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PROCESS OPTIMIZATION USING SIX SIGMA STRATEGY IN GARMENT MANUFACTURING

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ABSTRACT
Increasing competition among developed countries makes it increasingly pressing for the garment industry in developing economies such as Bangladesh to produce high-quality, defect-free products at competitive prices in order to remain globally viable. As one of the largest contributors to Bangladesh's economy, the garment sector faces constant pressure to balance quality with efficiency while responding to fluctuating international demand. Within this context, the present study investigates the effectiveness of the Six Sigma DMAIC (Define, Measure, Analyze, Improve, Control) methodology in optimizing the cutting process at Epyllion Group, a leading garment manufacturing company in Bangladesh. The choice of focusing on the cutting process was strategic, as this stage plays a critical role in determining dimensional accuracy, fabric utilization, and overall product quality. Even small errors in this stage can cascade into large-scale defects, increasing rework rates and operational costs.The research systematically identified inefficiencies that contributed to frequent production defects and heightened expenses. Among the most significant issues were fabric misalignment, which caused irregular cuts and waste; bundle mislabeling, which created confusion and delayed workflows; and inconsistent fabric tension, which compromised uniformity in cut panels. These problems were compounded by inadequate operator skills and limited preventive maintenance practices. To address these challenges, the study employed a structured data collection framework supplemented by analytical tools such as Pareto analysis and cause-and-effect diagrams. These techniques allowed the research team to isolate the root causes of the majority of defects and to design targeted solutions. The interventions included operator training programs aimed at enhancing technical precision, machine calibration and maintenance schedules to ensure equipment reliability, the installation of automated tension controllers to standardize material handling, and the introduction of standardized operating procedures to reduce process variation.
The impact of these measures was significant and measurable. Results following implementation revealed a 61.5% reduction in defect rates, which directly improved product quality and reduced waste. Machine downtime was cut by 66.7%, reflecting the success of preventive maintenance and calibration measures. Similarly, the product rework rate dropped by 55.6%, which not only lowered costs but also improved throughput and delivery reliability. Additional improvements were observed in measurement accuracy, which increased by 25%, and operator training scores, which rose by 38.5%, indicating that human capital development played a key role in sustaining process improvements. These results demonstrate the combined value of technological upgrades and workforce empowerment, showing that quality improvements in garment manufacturing require both structural and behavioral change.

KEYWORDS
Garment Manufacturing, Six Sigma, Misalignment, Measurements, Defects;

INTRODUCTION

The global textile and garment industry provides international trade with all-important leverage and significantly contributes to development, employment, and technological advancement (Patel & Patel, 2021). These rising consumer expectations for high-quality and price-competitive garments put immense pressure on manufacturers to improve production efficiency with reduced defects (Saad, 2020). In emerging economies such as Bangladesh, with the national economy firmly depending on the garment sector, these challenges assume special significance (Keane & Velde, 2019). There are systematic process optimization mechanisms that nowadays companies should incorporate so that productivity and quality remain high in their outputs in the rapidly changing market. They may comprise methodologies such as lean manufacturing, Total Quality Management (TQM), and Six Sigma. All these have become key in improving operational efficiency and reducing waste in mass production environments (Taylor, 2018). But Six Sigma has remained largely untested in the textiles and garment manufacturing sector, even though it has traveled into industries such as healthcare, automotive, electronics, and so on (Sharma & Singh, 2023).

Epyllion Group, a leading garment manufacturer in Bangladesh, is one of the companies that addresses production process optimization for compliance with international quality standards. However, despite its strong market presence, the company deals with the continuous problems of high levels of defects, poor workflows, and limitations in quality control (Fouji & Hoque, 2020). Inefficiency and production defects incur extra costs and, by implication, hurt the brand reputation and customer satisfaction. The Six Sigma problem-solving approach, with an emphasis on data-driven decision-making and the removal of defects, is potentially a panacea. But actual application of Six Sigma in the textile industry requires efficiently evaluating the effectiveness of Six Sigma in addressing industry-specific problems such as variation in fabric quality, labor-intensive processes, and supply chain variation (Sarker, 2024).

This study aims to examine the effect of Six Sigma on defect reduction and production efficiency in the garment industry. The potential benefits and limitations of Six Sigma have been investigated alongside its implementation at the Epyllion Group. This study postulates that the implementation of Six Sigma will result in a tangible reduction of defects and improvement in production efficiency. These findings will provide significant insights to industry practitioners as well as add to the body of knowledge concerning process optimization in textile manufacturing.

LITERATURE REVIEW

There is a lot of research on Six Sigma in manufacturing industries, with abundant literature affirming its capacity to improve quality control and reduce defects. Motorola pioneered this project in the 1980s. Six Sigma represents a data-driven approach to eliminate variations in a process for better operational efficiency (Ajmera & Umarani, 2017). Applications in various industries, from healthcare to aerospace and automotive manufacturing, have confronted the need for process standardization and quality enhancement (Kurnia et al, 2021). Thus, it is relatively new to the textiles and apparel industry and embarks on certain challenges. Since garment making is labor intensive, and raw materials vary, the application of Six Sigma needs to address such modifications industry-wise to guarantee implementation success.

Some researchers have dealt with the Lean and Six Sigma methodologies in textile productions, proving their capability to enhance production. According to (Kurnia et al, 2021), companies implementing Lean Six Sigma in textile industries report more tangible waste and defect rate reductions. (Saad, 2024) further reiterated the works of Six Sigma and data mining in production process optimization, insisting that statistics and process control weigh heavily in defect prevention. However, such literature is very scarce regarding large-scale garment manufacturers; more empirical work is needed for findings to be validated in real-time textile production.

