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An Integrated DMAIC-Real-Time Quality Control Framework for Quality Control in Garment Manufacturing

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Abstrak
Penelitian ini mengusulkan kerangka kerja terintegrasi DMAIC–Preventive Maintenance–Operator Retraining–Real-Time Quality Control (PM–RO–RT-QC) untuk perbaikan kualitas pada industri garmen. Penelitian dilakukan di sebuah perusahaan garmen skala menengah dengan menggunakan data Quality Control (QC) untuk Style XY yang dikumpulkan selama 18 hari produksi berturut-turut pada Agustus–September 2025. Sebanyak 10.346 unit garmen diproduksi dengan 1.165 cacat yang tercatat pada 31 titik pemeriksaan kualitas yang telah ditetapkan, dan 21 kategori di antaranya memuat cacat. Metode DMAIC diterapkan untuk mengukur kinerja kualitas awal, mengidentifikasi cacat dominan, menganalisis akar penyebab potensial, serta memprioritaskan risiko menggunakan Failure Mode and Effects Analysis (FMEA). Proses yang diamati mencapai tingkat sigma sebesar 4,18 sebagai indikator awal kinerja kualitas. Analisis Pareto mengidentifikasi tujuh kategori cacat dominan yang menyumbang sekitar 80% dari seluruh cacat yang tercatat, sedangkan Skipped Stitch dan Oil Stain dipilih untuk analisis akar penyebab secara rinci. Analisis Fishbone dan FMEA mendukung perumusan tindakan perbaikan. Berdasarkan temuan tersebut, kerangka PM–RO–RT-QC yang diusulkan menghubungkan preventive maintenance, pelatihan ulang operator, dan pengendalian kualitas real-time dengan DMAIC. Kerangka ini masih bersifat konseptual dan memerlukan implementasi serta validasi empiris pada penelitian selanjutnya.

***Kata Kunci**: Cacat produksi, Six Sigma, Perbaikan kualitas*

Abstract
This study proposes an integrated DMAIC–Preventive Maintenance–Operator Retraining–Real-Time Quality Control (PM–RO–RT-QC) framework for quality improvement in garment manufacturing. The study was conducted in a medium-scale garment manufacturer using Quality Control (QC) data for Style XY collected during 18 consecutive production days in August–September 2025. A total of 10,346 garments were produced, with 1,165 defects recorded across 31 predefined quality checkpoints, of which 21 categories contained recorded defects. DMAIC was applied to measure baseline quality perfo rmance, identify dominant defects, analyze potential root causes, and prioritize risks using Failure Mode and Effects Analysis (FMEA). The observed process achieved a sigma level of 4.18 as a baseline indicator of quality performance. Pareto analysis identified seven dominant defect categories accounting for approximately 80% of recorded defects, while Skipped Stitch and Oil Stain were selected for detailed root-cause analysis. Fishbone analysis and FMEA supported the formulation of improvement actions. Based on these findings, the proposed PM–RO–RT-QC framework connects preventive maintenance, operator retraining, and real-time quality control with DMAIC. The framework remains conceptual and requires future empirical implementation and validation.

***Keywords**: Production defect, Six Sigma, Quality improvemet*

1. Introduction

The garment industry is one of the most competitive manufacturing sectors in both domestic and global markets. Increasing pressure on product quality, on-time delivery, and cost efficiency requires firms to implement effective, adaptive quality control systems. Inconsistent product quality not only increases defect rates but also raises rework costs, customer complaints, and reputational damage in international markets (Fibriani et al., 2023).Studies indicate that poor quality can reach 16–30% of total production costs if not managed systematically (Fridkin et al., 2024). Without adopting modern quality improvement methods, companies may see declining efficiency and weakened competitive positioning (Psarommatis & Azamfirei, 2024).

In the observed garment manufacturing company, production efficiency is targeted at 87%, while the actual production efficiency remains at approximately 76%. This 11-percentage-point gap is due to rework required for defective products. Operators must spend production

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time correcting defective garments, reducing time available to produce new products and lowering overall production efficiency.

Six Sigma, particularly through the DMAIC (Define–Measure–Analyze–Improve–Control) methodology, has been widely adopted as a structured, data-driven quality improvement approach (Peruchi et al., 2020). Previous studies have reported significant defect reductions across various manufacturing sectors, including rubber and electronics industries (Mittal et al., 2023a),(Garg et al., 2020). However, most of these studies primarily focus on improvements achieved up to the Improve phase, while the Control phase remains relatively static and heavily dependent on final inspections or periodic evaluations.

In labor-intensive and dynamic environments such as garment manufacturing, conventional DMAIC implementation has several limitations. Garment production is characterized by frequent style changes, operator variability, and high workflow complexity. Under such conditions, reliance on historical data and periodic evaluations may reduce responsiveness to real-time process variations (Pranowo & Artanto, 2022), Therefore, strengthening the Control phase becomes essential to ensure continuous and adaptive quality assurance.

In addition, the increasing demand for fast production cycles in the garment industry has intensified the need for adaptive quality control systems that are capable of responding to dynamic production conditions. Conventional quality control approaches that rely on end-of-line inspection are no longer sufficient to ensure consistent product quality, particularly in labor-intensive environments where process variability is high.

