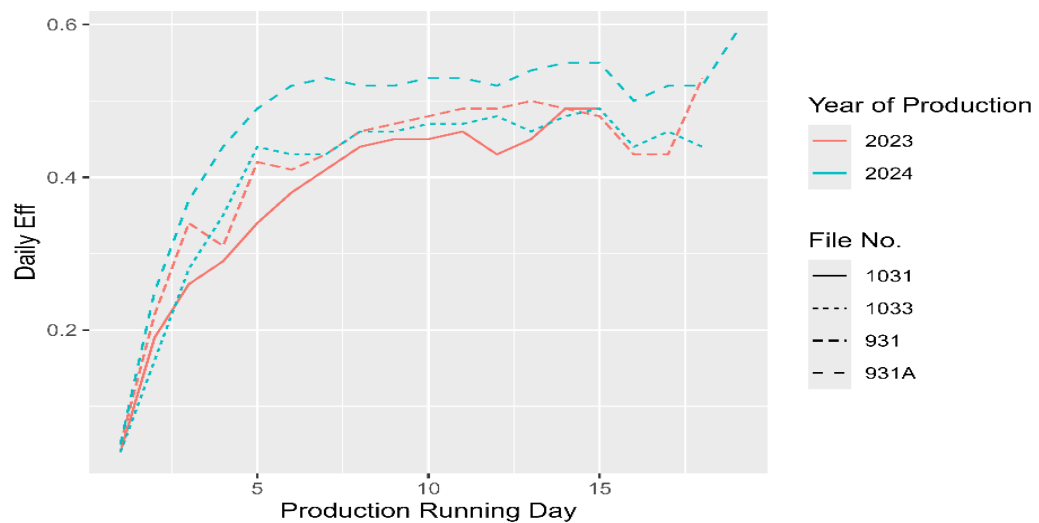
### 4.3.3: Production Efficiency Analysis

Figure 4.3a presents the daily production efficiency trends, while Figure 4.3b shows the cumulative average production efficiency achieved throughout the 2023 and 2024 production periods.

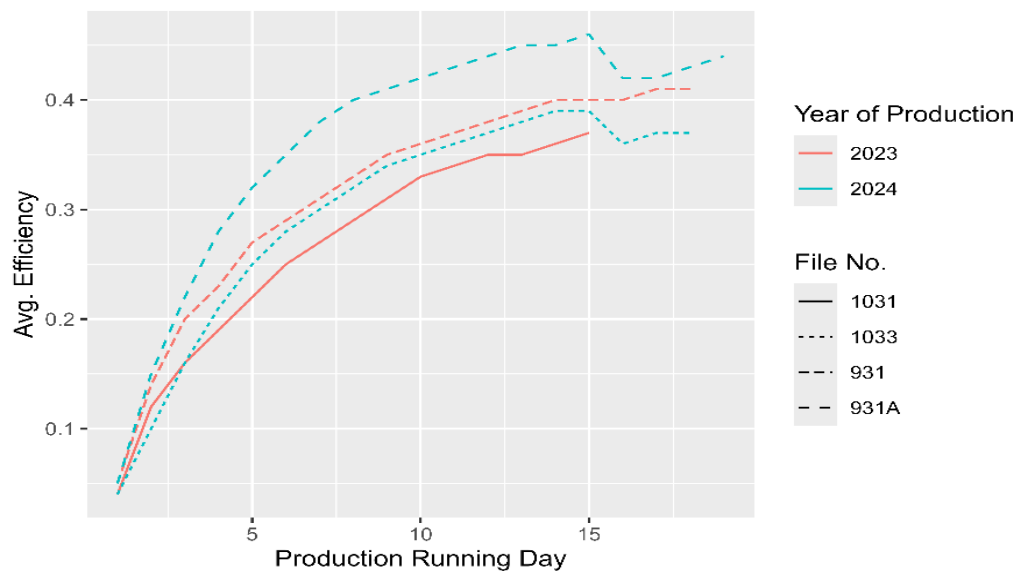
The daily efficiency plot (Figure 4.3a) shows that production efficiency increased gradually during the initial production days in both years before stabilizing. However, the 2024 production lines achieved higher efficiency levels earlier than those in 2023 and maintained this advantage throughout most of the production period. The efficiency curves for 2024 also reached higher peak values, indicating consistently higher daily production efficiency.

The cumulative average efficiency plot (Figure 4.3b) provides an overall comparison of production efficiency throughout the production period. For all selected production files, the cumulative average efficiency in 2024 remained consistently above the corresponding values recorded in 2023. The widening difference observed during the early and middle production stages indicates that the higher efficiency levels achieved in 2024 were maintained throughout the production cycle rather than being confined to isolated production days.

The higher efficiency observed in 2024 coincided with reductions in SMV and manpower utilization reported in Section 4.4, while production output increased over the same period, suggesting that these graphical patterns reflect a genuine improvement in operational performance rather than day-to-day variation. These observations are further examined through the descriptive and inferential statistical analyses presented in Sections 4.4 and 4.5.



**Figure 4.3a: Daily Efficiency Plot**



**Figure 4.3b: Average Efficiency Plot**

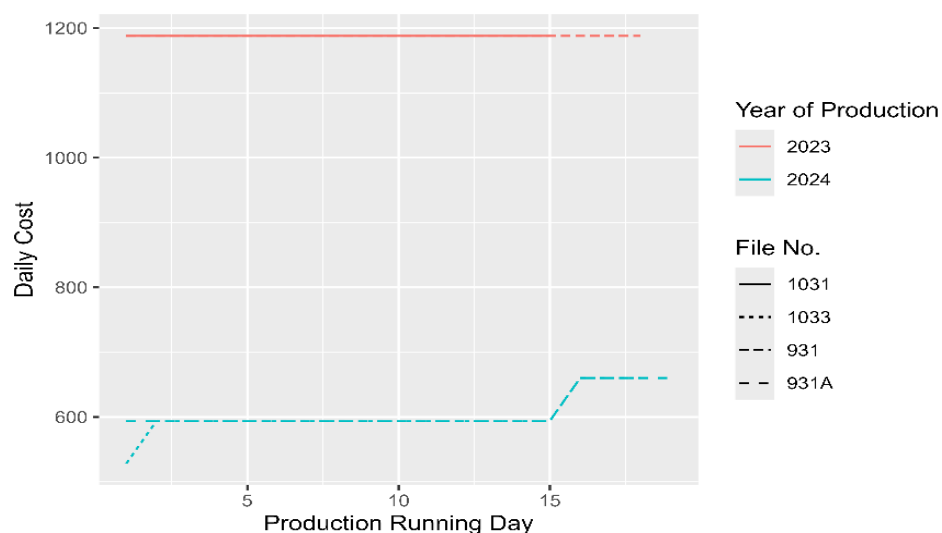
**Figure 4.3a & 4.3b: Production Efficiency Comparison**

#### 4.3.4: Cost Analysis

Figure 4.4 presents the variation in daily manufacturing cost across the production running days for the 2023 and 2024 production periods, with individual production files (1031, 1033, 931, and 931A) distinguished by line style within each year. A substantial difference is observed between the two production periods. The daily manufacturing cost in 2023 remained relatively stable at approximately USD 1,190 throughout the production period. In contrast, the corresponding cost in 2024 began at approximately USD 530 during the initial production days, stabilized between approximately USD 590 and USD 600 for most of the production period, and increased to approximately USD 660 during the later production days.

The figure shows that daily manufacturing costs remained consistently and substantially lower during the 2024 production period than during 2023, despite the higher production output and production efficiency observed during the same period. This pattern is consistent with the reductions in SMV, manpower utilization, and working hours reported in Section 4.4.

The relatively stable cost profile observed in 2023 indicates that daily manufacturing cost varied little throughout the production period. Although the manufacturing cost in 2024 remained substantially lower overall, a brief reduction was observed during the initial production days, followed by a prolonged period of relatively stable costs and a modest increase toward the end of the production period. Despite this later increase, manufacturing costs in 2024 remained consistently below those observed during the corresponding period in 2023.



**Figure 4.4:** Daily Production Cost Comparison

These graphical observations complement the descriptive and inferential statistical analyses presented in Sections 4.4 and 4.5, where the magnitude and statistical significance of the observed cost differences are evaluated.

#### 4.4: Descriptive Statistical Analysis

Descriptive statistical analysis was conducted to summarize the key production performance indicators and provide an overall comparison between the conventional production method implemented during 2023 and the optimized production method implemented during 2024. The descriptive statistics summarize the central tendency and variability of the production data and provide an overview of the operational and financial characteristics of the two production periods. Table 4.1 presents the descriptive statistics of the key production performance indicators for both production periods.

**Table 4.1: Descriptive Statistics of the Key Production Performance Indicators**

| Variable                      | Unit       | 2023 Mean (SD)      | 2024 Mean (SD)      |
|-------------------------------|------------|---------------------|---------------------|
| SMV                           | min/unit   | 28.62               | 13.65               |
| Manpower Utilization          | Operators  | 45                  | 30                  |
| Daily Working Hours           | h/day      | 11.70 (0.81)        | 9.08 (0.80)         |
| Daily Production Output       | Units/day  | 445.45 (138.23)     | 510.81 (155.02)     |
| Daily Production Efficiency   | Proportion | 0.39 (0.12)         | 0.44 (0.13)         |
| Daily Manufacturing Cost      | USD/day    | 1,188.00 (0.00)     | 604.70 (29.16)      |
| Daily CM Earnings             | USD/day    | 726.12 (225.38)     | 832.76 (252.69)     |
| Daily FOB Earnings            | USD/day    | 5,056.09 (1,568.92) | 5,797.81 (1,759.46) |
| Total Production              | Units      | 3,435.36 (2,469.84) | 4,385.54 (3,056.43) |
| Average Production Efficiency | Proportion | 0.29 (0.10)         | 0.33 (0.11)         |

*Note.* Values are presented as mean (standard deviation). Standard deviation is not applicable to Standard Minute Value and manpower utilization because these variables remained constant throughout each production period. The standard deviation of zero for 2023 daily manufacturing cost reflects that this cost was entirely determined by the fixed combination of 45 operators, 12 working hours, and a machine cost rate of USD 2.20 per hour, leaving no variation across observations.

As shown in Table 4.1, notable differences were observed across all key production performance indicators between the two production periods. The SMV decreased from 28.62 to 13.65 min/unit, representing a reduction of 52.31%, while manpower utilization was reduced from 45 to 30 operators. Average daily working hours decreased from 11.70 hours (SD = 0.81) in 2023 to 9.08 hours (SD = 0.80) in 2024, indicating that the optimized production method operated with substantially lower labor and time requirements than the conventional production method.

The descriptive statistics further indicate meaningful differences in the operational and financial performance indicators. Despite the reductions in SMV, manpower, and working hours, average daily production output increased from 445.45 units/day (SD = 138.23) in 2023 to 510.81 units/day (SD = 155.02) in 2024, while daily manufacturing cost decreased substantially from USD 1,188.00 to USD 604.70 (SD = 29.16). Similarly, daily CM earnings, daily FOB earnings, total production, and average production efficiency all showed higher mean values in 2024 compared with 2023. These descriptive observations are consistent with the graphical analyses presented in Section 4.3 and provide an initial indication of improved operational and financial performance during the 2024 production period.

Although the descriptive statistics provide an overview of the observed differences between the two production periods, they do not determine whether these differences are statistically significant. Therefore, inferential statistical analysis was conducted to evaluate the significance of the observed differences, and the results of the paired t-tests are presented in the following section.

#### **4.5: Inferential Statistical Analysis**

The findings in this section address RQ3 and RQ4: how production method optimisation influenced manpower utilisation, working hours, and overall operational performance, and whether the observed differences between the 2023 and 2024 production periods are statistically significant.

Inferential statistical analysis was conducted to determine whether the differences observed between the conventional production method (2023) and the improved production method (2024) were statistically significant. A paired t-test was performed using matched production records collected under comparable manufacturing conditions. This approach enabled a direct comparison of the two production methods

while minimizing the influence of external factors such as product type, production environment, and manufacturing process. The analysis evaluated changes in key operational and financial performance indicators following the implementation of the optimized production method.

Specifically, for each variable, the average daily values (across two file numbers) from 2023 and 2024 were considered a pair. All differences were calculated as the values in 2024 minus those in 2023. Each production day is considered a record. Since the total number of blankets produced may be different in different years, the total number of production days may differ as well. Production days with only one year of record were excluded from the analysis. The paired t-test results are presented in **Table 4.2**

**Table 4.2: Paired t-Test Results for Production Performance Variables**

| Serial Number | Variable         | t-value | p-value | Mean Difference | Result        |
|---------------|------------------|---------|---------|-----------------|---------------|
| 1             | Output           | 5.48    | <0.001  | 52.56           | Significant ↑ |
| 2             | Cost             | -90.98  | <0.001  | -584.83         | Significant ↓ |
| 3             | Efficiency       | 4.52    | <0.001  | 0.036           | Significant ↑ |
| 4             | CM               | 5.49    | <0.001  | 85.78           | Significant ↑ |
| 5             | FOB              | 5.48    | <0.001  | 596.44          | Significant ↑ |
| 6             | Total Production | 4.7     | <0.001  | 623.63          | Significant ↑ |
| 7             | Avg. Efficiency  | 4.75    | <0.001  | 0.027           | Significant ↑ |

The paired t-test results for **daily production output** indicate a statistically significant improvement after the implementation of the optimized production method ( $t = 5.48, p < 0.001$ ). The mean difference of **52.56 units** indicates that, on average, approximately 53 additional blankets were produced per production day in 2024 compared with 2023. Since the p-value is considerably lower than the 0.05 significance level, the observed increase in production output is unlikely to have occurred by chance. Instead, the results provide strong statistical evidence that the revised production method contributed to a measurable improvement in production capacity. This finding indicates that the manufacturing system was able to achieve higher production performance under similar operating conditions.