With an export-oriented orientation for major international brands, an interesting case study describing the Six Sigma impact on the garment sector could be the Epyllion Group. The company is primarily challenged by very high defect rates, which hinder productivity and thus profitability. This research made an attempt to address the key propositions:

Q1: How does a Six Sigma approach affect defect reduction in garment manufacturing?

Q2: What are the primary operational challenges facing the implementation of Six Sigma within the textile industry?

Q3: What other measurable improvements in production efficiency can be ascertained post-Six Sigma implementation?

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The other side of the argument in this study is that the implementation of Six Sigma will produce the following outcomes:
- A significant decrease in defect rates.
- Standardization of processes, therefore improving production efficiency.
- Improvement of overall quality control and customer satisfaction.

By addressing these research questions and subsequently testing the hypothesis in the context of Epyllion Group, this study intends to serve the advancement of the literature concerning Six Sigma applications in textile and garment manufacturing. These results would not only provide working recommendations for industry leaders but would permit some fine-tuning of Six Sigma methodologies for the specific challenges of this sector.

METHOD

The research investigates the optimization of the cutting system in garment manufacturing through the structured application of the Six Sigma DMAIC (Define, Measure, Analyze, Improve, Control) methodology. This methodological choice is particularly appropriate for addressing systematic inefficiencies because DMAIC provides a step-by-step framework for identifying, quantifying, and eliminating sources of variation and defects.

The process began with the scoping of the company's operations, involving close engagement with management and frontline stakeholders to build an accurate understanding of the production environment. This scoping phase ensured that the project objectives were aligned with the organization's strategic quality targets and that the voices of operators, supervisors, and quality controllers were integrated into the problem definition. The collaborative approach was important for recognizing both the technical and human factors that contribute to inefficiencies in the cutting system.

During the Define phase, the project team identified the core problem areas by mapping the existing cutting process and highlighting performance gaps. Stakeholder input and historical production records were used to specify the Critical to Quality (CTQ) characteristics, such as dimensional accuracy, proper alignment of fabric layers, and consistency in cut size. Establishing CTQs was essential to link customer expectations with process parameters and to develop measurable benchmarks against which improvements could later be evaluated.

The Measure phase focused on the systematic collection of data to confirm the existence of performance issues. Quantitative data were classified into measurable categories (e.g., defect counts, error percentages) while qualitative insights (e.g., operator observations) were used to contextualize these findings. Statistical process control (SPC) tools and preliminary Pareto charts were employed to assess the extent and distribution of errors across different shifts and workload conditions. These tools provided an evidence base to identify potential bottlenecks and recurring failure modes.

In the Analyze phase, root cause identification was prioritized through structured techniques such as Pareto analysis and cause-and-effect (fishbone) diagrams. These tools allowed the team to isolate the dominant factors contributing to quality failures, including mismatched fabric piles, machine calibration inconsistencies, and insufficient operator training. By distinguishing between primary and secondary causes, the analysis stage provided actionable insights while avoiding superficial problem-solving.

The Improve phase consisted of developing and testing targeted solutions. Depending on feasibility, some interventions were immediate, such as machine recalibration and adjustments to cutting protocols, while others required a more structured rollout, such as operator retraining and preventive maintenance schedules. A pilot testing approach was used to validate the impact of each intervention before scaling it across the production line. Figure 1 illustrates the structured cycle of improvements evaluated during this phase.

Finally, the Control phase ensured the long-term sustainability of improvements. Control charts and real-time monitoring systems were introduced to track process stability and maintain error reduction. Standard operating procedures (SOPs) were updated to reflect new practices, while continuous auditing mechanisms were instituted to safeguard against process drift. Lessons learned were documented and shared across departments to encourage organizational learning and foster a culture of continuous improvement. By following this systematic methodology, the study ensured that Six Sigma was not only applied as a defect-reduction tool but also as a holistic quality management strategy.