Although Six Sigma and DMAIC have been widely applied to improve manufacturing quality, previous studies have primarily focused on structured defect reduction and process improvement within specific manufacturing contexts (Peruchi et al., 2020; Mittal et al., 2023; Garg et al., 2020). These studies demonstrate the effectiveness of DMAIC as a systematic approach to identifying process problems, analyzing their causes, and developing improvement actions. However, the integration of preventive maintenance, operator retraining, and real-time quality monitoring as interconnected mechanisms within the DMAIC Control phase remains less explicitly addressed, particularly in labor-intensive garment manufacturing.

To address these limitations, this study proposes the integration of Real-Time Quality Control (RT-QC) into the DMAIC framework, reinforced by Preventive Maintenance (PM) and Operator Retraining (RO). This integrated approach extends the traditional Control phase from post-improvement monitoring into a proactive and dynamic quality management system capable of real-time detection and response during production.

Thus, this study aims to develop an integrated DMAIC–PM–RO–RT-QC quality control framework tailored to the characteristics of labor-intensive garment manufacturing. Theoretically, this research contributes by proposing an integration of the Six Sigma Control phase with dynamic and real-time quality control mechanisms. Methodologically, it provides an adaptation of Six Sigma implementation suitable for labor-intensive industries with high operational complexity and limited resources. Practically, it offers an applicable and cost-efficient quality control model for medium-scale garment manufacturers.

2. Research Methods

This study employs a case study approach by focusing on the implementation and development of quality control methods in a real production environment. The research was conducted in a medium-scale garment manufacturing company located in Klaten, Indonesia, aiming to analyze production defect levels and develop an integrated quality control framework based on Six Sigma DMAIC and RT-QC.

The case study approach was selected to enable in-depth analysis of actual production operational conditions, particularly in labor-intensive manufacturing environments with high process complexity. This research aims to produce quality control solutions that can be directly implemented in real production systems. Figure 1 shows the flowchart of the research stages, beginning with problem identification, data collection, causal analysis, and ending with improvement design and quality control documented in the research article.

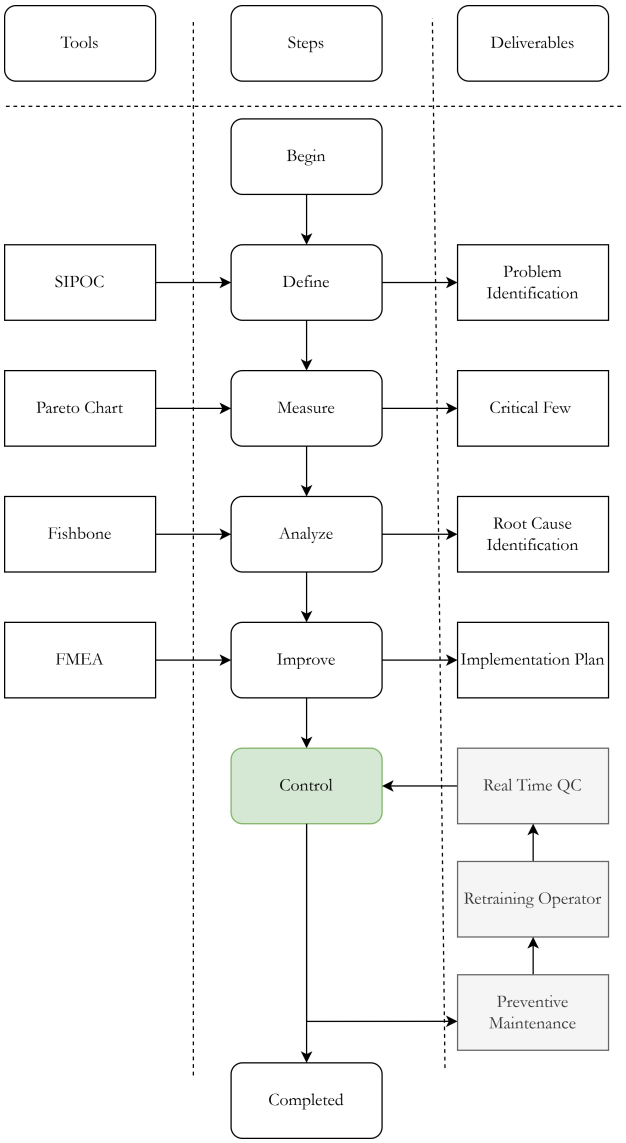


Figure 1: Research methodology stages

2.1. Data Collection

The research was conducted in a medium-scale garment manufacturing company producing a wide range of apparel products, including underwear, trousers, T-shirts, jackets, and dresses for both children and adults. The manufacturing facility operates a total of 45 active production lines. Each production line handles different product styles according to production scheduling and customer demand. Every style possesses distinct technical characteristics and production periods, resulting in variations in defect types and operational complexity across lines.

This study focuses on Style XY as the unit of analysis. Style XY represents a base-layer garment characterized by the use of lightweight and elastic materials that require high precision in stitching, material handling, and process control. The production of this style involves multiple sewing operations and frequent machine adjustments, leading to higher process complexity and a diverse range of potential defect types. The selection of Style XY was conducted using a purposive sampling approach, considering its production complexity and relatively significant defect occurrence during its production cycle. This approach enables in-depth analysis of defect patterns within a specific style without generalizing across production lines that have heterogeneous characteristics (Huang & Xiang, 2022).