The paired t-test for **daily production cost** produced a **t-value of -90.98** with a **p-value below 0.001**, indicating a highly significant reduction in manufacturing cost after the implementation of the improved production method. The mean difference of **-584.83** shows that the average production cost was substantially lower during the 2024 production period. Among all variables examined, production cost produced the largest absolute t-value, indicating that the reduction in cost was highly consistent across the matched production records. This result demonstrates that the financial benefits of the optimized production method were not isolated to a few production days but were consistently achieved throughout the study period.

The analysis of **daily production efficiency** also demonstrated a statistically significant improvement ( $t = 4.52, p < 0.001$ ), with a mean difference of **0.036**. This result indicates that the production system operated more efficiently following the implementation of the optimized production method. The increase in efficiency reflects better utilization of available production resources and indicates that a greater proportion of available production time was converted into productive manufacturing activities. The statistical significance confirms that this improvement represents a consistent operational change rather than normal variation in daily production performance.

The paired t-test results for **CM** also revealed a statistically significant increase ( $t = 5.49, p < 0.001$ ). The positive mean difference of **85.78** indicates that the manufacturing process generated higher CM earnings after production method optimization. Since CM represents the factory's manufacturing earnings, the increase reflects improved operational performance and more effective utilization of production resources. The statistical results therefore indicate that the revised production method contributed positively to the economic performance of the manufacturing process.

Similarly, **FOB earnings** showed a statistically significant improvement ( $t = 5.48, p < 0.001$ ) with a mean difference of **596.44**. Because the FOB price per blanket remained unchanged throughout both production years, the increase in FOB earnings cannot be attributed to changes in selling price. Instead,

the higher earnings resulted from increased production volume achieved through improvements in the manufacturing process. This finding demonstrates that production method optimization contributed directly to improved financial outcomes while maintaining the same product pricing structure.

The paired t-test for **total production** also indicated a statistically significant increase ( $t = 4.70, p < 0.001$ ). The mean difference of **623.63 units** demonstrates that the cumulative production volume during the study period was substantially higher under the improved production method. This finding confirms that the observed increase in daily production output was maintained throughout the production period and was not limited to isolated production days. The higher total production therefore reflects sustained improvements in manufacturing performance following the implementation of the optimized production method.

Finally, **average production efficiency** increased significantly ( $t = 4.75, p < 0.001$ ) with a mean difference of **0.027**. Unlike daily efficiency, which may fluctuate due to routine production variation, average production efficiency provides an overall measure of production system performance during the study period. The statistically significant increase indicates that the improved production method consistently achieved higher operational efficiency across the matched production records. This suggests that the production improvements were stable and repeatable rather than temporary or influenced by short-term operational conditions.

Overall, the paired t-test analysis confirms that all evaluated production and financial indicators changed significantly following the implementation of the optimized production method. The consistently low p-values ( $p < 0.001$ ) indicate that the observed improvements are statistically reliable and are unlikely to have occurred due to random variation. These findings provide strong quantitative evidence that the revised production method significantly improved manufacturing productivity, operational efficiency, CM, FOB earnings, and overall production performance.

#### **4.6: Simulation-Based Analysis**

In addition to the empirical analysis of historical production data, a simulation-based analysis was incorporated into this research to complement the statistical evaluation of manufacturing performance. While the empirical analyses presented in this chapter provide evidence based on observed production records, simulation enables the production system to be evaluated under conditions of operational variability and uncertainty.

The simulation-based analysis extends the empirical findings by providing an additional assessment of production performance under different manufacturing scenarios. A detailed description of the simulation

methodology, model development, assumptions, parameter estimation, and simulation results is presented separately in **Chapter 5**.

#### **4.7: Relationship Analysis**

Relationship analysis was conducted to examine how the key production variables influenced manufacturing performance and productivity. The results revealed a strong negative relationship between SMV and production output, indicating that lower SMV was consistently associated with higher productivity. Following the implementation of the optimized production method, the average SMV decreased from 28.62 minutes per unit in 2023 to 13.65 minutes per unit in 2024, representing a reduction of approximately 52.31%. This substantial reduction enabled the production line to manufacture more blankets within the available working time, resulting in increased output and improved operational efficiency.

In contrast, manpower and working hours exhibited comparatively weaker relationships with production output. Although manpower requirements decreased by approximately 33% and working hours were reduced by about 22%, production performance improved significantly. Daily production output increased by an average of 52.56 units, while total production increased by an average of 623.63 units. Similarly, daily production efficiency and average production efficiency increased by 0.036 and 0.027, respectively. These findings indicate that productivity improvement was achieved through production method optimization rather than by increasing labor input or extending working hours.

The relationship analysis further demonstrates that reducing SMV through systematic production method improvement was associated with a marked improvement in overall manufacturing performance. Lower SMV reduced processing time, minimized unnecessary operator movement, and improved workflow efficiency, allowing available resources to be utilized more effectively. As a result, production costs decreased significantly, while CM earnings, FOB earnings, and overall profitability increased. These findings indicate that production method optimization and SMV reduction were the primary contributors to the observed productivity improvement, cost reduction, and profitability enhancement in labor-intensive blanket manufacturing.

#### **4.8: Financial Analysis**

Financial analysis was conducted to evaluate the effect of production method optimization on the economic performance of the manufacturing process. The comparison between the 2023 and 2024 production periods shows a clear improvement in the financial performance of the production line following the implementation of the optimized production method. The improved production process

enabled the factory to produce a greater number of blankets while utilizing production resources more efficiently, resulting in a significant reduction in manufacturing costs.

The statistical analysis confirmed that production cost decreased significantly between the two production periods ( $t = -90.98$ ,  $p < 0.001$ ). At the same time, CM earnings increased significantly (mean difference = 85.78,  $t = 5.49$ ,  $p < 0.001$ ), while FOB earnings also showed a statistically significant increase (mean difference = 596.44,  $t = 5.48$ ,  $p < 0.001$ ). These findings indicate that the optimized production method enhanced the factory's financial performance by improving operational efficiency and reducing production costs.

Since the FOB price per blanket remained unchanged during both production years, the observed financial improvement cannot be attributed to changes in selling price. Instead, the increase in CM earnings and FOB earnings resulted from higher production output, improved operational efficiency, and lower manufacturing costs achieved through production method optimization. This demonstrates that improving the production method provides a practical and sustainable approach to enhancing financial performance without requiring major capital investment or increasing production resources.

#### **4.9: Profit and Loss Analysis**

Profit and loss analysis was performed to evaluate the overall financial outcome of the two production methods. The comparison shows a clear difference in financial performance between the two production periods. Based on the unit-level Monte Carlo simulation presented in Chapter 5, the 2023 conventional process generated a mean loss of approximately USD 0.98 per garment, whereas the 2024 optimized process generated a mean profit of approximately USD 0.51 per garment, representing an improvement of approximately USD 1.48 per unit. This improvement reflects the cumulative effect of the production method changes implemented during the study period and is examined in further detail in Sections 5.9 through 5.13.

#### **4.10: Summary of Findings**

This chapter presented the empirical evaluation of the conventional and improved production methods using historical production data collected from a labor-intensive blanket manufacturing environment. A comprehensive assessment was carried out through graphical analysis, descriptive statistics, inferential statistical analysis, relationship analysis, financial analysis, and profit and loss analysis to evaluate the impact of production method optimization on manufacturing performance.

The empirical analyses collectively demonstrated that the optimized production method substantially improved the operational and financial performance of the production system. The statistical analyses confirmed that the observed differences between the two production methods were significant, indicating that the improvements were consistently achieved throughout the production period rather than resulting from random variation. The findings also highlighted the importance of production method optimization in improving manufacturing efficiency and overall business performance.

Although the empirical analysis provides a comprehensive assessment based on historical production records, it represents the performance of the manufacturing system under observed production conditions. To obtain a broader understanding of production behavior under operational variability and uncertainty, a complementary simulation-based analysis was incorporated into this research.

The following chapter presents a detailed simulation-based evaluation of the production system, providing additional insight into the variability and reliability of the optimized production method under different manufacturing scenarios. Together, the empirical and simulation-based analyses provide a comprehensive evaluation of the effectiveness of production method optimization in improving productivity and profitability within a labor-intensive manufacturing environment.

## **CHAPTER 5: MONTE CARLO SIMULATION-BASED PROFIT DISTRIBUTION ANALYSIS**

### **5.1: Purpose of the Simulation**

The primary objective of this simulation was to evaluate the financial impact of the manufacturing process improvement implemented in 2024 relative to the conventional method used in 2023. Rather than assessing factory-wide profitability — which is influenced by production volume, buyer orders, and resource utilization — this analysis focuses on the unit-level profitability of producing a single garment. This approach eliminates the confounding effect of order quantity, enabling a direct and fair comparison of the two production methods on their own merit.

In addition, in the previous chapters, the analyses were based on fixed operational time (i.e., SMV) in each step during the manufacturing process. In this chapter, a Monte Carlo simulation methodology was adopted because real manufacturing environments are inherently stochastic. Operation times vary due to differences in operator skill and fatigue, machine conditions, workplace interruptions, and the probabilistic occurrence of quality defects requiring rework. A single average SMV value cannot adequately represent this variability. By generating 10,000 independent production outcomes per scenario, the simulation produces a probability distribution of profit per garment rather than a single deterministic estimate, providing a statistically robust and practically meaningful assessment.

Each simulation trial incorporated the following elements: process-level time variability modeled through truncated normal distributions; expert-defined lower and upper bounds for each operation; error-prone operations with empirically derived defect probabilities; stochastic rework time additions when errors occur; and actual ERP-derived production efficiency values to anchor the model in observed operational reality.

### **5.2: Data Sources**

The simulation was parameterized using three independent and complementary sources of industrial data, ensuring both statistical validity and practical realism.

**ERP Production Data:** Daily production records were extracted from the company's ERP system, providing actual output quantities, operator counts, daily working hours, machine operating costs, and buyer CM

prices. These records were used to calculate observed production efficiencies for both production periods, grounding the simulation in real factory performance rather than engineering targets.

Time Study Data: SMV for each operation in both processes were obtained from formal industrial engineering time studies. Observed times were adjusted using standard performance rating and allowance procedures to produce the mean values ( $\mu$ ) used in the simulation distributions.

Expert Judgement: Experienced industrial engineers who conducted the time studies provided the lower and upper bounds for each operation's distribution, as well as identifying error-prone operations and their associated rework time ranges. This expert input ensured that the simulation's distributional parameters reflected actual shop-floor performance boundaries rather than statistical approximations.

**5.3: Production Process Comparison**

This section compares the conventional 2023 production method with the optimized 2024 method to quantify the impact of method optimization on labor-intensive manufacturing performance. The comparison focuses on the number of operations, the SMV of each process, and the resulting implications for productivity and cost. The two processes are examined in turn before their statistical and financial differences are analyzed in the subsequent sections.

**5.3.1: 2023 Conventional Process**

The 2023 production method comprised eleven sequential operations (X1 through X11 in Table 5.1), reflecting a traditional manufacturing approach in which tasks were optimized individually rather than as an integrated flow. The total SMV for this process was 28.62 minutes per garment — a relatively high cycle time that indicated substantial direct labor and machine time requirements per unit. This elevated SMV, combined with the cost of machine operation, placed the manufacturing cost per garment dangerously close to or above the contractual CM price, creating the conditions for systematic financial loss at the unit level.

**Table 5.1: SMV for each step in the Conventional Manufacturing (2023) Process**

| Process Number | Conventional Process Name             | Machine Type | Cycle Time (Sec) | SMV  |
|----------------|---------------------------------------|--------------|------------------|------|
| X1             | Lower part corner making and turning  | S/N          | 56               | 1.05 |
| X2             | Upper and lower part corner stay tuck | S/N          | 168              | 2.8  |

| Process Number  | Conventional Process Name                                   | Machine Type | Cycle Time (Sec) | SMV          |
|-----------------|-------------------------------------------------------------|--------------|------------------|--------------|
| X3              | Upper and lower part joining                                | 4TO/L        | 429              | 4.46         |
| X4              | Body turning                                                | H/P          | 26               | 0.4          |
| X5              | Upper part corner tuck with lower part                      | S/N          | 160              | 2.56         |
| X6              | Upper and lower part stay stitch (false stitch)             | S/N          | 226              | 3.96         |
| X7              | Upper and lower part zigzag top stitch                      | F/L          | 217              | 2.51         |
| X8              | False stitch removal                                        | H/P          | 645              | 8.9          |
| X9              | Care label making                                           | S/N          | 13               | 0.22         |
| X10             | Care label attachment, fold tuck, and main label attachment | S/N          | 44               | 0.76         |
| X11             | Thread trimming                                             | H/P          | 60               | 1            |
| <b>Sum of X</b> | <b>Conventional Total SMV</b>                               |              |                  | <b>28.62</b> |

### 5.3.2: 2024 Improved Process

Following a systematic process improvement initiative — informed by value stream analysis, operation clustering, and production supervisor feedback — the manufacturing sequence was redesigned to eliminate redundant steps and combine compatible operations. The improved process reduced the total number of operations to eight (Y1 through Y8) and the total SMV to 13.65 minutes per garment. The magnitude of this improvement is expressed as:

$$\text{SMV Reduction (\%)} = ((28.62 - 13.65) / 28.62) \times 100 = 52.31\%$$

A 52.31% reduction in SMV means the improved process requires only half the standard production time of its predecessor. This was achieved not by accelerating individual operations — which would compromise

quality — but by eliminating unnecessary steps and reorganizing the production flow. The consequence is a proportional reduction in manufacturing cost per unit, which transforms the economic viability of production at the prevailing CM price.