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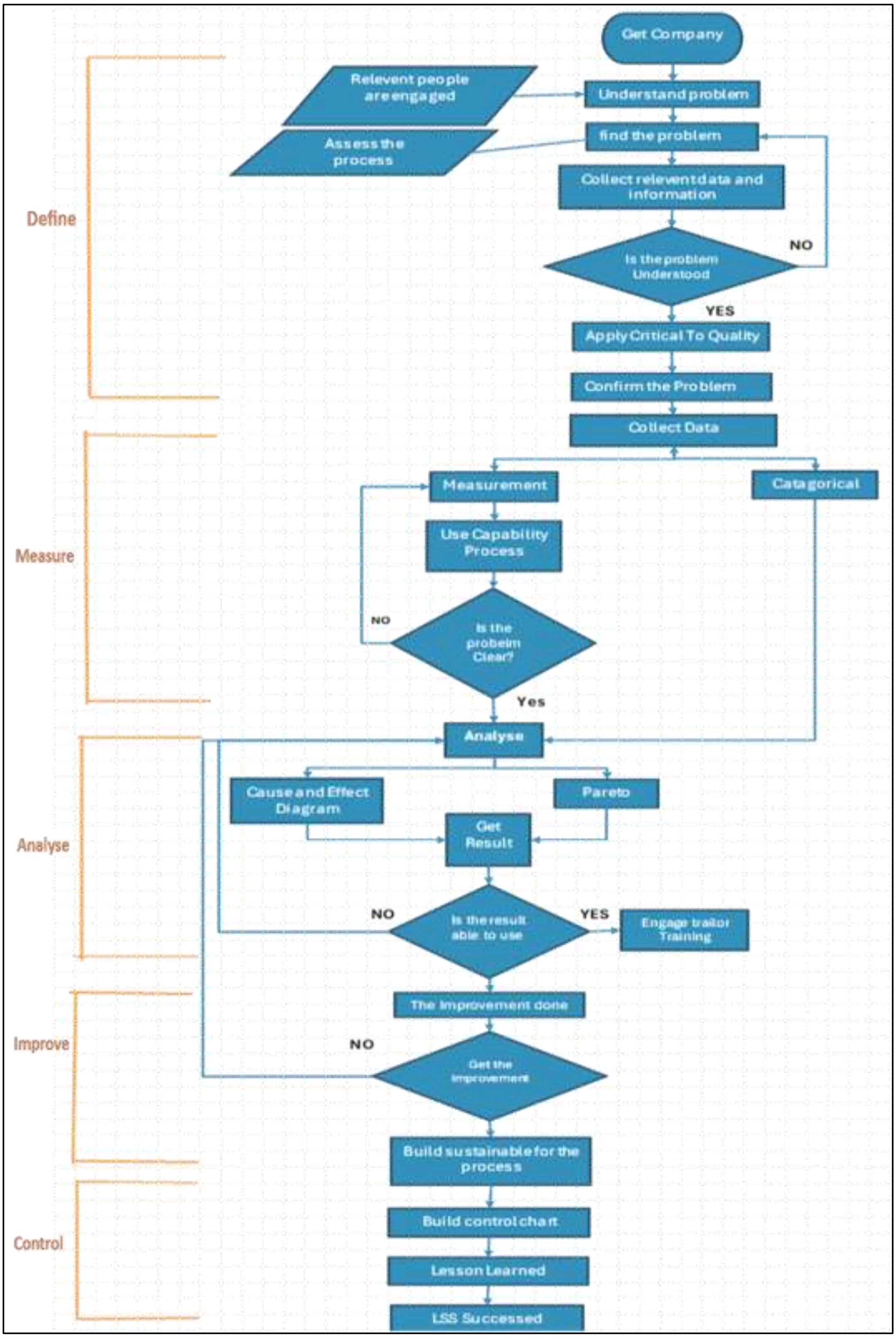
Figure 1: Research methodology



FINDINGS

To optimize the cutting process in the Epyllion Group, a project was initiated and completed using the Six Sigma DMAIC (Define, Measure, Analyze, Improve, Control) methodologies. Such a methodology emphasizes the identification of inefficiencies therein: the structural data-driven

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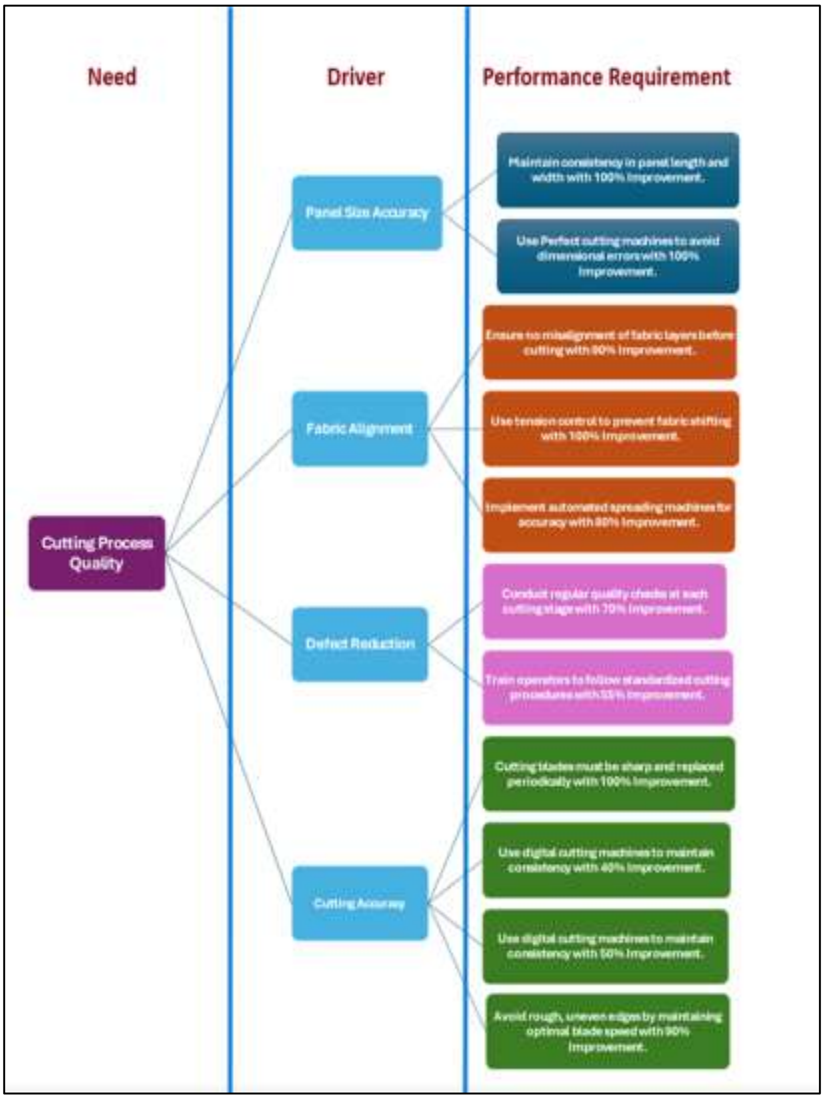
approach with fewer errors and higher standards. To ensure that all the information collected was relevant and credible, data was collected through the company itself, supplemented by leveraging historical production records and finding relevant industrial reports. Besides, three management personnel with one operator appointed, which formed an insightful discussion about the cutting process, helping us to relate to root causes affecting our standards: their constructive input has been important in pointing out our major weaknesses that require specific improvement actions.

