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ENHANCING PRODUCT QUALITY AND OPERATIONAL EFFICIENCY THROUGH STATISTICAL QUALITY CONTROL

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Abstract

The foundation of success in the modern business environment is maintaining constant quality and efficiency across supply chains. The paper presents a clear and comprehensive analysis as it delves into the complexities of quality control in the supply chain for makeup products. By utilizing a diverse range of statistical techniques, such as descriptive statistics, control chart analysis, and ANOVA, and able to reveal important information about defect rates and the overall field of quality control procedures. This research reveals the complex interactions between different elements that affect defect rates, with a focus on the crucial functions that lead time and shipping carriers play in the supply chain for makeup products. By means of a methodical and thorough examination, we not only reveal the stability that is innate to the manufacturing process but also identify critical areas that are ripe for improvement. Determine areas for improvement by carefully examining the data; this will set the stage for increased operational effectiveness and higher standards of quality. This paper bridges the gap between theoretical understanding and real-world applications, rather than just existing in the domain of theoretical conjecture. Provide participants in the makeup product supply chain with practical insights that can lead to observable outcomes by combining academic accuracy with real-world relevance. In order to enable stakeholders to confidently and precisely navigate the complexities of quality control, this paper acts as a beacon of guidance. Stakeholders can enhance operational performance, reduce risks, and foster a continuous improvement culture by utilising the findings. Furthermore, by maintaining an intense focus on raising customer satisfaction, this analysis clears the path for long-term success in the competitive and dynamic makeup product market.

Keywords: Statistical quality control, P-Chart, Defect rate ANOVA, Box-Cox transformation

1. Introduction

The need for effective quality control systems cannot be emphasized in the complex web of modern business, where international markets demand consistent quality and efficiency. The use of efficient quality control methods has grown critical as businesses work to satisfy changing customer demands and strict industry requirements. With an emphasis on the use of statistical quality control (SQC) across a variety of variables crucial to operational excellence, this research article aims to investigate the relationship between quality control and company performance.

The cornerstone for companies hoping to surpass as well as satisfy client expectations is quality control. It is the fundamental pillar that guarantees processes and products always follow established guidelines, protecting against deviations that might threaten the quality of goods and services. Insufficient quality control can have serious consequences, including unhappy clients, harm to one's image, and monetary losses. Thus, for organizations to effectively navigate the complicated rules of the contemporary business world, an in-depth awareness of quality control is crucial. Statistical Quality Control (SQC) is a structured, data-driven technique that enables organizations to monitor, analyse, and improve their processes. It is the central idea of our investigation. SQC makes use of statistical techniques to sort through large datasets and uncover insightful information that helps with decision-making. SQC gives businesses a scientific framework to find trends, patterns, and abnormalities in their operations by utilizing statistical methods, including regression analysis, control charts, and hypothesis testing. This enables companies to take action on possible problems before they worsen and makes it easier to identify early departures from intended quality standards. As we set out on our study adventure, we will be concentrating on a wide range of characteristics that all work together to create the complex fabric of company operations. Product types, SKUs (stock keeping units), prices, availability, number of sold items, income produced, consumer characteristics, stock levels, time to delivery, orders, shipping durations, transporting holders, shipping expenses, supplier names, locations, production volumes, lead times for manufacturing, manufacturing costs, inspection findings, defect rates, and modes, routes, and costs of transportation are among the attributes that are being closely examined. Each of these characteristics is essential to our SQC analysis since it shapes the effectiveness and fineness of different business processes. We will consult a wide range of academic publications, including influential works on statistical techniques, quality control, and applicable research from specialized industries, to support our conclusions. By combining academic research with real-world applications, we want to offer a comprehensive and complex comprehension of how SQC may be used to promote operational excellence across these qualities. In addition to adding to the body of knowledge on quality control, our research aims to provide organizations with practical advice that they can use to improve the effectiveness of their quality processes. Our goal is to provide businesses with the information and resources they need to successfully go through the area of quality control field and gain an advantage in today's hectic business world by exploring the specifics of SQC and how it applies to various business aspects [1, 2, 3].