However, the above calculation is deterministic, meaning that we have assumed that the SMVs will always remain the same, an assumption that is not tangible, as the actual production time varies from process to process, from garment to garment. The simulation study below allows us to study the reduction in production time, and hence the improvements in profit, under variable conditions mimicking real manufacturing processes. Table 5.2 presents the corresponding step-level SMV breakdown for the 2024 improved process, following the same eight-operation structure (Y1\u2013Y8) used in the Monte Carlo simulation.

**Table 5.2: SMV for each step in 2024 Improved Process**

| <b>Process Number</b> | <b>Improved Process Name</b>                                | <b>Machine Type</b> | <b>Cycle Time (Sec)</b> | <b>SMV</b> |
|-----------------------|-------------------------------------------------------------|---------------------|-------------------------|------------|
| Y1                    | Lower part corner making and turning                        | S/N                 | 56                      | 1.17       |
| Y2                    | Lower part corner fold tuck                                 | S/N                 | 49                      | 0.93       |
| Y3                    | Upper part corner tuck with lower part                      | S/N                 | 160                     | 3.04       |
| Y4                    | Upper and lower part joining                                | S/N                 | 210                     | 3.99       |
| Y5                    | Upper and lower part zigzag top stitch                      | F/L                 | 129                     | 2.45       |
| Y6                    | Care label making                                           | S/N                 | 13                      | 0.23       |
| Y7                    | Care label attachment, fold tuck, and main label attachment | S/N                 | 44                      | 0.84       |
| Y8                    | Thread trimming                                             | H/P                 | 60                      | 1          |
| Sum of Y              | Updated Total SMV                                           |                     |                         | 13.65      |

## 5.4: Operational Times

Operation times in manufacturing do not remain constant — they vary around a central mean due to natural fluctuations in human performance, machine behavior, and environmental conditions. A normal distribution is a natural modeling choice for this variability, but its theoretically infinite tails allow the generation of negative values or unrealistically extreme times, which are physically impossible in production. In addition, the usual normal distributions are symmetrical. However, in real-world processes, the production times may not be symmetrical about the mean. To prevent these, a truncated normal distribution was applied to each operation:

$$X \sim \text{TN}(\mu, \sigma, a, b)$$

where  $a \leq \mu \leq b$  is the mean operation time,  $\sigma$  is the standard deviation,  $a$  is the minimum physically achievable time (lower bound), and  $b$  is the maximum realistic time (upper bound). Truncating at these bounds ensures that all simulated operation times remain within the observable performance range of real operators and machines, preserving both the statistical properties of the normal distribution and the practical validity of the simulation output.

### 5.4.1: Lower and Upper Bounds

To realistically represent the variability of sewing operation times in the Monte Carlo simulation, a lower bound ( $a$ ) and an upper bound ( $b$ ) were assigned to every operation. These bounds define the minimum and maximum realistic operation times within which all simulated values must fall. The purpose of introducing these limits was to ensure that the simulation generated practically achievable operation times and avoided unrealistic extreme values that may occur when using an unrestricted probability distribution.

The lower and upper bound values were obtained from an experienced Industrial Engineering (IE) professional from the factory who conducted time studies for both the 2023 and 2024 blanket production methods during actual production. Although the original detailed time-study report was unavailable, the engineer provided the minimum and maximum operation times based on direct shop-floor observations and extensive practical experience with the production process. Therefore, the bounds used in this study represent realistic operating limits observed in industrial practice rather than theoretical assumptions.

The lower bound represents the fastest achievable operation time under favorable production conditions, where a skilled operator performs the task efficiently with minimal interruptions. In contrast, the upper bound represents the maximum realistic operation time that may occur due to minor production disturbances such as operator variability, material handling delays, machine adjustments, or brief

interruptions during the sewing process. These limits were considered more appropriate than using statistical approximations because they are grounded in actual factory experience and reflect the true behavior of the production system. Table 5.3 presents the lower bounds, mean SPTs, and upper bounds used for all operations in both the conventional 2023 production method and the improved 2024 production method.

**Table 5.3: Lower and Upper Operation Time Bounds for the 2023 and 2024 Production Methods**

| Operation No.                               | Lower Bound (min) | Mean SPT (min) | Upper Bound (min) |
|---------------------------------------------|-------------------|----------------|-------------------|
| <b>2023 Conventional Process (X1 – X11)</b> |                   |                |                   |
| X1                                          | 0.8               | 1.05           | 1.5               |
| X2                                          | 2                 | 2.8            | 3.8               |
| X3                                          | 3.5               | 4.46           | 6                 |
| X4                                          | 0.2               | 0.4            | 0.8               |
| X5                                          | 2                 | 2.56           | 3.5               |
| X6                                          | 3                 | 3.96           | 5.5               |
| X7                                          | 2                 | 2.51           | 3.5               |
| X8                                          | 7                 | 8.9            | 11.5              |
| X9                                          | 0.1               | 0.22           | 0.5               |
| X10                                         | 0.5               | 0.76           | 1.3               |
| X11                                         | 0.7               | 1              | 1.5               |

| Operation No.                          | Lower Bound (min) | Mean SPT (min) | Upper Bound (min) |
|----------------------------------------|-------------------|----------------|-------------------|
| <b>2024 Improved Process (Y1 – Y8)</b> |                   |                |                   |
| Y1                                     | 0.9               | 1.17           | 1.7               |
| Y2                                     | 0.7               | 0.93           | 1.4               |
| Y3                                     | 2.3               | 3.04           | 4.2               |
| Y4                                     | 3                 | 3.99           | 5.2               |
| Y5                                     | 2                 | 2.45           | 3.3               |
| Y6                                     | 0.1               | 0.23           | 0.5               |
| Y7                                     | 0.5               | 0.84           | 1.3               |
| Y8                                     | 0.7               | 1              | 1.5               |

The data presented in Table 5.3 indicate noticeable differences between the two production methods. The 2023 process consists of eleven operations with relatively wider time ranges, reflecting a more complex production sequence and greater variability in operation performance. In contrast, the 2024 process consists of only eight operations and generally exhibits narrower operating ranges. This reduction in variation suggests that the improved production method achieved greater process consistency and operational stability.

A comparison of the lower and upper limits further shows that the upper bounds are generally farther from the mean values than the lower bounds. This pattern reflects the practical nature of garment manufacturing operations. While opportunities for completing an operation significantly faster than the standard time are limited, production delays caused by minor interruptions, handling difficulties, machine adjustments, or operator-related factors can extend operation times to a greater extent. Consequently, the operational ranges

are slightly skewed toward longer processing times, which realistically represents the behavior of production activities on the factory floor.

Overall, the lower and upper bounds form an essential component of the simulation model by defining realistic operational limits for each activity. Their inclusion improves the reliability of the Monte Carlo simulation and ensures that the generated SPT distributions accurately reflect the variability observed in actual garment manufacturing processes.

### **5.5: Error-Prone Operations**

Certain sewing operations are more susceptible to defects due to their technical complexity, tight dimensional tolerances, or multi-layer fabric handling requirements. When a defect occurs, the operator must perform rework — undoing and repeating the faulty operation — which adds non-trivial time to the production cycle and increases the effective cost per garment. To model this, specific operations were designated as error-prone based on historical defect records, with error probabilities calculated as:

$$P(\text{error}) = \text{Number of Defects} / \text{Total Units Inspected}$$

When an error event was triggered in a simulation trial, an additional rework duration drawn from a uniform distribution within an operation-specific range was added to that trial's operation time.

#### **5.5.1: 2023 Process — Error-Prone Operations**

Two operations were identified as error-prone in the 2023 conventional process. Operation X6 carried an error probability of  $P(X6) = 24/226 \approx 10.6\%$ , with rework times ranging from 30 to 60 seconds per event. Operation X7 had a higher error probability of  $P(X7) = 43/217 \approx 19.8\%$ , reflecting its greater technical complexity, with rework times of 90 to 120 seconds — representing the complete removal and re-sewing of a structurally critical seam. In the simulations, the additional reworking times are assumed to follow a uniform distribution with the aforementioned limits. Combined, these two operations introduced substantial stochastic cost additions into the 2023 production cycle.

#### **5.5.2: 2024 Process — Error-Prone Operations**

The process of redesign effectively eliminated or redesigned the conditions that gave rise to high defect rates in X6 and X7. In the improved 2024 process, only one operation remained error-prone: Operation Y5, with an error probability of  $P(Y5) = 23/129 \approx 17.8\%$  and rework times of 90 to 120 seconds. The reduction from two error-prone operations to one is a concrete indicator that the improved process is inherently more

robust — simpler operations are less susceptible to defects, reducing both the frequency and aggregate cost of rework events.

### 5.6: Efficiency Calculation

Production efficiency quantifies how effectively the production system converts available labor time into productive output. It is a critical parameter in the cost model because manufacturing cost per garment is inversely proportional to efficiency: lower efficiency means more time is consumed per unit of output, increasing per-unit cost. Efficiency was calculated empirically from ERP records — not assumed from engineering standards — using the formula:

$$\text{Efficiency (\%)} = (\text{SMV} \times \text{Output}) / (\text{Manpower} \times \text{Working Hours} \times 60) \times 100$$

where Output is daily garments produced, Manpower is the number of operators, and Working Hours is the scheduled shift duration. Separate efficiency values were computed for the 2023 and 2024 production periods and incorporated as fixed parameters in their respective simulation models, ensuring the simulation reflects actual factory performance rather than idealized targets.

### 5.7: Cost per Piece Calculation

CM refers to the manufacturing cost incurred by the factory to produce one garment. It represents the cost associated with labor, machine usage, and production resources required to convert raw materials into a finished product. CM is an important performance indicator because it directly affects the profitability of a manufacturing operation.

The basic CM formula is:

$$\text{CM} = (\text{SMV} \times \text{Cost Per Minute}) / \text{Efficiency}$$

where:

$$\text{Cost Per Minute} = \text{Machine Cost Per Hour} / 60$$

and

$$\text{Efficiency} = (\text{SMV} \times \text{Total Output}) / (\text{Number of Workers} \times \text{Working Hours} \times 60)$$

**Explanation:**

The SMV represents the standard time required to produce a garment under ideal production conditions. Therefore, calculating CM using only SMV and cost per minute assumes that the production line is operating at 100% efficiency.

In reality, production systems rarely achieve perfect efficiency due to factors such as operator fatigue, machine interruptions, waiting time, material handling, and quality-related activities. As a result, the actual utilization of manpower and working hours differs from the ideal condition assumed by the SMV.

To reflect real factory performance, efficiency is incorporated into the CM calculation. Including efficiency adjusts the standard manufacturing cost according to the actual utilization of labor time and production resources. Consequently, the calculated CM represents a more realistic estimate of the true manufacturing cost of producing a garment under actual factory conditions rather than under ideal conditions.

The machine operating cost was USD 2.20 per operating hour, encompassing electricity, maintenance provisions, and depreciation. Converting it to a per-minute rate:

$$\text{Cost Per Minute} = 2.20 / 60 = \text{USD } 0.0367 \text{ per minute}$$

### **5.8: Profit per Piece Calculation**

Profits depend on the price and quantity. To ensure a fair comparison between the 2023 and 2024 processes, we calculate the profit based on a single garment, assuming the same price. Revenue per garment was determined by the contractual Cut and Make (CM) price agreed with the buyer:

$$\text{Revenue per Garment} = \text{USD } 1.63$$

This figure was held constant across both production scenarios — a deliberate methodological choice that isolates the effect of manufacturing cost differences on profitability. Profit per garment was then:

$$\text{Profit} = \text{Revenue} - \text{Cost per Piece} = 1.63 - \text{Cost per Piece}$$

A positive value indicates the garment was produced at a cost below the CM price, generating a margin. A negative value indicates production cost exceeded the CM price, resulting in a per-unit financial loss.

### **5.9: Simulation Results**

The Monte Carlo simulation was performed using 10,000 iterations for each production scenario to evaluate the profitability of producing a single garment under different operating conditions. Four scenarios were analyzed: the 2023 conventional process without rework, the 2023 conventional process with rework, the

2024 improved process without rework, and the 2024 improved process with rework. For each iteration, operation times were randomly generated within their specified lower and upper bounds using truncated normal distributions. The resulting SPTs were then used to calculate manufacturing cost and profit per garment. This approach enabled the variability inherent in the production process to be incorporated into financial analysis.

**Table 5.4** presents the descriptive statistics of the simulated profit distributions, including the minimum value, first quartile (Q1), median, mean, third quartile (Q3), maximum value, and standard deviation. The quartiles were calculated from the 10,000 simulated profit values and provide additional information about the spread and consistency of the results. Specifically, Q1 (25th percentile) represents the value below which 25% of the simulated profits fall, while Q3 (75th percentile) represents the value below which 75% of the simulated profits fall. Together, these statistics provide a comprehensive summary of the central tendency and variability of the simulated profit distributions.