Data collection was carried out through direct observation at the production site and interviews with the production department, particularly for Style XY. Data collection and access to the production process were conducted with the permission of the company. The QC records were used as the primary source for production and defect data, while observations and interviews were used to provide contextual information and support the interpretation of the identified quality problems. The interview respondents were purposively selected from key functional roles involved in the production of Style XY, as summarized in table 1.

Table 1: Respondent Category

Respondent Category	Number of Respondents	Selection Criteria
Sewing operators	5	Directly involved in production and experienced defect occurrences during operation
Quality control staff	2	Responsible for defect identification and quality monitoring on the production line
Mechanical staff	1	Involved in machine adjustment related to defect occurrence and process instability
Production supervisor	2	Oversee workflow, operator performance, and defect handling decisions
Industrial engineering staff	1	Responsible for process control, efficiency analysis, and quality improvement tasks

This study utilized Quality Control (QC) historical data for Style XY. The study focused on Style XY because the production system in the company is characterized by relatively short production cycles, in which each style is generally produced for approximately two weeks to three months before being replaced by another style according to customer orders. Style XY was purposively selected because it was a newly introduced style assigned to the observed production line, providing an opportunity to examine the development of the line's production performance from the beginning of the style's production cycle.

The total production period of Style XY was 25 days; however, company data access for this study was limited to 18 production days. Therefore, the observation period was defined as the first 18 consecutive production days of Style XY, starting from the first day of production. The use of consecutive observations from the beginning of production was intended to capture the development of the production line's performance and defect patterns during the early production period, rather than selecting individual days based solely on defect frequency or production outcomes. Accordingly, the 18-

day dataset represents the defined observation period available for this study and is not claimed to constitute a statistically representative sample of all 25 production days.

To ensure data validity and reliability, triangulation techniques were applied by combining direct observation, interview results, and historical QC records. This approach minimizes bias and enhances the accuracy of defect identification and root cause analysis. Furthermore, repeated verification with production personnel was conducted to confirm the consistency of the collected data with actual production conditions.

2.2 Data Processing

This study processed the data using the DMAIC method. The following are the steps in data processing:

1. Define: After the data were collected, the information was presented in the form of a defect table describing the number of defects for each type of production defect.
2. Measure: This stage involves measuring the sigma level and determining the top 20 percent of defect types in the production process using a Pareto chart to facilitate data visualization. The sigma level measurement is formulated as follows (Mittal et al., 2023):

$$DPU = \frac{Total\ Defects}{Total\ Units} \quad (1)$$

$$PMO = \left(\frac{Total\ Defect}{Total\ Units \times\ Opportunity}\right) \times 1.000.000 \quad (2)$$

$$Sigma\ Level = NORMSINV\ (1 - DPMO/1.000.000) + 1{,}5 \quad (3)$$

3. Analyze: The identified defect causes were analyzed using a Fishbone diagram based on direct observations of the production process and interviews with relevant production personnel. The observations were conducted to examine the actual production conditions and practices associated with the occurrence of defects, while the interviews were used to obtain additional information and confirmation regarding the potential causes.
4. Improve: Once the root causes of defects are identified, improvement actions are required to eliminate defects in the production process. FMEA is used to determine the priority improvement steps. Each identified failure mode was evaluated by all 11 participants using a structured interview questionnaire based on the three FMEA dimensions: Severity (S), Occurrence (O), and Detection (D). Each participant independently assigned a score from 1 to 10 for each dimension based on the qualitative descriptors provided in the questionnaire, adapted from Silva et al. (2014). The ratings from the 11 participants were subsequently discussed to reach a consensus score for each failure mode and FMEA dimension. The agreed S, O, and D scores were then used to calculate the Risk Priority Number (RPN).
5. Control: This stage designs an integrated quality control system that combines Preventive Maintenance, Retraining Operator, and Real-Time Quality Control.

This study focuses on the development of the proposed DMAIC–RT-QC framework based on actual production conditions, without conducting empirical implementation.

3. Results and Discussion

3.1 Define

In this phase, a SIPOC diagram was developed to identify the key elements of the production process, including Suppliers, Inputs, Processes, Outputs, and Customers. This stage aims to provide a comprehensive overview of the process flow and determine the primary quality issues that will be analyzed in subsequent phases (Faishal et al., 2024). Table 1 shows the SIPOC diagram of this study.

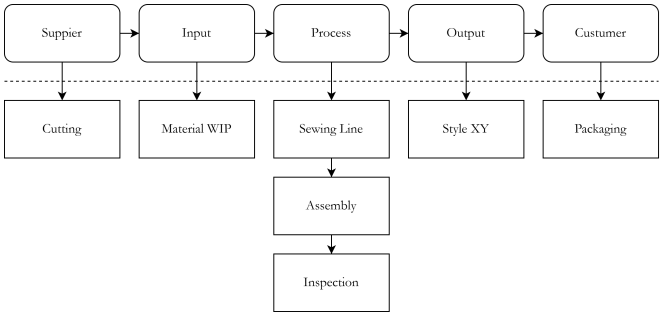


Figure 2: SIPOC diagram

The SIPOC shows that the Cutting department functions as the Supplier providing materials as Inputs to the Sewing Line, Assembly, and Inspection processes. The final output of these processes is the Style XY product, which is then delivered to the Packaging department as the Customer. As a company serving both export and domestic markets, the garment manufacturer maintains varying quality standards across customers, making the identification of quality issues more complex.