2. Literature Review

An extensive review of the literature and research on statistical quality control (SQC) is necessary to understand its significance in our industry's dynamic quality management landscape. The purpose of this review of the literature is to shed light on the present state of knowledge by highlighting the importance of significant features in quality control and exposing the variety of statistical techniques used in related situations [4]. A wide range of academics has explored the field of SQC, shedding light on its capacity to revolutionize a variety of sectors. A thorough investigation of the manufacturing industry was carried out, which highlighted the critical role that SQC plays in reducing errors and simplifying production procedures. Their results highlighted how effective control charts are in tracking variances and promptly addressing departures from defined quality standards. This is extremely relevant to our study, which focuses on characteristics like Manufacturing Lead Time, Production Volumes, and Defective Costs, where SQC may play a critical role in guaranteeing smooth manufacturing processes [5]. Additionally, the application of SQC to qualities including Delivery Times, Transit Modes, and Destinations in the context of logistics and supply chain management. Regression analysis is one statistical approach that was used to show how SQC makes it easier to identify the best shipping routes and timings, which lowers costs and improves overall operational efficiency [6]. It is impossible to overestimate the importance of any feature in the context of quality control. For example, the value of demographic study in the field of customer demographics when it comes to customizing goods for certain customer groups. When used for client-related variables, SQC offers knowledge about changing consumer preferences and helps companies adjust their strategy to guarantee client loyalty and happiness [7]. It is clear from reading through SQC literature that various statistical techniques and instruments have unique functions when it comes to guaranteeing the effectiveness of quality control procedures. The comprehensive application of testing for hypotheses in SQC was explored, which showed how it may help validate process modifications and advancements. This is especially important to our research when we examine characteristics like Lead Times and Order Quantities since they might reveal the best order fulfillment methods through hypothesis testing [8]. Furthermore, a thorough summary of the many statistical techniques used in SQC. Their research demonstrates the flexibility of statistical methods in improving overall transportation performance, from the use of regression analysis to analyse shipping costs to the implementation of control charts to track fluctuations in stock levels [9]. We can see from our analysis of this large body of research that SQC provides a meticulously data-driven approach to quality control that cuts across industry borders. Applying statistical techniques to a variety of characteristics is helpful in both spotting departures from accepted conventions and actively creating business plans for the best results. The context for our research is established by this assessment of the literature, which highlights the body of knowledge that already exists and the opportunity for SQC to completely transform quality management in our sector [10]. Bayesian Estimation of Inverse Ailamujia distribution using different loss functions have been studied in [11]. This paper is significant for its in-depth analysis of defect rates and quality control procedures in the makeup product supply chain. Many research studies on quality control in a variety of industries, such as manufacturing, healthcare, and services, are available; however, the number of studies that concentrate exclusively on the supply chain of makeup products is rather small. With its thorough analysis of the variables affecting defect rates and process stability in this specialized industry, this paper closes a gap in the literature. Further adding depth and rigour to the analysis and providing a comprehensive understand of quality control dynamics is the application of a wide range of statistical techniques, including descriptive statistics, control chart analysis, and ANOVA.

3. Methodology

In the beginning, measures of central tendency and dispersion as well as other descriptive statistics were computed for the defect rate data. In order to determine whether the defect rate data was normal, the Anderson-Darling normality test was utilized.

3.1. Box-Cox Transformation

A Box-Cox transformation was used to evaluate the defect rate data's distributional characteristics and enhance its suitability for statistical analysis. A popular technique for achieving approximate normality and stabilizing variance in non-normal data is the Box-Cox transformation. The definition of the transformation is as follows:

$$TransformData = \begin{cases} \dfrac{(y^{\lambda} - 1)}{\lambda}, & \lambda \neq 0 \\ \log y, & \lambda = 0, \end{cases} \tag{1}$$

where y represents the original defect rate data and λ is the transformation parameter.