**Table 5.4: Descriptive Statistics of Simulated Profit per Garment Based on 10,000 Monte Carlo Iterations**

| Production Year | Scenario             | Minimum | Q1     | Median | Mean    | Q3     | Maximum | Standard Deviation |
|-----------------|----------------------|---------|--------|--------|---------|--------|---------|--------------------|
| 2023            | No Error (No Rework) | -1.415  | -1.055 | -0.975 | -0.977  | -0.898 | -0.638  | 0.114              |
| 2023            | Error (With Rework)  | -1.535  | -1.114 | -1.022 | -1.0266 | -0.932 | -0.593  | 0.134              |
| 2024            | No Error (No Rework) | 0.348   | 0.474  | 0.506  | 0.5054  | 0.537  | 0.662   | 0.047              |
| 2024            | Error (With Rework)  | 0.209   | 0.464  | 0.501  | 0.4947  | 0.534  | 0.657   | 0.059              |

The results indicate a substantial difference in profitability between the two production methods. For the 2023 conventional process, both scenarios generated negative mean profits, indicating that the manufacturing cost exceeded the buyer's CM price under most simulated conditions. The average profit

decreased from -0.9772 USD per garment under normal conditions to -1.0266 USD per garment when rework was included, demonstrating the adverse financial impact of additional processing time and production inefficiencies. Furthermore, the wider interquartile range and larger standard deviation observed in the error scenario indicate greater variability and less predictable financial performance.

In contrast, the 2024 improved process generated positive mean profits under both scenarios. The mean profit was 0.5054 USD per garment under normal conditions and 0.4947 USD per garment when rework was included. These findings indicate that the substantial reduction in SMV achieved through process optimization significantly reduced the manufacturing cost per garment and enabled production to remain profitable even when additional rework time was considered. The relatively small difference between the normal and error scenarios further suggests that the improved process is less sensitive to production disturbances and quality-related issues.

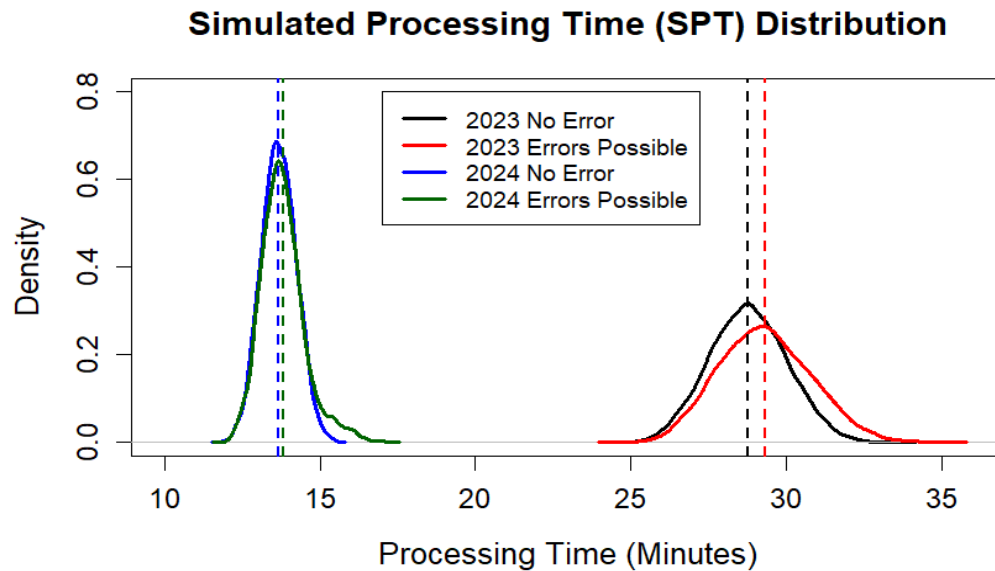
The quartile values provide additional insight into the consistency of profitability. For the 2024 normal scenario, 50% of all simulated profit values lie between 0.4736 USD and 0.5374 USD, indicating a relatively stable and predictable profit distribution. In comparison, the 2023 scenarios exhibit wider profit ranges and are entirely located within the negative profit region, confirming that losses are likely under most operating conditions. The lower standard deviations observed for the 2024 process also indicate reduced variability and improved process stability compared with the conventional production method.

Although the mean profit provides a useful overall measure of financial performance, it does not fully describe the behavior of the simulated distributions. Therefore, density plots are presented in the following sections to visualize the probability distributions, and variability of profit outcomes across all production scenarios. These graphical analyses provide a deeper understanding of the financial implications of process improvement and the robustness of the redesigned production method.

#### **5.10: Simulated Processing Time (SPT) Distribution Analysis**

Before evaluating the profitability outcomes, it is important to examine the distribution of the **Simulated Processing Time (SPT)** generated by the Monte Carlo simulation. In this study, the term *SPT* is used instead of SMV because SMV represents a fixed standard time obtained from time-study observations, whereas SPT represents the range of total processing times generated during the simulation after incorporating operational variability, lower and upper bounds, and probabilistic rework events. Therefore, SPT provides a more realistic representation of actual manufacturing performance under uncertain production conditions.

Figure 5.1 presents the probability density distributions of simulated processing times for four production scenarios: **2023 No Error**, **2023 Errors Possible**, **2024 No Error**, and **2024 Errors Possible**. The density curves illustrate the likelihood of different processing times occurring during the 10,000 Monte Carlo simulation trials and provide a visual representation of both the expected processing time and the variability associated with each production method.



**Figure 5.1: Simulated Processing Time (SPT) Distributions for the 2023 and 2024 Production Processes (No Error and Errors Possible)**

The distributions corresponding to the **2023 process** are positioned on the right-hand side of the figure, with mean processing times close to **29 minutes**. The **2023 No Error** distribution is centered at approximately **28.9 minutes**, while the **2023 Errors Possible** distribution is shifted slightly to the right, with a mean processing time of approximately **29.3 minutes**. This rightward shift occurs because rework events add additional processing time to selected operations, increasing the total time required to manufacture a garment. The broader shape of the 2023 distributions indicates greater variability in processing time, reflecting the complexity of the conventional eleven-operation production method and the cumulative effect of variability across multiple operations.

In contrast, the distributions associated with the **2024 improved process** are concentrated on the left-hand side of the figure, with mean processing times near **13.7–13.8 minutes**. The **2024 No Error** distribution

is centered around **13.7 minutes**, while the **2024 Errors Possible** distribution exhibits only a slight shift towards higher processing times. The close overlap between these two distributions indicates that rework has a relatively small influence on the overall performance of the improved process. This suggests that the redesigned production method is more resilient to production disruptions and quality-related issues than the conventional process.

A clear separation exists between the 2023 and 2024 distributions. The 2024 distributions are located entirely below the 2023 distributions, with virtually no overlap between the two production methods. This complete separation demonstrates that the reduction in processing time achieved through process improvement was substantial and consistent across all simulated outcomes. The average processing time decreased from approximately 29 minutes in the conventional process to approximately 14 minutes in the improved process, representing a reduction of about 52%. Importantly, this reduction is evident across the entire distribution rather than only at the mean value, indicating that the improvement was achieved consistently throughout the simulation.

The density curves also provide insight into process variability. The 2024 distributions are noticeably narrower and more sharply peaked than the corresponding 2023 distributions. A narrower density distribution indicates lower variability and greater process consistency. From an operational perspective, reduced variability is highly desirable because it improves production planning, line balancing, capacity utilization, and delivery reliability. The lower variability observed in the 2024 process can be attributed to the simplified production sequence, reduced number of operations, and elimination of unnecessary processing activities.

The effect of rework is also evident from the displacement between the No Error and Errors Possible distributions. For the 2023 process, rework produces a noticeable shift towards longer processing times, indicating that the conventional process is sensitive to quality-related disruptions. In contrast, the shift between the 2024 No Error and Errors Possible distributions is relatively small, suggesting that the improved process is less affected by rework and therefore more robust in practical manufacturing environments.

Overall, Figure 5.1 demonstrates that the process improvements implemented in 2024 achieved two important objectives simultaneously. First, the redesigned process substantially reduced the total processing time required to manufacture a garment. Second, it reduced process variability and improved operational stability. These findings confirm that the benefits of the process improvement extend beyond simple time reduction and include enhanced consistency, predictability, and resilience. The reduction in

simulated processing time observed in Figure 5.1 forms the basis for the manufacturing cost savings and profitability improvements discussed in the subsequent sections of this chapter.

### 5.11: Profit Density Distribution Analysis

The kernel density plot in Figure 5.2 presents the probability of distributions of profit per garment for the four simulation scenarios. The 2023 No Error distribution (black curve) is centered around a mean profit of  $-0.977$  USD per garment and lies entirely within the negative-profit region. This indicates that all simulated production outcomes under the conventional 2023 process resulted in a financial loss. The distribution exhibits a smooth, approximately bell-shaped form, suggesting that the negative profitability is a consequence of the underlying process structure rather than a small number of extreme observations. The combination of a high processing time and the resulting manufacturing cost exceeded the fixed CM price across the entire range of simulated outcomes.

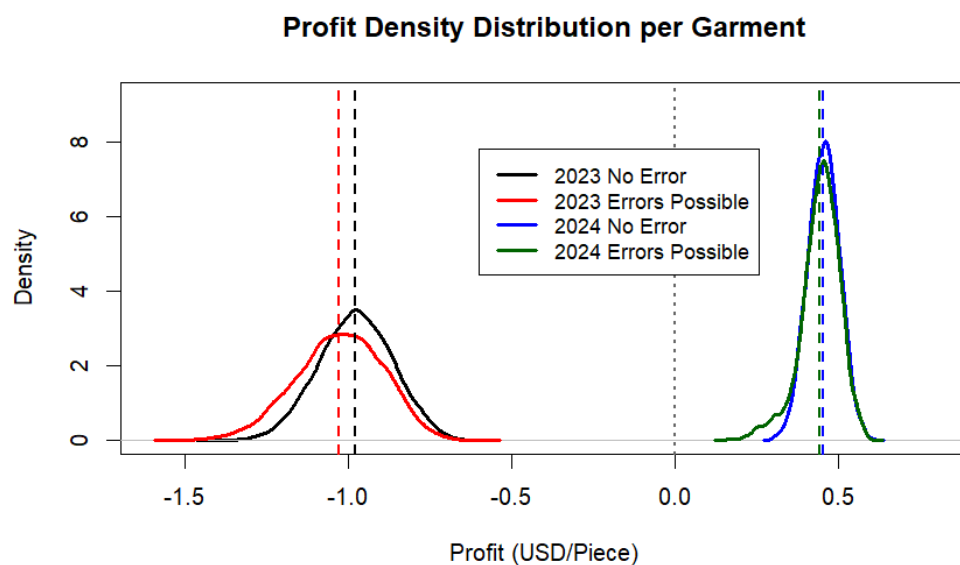
The 2023 Errors Possible distribution (red curve) is shifted further to the left and has a mean profit of  $-1.027$  USD per garment. This shift reflects the additional manufacturing cost generated by rework events in Operations X6 and X7. Compared with the No Error scenario, rework reduced mean profit by approximately  $0.050$  USD per garment, demonstrating that quality-related disruptions further worsen the economic performance of an already loss-making process.

In contrast, the 2024 No Error distribution (blue curve) lies entirely within the positive-profit region and is centered around a mean profit of  $0.505$  USD per garment. The complete separation between the 2023 and 2024 distributions highlights the substantial financial impact of the redesign process. The improvement of approximately  $1.48$  USD per garment in mean profit is primarily attributable to the reduction in processing time, which lowered manufacturing cost while the CM price remained unchanged. The 2024 distribution is also noticeably taller and narrower than the 2023 distributions, indicating lower variability and greater consistency in profit outcomes. While production method optimisation is the primary intervention evaluated here, part of the observed improvement may also reflect factors such as operator learning or management attention associated with the project; these alternative explanations are discussed further in Section 6.9.

The 2024 Errors Possible distribution (green curve) shows only a slight leftward displacement relative to the 2024 No Error distribution. Mean profit decreases marginally from  $0.505$  USD to  $0.495$  USD per garment, representing a reduction of only  $0.010$  USD per garment. The substantial overlap between the blue and green curves demonstrates that rework has a relatively minor effect on the profitability of the

improved process. This finding suggests that the redesigned production method is not only more efficient but also more resilient to quality-related disruptions.

Overall, the density plot clearly demonstrates a transition from consistently negative profitability in the 2023 process to consistently positive profitability in the 2024 process. Furthermore, the reduced separation between the No Error and Errors Possible distributions in 2024 indicates that the improved process is less sensitive to rework events, resulting in greater financial stability and operational robustness.



**Figure 5.2: Profit Density Distribution Per Piece**

### 5.12: Comparative Discussion

The convergent findings from the density graph indicate that the 2024 process optimization was the primary contributor to the improvement in per-unit profitability. This change was associated with lower manufacturing cost per garment through reduced operational times, transforming the process from one that was structurally loss-making into one that generates a consistent positive margin at the prevailing CM price.

The financial impact of rework events can be precisely quantified from the simulation output. In the 2023 process, rework reduced the **mean profit** from **−0.977 USD** to **−1.027 USD** per garment:

$$\begin{aligned} &\textbf{Impact of Rework (Mean Profit, 2023):} \\ &-1.027 - (-0.977) = \textbf{-USD 0.050 per garment} \end{aligned}$$

Similarly, the **median profit** decreased from **−0.976 USD** to **−1.022 USD** per garment:

**Impact of Rework (Median Profit, 2023):**

$$-1.022 - (-0.976) = -\text{USD } 0.046 \text{ per garment}$$

In the 2024 process, rework reduced the **mean profit** from **0.505 USD** to **0.495 USD** per garment:

**Impact of Rework (Mean Profit, 2024):**

$$0.495 - 0.505 = -\text{USD } 0.010 \text{ per garment}$$

Likewise, the **median profit** decreased from **0.506 USD** to **0.501 USD** per garment:

**Impact of Rework (Median Profit, 2024):**

$$0.501 - 0.506 = -\text{USD } 0.005 \text{ per garment}$$

The simulation results indicate that the improved process reduced the financial impact of rework by approximately 80%. In the conventional 2023 process, rework reduced mean profit by approximately USD 0.050 per garment, whereas in the improved 2024 process the reduction was only USD 0.010 per garment. This substantial decrease suggests that the redesigned production method is considerably less sensitive to quality-related disruptions.