Based on the Define phase, historical defect data from the production of Style XY during the period August–September 2025 were reviewed through the SIPOC diagram to identify the process stage with the most dominant defect occurrence. The results indicate that the sewing process exhibits a higher incidence of defects compared to other production stages. Therefore, this study concentrates on defects occurring in the sewing line to ensure that improvement efforts are more focused and relevant to product quality enhancement. The identified defect data are then utilized in the Measure phase to assess process performance and categorize defect type.

The selection of the DMAIC method in this study is based on its systematic and data-driven approach, which is suitable for identifying, analyzing, and reducing

process variation. Compared to other quality improvement methods, DMAIC provides a structured framework that integrates problem identification, measurement, root cause analysis, and continuous control, making it highly applicable in complex production environments such as garment manufacturing.

3.2 Measure

This phase aims to determine the actual condition of the production process and serves as the basis for quality evaluation. Measure assesses the current performance before implementing improvement actions. The measurements include calculating DPU, DPMO, and Sigma Level.

Table 3: Sigma Level

Measurement	Result
Opportunity per unit	31
Total Defect	1165
Total Production	10346
DPU	0,1126
DPMO	3,632
Sigma Level	4,184457

Based on the measurement results, the manufacturer achieved an estimated sigma level of 4.18 during the observation period. This value is used as a baseline for assessing the current quality performance of the production process and identifying areas for improvement. Comparisons with sigma levels reported in previous studies, such as Mittal et al. (2023), should be interpreted in consideration of differences in production contexts, defect definitions, and calculation methods. One monitoring strategy to keep defect levels under control is through continuous improvement. This approach utilizes statistical methods and control charts to measure and monitor defects occurring during a given production period. By doing so, the company can evaluate process stability, manufacturing capability, and ensure processes remain within established control limits. The company provides defect data for Style XY sourced from Quality Control (QC) records. The table below presents defect data collected over 18 production days.

Table 4: Data Defect

No	Code	Defect type	Amount
1	M	Skipped Stitch	213
2	I	Oil	183
3	A	Uncut Thread End	166
4	B	Broken Stitch	154
5	AE	HTL	96
6	AD	Peel Off	92
7	N	Uneven Margin	50
8	AA	Impropare Sewing OPR	39
9	AC	Needle Hole	39
10	P	Twisted	35
11	C	Open Seam	32
12	G	Puckering	18
13	H	Pleated	16
14	V	Missing Label and Snap	7
15	L	Over Lap	6
16	J	Soil	5
17	O	Bubbling	4
18	Q	Wavy	4
19	Z	Improopare Shape	4
20	D	Run of Stitch	1
21	X	Fabric Defect	1
22	E	Hi-Low / Unsimetry	0
23	F	Missing Operation	0
24	K	Expose / Visible Stitch	0
25	R	Incorect Size	0
26	S	Incorect Component	0
27	T	Slanted	0
28	U	Visible Allowance	0
29	W	Not Aligmnet Seam	0
30	Y	Loose Stitch	0
31	AB	Trash	0
Total			1165

The company established 31 predefined quality checkpoints for the production process, covering the potential defect categories used for quality inspection. During the 18 day observation period, defects were revealed a total of 1,165 defects appearing across in 21 of these 31 predefined categories, while the remaining 10 categories had no recorded defects. For the Six Sigma analysis, the 31 predefined quality checkpoints were treated as defect opportunities per garment because each garment was assessed against these 31 quality criteria during the inspection process. Accordingly, the total number of defect opportunities was calculated as the number of units produced multiplied by 31.

These data indicate that most quality issues in Style XY are related to cleanliness and stitching results, such as oil stains, unclean thread ends, skipped stitches, and broken stitches. The data were then processed to determine the percentage of each defect type. A Pareto chart was used to identify the major issues and determine which defects occur most frequently.

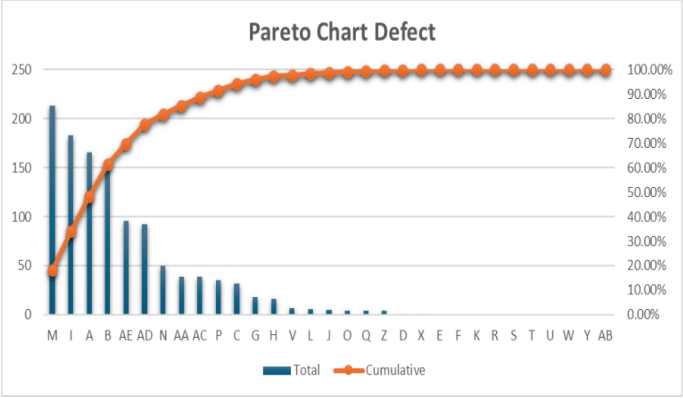


Figure 3: Pareto Chart Defect

The Pareto chart shows that the top seven defect types contribute approximately 81,89% of total defects. These include Skipped Stitch (18.28%), Oil Stain (15.71%), Uncut Thread End (13.43%), Broken Stitch (11.43%), HTL Misaligned/Broken/Detached (8.57%), Peel Off (7.14%), and Uneven Margin (5.71%). These defects significantly influence production quality compared to others, which appear less frequently.