Define phase

The define phase establishes a structural approach to improve the cutting process in the Epyllion Group. It detects the efficiency of the production and the main quality that affects the rate of error directly. Critical to Quality (CTQ) analysis plays a basic role at this stage. The reason is that it helps to determine the parameters of the process - the size of the panel, the alignment of the fabric, the reduction of the error, and the accuracy of the cut. These factors are related to direct operational inefficiency and ensuring the continuity of the product.

Figure 2 : Critical To Quality



In Figure 2, the CTQ requirements arise from the common defects identified in the cutting process, such as dimensional mistakes, disorganization of fabric layers, and irregular cutting edges. Applying CTQ allows setting the benchmark of measurable functioning. Automatic tension controls the fabric transfer and reduces the waste of the ingredients by 5%. Regular quality tests and operator training programs have been shown to reduce the defects by humans up to 55%, to improve the process continuity. In addition, the sharpness of the blades and the digital cutting machines shows an impairment of 40-50% in achieving the uniformity that is optimized. By integrating the CTQ metrics

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into the define phase, this study identifies the root cause of inefficiency and confirms a data-driven method to prioritize the improvement.

Measure Phase

By so much cross-hatching and matrix analysis, data was collected and quantified, to help understand what errors are associated with the cutting process in the Epyllion group. Many of these, for example, like the control chart and a binomial process capacity, were used simultaneously to find out where and for what the issues are.

Table 1 mentioned that over a 30-day data analysis, the defect rates ranged between 0.001 and 0.017. In fact, on several of its occasions, such as the 3rd day, the 5th day, and even the 19th day, the highest number of errors occurring on a single day was 13. Days that usually have a bigger load than the rest, operator error, and machine malfunction were among the conditions in which these days exhibited more evidence of problems. For the least number of errors, just one was reported to have occurred on the 12th day. Table 1 presents the measurements.

Table 1: Number of defects from 30 days with a sample size of 750

Sample (Day)	no defects	Conformance percentage	Sample (Day)	no defects	Conformance percentage
1	5	0.007	16	2	0.003
2	4	0.005	17	6	0.008
3	13	0.017	18	3	0.004
4	3	0.004	19	13	0.017
5	13	0.017	20	7	0.009
6	5	0.007	21	6	0.008
7	5	0.007	22	6	0.008
8	7	0.009	23	6	0.008
9	3	0.004	24	3	0.004
10	5	0.007	25	5	0.007
11	8	0.011	26	2	0.003
12	1	0.001	27	8	0.011
13	4	0.005	28	6	0.008
14	4	0.005	29	9	0.012
15	4	0.005	30	3	0.004

Process Capability process

Figure 3 shows the tendency of defects using the P Chart, Binomial plot, and Histogram. The P chart shows a spike in the error in 3, 5, and 19 days, the control limit exceeds 0.017 (1.7%), where the minimum error rate of 0.001 (0.1%) indicates advanced control over the 12th day. The binomial plot confirms the distribution of unstable flaws with unexpected fluctuations (Saad, 2024). The Histogram shows the rate of error between 0.004 (0.4%) and 0.009 (0.9%), but the extreme values, such as 0.017 (1.7%) indicate the inconsistency of the process. These charts highlight the need for redesign, operator training, and workload balance to stabilize the cutting process. his analysis shows that the rate of error on the high-production day increases, which means that heavy work pressure is a major cause of error. Mismatched piles and fabric misalignment show that the management of the material needs to be improved. The number of errors can mean sudden growth that the machines have not been set up properly, or cutting tools are turning. These results will help in the next phase, where need to focus on employee training, a regular machine maintenance schedule, and smoothing the cutting process and reducing errors to reduce the defects.

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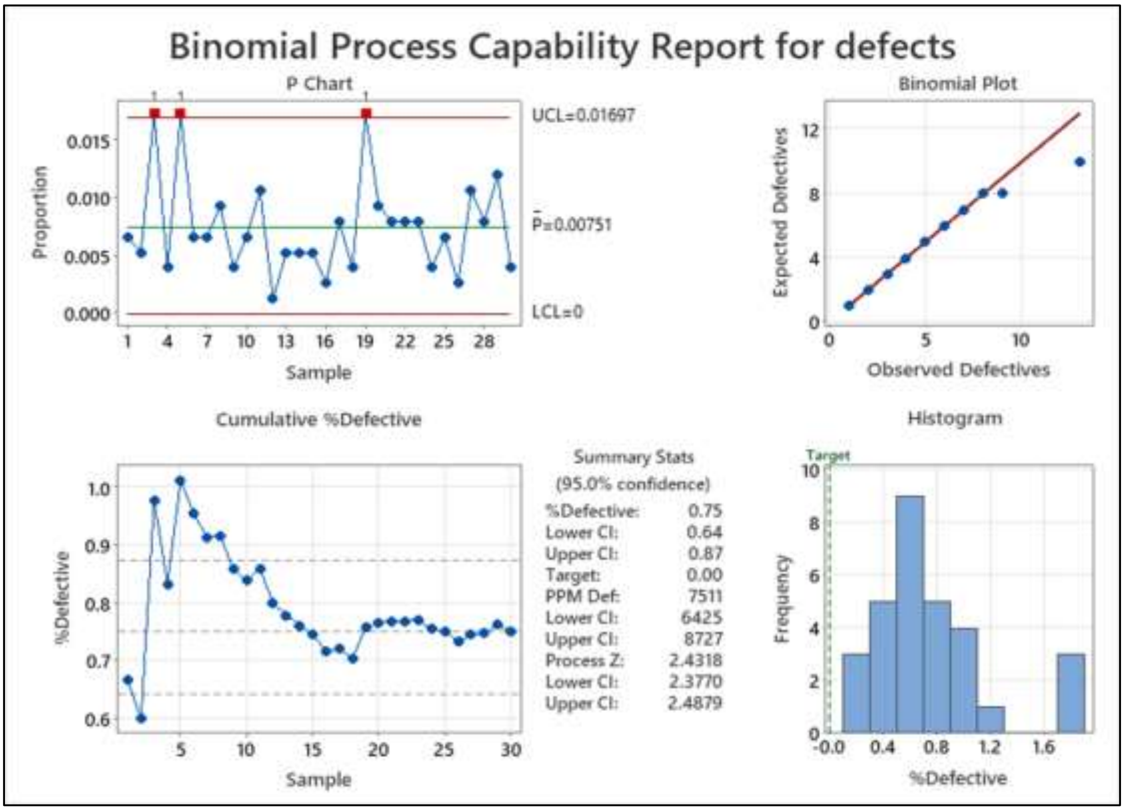
Figure 3 : Process capability report