The improvement can be attributed to two key factors. First, the redesigned process eliminated one error-prone operation, thereby reducing opportunities for rework. Second, the lower simulated processing time resulted in a substantially lower manufacturing cost per garment, reducing the marginal financial impact of any individual rework event. Consequently, the improved process not only reduced production time but also enhanced process robustness and operational stability.

These findings demonstrate that process simplification can provide benefits beyond direct productivity improvement. In addition to reducing processing time, a simpler production system can improve consistency, reduce variability, and minimize the financial risks associated with production errors. As a result, the improved process delivers a more predictable and resilient manufacturing system.

When applied to typical production orders consisting of several thousand garments, the increase in mean profit from approximately −USD 0.98 per garment in 2023 to +USD 0.51 per garment in 2024 represents a substantial improvement in overall financial performance. The simulation results therefore provide strong evidence that the 2024 process improvement initiative delivered significant operational and economic benefits.

### 5.13: Conclusion

This chapter applied Monte Carlo simulation to evaluate the per-unit profitability of the 2023 conventional and 2024 improved garment manufacturing processes under realistic, variable conditions. By generating 10,000 iterations per scenario using truncated normal distributions and stochastic rework events, the analysis moved beyond the limitations of deterministic SMV-based cost calculations to produce probability distributions of profit per garment.

The results were unambiguous. The 2023 conventional process — comprising eleven operations with a total SMV of 28.62 minutes — consistently produced negative per-unit profits across all simulated outcomes, with a mean loss of approximately USD 0.98 per garment under normal conditions, deteriorating further to USD 1.03 when rework costs were included. This confirms that the conventional process was structurally loss-making at the prevailing CM price of USD 1.63, regardless of operational variability.

In contrast, the 2024 improved process — redesigned to eight operations with a total SMV of 13.65 minutes, a 52.31% reduction — generated positive profits across virtually all simulated trials. The mean profit of approximately USD 0.51 per garment remained stable even when rework was factored in (USD 0.49), demonstrating both economic viability and resilience to production disruptions.

Beyond the shift from loss to profit, the simulation revealed two additional dimensions of improvement. First, process variability was substantially reduced: the 2024 scenarios exhibited narrower profit distributions and lower standard deviations, indicating a more consistent and predictable manufacturing system. Second, the financial sensitivity to rework declined by approximately 80% from USD 0.050 per garment in 2023 to USD 0.010 in 2024 — reflecting the redesigned process's inherent robustness, achieved through eliminating one error-prone operation and reducing the overall cost base.

Taken together, these findings demonstrate that the 2024 process improvement initiative delivered gains that were both statistically robust and practically significant. The redesigned process does not merely reduce production time; it transforms the economic structure of manufacturing, converting systematic losses into consistent positive margins while simultaneously improving stability and reducing financial exposure to quality-related disruptions. When scaled across production orders of several thousand garments, the aggregate financial impact is substantial, providing strong quantitative justification for the investment in process redesign.

## **CHAPTER 6: DISCUSSION**

### **6.1: Introduction**

This chapter interprets the empirical findings presented in Chapters 4 and 5 in relation to the research objectives, research questions, and the existing body of knowledge on productivity improvement in labor-intensive manufacturing. While the preceding chapters established the statistical significance and practical outcomes of the implemented production method optimization, this chapter examines the broader engineering implications of those findings and explains the mechanisms through which the observed improvements were achieved.

The discussion focuses on the influence of production method optimization on productivity, operational efficiency, manufacturing cost, and profitability within a labor-intensive blanket manufacturing environment. Particular attention is given to the role of SMV as a strategic engineering performance indicator that links production method design, resource utilization, and manufacturing performance. The chapter also considers how engineering interventions—including process redesign, workflow optimization, machine layout modification, enhanced pre-production planning, and multidisciplinary technical coordination—collectively contributed to the observed improvements.

In addition to interpreting the empirical findings, this chapter evaluates the robustness of the results by considering the simulation-based validation presented in Chapter 5 and comparing the findings with previous studies. The discussion further examines the industrial and academic contributions of the research, acknowledges its limitations, and identifies opportunities for future research. Collectively, these discussions provide a broader understanding of how data-driven production method optimization can improve productivity and profitability without requiring major technological investment, thereby offering practical guidance for labor-intensive manufacturing organizations operating under resource constraints.

### **6.2: Impact of Production Method Optimization on Productivity**

One of the most important findings of this research is that substantial improvements in manufacturing productivity were achieved through production method optimization rather than through additional labor input or extended working hours. The comparative analyses presented in Chapter 4 demonstrated that production output increased despite simultaneous reductions in manpower utilization and daily working hours, while the inferential statistical analyses confirmed that these improvements were statistically

significant. These findings indicate that the production system became more efficient by improving the way work was performed rather than by increasing the quantity of resources available.

From an engineering perspective, this finding suggests that the primary production constraints within the original manufacturing system were process-related rather than resource-related. The root-cause analysis identified several operational deficiencies, including redundant production activities, inefficient workflow organization, unnecessary operator movements, and suboptimal machine configuration. Collectively, these factors increased the SMV, reduced workflow continuity, and limited production throughput. The engineering interventions introduced during the 2024 production period addressed these underlying constraints through systematic process redesign, machine layout optimization, improved operation sequencing, enhanced pre-production planning, and closer coordination among the Industrial Engineering, Production, and Mechanical departments. Rather than adding new production resources, these interventions improved the utilization of existing resources by reducing non-value-added activities and increasing the proportion of productive operating time.

The observed productivity improvement demonstrates that manufacturing performance is strongly influenced by the efficiency of the production method itself. Although labor-intensive manufacturing is often characterized by dependence on manual operations, the findings of this study indicate that productivity is not determined solely by workforce size or labor intensity. Instead, the effectiveness with which production activities are organized and coordinated plays a more critical role in determining manufacturing output. Consequently, engineering-based process optimization can generate substantial productivity gains even within conventional manufacturing systems that operate without advanced automation or major capital investment.

These findings are consistent with previous research emphasizing the importance of production method design, line balancing, workflow organization, and work measurement in improving manufacturing productivity. For example, studies by Teshome et al. (2024) and Vergara et al. (2025) demonstrated that systematic improvements in production methods and workflow organization contribute to higher production efficiency and increased manufacturing output. The present research extends these findings by providing empirical evidence from a real industrial environment using historical ERP-derived production data rather than controlled laboratory observations or theoretical production models. Furthermore, unlike many previous studies that focused primarily on operational indicators, this research demonstrates that production method optimization can simultaneously improve productivity, reduce manufacturing cost, and restore profitability within the same production system.

Another important contribution of this study is the demonstration that significant productivity improvement can be achieved without increasing labor intensity or relying on overtime production. In many labor-intensive manufacturing industries, productivity improvement is often pursued through workforce expansion, extended working hours, or investment in advanced production technologies. While these approaches may increase production capacity, they frequently involve higher operating costs and greater financial risk. In contrast, the findings of this research show that substantial productivity gains can be achieved by systematically improving the existing production method and eliminating process inefficiencies. This highlights the practical value of engineering process optimization as a cost-effective strategy for enhancing manufacturing performance, particularly for small- and medium-sized manufacturing enterprises operating under financial and technological constraints.

Overall, the findings indicate that production method optimization should be regarded as a strategic engineering activity rather than merely an operational adjustment. By integrating historical production data, root-cause analysis, engineering expertise, and empirical validation, the optimized production method transformed an inefficient production system into one capable of achieving higher output with fewer resources. This demonstrates that sustainable productivity improvement depends not only on the availability of production resources but also on the effectiveness with which those resources are planned, organized, and utilized throughout the manufacturing process.

### **6.3: Influence of SMV Reduction on Manufacturing Performance**

One of the central findings of this research is that the substantial reduction in SMV was a primary driver of the improvements observed in productivity, operational efficiency, manufacturing cost, and profitability. The average SMV decreased from 28.62 min/unit in the 2023 production period to 13.65 min/unit in 2024, representing a reduction of approximately 52.31%. Rather than being an isolated performance indicator, SMV functioned as a key engineering parameter that influenced multiple aspects of manufacturing performance simultaneously.

From a production engineering perspective, SMV represents the standard time required to complete a manufacturing operation under defined working conditions. Consequently, an overestimated or inefficient SMV directly increases labor requirements, production cycle time, and manufacturing cost while reducing the production capacity that can be achieved within available working hours. The findings of this study demonstrate that the excessive SMV observed during the 2023 production period reflected underlying inefficiencies in the production method rather than inherent limitations of the manufacturing process itself. These inefficiencies included redundant operations, inefficient workflow sequencing, unnecessary

operator movements, suboptimal machine configuration, and inadequate coordination during pre-production planning.

The engineering interventions implemented during the 2024 production period addressed these underlying process deficiencies through systematic production method optimization. The elimination of non-value-added activities, refinement of operation sequences, machine layout optimization, improved pre-production planning, and enhanced technical coordination collectively reduced the time required to manufacture each blanket. As a result, production resources were utilized more efficiently, enabling greater manufacturing output to be achieved using fewer operators and shorter working hours. These findings indicate that SMV should be viewed not merely as a measurement tool but as a strategic engineering indicator that links production method design with manufacturing performance.

The relationship analyses presented in Chapter 4 further demonstrated a strong inverse association between SMV and production output. As SMV decreased, production output and production efficiency increased, while manufacturing cost declined. This relationship illustrates the interconnected nature of production performance indicators within labor-intensive manufacturing systems. Improvements in SMV not only reduced the time required to manufacture individual products but also increased production throughput, improved labor utilization, and enhanced the financial performance of the manufacturing system. Consequently, optimizing SMV produced cumulative benefits that extended beyond individual production operations and influenced the overall effectiveness of the production system.

These findings are consistent with previous studies emphasizing the importance of work measurement, production method analysis, and process standardization in improving manufacturing performance. Earlier research has shown that reductions in standard operation time contribute to higher productivity and improved line performance through more effective resource utilization and workflow organization. The present study extends this body of knowledge by demonstrating, using real ERP-derived production data, that substantial reductions in SMV can simultaneously improve operational and financial performance under actual industrial conditions. Furthermore, the integration of statistical validation and simulation-based analysis provides stronger empirical evidence than studies relying solely on observational productivity measures or theoretical production models.

Overall, the findings demonstrate that effective SMV management should be regarded as a strategic component of production engineering rather than simply a work measurement exercise. Continuous evaluation and optimization of SMV can provide manufacturing organizations with a practical mechanism for increasing productivity, reducing manufacturing cost, and improving profitability without requiring substantial investment in new production technologies. This is particularly important for labor-intensive

manufacturing industries, where sustainable competitive advantage often depends on maximizing the efficiency of existing production resources.

#### **6.4: Operational Efficiency and Resource Utilization**

The findings of this research demonstrate that production method optimization substantially improved operational efficiency while simultaneously reducing resource requirements. The descriptive and inferential statistical analyses presented in Chapter 4 showed that higher production output was achieved despite reductions in manpower utilization and daily working hours. This indicates that the improvements observed during the 2024 production period resulted primarily from more effective utilization of available production resources rather than from an increase in resource quantity.

From an engineering perspective, operational efficiency depends on the extent to which labor, equipment, and production time are converted into productive output. The findings suggest that the conventional production method employed during 2023 contained several operational inefficiencies that limited resource utilization. These included unnecessary production activities, workflow interruptions, inefficient machine arrangement, and inadequate synchronization among production operations. Collectively, these factors reduced the proportion of productive operating time and constrained manufacturing throughput, resulting in lower production efficiency despite greater labor input.

The optimized production method addressed these operational constraints through a combination of engineering interventions. Process redesign simplified the production workflow by eliminating unnecessary operations, while machine layout optimization reduced unnecessary material movement and improved workflow continuity. Enhanced pre-production planning ensured that machines, technical resources, and production personnel were appropriately coordinated before manufacturing commenced. In addition, improved collaboration among the Industrial Engineering, Production, and Mechanical departments reduced implementation delays and enabled the revised production method to be applied consistently throughout the production period. These interventions improved resource utilization by increasing the proportion of value-added production activities without increasing labor intensity.

An important implication of these findings is that operational efficiency is influenced more by the organization and coordination of production activities than by the absolute quantity of production resources available. Simply increasing workforce size or extending production hours does not necessarily improve manufacturing performance if underlying process inefficiencies remain unresolved. Instead, systematic evaluation of production methods, workflow organization, and resource allocation can often generate greater improvements in productivity while simultaneously reducing operating costs. This

observation has important practical implications for labor-intensive manufacturing organizations that frequently face financial constraints and limited opportunities for capital investment.

The findings also demonstrate the close relationship between operational efficiency and financial performance. More efficient utilization of labor and production time reduced manufacturing cost while increasing production output and profitability under the fixed FOB pricing structure considered in this study. Consequently, improvements in operational efficiency produced benefits that extended beyond production performance alone, contributing directly to the overall financial sustainability of the manufacturing system. This reinforces the importance of viewing operational efficiency as both an engineering objective and a strategic business objective.

These findings are consistent with previous research highlighting the role of process optimization, workflow improvement, and line balancing in enhancing manufacturing efficiency. However, the present study extends existing knowledge by demonstrating that engineering-based production method optimization can simultaneously improve operational efficiency, reduce resource consumption, and increase profitability using real industrial production data validated through statistical analysis and Monte Carlo simulation. This integrated evaluation provides stronger empirical support for production method optimization than approaches based solely on descriptive productivity measures.