Following the Pareto principle (80/20), most quality problems are caused by a few dominant defects (Kwilinski & Kardas, 2024). Therefore, quality control should prioritize these major defect types to achieve optimal improvement.

These findings indicate that although the sigma level is relatively high, the presence of dominant defects suggests that the process is not yet fully optimized. Similar studies in garment manufacturing have reported that achieving a sigma level above 4 still requires continuous improvement efforts, particularly in processes with high manual involvement. Therefore, focusing on dominant defect types is essential to further enhance process capability and reduce variability.

3.3 Analyze

This phase analyzes the root causes of defects occurring in the Style XY production process at PT XYZ. The Analyze phase focuses on identifying the underlying factors causing high defect rates, particularly the dominant defect types.

According to the Pareto analysis, seven defect categories accounted for approximately 80% of the total recorded defects. However, conducting a detailed root cause analysis for all seven categories would result in overlapping causal factors and would not necessarily provide additional insights into the dominant quality problems. Therefore, two defect categories with the highest frequencies, Skipped Stitch and Oil Stain**,** were selected for Fishbone analysis. The selection was based on their contribution to the overall defect occurrence and their ability to represent two distinct sources of quality problems: process-related defects associated with the sewing operation and contamination-related defects associated with oil contamination. Analyzing these two dominant and distinct defect categories enables the study to investigate the major causal mechanisms contributing to the observed quality problems while maintaining a focused and systematic root cause analysis. The identified causal factors were subsequently used as inputs for the FMEA-based risk prioritization.

3.3.1 Skipped Stitch

The Fishbone Diagram is an analytical tool used to illustrate the relationship between causes and effects of problems occurring in the production process. In this study, the Fishbone Diagram is employed to identify and trace the root causes of the main defects, skipped stitch and oil stain found in the sewing line of Style XY at PT XYZ.

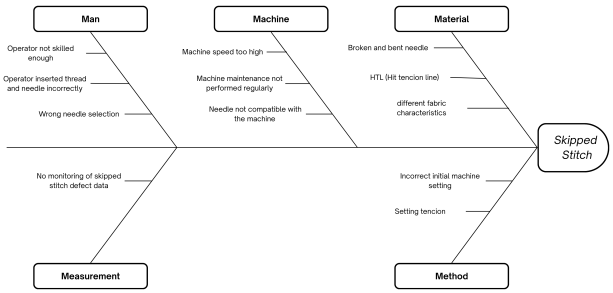


Figure 4: Fishbone skipped stitch defect

Based on the identification of root causes using the Fishbone Diagram in Figure 4, the defect type *Skipped Stitch* is caused by several major factors, namely man, machine, material, method, and measurement.

a. *Man*: Human factors significantly influence the occurrence of skipped stitches. Identified causes include insufficient operator skills, errors in threading and inserting the needle, and the use of needles inappropriate for the fabric type. These findings indicate that operator skill and accuracy are crucial in maintaining stitching consistency (Margetis et al., 2025).
b. *Machine*: Machine-related issues include excessively high machine speed, which often prevents the thread from being properly caught by the needle, resulting in skipped stitches. Furthermore, irregular machine maintenance and the use of incompatible needles increase defect likelihood. These issues highlight the importance of routine preventive maintenance and standardized machine component selection.
c. *Material*: Skipped stitches are also influenced by material quality. Broken or bent needles, HTL (Heat Transfer Label) materials that peel or snap easily, and fabric color shading (differences in color or texture) may disrupt sewing performance. Materials that fail to meet specifications pose risks to machine functionality and final product quality.
d. *Method*: Inappropriate work methods contribute to this defect. Initial machine settings are often incorrect, and thread tension is not optimally adjusted. Non-standardized work procedures lead to variations in outcomes among operators and across machines (Pranowo & Artanto, 2022).
e. *Measurement*: The absence of a monitoring system for skipped stitch data makes it difficult for the company to track defect patterns and frequency. Without historical records, the evaluation and quality control processes become less effective.