Analyze phase

The analysis phase focuses on identifying and confirming the root causes of errors using data from the Measuring episode. Data was collected directly within the company and through a review of older production records and industrial reports to ascertain validity and relevance. Also engaged were three management personnel and one operator possessing firsthand information of the cutting process, which aided in exposing the primary issues affecting our standards. Applied Pareto analysis, error frequency distribution, and the primary factory identification methods to discern the cutting process's influences of the largest significance.

Pareto Analysis

The Pareto Chart focuses on the few critical defects that influence the bulk of quality issues based on the 80/20 principle. The three major errors of pile matching, numbers and bundle mislabeling, and tension relaxation, which are reported in Table 2, account for a significant share of all errors with 26% and 52% respectively. The errors sum to over 50% concerning total quality complaints, hence paying attention to these would yield considerable improvement. Less prominent defects such as Boeing (56%), Narrow Goods (61%), and Bias are present but to a certain lesser extent than the prime three.

Table 1: Number of defects

Defects	Num. of abnormalities	Frequency (Percentage)	Defects	Num. of abnormalities	Frequency (Percentage)
Matching piles	120	26%	Leaning	21	80%
Number and bundling	88	45%	Skew	21	85%
Tension loose	32	52%	Rugged cut	20	89%
Bowing	23	56%	Miss cut	17	92%
Narrow goods	23	61%	Miss accurate dimension	13	95%
Bias	23	66%	Fabric way	11	98%
Notch mark	22	71%	Alignment	11	100%
Measurement	21	76%	Leaning	21	80%

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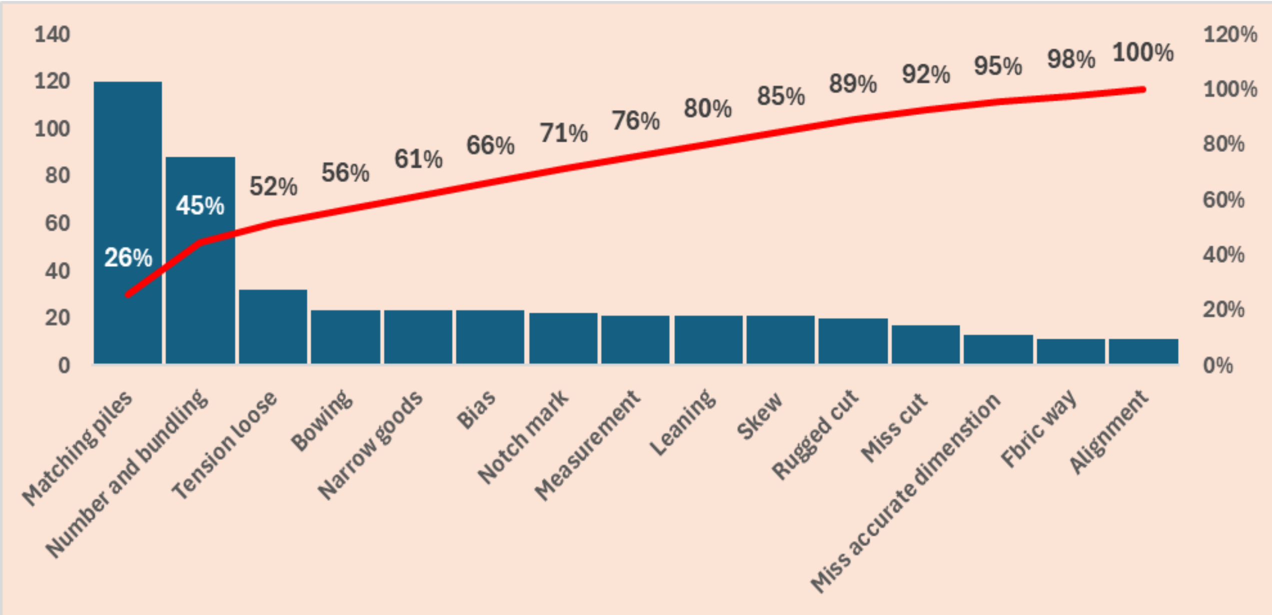
Pareto analysis was used to detect the main cause of the error in the cutting process. This method follows the 80/20 rule, which means that some of the main problems are mostly caused by error. The analysis shows that three main defects - matching piles (26%), numbers and bundling mistakes (45%), and tension irregularities (52%) - are responsible for 71% of the total error. Other errors, such as low (56%) and narrow products (61%), also had an effect, but less frequently. By focusing on the top three subjects, the company can reduce the defects more effectively instead of spreading resources across all problems. The extra value of the parrot analysis is that it helps give priority to solutions, saving time and cost. In the next phase, these results will indicate improvements such as machine calibration, a color-coded tagging system, and defects to reduce the defects and improve skills.