Overall, the findings indicate that sustainable improvements in manufacturing performance are more likely to be achieved through systematic engineering optimization than through expansion of production resources. By improving the efficiency with which existing labor, equipment, and production time are utilized, manufacturing organizations can achieve higher productivity, lower manufacturing cost, and improved profitability without relying on major technological investment. These results highlight the strategic importance of operational efficiency as a foundation for sustainable competitiveness in labor-intensive manufacturing environments.

## **6.5: Financial Implications of Production Method Optimization**

One of the most important outcomes of this study is that production method optimization generated substantial financial benefits without requiring major capital investment. Although productivity improvement is often the primary objective of manufacturing optimization, the findings demonstrate that improvements in production methods also translated directly into better financial performance. Under the fixed FOB pricing structure considered in this study, reductions in manufacturing cost increased contribution margins and profitability, highlighting the close relationship between engineering decisions and business performance.

The analyses presented in Chapter 4 showed a substantial reduction in daily manufacturing cost following implementation of the optimized production method, while daily CM earnings and FOB earnings increased simultaneously. These improvements were achieved despite reductions in manpower utilization and working hours, indicating that the financial gains resulted from more efficient use of existing production resources rather than increased expenditure or additional labor input. This demonstrates that improvements in production efficiency can generate meaningful economic benefits without changes to product pricing or production capacity.

A key factor underlying these financial improvements was the reduction in SMV. Lower SMV reduced the labor time required to manufacture each blanket, decreasing labor cost per unit while allowing more units to be produced within the available production time. Because the selling price remained unchanged, the reduction in production cost translated directly into higher profit per piece. This finding illustrates how engineering improvements implemented at the process level can influence overall financial performance throughout the manufacturing system.

These findings have important implications for manufacturing organizations operating under financial constraints. Productivity improvement is frequently associated with investment in automation, additional machinery, or expanded production capacity. While such investments may increase output, they often require substantial capital and involve considerable implementation risk. The present study demonstrates that systematic evaluation and optimization of existing production methods can achieve comparable operational and financial improvements without major technological investment. This approach is particularly relevant to labor-intensive manufacturing industries, where improving the efficiency of existing resources often represents the most practical and economically viable strategy.

The findings also reinforce that productivity, and profitability should not be viewed as separate organizational objectives. Instead, they are closely interconnected through the efficiency with which production resources are utilized. Improvements in workflow organization, operation sequencing, machine utilization, and labor efficiency reduced manufacturing cost while simultaneously increasing production output and profitability. Consequently, production method optimization should be considered both an engineering strategy for improving manufacturing performance and a business strategy for enhancing long-term competitiveness.

Overall, the financial analysis demonstrates that engineering-based production method optimization provides benefits extending well beyond operational performance. By lowering manufacturing cost while increasing production capacity and profitability, the optimized production method transformed a loss-incurring production system into a profitable manufacturing operation. These findings highlight the

strategic value of process optimization as a practical and sustainable approach to improving manufacturing competitiveness.

## **6.6: Validation of Production Method Optimization Using Monte Carlo Simulation**

The statistical analyses presented in Chapter 4 confirmed that the optimized production method significantly improved productivity and financial performance. However, those analyses were based on historical production observations and average performance measures. Manufacturing systems rarely operate under fixed conditions, and daily production performance is influenced by variability in operator performance, machine condition, material handling, production interruptions, and occasional rework. Consequently, statistical analysis alone cannot determine whether the observed improvements remain reliable under normal production variability. The Monte Carlo simulation was therefore used to evaluate the robustness of the optimized production method under realistic manufacturing conditions.

Unlike the statistical analyses, which evaluate observed historical performance, the simulation assessed how the production system behaved across a wide range of possible operating conditions. By incorporating variability in operation times, production efficiency, and error-prone operations, the model represented the uncertainty that characterizes routine manufacturing. Across 10,000 simulation iterations, the optimized production method consistently produced lower manufacturing cost and higher profit per piece than the conventional production method. These results indicate that the observed improvements were not limited to average production conditions but remained stable under realistic operational variability.

From an engineering perspective, this finding is particularly important because manufacturing decisions are rarely made under deterministic conditions. Production managers must routinely account for uncertainty arising from human performance, equipment reliability, material variability, and production disruptions. The simulation therefore provides an additional level of confidence by demonstrating that the optimized production method remains effective even when these uncertainties are considered. Rather than relying solely on historical averages, the simulation evaluates the probability of achieving improved performance across a broad range of manufacturing scenarios.

The integration of Monte Carlo simulation also strengthens the methodological contribution of this research. Previous studies have commonly evaluated production improvement using descriptive statistics or hypothesis testing based on historical observations. While these methods establish whether performance differs significantly between production methods, they provide limited insight into the stability of those improvements under operational uncertainty. By combining historical ERP data,

statistical validation, engineering process optimization, and probabilistic simulation within a single evaluation framework, this study provides a more comprehensive assessment of manufacturing performance than approaches based solely on deterministic analysis.

The simulation results also have practical value for industrial decision-making. Manufacturing organizations frequently need to evaluate proposed process improvements before implementing them on the production floor. Simulation enables alternative production methods to be assessed under a range of operating conditions without disrupting ongoing production or introducing operational risk. As a result, the framework developed in this study can serve as a practical decision-support tool for evaluating process improvements in other labor-intensive manufacturing environments where production variability influences both operational and financial performance.

Overall, the Monte Carlo simulation substantially strengthens the conclusions of this research. While the statistical analyses established that the optimized production method produced significant improvements in productivity and profitability, the simulation demonstrated that these improvements remained robust under realistic manufacturing uncertainty. Together, the statistical and simulation results provide strong evidence that production method optimization offers a reliable and sustainable approach to improving manufacturing performance in labor-intensive production systems.

## **6.7: Comparison with Previous Studies**

The findings of this research are broadly consistent with the existing literature on production method optimization, SMV reduction, and workflow improvement in labor-intensive manufacturing, while extending that body of knowledge in several important respects.

The 52.31% reduction in SMV achieved in the present study substantially exceeds the productivity improvements reported in comparable garment manufacturing contexts. Kamruzzaman et al. (2024) demonstrated a 15.71% improvement in overall productivity and a reduction in SMV of approximately 2.36 minutes following optimized technical layout implementation in a garment sewing division. Teshome et al. (2024) similarly achieved significant line efficiency improvements through simulation-validated workstation reallocation in a garment factory. The substantially larger SMV reduction documented in the present study suggests that the concurrent application of multiple engineering interventions — including redundant operation elimination, machine layout redesign, enhanced pre-production planning, and cross-functional technical coordination — produces compounding improvements that exceed what any single intervention achieves independently. This cumulative effect of

integrated method optimization has not been explicitly quantified in the existing literature and represents a meaningful empirical contribution.

The line efficiency improvements documented by Ara et al. (2025), who raised sewing-line efficiency from 43.70% to 79.80% by reducing workstations from forty-two to twenty-three in a Bangladeshi garment hemming unit, are consistent with the general direction of the present findings but were achieved through heuristic line-balancing algorithms applied within a controlled redesign exercise rather than through the empirical analysis of consecutive real production years adopted in the present study. Similarly, Khan et al. (2025) and Subramaniam et al. (2026) demonstrated that Lean Six Sigma (LSS) methodologies and engineering-based process improvement techniques can substantially enhance manufacturing performance in the textile and garment industry. By integrating tools such as DMAIC, RPW, VSM, MSA, and statistical process control, these studies reported significant improvements in production efficiency, line balancing, cycle time, defect reduction, process capability, and product quality. Their findings provide strong evidence that structured engineering interventions supported by systematic analysis can improve operational performance and manufacturing efficiency in labor-intensive production environments. However, these studies primarily focused on process improvement and quality enhancement rather than providing a comprehensive evaluation of the relationship between production method optimization, SMV, operational performance, and financial outcomes using matched historical ERP production records. By integrating root-cause analysis, historical production data, statistical evaluation, financial analysis, and simulation-based modeling within a single longitudinal case study, the present research extends existing knowledge by providing a more comprehensive framework for evaluating productivity and profitability improvement in labor-intensive manufacturing.

An important point of differentiation concerns the nature of the performance outcomes reported. Previous studies in lean garment manufacturing have predominantly reported productivity and efficiency outcomes without examining corresponding financial performance. Vergara et al. (2025) documented productivity growth exceeding 170% using standardized work and Poka-Yoke principles in a garment manufacturing case study, while Begum et al. (2024) identified substantial efficiency and waste reduction gains from lean implementation across sixty studies in the textile sector. However, neither study evaluated how operational improvements translated into profitability recovery under fixed pricing conditions. The present research addresses this gap directly by demonstrating that a 52.31% reduction in SMV, implemented within a fixed FOB pricing structure, can transform a loss-incurring production system into a profitable manufacturing operation — a finding that is empirically documented here for the first time in the blanket manufacturing context.

The present findings also differ from the literature in one important respect regarding the role of technology. Several studies have emphasized advanced computational and simulation tools for SMV estimation and production optimization (Shao et al., 2022; Shen & Ji, 2024; Jung et al., 2022), while the broader Industry 4.0 literature (Tsai et al., 2024) advocates digital transformation as a primary pathway to manufacturing performance improvement. The results of the present study provide a counterpoint to this position by demonstrating that substantial productivity improvement can be achieved through systematic engineering-based process analysis and improvement using existing production infrastructure, without automation, machine learning, or digital twin modeling. This finding is particularly relevant to labor-intensive manufacturers in developing economies where access to advanced technology remains constrained by cost and infrastructure barriers, as reflected in research on organizational readiness for Industry 4.0 adoption in clothing (Kanakana-Katumba et al., 2024).

### **6.8: Industrial and Academic Contributions**

This research makes specific and distinguishable contributions to both industrial practice and academic knowledge that extend beyond the general empirical findings presented in the preceding chapters.

From an industrial perspective, the study demonstrates a practically implementable, low-cost improvement framework for labor-intensive manufacturing that requires no capital investment in new technologies. Specifically, it demonstrates that a structured combination of root-cause diagnosis using fishbone analysis, ERP-derived historical data evaluation, cross-functional engineering consultation, machine layout optimization, and production method redesign can achieve a 52.31% reduction in SMV within a single production cycle. This magnitude of improvement — transforming a loss-incurring production system into a profitable operation within one production year — provides a concrete and replicable benchmark for manufacturing managers in comparable organizations. The framework is particularly relevant to export-oriented textile manufacturers in developing countries, where productivity improvement must frequently be achieved through engineering process optimization rather than technology acquisition, and where the practical value of a demonstrated real-industrial case with verified production data is substantially higher than frameworks proposed on theoretical or simulation-only grounds.

A second and more specific industrial contribution concerns the utilization of ERP production records as the primary data source for systematic engineering diagnosis and performance evaluation. As noted by Deepthi and Bansal (2024), ERP production records are routinely collected but frequently underutilized by manufacturing organizations for systematic performance analysis. The analytical pipeline developed in this study — from ERP data extraction through root-cause analysis, comparative statistical evaluation,

and Monte Carlo simulation validation — provides manufacturing organizations with a structured methodology for extracting engineering value from existing production data without additional data collection investment. This is not merely a conceptual argument: the pipeline is demonstrated end-to-end using verified industrial data, which distinguishes it from improvement frameworks proposed on theoretical grounds alone.

From an academic perspective, this study makes three important contributions to the existing body of knowledge. First, it provides a comprehensive empirical evaluation of substantial reductions in SMV achieved through systematic engineering-based production method optimization in blanket manufacturing without major capital investment. By demonstrating a reduction of more than 52% in SMV under actual industrial conditions, the study establishes a practical performance benchmark for blanket manufacturing and extends existing research on manufacturing productivity, which has primarily focused on work-time study, production line balancing, and process optimization in garment manufacturing (Erol, 2025).

Second, this study broadens the scope of manufacturing productivity research by integrating operational, statistical, and financial performance evaluation within a single analytical framework. Although previous studies have demonstrated improvements in productivity, production efficiency, and process performance following engineering interventions, relatively limited attention has been given to examining how production method optimization influences financial performance using longitudinal historical production data. By simultaneously evaluating production output, production efficiency, production cost, CM earnings, FOB earnings, and overall profitability, this study provides a more comprehensive assessment of manufacturing performance than is typically reported in the existing literature (Subramaniam et al., 2026).

Third, the integration of ERP-based historical production data, inferential statistical analysis, and Monte Carlo simulation within a single before-and-after empirical evaluation provides a more comprehensive methodological framework than approaches based solely on time-study observation, controlled experimental redesign, or descriptive productivity measurement as has been common in the garment manufacturing optimization literature (Shao et al., 2022; Teshome et al., 2024). These three contributions collectively strengthen the empirical and methodological foundations of production method optimization research in labor-intensive export manufacturing.

## **6.9: Limitations of the Study**

Several limitations should be acknowledged when interpreting the findings of this research, as they affect both the internal validity of specific analyses and the external generalizability of the conclusions.

The most significant limitation concerns the single-organization, single-product scope of the study. The empirical data were obtained from one manufacturing organization and focused exclusively on blanket production operations conducted over two consecutive production years. While this within-case design strengthens internal validity by holding organizational context, workforce, equipment, and product type constant — thereby enabling observed performance differences to be attributed more confidently to production method changes — it limits the direct generalizability of the specific SMV benchmarks and financial outcomes to other organizations, product types, or manufacturing contexts. It is important to distinguish, however, between the generalizability of the specific quantitative findings and the generalizability of the methodological framework. The ERP-based historical data analysis, root-cause diagnosis, statistical evaluation, and simulation validation pipeline developed in this study is designed to be transferable and replicable across comparable labor-intensive manufacturing environments, even where the specific performance outcomes would differ.