3.3.2 Oil Stain

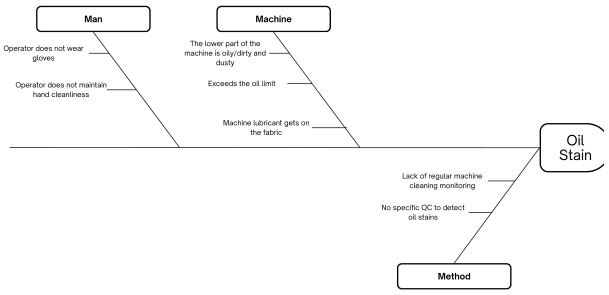


Figure 5: Fishbone oil stain defect

Based on the analysis using the Fishbone Diagram, oil stain defects are caused by a combination of human, machine, and non-standardized work method factors. This defect frequently occurs when fabric is exposed to oil splashes or leakage from sewing machines.

a. *Man*: Human factors contribute to oil stains due to operator negligence in maintaining personal cleanliness during work. Operators who do not use gloves or fail to keep their hands clean may transfer oil to the fabric. This indicates a need for improved awareness and compliance with workplace hygiene procedures, which can be enforced through training and regular QC supervision.
b. *Machine*: The primary machine-related causes include dirty and oily machine undersides, excessive lubrication beyond standard limits, and oil leakage from lubrication points that may come into contact with fabric. These findings indicate inconsistencies in machine maintenance procedures, resulting in oil accumulation that risks contaminating production materials.
c. *Method*: Method-related issues also significantly contribute to oil stains. The lack of scheduled monitoring of machine cleaning activities results in uncontrolled oil residue. Moreover, the absence of specific QC inspection procedures for oil stains at early production stages often leads to late detection, increasing rework and delaying product delivery (Garcia-Garcia et al., 2021).

The root cause analysis demonstrates that defect occurrence is not caused by a single factor but rather by the interaction between human, machine, and method variables. This finding is consistent with previous studies indicating that labor-intensive industries are highly sensitive to operator skills and machine conditions. Therefore, a comprehensive improvement strategy that addresses multiple factors simultaneously is required to effectively reduce defect rates.

3.4 Improve

At this stage, the Failure Mode and Effects Analysis (FMEA) method is employed to improve the process based on the results obtained from the *Analyze* phase. The application of FMEA in this study aims to identify process failure causes that pose the highest risk to product quality. This is achieved by combining the parameters of severity, occurrence, and detection into the Risk Priority Number (RPN) (Wahyu Purnomo & Hermansyah, 2025). FMEA enables the identification of the most critical and severe failure causes, allowing corrective actions to be prioritized toward the most significant sources of risk.

The FMEA values in this study were determined based on interviews with supervisors, mechanics, and quality control personnel on the production line. The results of the improvement actions derived from the FMEA analysis are presented in the following table.

Table 5: FMEA results

Faktor	Failure Mode	Failure Cause	S	O	D	RPN	Total
Man	Skipped Stitch	Unskilled operator	7	9	10	630	1310
		The operator incorrectly inserted the thread and needle	2	8	6	96	
		Wrong needle selection	2	3	6	36	
	Oil Stain	The operator does not wear gloves	5	10	10	500	
		The operator does not maintain hand cleanliness	4	2	6	48	
Machine	Skipped Stitch	Machine speed is too high	9	8	9	648	2938
		Maintenance is not regularly controlled	7	10	10	700	
		Needle is not compatible with the machine	2	2	6	24	
	Oil Stain	The lower part of the machine is dirty and oily	8	9	10	720	
		Oil exceeds the limit	9	2	7	126	
		Machine lubricant gets on the fabric	8	9	10	720	
Material	Skipped Stitch	Needle is broken and bent	6	10	6	360	612
		Hight tension line	3	8	6	144	
		Fabric has different characteristics	9	2	6	108	
Measurement	Skipped Stitch	No monitoring of skipped stitch data	9	10	10	900	900
Method	Skipped Stitch	Initial setting is incorrect	9	2	9	162	1368
		Setting tencion	3	2	6	36	
	Oil Stain	Lack of monitoring of scheduled machine cleaning	9	10	3	270	
		No specific QC for oil stains	9	10	10	900	

Based on the FMEA results, the individual failure modes associated with machine-related causes showed relatively high RPN values, ranging from 700 to 720. These failure modes were associated with irregular machine maintenance, dirty and oily machine undersides, and lubricant contact with the fabric, particularly in relation to skipped stitches and oil stains. The aggregated RPN for the Machine category was 2,938, which was higher than the aggregated values for Method (1,368), Man (1,310), Measurement (900), and Material (612). These aggregated values are presented descriptively to show the distribution of identified risks across the 5M categories; however, they were not used as the basis for determining risk priority because the number of failure modes differs among categories. Risk prioritization was therefore based on the RPN of individual failure modes.

The Method-related failure modes included incorrect initial machine settings and the absence of dedicated quality inspection for oil stains, indicating potential weaknesses in work procedures and quality control practices. The Man-related failure modes included low operator skill and errors in threading or needle insertion, indicating the need for operator training and retraining of standardized work practices. Meanwhile, Measurement-related failure modes included the absence of a monitoring system for skipped-stitch defects, which limits the availability of systematic information for ongoing defect control. Material-related failure modes were associated with broken or bent needles and variations in fabric characteristics.

Overall, the FMEA results indicate that several individual failure modes require greater attention based on their respective RPN values. The identified priorities were used to formulate improvement actions related to preventive machine maintenance, work-method refinement, operator training, defect monitoring, and material control. These improvement actions subsequently serve as the basis for the proposed PM–RO–RT-QC framework. Since the proposed actions were not implemented and empirically tested within the scope of this study, their effectiveness in reducing defect rates remains to be validated through future implementation.