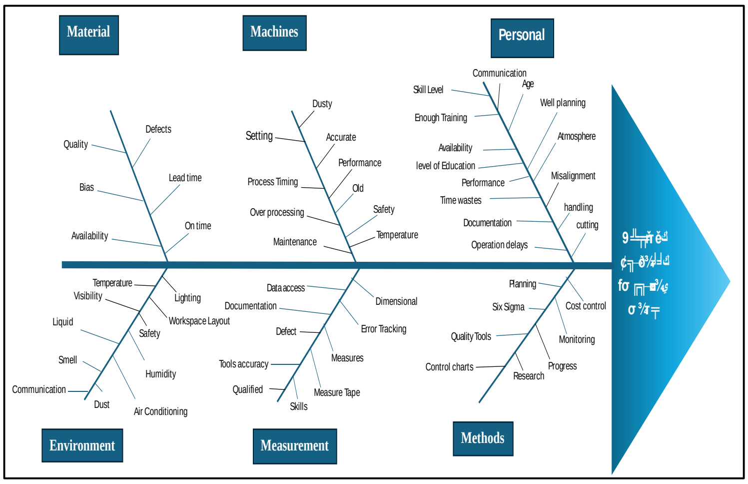
Figure 4: Pareto Analysis



Cause and Effect Diagram

In Figure 5, the fishbone diagram, popularly known as the cause-and-effect diagram, can be a potent tool to track down defects in the garment cutting process. It catalogues the potential causes into head categories: materials, methods, machines, and people, concerning which the diagram helps identify almost every avenue that results in cutting defects-in-ease, wastage of fabric, or misalignment. The relationship so visualized pinpoints the isolated root causes, poor fabric quality, training inadequacies, or machine malfunctioning, resulting from corrective action directed toward improvement in process accuracy, reduced defects, and improved total production efficiency in the garment sector.

Figure 5. Cause-and-effect diagram



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By considering the Cause-and-Effect Diagram, it is identified the main reasons that contribute to the cutting process. This analysis has helped to divide the problem into four main cases: staff, elements, procedures, and measurements, as presented in table 3. The image shows that low operator skills, poor material management, wrong machine settings, and incorrect measurement are the main causes of error. The additional value of this method is that it only helps find the root causes instead of fixing surface problems. By understanding these factors, target solutions such as operator training, strict quality control, and better machine calibration can be applied. In the next phase, these results will indicate the effort to reduce the error and make the cutting process more stable and efficient.

Table 3: Main causes of the problem

Main causes	Priority	Sub causes	Improvement
Personnel	High	Skill level, handling, cutting, performance, and documentation process	Improvement of accuracy measurements
Material	Medium	Bias, Defects, and quality	Stricter quality control implementation methods
Method	Medium	Quality tools, Six Sigma, research, monitoring	Standardization of processes and integration of advanced quality control tools
Measurement	High	Defect, Error tracking, Dimensional skills, measuring tape	Enhancement of calibration of measuring tools and training on measurement techniques

Improve Phase

It testified to the improvement phase whereby action was taken to applying solutions for root causes which had been identified during the analysis. Cutting-process-in-this-study errors, such as matched piles, defective numbering-and-bundling, and tension-loose lead to the causes of such inefficiencies. To alleviate these defects and improve the cutting process in the Epyllion group, a structural improvement strategy was created, and operator training, machine maintenance, and process standardization were integrated. To solve the combined pile defects, a rearrangement has applied the protocol, which confirms the location of the specific fabric before cutting.

Table 4: Kaizen continuous improvement

Issue	Possible Solution	Expected Impact	Ease of Implementation (1 Hard - 10 Easy)	Cost Benefits (1 Low - 10 High)	Rank (Effect)	Responsible Personnel
Cutting Process	Create exact setting	Reduce variation	4	8	32	Supervisor 1
Employee Engagement	Implement customized training	Improve quality	2	9	18	Supervisor 1 & 3
Misalignment Realign	Adjust component positioning	Improve process control	7	7	49	Supervisor 2
Machine Use	Assign Machines and Operators to One Specific	Increase productivity	6	4	24	Supervisor 2 & 3
Measurement	Set up high precision	Improve reliability	10	7	70	Supervisor 3
Tension Loose	To cut down on risk factor	Improve safety	6	6	36	Supervisor 1

Operators were trained in pile handling strategies, which reduced the possibility of confusion. Similarly, to reduce the numbers and bundling defects, a color-coded tagging system, which operates more efficiently to distinguish the fabric departments and reduces labeling and company

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errors. To solve the problems of tension loose, the automatic fabric tension controller is installed to maintain compatible material throughout the cutting process. In addition, a regular calibration and maintenance schedule was implemented so that the cutting tools could be sharp and precise.

A training program is provided with 15 cutting operators and 3 supervisors focusing on the error resistance strategy, proper machine calibration, and quality control checkpoint. The training with weekly assessment to measure education and improve practical skills as shown in table 4.

After 3 months, the process was evaluated,

Fabric Pile Handling

➤ What Did:

Fabric pile handling operations were retrained. This was aided by a clearly defined protocol of alignment for the entire batch of fabric. There was a color-coding program of fabric layers, bundles, and sizes that helped prevent pile-mismatching and bundling errors based on labeling.

Advantages: This has resolved the defects regarding pile-matching (26%) and bundling errors (45%), according to Pareto analysis.

Automated Tension Controller

➤ What Did:

Installed an automatic tension on the cloth, removing all the changes of tension when performing material cut-off operations.

➤ Why It Matters:

This has abolished the flaws owed to tension variability, which composed 52% of tension defects, and assured equal size cut without stretch or skew.

Machine Calibration & Maintenance Schedule

➤ What Did:

There was a preventive maintenance plan in place each month. Operators were taking machine settings and blade conditions to ensure accuracy.