A second limitation concerns the duration of the observation period. The comparative analysis was conducted using production data from two consecutive years, providing a before-and-after evaluation of the immediate impact of production method optimization. While this design is appropriate for evaluating short-term performance changes, it does not capture whether the observed improvements are sustained over multiple production cycles, whether further performance gains or regressions occur over time, or whether the optimized production method requires ongoing management attention to maintain its effectiveness. Future research employing longitudinal data from three or more consecutive production periods would provide stronger evidence of the long-term sustainability of engineering-based productivity improvements.

A third limitation relates to the Monte Carlo simulation model. The simulation was developed using operation-level time-study data and expert-defined assumptions regarding operational variability ranges and rework probability. While every effort was made to ensure that these parameters reflected realistic manufacturing conditions, the simulation model was necessarily a simplification of actual production system complexity. Actual production environments may contain additional sources of variability not fully captured by the model, including supply chain disruptions, absenteeism patterns, machine maintenance cycles, and seasonal demand fluctuations. Furthermore, the simulation distributions were based on estimated variability bounds rather than empirically fitted probability distributions derived from large samples of repeated time observations. Future studies incorporating empirical distribution fitting from extended time-study data would improve simulation fidelity and provide more precise uncertainty quantification.

A fourth limitation concerns the potential influence of learning and experience effects over the two-year observation period. It is possible that some portion of the productivity improvement observed in 2024 reflects increased operator familiarity with the blanket manufacturing process rather than solely the effect of the production method changes. Although the engineering interventions implemented were substantive and systematically applied, the study design does not allow the contribution of operator experience accumulation to be fully isolated from the contribution of the optimized production method. This should be considered when interpreting the magnitude of the productivity gains reported.

Despite these limitations, the study provides empirically grounded and practically valuable evidence that data-driven production method optimization can substantially improve manufacturing productivity and financial performance. The limitations identified are not unique to this study but are inherent characteristics of empirical industrial research conducted under real manufacturing conditions rather than controlled laboratory settings. Beyond marking the boundaries of the current research, these limitations point to underexplored areas in the existing literature, and it is on this basis that the formal recommendations for future research are presented in the final chapter of this thesis.

#### **6.10: Chapter Summary**

This chapter interpreted the empirical findings presented in Chapters 4 and 5 and examined their implications for manufacturing productivity, operational efficiency, and profitability in the context of the existing literature on production method optimization in labor-intensive manufacturing.

The discussion demonstrated that the productivity improvements observed in the 2024 production period were achieved through more effective utilization of existing production resources rather than through additional labor input or capital investment. From an engineering perspective, the root causes of underperformance in the 2023 production period were identified as process-related rather than resource-related, and the coordinated engineering interventions implemented in 2024 — including operation elimination, machine layout redesign, enhanced pre-production planning, and cross-functional technical coordination — addressed these underlying constraints by increasing the proportion of value-added production activity within available working time.

The chapter further demonstrated that SMV functioned as a central engineering parameter linking production method design, resource utilization, manufacturing cost, and financial performance simultaneously. The 52.31% reduction in SMV achieved through the optimized production method was shown to be substantially larger than comparable improvements reported in the existing literature, and the

discussion identified the concurrent application of multiple integrated engineering interventions as the mechanism most likely responsible for this compounding performance gain.

The validation of findings using Monte Carlo simulation strengthened the conclusions of the empirical analysis by demonstrating that the improvements observed in historical production data remained robust under realistic manufacturing variability, including operational uncertainty, error-prone conditions, and rework requirements. This simulation-based validation extends the evidentiary basis for the conclusions beyond what historical average performance measures alone can establish and provides an additional level of confidence relevant to industrial decision-making under uncertainty.

The comparison with previous studies confirmed that while the directional findings of this research are consistent with the broader productivity improvement literature, the present study makes three distinguishable contributions: a new empirical benchmark for SMV reduction magnitude in blanket manufacturing achieved without capital investment; an integrated operational and financial evaluation framework that extends the scope of prior productivity studies; and a comprehensive ERP-to-simulation methodological pipeline that provides stronger empirical evidence than approaches based on descriptive productivity measures or controlled experimental redesign alone.

The chapter acknowledged four limitations — single-organization scope, two-year observation period, simulation model simplifications, and potential learning effects — and identified specific future research directions that would address each of these limitations while extending the findings to broader manufacturing contexts, longer time horizons, higher-fidelity simulation, predictive SMV modeling, and the social and environmental dimensions of sustainable manufacturing improvement.

Overall, the findings of this chapter support the conclusion that data-driven, engineering-based production method optimization represents a practical, low-cost, and empirically validated strategy for achieving substantial productivity improvement and profitability recovery in labor-intensive manufacturing environments operating under resource constraints. These conclusions are synthesized in the final chapter of the thesis.

## **CHAPTER 7: CONCLUSION AND RECOMMENDATIONS**

### **7.1: Introduction**

This chapter presents the conclusions of the empirical study and evaluates their significance for manufacturing productivity, profitability, and production engineering practice. The preceding chapters established — through descriptive statistical analysis, inferential hypothesis testing, financial evaluation, and Monte Carlo simulation — that systematic production method optimization produced substantial and statistically significant improvements in all key operational and financial performance indicators within a labor-intensive blanket manufacturing environment. This chapter synthesizes those findings into a coherent set of conclusions, evaluates the extent to which each research objective was achieved and each research question was answered, identifies the specific contributions this study makes to industrial practice and academic knowledge, and proposes concrete recommendations for manufacturing practitioners and future researchers.

The central argument that emerges from the findings of this research is that productivity improvement and profitability recovery in labor-intensive manufacturing are achievable through systematic engineering-based process optimization without capital investment in new technologies. The evidence presented in this thesis demonstrates that this argument holds not only under average production conditions — as established by the statistical analyses in Chapter 4 — but also under realistic manufacturing uncertainty, as confirmed by the Monte Carlo simulation in Chapter 5. Together, these findings provide a robust empirical foundation for the conclusion that production method design, rather than resource quantity or technological capability, is the primary determinant of manufacturing performance in labor-intensive production systems operating under resource constraints.

### **7.2: Achievement of Research Objectives**

This research pursued six objectives, all of which were achieved. The discussion below evaluates not only whether each objective was accomplished but what the outcome of each reveals about manufacturing performance improvement in labor-intensive environments.

The first objective — to analyze historical production performance in terms of SMV, manpower utilization, working hours, and output — was achieved through a comprehensive descriptive and graphical analysis of ERP-derived production records from two consecutive production years. This analysis established a detailed quantitative baseline for the 2023 conventional production method and

revealed that average SMV of 28.62 minutes per unit, combined with average manpower of 45 operators and daily working hours of 11.70 hours, produced a production system that was not financially viable under the prevailing FOB pricing structure. The significance of achieving this objective lies not merely in completing the analysis but in what it revealed: that the production system's underperformance was entirely attributable to process inefficiency rather than inadequate resources, establishing the engineering basis for the interventions that followed.

The second objective — to identify root causes of productivity inefficiency using ERP-based observation and fishbone analysis — was achieved through structured cause-and-effect analysis that identified five principal root cause categories: Production Method, Excessive Operations, Machine Configuration, Workflow and Layout, and Technical Coordination. The significance of this objective is that it determined which interventions would be most effective and in what sequence they should be implemented. Without this diagnostic step, corrective actions would have been directed at symptoms rather than underlying causes, reducing the likelihood of achieving sustained improvement.

The third objective, to implement and evaluate production method optimization through engineering-based corrective interventions, was successfully achieved through a coordinated series of process improvements, including the elimination of non-value-added operations, machine layout redesign, enhanced pre-production planning, workflow optimization, and improved coordination between technical and mechanical teams. Collectively, these interventions reduced the SMV from 28.62 to 13.65 minutes per unit, representing a 52.31% reduction, without requiring investment in new machinery or advanced manufacturing technologies. This substantial improvement demonstrates the effectiveness of systematic engineering interventions in enhancing manufacturing performance through more efficient production methods and resource utilization. Although previous studies have shown that work-time study, production line balancing, and process optimization can improve operational performance in garment manufacturing, the findings of the present study indicate that integrating multiple engineering interventions within a single improvement framework can produce considerable gains in productivity under actual industrial conditions (Erol, 2025).

The fourth objective — to statistically compare productivity and financial outcomes between the two production periods — was achieved through paired t-tests applied to seven production performance variables. All observed differences were statistically significant at  $p < .001$ , confirming that the improvements were systematic and consistent across matched production records rather than the product of random daily variation. Notably, the cost reduction variable produced a t-value of  $-90.98$ , the largest absolute t-value in the analysis, indicating that the manufacturing cost reduction was not only statistically

significant but extraordinarily consistent throughout the production period — a finding that provides particularly strong evidence of the reliability of the optimized production method.

The fifth objective — to develop and apply a Monte Carlo simulation model evaluating the influence of operational variability on SMV — was achieved through a 10,000-iteration simulation that incorporated process-level time variability, error-prone operations with empirically derived defect probabilities, and stochastic rework time additions. The simulation demonstrated that under realistic manufacturing uncertainty, the 2024 optimized process consistently produced lower manufacturing cost and higher profit per piece than the 2023 conventional process across the full range of simulated outcomes. This finding is particularly significant because it establishes that the observed productivity gains are robust to realistic production variability, not merely artifacts of average-condition analysis.

The sixth objective — to develop an empirical framework for productivity and profitability improvement applicable to labor-intensive manufacturing industries — was achieved through the integration of ERP data extraction, root-cause diagnosis, statistical evaluation, and simulation-based validation into a coherent, end-to-end methodological pipeline. The practical value of this framework is that it requires no new capital investment, relies on production data that organizations already collect, and has been demonstrated to produce substantial operational and financial improvements under real industrial conditions.

### **7.3: Answers to the Research Questions**

#### **Research Question 1: How does SMV influence production output, efficiency, and production cost in labor-intensive manufacturing?**

SMV functions as a central engineering parameter that simultaneously determines production capacity, labor requirements, manufacturing cost, and profitability within labor-intensive manufacturing systems. The findings demonstrate that the 52.31% reduction in average SMV — from 28.62 to 13.65 minutes per unit — produced a cascade of performance improvements across all operational and financial indicators. Lower SMV enabled more blankets to be manufactured within the same available working time, increasing average daily output by 52.56 units and average production efficiency by 0.036. Simultaneously, lower SMV reduced the labor time required per unit, cutting average daily manufacturing cost by USD 584.83. Because the FOB selling price remained constant, this cost reduction translated directly into improved profitability. These findings establish that SMV is not merely a productivity indicator but the primary engineering lever connecting production method design to manufacturing economics in fixed-price labor-intensive production environments.

### **Research Question 2: What operational factors contribute to increased SMV and reduced productivity within the blanket manufacturing process?**

The root-cause analysis identified five categories of operational factors that collectively produced the excessive SMV of 28.62 minutes per unit observed in the 2023 production period. First, production method deficiencies including unnecessary process steps and non-standardized work sequences increased total operation time beyond what the manufacturing process inherently required. Second, excessive operations including redundant stitching sequences and repeated handling activities added non-value-added time at multiple points in the production workflow. Third, machine configuration problems including missing attachments and guides and improper setup increased individual operation times and generated inconsistent output. Fourth, workflow and layout inefficiencies including excessive material movement and idle time between operations disrupted production continuity and reduced the proportion of time devoted to value-added activities. Fifth, inadequate technical coordination between industrial engineering, production, and mechanical departments delayed the identification and resolution of process problems, allowing inefficiencies to persist throughout the production period. The interaction of these five categories — rather than any single factor in isolation — accounted for the severity of the SMV elevation and the corresponding productivity loss.

### **Research Question 3: How does production method optimization influence manpower utilization, working hours, and overall operational performance?**

The implementation of the optimized production method reduced manpower requirements from 45 to 30 operators — a reduction of approximately 33% — and reduced average daily working hours from 11.70 to 9.08 hours — a reduction of approximately 22%. Despite these simultaneous reductions in two major production resource inputs, average daily production output increased by 52.56 units and average production efficiency increased by 0.036. This pattern of findings is theoretically important because it demonstrates that the relationship between resource input and production output in labor-intensive manufacturing is not linear or fixed but is fundamentally mediated by the efficiency of the production method. When the production method is suboptimal, additional resources produce diminishing returns; when the production method is optimized, fewer resources can achieve higher output because a greater proportion of available time is converted into productive manufacturing activity. This finding has direct practical implications for manufacturing managers who routinely face pressure to increase productivity through workforce expansion or overtime — the present study demonstrates that systematic process optimization is a more effective and less costly alternative.

**Research Question 4: Are the observed differences in productivity, efficiency, cost, and earnings between the 2023 and 2024 production periods statistically significant?**

All seven production performance variables examined using paired t-tests showed statistically significant improvements at  $p < .001$ . Daily production output increased by a mean of 52.56 units ( $t = 5.48$ ), daily manufacturing cost decreased by a mean of USD 584.83 ( $t = -90.98$ ), daily production efficiency increased by a mean of 0.036 ( $t = 4.52$ ), daily CM earnings increased by a mean of USD 85.78 ( $t = 5.49$ ), daily FOB earnings increased by a mean of USD 596.44 ( $t = 5.48$ ), total production increased by a mean of 623.63 units ( $t = 4.70$ ), and average production efficiency increased by a mean of 0.027 ( $t = 4.75$ ). The uniformity of statistical significance across all seven variables is noteworthy — it indicates that the performance improvements were not concentrated in one or two indicators but constituted a broad and consistent transformation of the production system. The extraordinarily large t-value for the cost variable ( $-90.98$ ) is particularly significant, as it indicates that the daily cost reduction was so consistent across matched production records that random variation played virtually no role in explaining the observed difference.