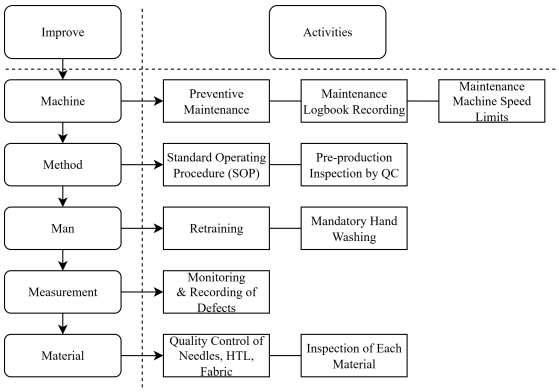


Figure 6: Improvement steps

a. The company may implement preventive maintenance with scheduled cleaning and lubrication, documented in a maintenance logbook. Machine speed should be kept at optimal levels, and needle replacement must be conducted periodically to prevent wear and deformation. Quality control during production must be supported by proper equipment maintenance to ensure machine stability and reduce defect occurrence (Mustafa Ibrahim, 2023).
b. The company may develop SOPs and work instructions that are detailed and easy for operators to understand, covering machine setup, pre-production checks, and daily QC inspections. Flexible and implementable SOPs can accelerate decision-making and improve resource efficiency (Ahmad et al., 2025).
c. Improvements include retraining operators to ensure proper stitching techniques, needle installation, and tension settings. Job training enhances skill mastery and productivity while reducing defect rates (Iqbal et al., 2024). Operators must also wash their hands after contact with machine oil to prevent contamination. According to Sharif Hosen et al. (Hosen et al., 2024), training contributes to improved productivity, efficiency, and organizational performance. Product quality control depends not only on machines and methods but also on workforce discipline and competency (Putra et al., 2025).
d. Improvements include establishing a structured defect monitoring and recording system. Companies should prepare daily inspection forms, check sheets, or digital defect tracking to record skipped stitch occurrences in real time. Systematic defect measurement using tools such as check sheets and control charts enhances garment quality monitoring (Haridy et al., 2023).
e. Quality control should be implemented for materials such as needles, HTL, and fabric. All materials must undergo inspection to prevent color or texture inconsistencies. Real-time monitoring technologies including information systems, sensors, and artificial intelligence can enhance detection efficiency and reduce defect rates (Wang et al., 2023).

3.5 Control

The Control stage is the final step in the DMAIC method, intended to ensure that implemented improvements can be maintained sustainably (Ahmad et al., 2025). This study focuses control measures on the two main defects, skipped stitches and oil stains that contribute most to defects in Style XY production. The proposed control measures for the two types of defects are as follows:

1. Control of Skipped Stitch

a. Inspect needle condition, thread tension, and feeding mechanism synchronization.
b. Provide routine weekly retraining to ensure stitching technique consistency, proper sewing speed adjustment, and correct needle selection according to fabric type.

2. Control of Oil Stain
a. Establish oil-free zones in sewing areas and ensure machines have enclosed lubricant reservoirs.
b. Conduct routine machine cleaning with microfiber cloths and non-oil-based cleaning agents after each shift.
c. Place warning labels in oil-prone areas and provide protective fabric covers during assembly.
d. Maintenance personnel must record oil usage and refilling schedules in a logbook to ensure control.

To prevent recurrence of the two major defects, this study proposes an integrated DMAIC model consisting of Preventive Maintenance (PM), Retraining Operator (RO), and Real-Time Quality Control (RT-QC)**.** This model emphasizes proactive and continuous quality control by strengthening machine reliability, operator capability, and real-time supervision. The model can also address potential defects throughout the production process. Fig 6. Shows the proposed control integration.

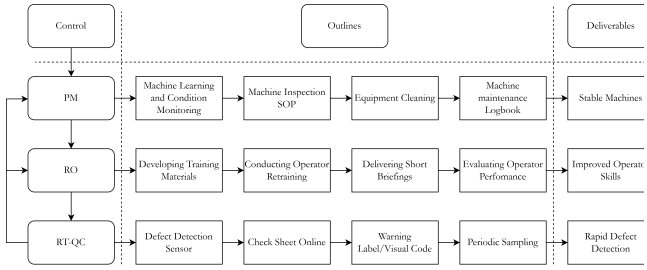


Figure 7: Controlled Integration

1. Preventive Maintenance (PM)

This approach focuses on preventing machine failures or deviations before defects occur. Its objective is to ensure sewing machines and work areas remain production-ready and free from potential defect sources. Consistent PM minimizes defects such as skipped stitches and oil stains. According to Akbar et al. (Akbar et al., 2024), preventive maintenance within DMAIC can reduce oil stains by up to 40% by the following steps:

a. Utilizing machine learning and condition monitoring technologies to detect potential machine failures. Predictive maintenance effectively identifies faults early, minimizing downtime and defects (Surucu et al., 2023).
b. Establishing SOPs for pre-shift machine inspections, including needle condition, thread tension, feeding synchronization, and pedal function. Daily check sheets ensure consistent inspection at every shift. Check sheet usage assists in detecting recurring defect patterns and improving stitch consistency (Hoque & Maalouf, 2022).
c. Conducting routine machine and production area cleaning to prevent defects caused by dirt.
d. Implementing maintenance logbooks containing lubricant schedules, needle replacement, and inspection results. Data-based maintenance integration helps extend machine lifespan and improve production reliability (Lucantoni et al., 2025).