➤ Why It Matters:

This reduced cut size variation and downtime on machines by 66.7%.

Organized Operator Training with Weekly Test

➤ What Did:

Trained 15 operators in measurement techniques, machine operation, and quality check points, and supervised three supervisors. Bi-weekly testing improved knowledge and skill tracking improvement.

➤ Why It Matters:

Average training scores increased by 38.5%, ensuring better process control and fewer human errors.

Table 5: Measured Improvement

Metric	Baseline Value	Post-Implementation Value	Improvement (%)
Defect Rate	26%	10%	61.50%
Employee Training Score	65%	90%	38.50%
Measurement Accuracy	76%	95%	25%
Process Efficiency	70%	88%	25.70%
Machine Downtime	15%	5%	66.70%
Product Rework Rate	18%	8%	55.60%

The measures of this improvement have combined with the perfection of cutting, reducing the waste of the material and improving the overall production skills so that the fabric alignment and the accuracy of the cut ensure the accuracy of the cut.

Control Phase

The control phase ensures the durability of the cutting process and prevents the defects from repeating. Special attention was paid on the 3rd, 5th, and 19th days. It recorded the maximum error rate due to increased workload, operator fatigue, and machine calibration inconsistencies. To solve these problems, a work stress balance strategy was introduced. To avoid operator strain, the production was distributed more equally across the shift. A real-time quality inspection system was also applied, and caretakers enable and enable the cutting defects immediately to detect and correct.

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In those highly defective days, 15 operators and 3 supervisors managed various steps in the cutting process. To strengthen the control, an additional standard control inspector was appointed to focus on fabric alliance, numbering, and machine settings, which allow the initial detection of defects to prevent the final output from being affected.

Statistical Process Control

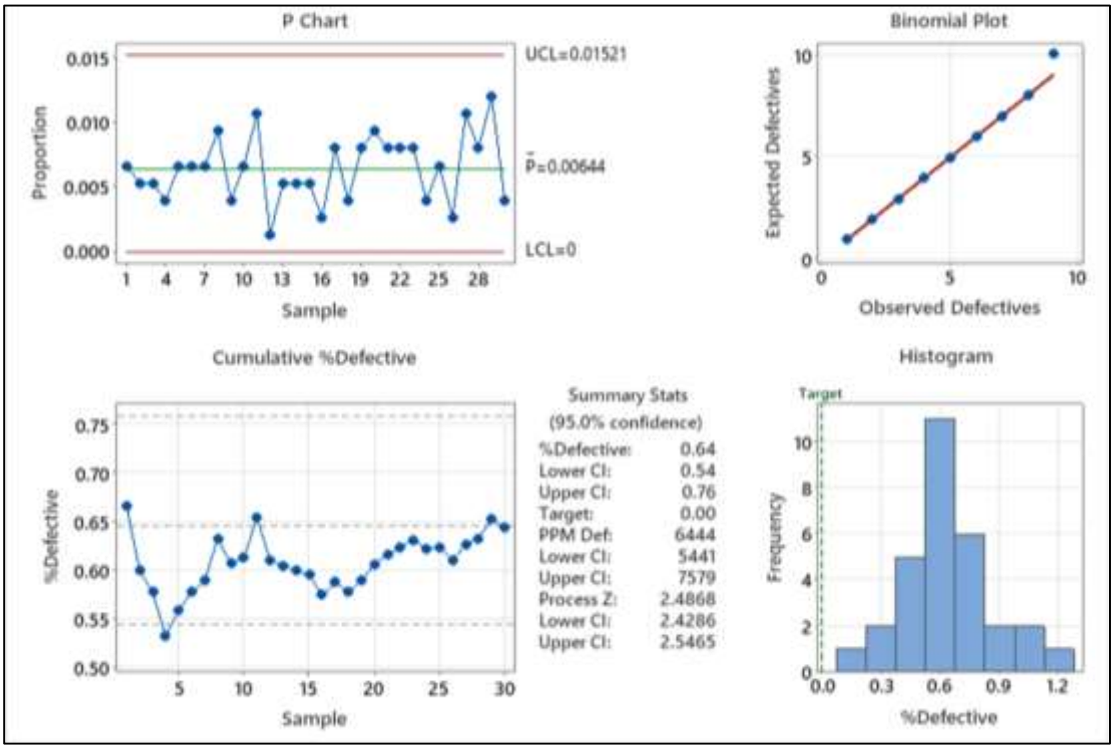
➤ What You Did:

P-charts monitored daily defect rates, with peaks on Days 3, 5, and 19 closely examined.

➤ Why It Is Important:

Through real-time monitoring, SPC allowed you to see the process and identify irregularities quickly so that you could take immediate action.

Figure: 5 Process capability report for defects in control phase



Standard Operating Procedure

➤ What You Did:

SOPs were developed on the major tasks—fabric layout, tagging, and machine calibration.

➤ Why It Matters:

These SOPs served to standardize operator behaviors, reducing variation and thereby allowing the process to be repeated or scaled.

Poka-Yoke

➤ What Did:

Implement sensor triggers and optical inspection to prevent cuts misalignments or fabric tension inconsistencies in the final product.

➤ Why It Matters:

Poka-Yoke allowed for the detection of errors early on, so rework efforts (55.6% reduction) were significantly minimized.

Visual Management & Real-Time Feedback

➤ What Did:

Implementation of the dashboard tracking defect rates and machine status with facility for supervisors to change operational parameters in real-time.

➤ Why It Matters:

Visibility generated a sense of belonging among employees and 88% operational efficiency was guaranteed.

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Regular practices and audits

➤ What did:

Bimonthly refresher courses kept operator knowledge fresh and were followed by purposeful weekly auditing to maintain new systems' accountability.