**Research Question 5: How does operational variability and error-prone production behavior influence total Simulated Processing Time (SPT) under different manufacturing conditions?**

The Monte Carlo simulation demonstrated that operational variability and error-prone production behavior increased the spread of SPT distributions under both production methods, reflecting the inherent uncertainty of real manufacturing environments. However, the key finding is that even under the most adverse simulated conditions — including maximum variability and simultaneous defect occurrence in multiple error-prone operations — the 2024 optimized process consistently maintained lower SPT values than the 2023 conventional process. The narrower SPT distribution observed for the 2024 process indicates not only lower average processing time but also greater operational stability and lower sensitivity to production disturbances. This finding suggests that the engineering interventions implemented in 2024 not only reduced average SMV but also improved the structural robustness of the production process, making it less susceptible to the performance degradation that typically accompanies real-world operational variability.

**Research Question 6: Can simulation-based modeling provide additional insight into manufacturing uncertainty and process variability within labor-intensive production systems?**

The Monte Carlo simulation provided three specific insights that the historical statistical analysis alone could not establish. First, it confirmed that the improvements observed in historical average production

data were not dependent on idealized production conditions but remained consistent across 10,000 simulated manufacturing scenarios incorporating realistic levels of variability. Second, it provided probability distributions of profit per garment under both production methods, enabling a probabilistic rather than deterministic assessment of financial performance — a form of evidence more appropriate to real manufacturing decision-making, where outcomes are inherently uncertain. Third, it demonstrated that the 2024 optimized method maintained its performance advantage under error-prone conditions, confirming the structural superiority of the optimized process rather than merely its average performance advantage. Together, these insights demonstrate that simulation-based modeling is a valuable complement to empirical statistical analysis in manufacturing performance evaluation, capable of strengthening the evidentiary basis for engineering decisions in ways that historical data analysis alone cannot achieve.

#### **7.4: Key Contributions of the Study**

This research makes three distinct contributions to both industrial practice and the existing body of knowledge on manufacturing productivity improvement. By combining engineering process optimization with empirical evaluation under real manufacturing conditions, the study extends current understanding of productivity improvement in labor intensive textile manufacturing.

The first contribution of this study is the empirical demonstration of a 52.31% reduction in SMV achieved in blanket manufacturing through systematic production method optimization without major capital investment. This improvement was accomplished through a coordinated series of engineering interventions, including the elimination of non-value-added operations, machine layout redesign, enhanced pre-production planning, workflow optimization, and improved coordination between technical and mechanical teams. Previous research has demonstrated that systematic work measurement and accurate determination of Standard Allowed Minute to provide the foundation for improving production planning, operational efficiency, resource utilization, cost reduction, and the elimination of non-value-added activities in garment manufacturing (Nchalala et al., 2023). Building on these principles, the present study demonstrates that integrating multiple complementary engineering interventions within a single improvement framework can substantially reduce SMV while significantly improving productivity under actual industrial production conditions.

The second contribution is the first empirically documented case in the blanket manufacturing literature of a complete profitability transformation — from financial loss to sustainable profit — achieved through engineering-based production method optimization under fixed FOB pricing conditions. Previous productivity studies in labor-intensive manufacturing have predominantly focused on operational performance indicators such as output, efficiency, and SMV without examining how these operational

improvements translate into financial outcomes (Vergara et al., 2025; Begum et al., 2024). The present study demonstrates that a 52.31% reduction in SMV, under fixed selling prices, generates a direct and quantitatively predictable improvement in profitability through cost reduction alone — a finding with important implications for the financial planning and strategic decision-making of labor-intensive manufacturers operating under competitive pricing pressure.

The third contribution is methodological. The integration of ERP-based historical production data analysis, structured root-cause diagnosis, inferential statistical testing, financial performance evaluation, and Monte Carlo simulation within a single empirical before-and-after evaluation framework provides a more comprehensive and rigorous methodological approach than is commonly reported in the manufacturing productivity literature. Prior studies have typically employed one or two of these analytical components in isolation — descriptive productivity analysis (Kamruzzaman et al., 2024), simulation-based line balancing (Teshome et al., 2024), or lean implementation review (Arafat et al., 2026) — without integrating them into a unified evaluation pipeline. The analytical framework demonstrated in this study is designed to be transparent, replicable, and transferable to other labor-intensive manufacturing organizations, and its application requires no additional data collection beyond the ERP records that most modern manufacturing organizations already generate.

## **7.5: Practical Recommendations**

The findings of this study support the following specific recommendations for labor-intensive manufacturing organizations seeking to improve productivity and profitability through engineering-based process optimization.

First, manufacturing organizations should conduct structured SMV diagnostic reviews before assuming that productivity problems require additional labor or capital investment. The findings of this study demonstrate that an initial SMV of 28.62 minutes per unit — more than double the optimized value of 13.65 minutes — was sustained for an entire production year without systematic diagnosis, generating ongoing financial loss that was entirely preventable through engineering analysis. A structured SMV review, drawing on ERP production records and direct process observation, should be treated as the first response to any sustained productivity shortfall.

Second, ERP production records should be systematically analyzed as a primary tool for engineering performance evaluation and continuous improvement. The present study demonstrates that the production data organizations already collect — output, working hours, manpower, cost, efficiency, and earnings — contain sufficient information to diagnose productivity problems, evaluate the effectiveness of

engineering interventions, and monitor production performance over time. Organizations that collect ERP data but do not analyze it systematically for engineering improvement are forgoing a low-cost, high-value resource that is already available to them.

Third, production method optimization should be pursued as a coordinated, multi-intervention engineering activity rather than a series of isolated adjustments. The findings indicate that the 52.31% SMV reduction achieved in this study resulted from the concurrent application of five complementary interventions — operation elimination, machine layout redesign, pre-production planning enhancement, and cross-functional technical coordination. Implementing any one of these interventions in isolation would likely have produced a more modest improvement. Organizations should therefore approach production method review comprehensively, addressing all identified root cause categories simultaneously rather than sequentially.

Fourth, cross-functional collaboration between industrial engineering, production management, and mechanical maintenance teams should be formally integrated into production method review processes. The root-cause analysis conducted in this study identified inadequate technical coordination as one of the five principal contributors to elevated SMV, indicating that organizational and communication factors can be as influential as technical factors in determining production efficiency. Establishing formal cross-functional review mechanisms — rather than relying on informal coordination — can reduce the time required to identify and resolve process problems and sustain the benefits of method optimization over longer production periods.

Fifth, Monte Carlo simulation should be adopted as a standard tool for evaluating proposed process improvements before implementation. The simulation conducted in this study demonstrated that the 2024 optimized process maintained its performance advantage under realistic operational uncertainty, providing a level of confidence in the engineering decision that historical average data alone could not have established. For manufacturing organizations considering significant process changes, simulation-based evaluation using existing operation-time data can substantially reduce the implementation risk associated with method redesign, consistent with the simulation-validated approaches demonstrated by Teshome et al. (2024) and Jung et al. (2022).

## **7.6: Recommendations for Future Research**

The findings and limitations of this study identify five specific research directions that would extend and strengthen the evidence base for engineering-based productivity improvement in labor-intensive manufacturing.

The most immediate research priority is multi-organization replication. The present study was conducted within a single organization focused on blanket manufacturing, and while the methodological framework is designed to be transferable, the specific magnitude of SMV reduction and profitability improvement may vary across different production environments, product types, and organizational contexts.

Comparative studies applying the same ERP-based before-and-after evaluation framework across multiple garment manufacturing organizations — building on the multi-factory approach of Ara et al. (2025) — would determine whether the performance benchmarks established here are specific to blanket manufacturing or generalizable to broader labor-intensive garment production contexts.

Second, longitudinal evaluation of production method sustainability is needed. The present study captured the immediate impact of production method optimization over two consecutive production years but could not determine whether the observed improvements are maintained over time, whether further gains accumulate through continuous improvement, or whether performance regression occurs without ongoing engineering management. Future research tracking production performance across three or more consecutive years following method optimization would provide the longitudinal evidence currently absent from the garment manufacturing productivity literature and would be particularly valuable for manufacturing organizations making long-term investment decisions about process improvement programmes.

Third, empirical probability distribution fitting should be incorporated into future simulation models. The Monte Carlo simulation in this study used expert-estimated variability bounds and assumed truncated normal distributions for operation times. While these parameters reflected practitioner knowledge of shop-floor performance boundaries, future studies could strengthen simulation fidelity by fitting empirical probability distributions from large samples of repeated time-study observations and incorporating additional sources of production variability — including machine downtime cycles, operator absenteeism patterns, and supply chain disruptions. Building on the real-time data-driven simulation approach demonstrated by Jung et al. (2022), simulation frameworks developed along these lines would provide more precise uncertainty quantification and stronger predictive capability for manufacturing decision support.

Fourth, the integration of machine learning and predictive analytics for prospective SMV estimation represents a valuable extension of the present study's retrospective evaluation approach. The present research relied on direct empirical SMV measurement from ERP production records and time-study observation. Hemal et al. (2025), Shao et al. (2022), and Shen and Ji (2024) have demonstrated that machine learning models trained on historical production data can predict SMV with accuracy

comparable to manual time study. Future research investigating whether such predictive models can identify SMV reduction opportunities before physical process changes are implemented — enabling prospective rather than retrospective optimization — would extend the present study's contribution from performance evaluation toward proactive engineering decision support.

Fifth, future research should investigate the broader organizational and human dimensions of production method optimization that were outside the scope of the present study. The present research evaluated operational and financial outcomes but did not examine the influence of production method changes on worker satisfaction, ergonomic conditions, skill development requirements, or environmental sustainability. As labor-intensive manufacturing organizations face increasing pressure from international buyers and regulatory bodies to demonstrate social and environmental responsibility alongside operational performance, research integrating productivity improvement with worker wellbeing and carbon footprint reduction would provide a more complete basis for sustainable manufacturing strategy. The green production frameworks proposed by Tsai et al. (2024) and the sustainability dimensions of lean implementation identified by Begum et al. (2024) offer productive starting points for this extended research agenda.

## **7.7: Concluding Remarks**

This research set out to investigate whether systematic engineering-based production method optimization could substantially improve productivity and profitability in a labor-intensive manufacturing environment without capital investment — and the empirical evidence presented in this thesis answers that question affirmatively and with quantitative precision.

The conventional production method employed at Esquire Knit Composite Ltd. during 2023 was characterized by an average SMV of 28.62 minutes per unit, manpower of 45 operators, daily working hours of 11.70, and a financial outcome that was unsustainable — the production system generated consistent losses under a fixed FOB pricing structure because manufacturing cost per unit exceeded available earnings. The optimized production method implemented in 2024 reduced average SMV to 13.65 minutes per unit — a reduction of 52.31% — while simultaneously reducing manpower to 30 operators and daily working hours to 9.08 hours. Despite these substantial reductions in resource consumption, daily production output increased by an average of 52.56 units, manufacturing cost decreased by an average of USD 584.83 per day, CM earnings increased by USD 85.78 per day, and FOB earnings increased by USD 596.44 per day. All improvements were confirmed statistically significant at  $p < .001$ . Monte Carlo simulation across 10,000 production scenarios confirmed that these improvements

remained robust under realistic manufacturing uncertainty, including operational variability, error-prone conditions, and stochastic rework requirements.

Three conclusions of broader significance emerge from these findings. The first is that production method design is the primary determinant of manufacturing performance in labor-intensive systems — more influential than workforce size, working hours, or technological capability. The production system studied here achieved higher output with fewer operators and shorter working hours not because more resources were added but because the existing resources were organized and utilized more effectively. This conclusion has important strategic implications for labor-intensive manufacturers in developing economies, where productivity improvement is frequently pursued through workforce expansion or overtime at the cost of profitability, when systematic process optimization would achieve superior results at lower cost.

The second broader conclusion concerns the value of historical production data as an engineering resource. The analytical framework demonstrated in this study extracted actionable engineering knowledge entirely from production records that the organization already collected through its ERP system. No additional data collection was required. This demonstrates that the gap between underperformance and improvement in many labor-intensive manufacturing organizations is not a gap in data availability but a gap in systematic analytical practice — organizations that routinely collect operational data but do not analyze it for engineering improvement are forgoing the most accessible and lowest-cost source of manufacturing intelligence available to them.

The third conclusion is methodological. The integration of ERP-based historical analysis, root-cause diagnosis, inferential statistical testing, financial evaluation, and Monte Carlo simulation within a single empirical framework provides a level of evidentiary rigor that any single analytical component alone cannot achieve. Statistical analysis establishes that improvements are significant; simulation establishes that they are robust; financial analysis establishes that they are economically meaningful; and root-cause diagnosis establishes the specific engineering mechanisms through which they were achieved. Together, these components constitute a comprehensive framework for manufacturing performance evaluation that is transferable, replicable, and grounded in the production data that labor-intensive manufacturers already generate.

The principal contribution of this research is both empirical and methodological. Empirically, the study documents a measurable transformation in productivity and profitability achieved through systematic production method optimization, providing evidence that extends existing benchmarks in the **labor-intensive** manufacturing literature. Methodologically, it presents a rigorous and practical analytical

framework that integrates historical production data, root cause analysis, statistical evaluation, financial analysis, and simulation-based assessment. This framework can be readily adapted by other manufacturing organizations and researchers to evaluate and improve production performance in similar industrial settings. In an era of increasing production costs, intense global competition, and resource constraints, the ability to achieve substantial productivity improvement through engineering expertise rather than major capital investment is not merely advantageous but strategically essential.

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