2. Retraining Operator (RO)

This aspect focuses on strengthening operator skills, discipline, and responsibility to maintain stable work quality. Continuous RO implementation effectively reduces defect rates and improves productivity. The proposed steps are:

a. Developing DMAIC-based training materials integrated with QC monitoring results.
b. Conducting routine retraining on stitching techniques, sewing speed adjustments, needle selection, and personal quality control procedures. DMAIC-based training significantly reduces defect rates (Mittal et al., 2023a).
c. Conducting pre-shift briefings emphasizing operator responsibility and workspace cleanliness.
d. Performing weekly operator performance evaluations to ensure consistent stitching quality.

3. Real Time Quality Control (RT-QC)

RT-QC functions as a dynamic quality-control layer that operates during production to detect, record, prevent, and respond to quality deviations before defective products accumulate. The proposed RT-QC system combines real-time or frequent defect detection, routine condition monitoring, visual contamination control, and QC verification. The system is designed as a practical quality-control mechanism that can be adapted to the available technology and operational conditions of the garment manufacturer. The operational flow consists of the following steps:

a. Vision sensors or simple inspection cameras are proposed at relevant production or inspection points to detect visible quality deviations, particularly skipped stitches and oil stains, at an early stage. When a deviation is identified, the affected garment is flagged for QC verification and corrective action.
b. Digital check sheets are used to record machine and stitching conditions at hourly intervals. The recorded information includes relevant machine conditions, stitching quality, and detected abnormalities. These records provide a traceable basis for identifying recurring deviations and supporting subsequent corrective actions. Periodic inspections and systematic check-sheet use have been reported as mechanisms for improving quality control (Hoque & Maalouf, 2022).

c. Warning labels and fabric protectors are placed in areas identified as prone to oil contamination. These visual controls serve as preventive measures within the RT-QC system by reminding operators of contamination risks and reducing direct contact between potential oil sources and fabric. Visual control has been applied as a mechanism for reducing contamination-related risks (Mittal et al., 2023a).
d. QC personnel conduct random sampling to verify compliance with stitching standards and inspect flagged or potentially affected products. When a deviation is detected, the responsible QC personnel communicate the finding to the relevant operator or production personnel for immediate corrective action. The detected condition and corrective action are subsequently recorded in the check sheet to provide feedback for continued monitoring (Hoque & Maalouf, 2022).

The company must conduct monthly internal quality audits to evaluate the effectiveness of PM, RO, and RT-QC. Internal audits are crucial in preventing defect rate increases and maintaining quality performance (Hoque & Maalouf, 2022). If defect rates rise again, RT-QC triggers the Corrective and Preventive Action (CAPA) procedure. RT-QC provides feedback to PM and RO, where PM performs machine reinspection, while operators receive rapid corrective instructions. In addition, QC data can be utilized to design targeted retraining programs as part of preventive actions.

The proposed framework is designed to support earlier detection and response to quality deviationsThis integrated control mechanism not only strengthens operational responsiveness but also reflects a broader approach to quality management.

The findings of this study are consistent with previous research emphasizing the importance of integrating technical and human factors in quality improvement. However, this study indicates that the incorporation of Real-Time Quality Control (RT-QC) within the DMAIC framework has the potential to provide a more responsive control mechanism compared to conventional approaches that primarily rely on post-production inspection.

The integration of RT-QC is expected to enable earlier detection of defects during the production process, thereby reducing the likelihood of defect accumulation and minimizing rework. This suggests that the proposed framework can be more adaptive to the dynamic conditions of labor-intensive garment manufacturing, where process variability is relatively high and immediate corrective action is required.

4. Conclusion

This study applied the DMAIC methodology to analyze quality performance in Style XY within an Indonesian garment manufacturing process. The analysis identified a sigma level of 4.18 as the baseline quality performance during the observation period. Pareto analysis identified seven dominant defect categories accounting for approximately 80% of the recorded defects, with Skipped Stitch and Oil Stain selected for detailed root cause analysis because they represented prominent and distinct defect mechanisms. Fishbone analysis and FMEA were subsequently used to identify and prioritize the relevant failure modes and potential improvement actions.

Based on these findings, this study proposes an integrated PM–RO–RT-QC framework to strengthen the Control phase of DMAIC. The proposed framework connects preventive machine maintenance, operator-related improvement, and real-time quality control to support earlier detection, monitoring, and response to quality deviations during production. The framework is presented as a conceptual improvement model derived from the diagnostic findings of the observed production process rather than as an empirically validated intervention.

The study is limited to one production style and an 18-day observation period, and the proposed PM–RO–RT-QC framework was not implemented during the study. Consequently, its effectiveness in reducing defect rates, rework, response time, or process variation could not be empirically established. Future research should therefore conduct a pilot implementation of the proposed framework on the production line and evaluate its performance using before-and-after or controlled comparisons. Relevant evaluation measures should include defect rate or DPMO, rework, corrective-response time, production efficiency, and, where appropriate, process stability. Further studies should also test the framework across multiple garment styles and longer production periods to assess its applicability under different production conditions.

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