➤ Why is it important:

These add-ons assisted with ensuring stayed at a post-training high score of 90 and remained consistent with having operators adhere to established new standards.

Several control systems were established to maintain improvement. Standard operating methods were created for fabric handling, numbering, and machine calibration to ensure consistency. A preventive maintenance plan was introduced to inspect the machine, and the mistakes and inconsistencies were dealt with. A weekly quality audit was applied to monitor the rate of error and strengthen the loyalty of new processes. The ongoing training sessions are determined every two months to maintain the efficiency of the operator, strengthen the best practice, and update staff on process changes.

DISCUSSION

The findings of this meta-analysis affirm that Management Information Systems (MIS) significantly The findings from the Six Sigma DMAIC implementation in the garment cutting process highlight the transformative potential of structured quality improvement tools in labor-intensive industries. The systematic approach undertaken revealed how identifying and prioritizing Critical to Quality (CTQ) parameters such as fabric alignment, dimensional accuracy, and cut consistency can provide a strong foundation for tackling recurring defects. By breaking down the production process into measurable components, the project demonstrated that operational inefficiencies are not random occurrences but rather patterned outcomes of controllable variables. This reinforces the notion that a data-driven approach is essential in environments where minor errors can translate into substantial rework costs and reduced customer satisfaction. The results indicate that defect reduction is achievable when root causes are explicitly identified and corrective actions are carefully aligned with operational goals.

One of the most significant outcomes was the reduction of defects through targeted interventions such as operator training, machine calibration, and improved material handling protocols. The study showed that focusing on the top three sources of errors—pile mismatching, number and bundling errors, and fabric tension inconsistencies—was far more effective than dispersing resources across all identified problems. Concentrating on high-impact areas allowed measurable gains to be made with relatively modest investments in training and maintenance. This strategic prioritization is a critical insight, as it demonstrates that quality improvements can be scalable when organizations focus on key leverage points within the production system. In practice, this means that future applications of Six Sigma in garment manufacturing should prioritize interventions that offer maximum returns on quality and efficiency.

The role of human factors in achieving process optimization also became evident through the intervention phases. The structured training programs, coupled with weekly assessments and supervisor oversight, not only improved operator skill levels but also created a culture of accountability and precision. Workers became more engaged in ensuring that machine calibration and fabric alignment were carried out properly, which resulted in a significant reduction in human error. The study illustrates that sustainable process improvement cannot be achieved through technology or process redesign alone; it requires the cultivation of a skilled and motivated workforce. The evidence suggests that building competencies at the operator level has a multiplier effect, as better-trained personnel also contribute to faster problem detection and improved teamwork on the shop floor.

Equally important was the role of technology and systematic monitoring in reinforcing improvements. The introduction of automatic tension controllers, standardized operating procedures, and preventive maintenance schedules ensured that variations were minimized and that corrective measures became embedded into daily operations. The implementation of real-time dashboards and statistical process control techniques further allowed supervisors to monitor error rates continuously, preventing minor deviations from escalating into significant quality issues. These technological and procedural safeguards provide a framework for long-term stability and sustainability of the improvements achieved. The success of these control mechanisms demonstrates

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that Six Sigma is not just a one-time project but an ongoing cycle of improvement where monitoring, learning, and adaptation remain central.

Finally, the broader implications of this study lie in its ability to show how Six Sigma can be customized to the unique challenges of the garment industry. Unlike fully automated industries, garment manufacturing is characterized by variability in raw materials and high dependence on manual labor. The successful application of DMAIC in this context proves that quality management systems can be tailored to industries where human involvement is critical and material inconsistencies are common. The reduction in defect rates, downtime, and rework, coupled with measurable improvements in operator skills and production efficiency, provides evidence that Six Sigma can serve as a strategic enabler of competitiveness in global markets. By embedding a culture of continuous improvement, garment manufacturers can not only meet international quality standards but also position themselves for long-term sustainability and resilience in a highly competitive industry.

RECOMMENDATION

Since the project has had such impressive results, it should be institutionalized as a strategic quality tool for the entire garment production life cycle. The successful DMAIC application at Epyllion Group has confirmed that organized training, preventive maintenance, and real-time monitoring significantly reduce error rates and inefficiencies. Future initiatives should aim at extending the Six Sigma integration across the upstream and downstream activities, such as stitching and packaging, leading to an end-to-end lean quality framework. Frequent cross-department collaboration and review of KPIs would be the principal drivers for keeping the results achieved and stimulating continuous improvement

CONCLUSION

The successful application of the Six Sigma DMAIC methodology in this research considered the optimization of cutting processes in Epyllion Group, one of the largest garments manufacturers in Bangladesh. The tasks were systematically followed under Define, Measure, Analyze, Improve, and Control, identification of major inefficiencies in the cutting processes evident in pile mismatching, number mismatch, and fabric tension problems. By employing tools like Pareto analysis, control charts, and cause-and-effect diagrams, the defects and consequently the root causes of the defects were identified and the necessary improvement actions such as operator training, calibration of machines, and automatic tension controllers were implemented. These improvements were coupled with visual management tools and standardized operating procedures for guaranteed precision and reliability of operations daily.

As an affirmation of the robustness of Six Sigma in what is exclaimable as a labor-intense and quality-conscious environment, defect rates plummeted from 26 percent to 10 percent; machine downtime was curtailed by 66.7 percent, while product rework rates saw a reduction of 55.6 percent. At the same time, operator training scores and measurement accuracy improved significantly. The results not only supported the research hypothesis but also developed a scalable model for quality and process control for the garment industry. Portraits painted the picture of Six Sigma customized and carefully implemented to be a potential activator of operational excellence and defect reduction towards sustainable quality improvements in textile manufacturing systems.

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