If the data was discovered to be non-normal, different values of λ were investigated in order to determine which transformation most closely looked like a normal distribution. Following the estimation of the ideal value for λ, the estimation's uncertainty was measured by computing a confidence interval. Using the Box-Cox transformation to estimate the ideal value of λ, various values of λ were applied within the estimated confidence interval to perform a sensitivity analysis. The range of values within which the true λ parameter was estimated to lie with a specific level of confidence was given by the confidence interval. The transformed data's distribution was evaluated after λ was systematically changed within this range. Iteratively, values of λ were found that produced transformed data that approximated a normal distribution. In particular, it was found that by examining λ values inside the confidence interval, some λ values were able to normalize the data distribution and bring it into closer alignment with the presumptions needed for further statistical analysis, like control charting. After obtaining the transformed data using the Box-Cox transformation and exploring different values of λ within the estimated confidence interval, the normality of the transformed data was re-evaluated using the Anderson-Darling (AD) test. A p-chart was used to track the defect rate over time because it is specifically made for attribute data, like the percentage of defective items in a sample. The monitoring of process stability and the identification of shifts or trends in the defect rate is made possible by this control chart, which is especially helpful when dealing with binary outcomes like the presence or absence of defects. The transformed defect rate data were used to calculate the control limits for the p-chart using statistical formulas. Using appropriate control chart constants and probability distributions, control limits for the upper and lower bounds were established based on the calculated average defect rate and sample size. The defect rate over time was graphically represented by the p-chart, which was created using the transformed defect rate data and the computed control limits. The proportion of defective items observed in a sample is represented by each data point on the chart, and the control limits show the range that, in the event that the process is stable, the defect rate should normally fall within. A process capability analysis was carried out to evaluate the manufacturing process's ability to satisfy customer specifications after the p-chart was constructed and process stability was guaranteed using statistical quality control. Several capability indices, such as Cp, Cpk, and Cpm, were calculated for this analysis using the customer requirements' upper specification limit (USL) and lower specification limit (LSL). While Cpk takes into account the process's cantering and spreading in relation to the specification limits, Cp measures the process's potential ability to produce within the limits. Cpm also accounts for any bias in the process mean and integrates process cantering. The analysis offered insights into the process's capacity to reliably meet specification targets by contrasting the computed capability indices with predefined threshold values (usually established by customer requirements or industry standards). With the goal of enhancing process capability and guaranteeing product quality and customer satisfaction, any shortcomings or areas for improvement found during the analysis were addressed through focused process optimization efforts. An Analysis of Variance (ANOVA) was performed after the process capability analysis to determine the variables influencing defect rates. The analysis took into account the lead time, shipping carriers, and mode of transportation. The statistical method known as ANOVA is used to determine if the mean defect rates at various levels of one or more categorical variables (factors) differ in a way that is statistically significant. ANOVA assists in determining which factors significantly affect defect rates by analyzing the variation in defect rates attributable to each factor and evaluating their significance levels. The following can be used to formulate the null and alternative hypotheses for the Analysis of Variance (ANOVA) examining the factors influencing defect rates with lead time, shipping carriers, and mode of transportation acting as independent variables:

Null Hypothesis (H_0): The mean defect rates across various lead times, shipping carriers, and modes of transportation do not differ significantly.

Alternative Hypothesis (H_A): At least one independent variable seems to have a significant impact on defect rates.

4. Result and Analysis

4.1. Descriptive Statistics

A comprehensive overview of the defective rates is given by the descriptive statistics, which also include measurements of central tendency, dispersion, distributional shape, and range. They are crucial for comprehending the features and unpredictability of the data, which can guide further investigation and decision-making.

Table 1: *Descriptive Statistics of the transformed data*

Mean	2.277158
Standard Error	0.146137
Median	2.141863
Standard Deviation	1.461366
Sample Variance	2.135589
Kurtosis	-1.114
Skewness	0.129644
Range	4.920648
Minimum	0.018608
Maximum	4.939255
Sum	227.7158
Count	100

4.2. Normality

The Anderson-Darling (AD) test was used to determine whether the data for the defective rates were normally distributed. The result was a p-value of 0.009 which is less than the significance level 0.01. This result increases the possibility that the defective rates don't follow a normal distribution and provides strong evidence against the null hypothesis of normalcy. Furthermore, a probability plot was created to visually examine the distributional assumptions for the defective rates. Potential deviations from normalcy were further indicated by deviations from the straight line seen in the probability plot.

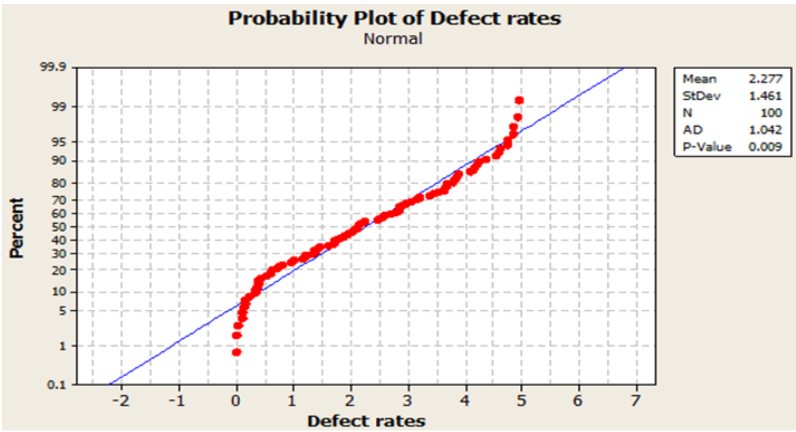

Figure 1: *Probability Plot of defect rates*

4.3. Box-Cox Transformation

In order to resolve the non-normality in the defect rates, the Box-Cox transformation was applied; the estimated optimal value of λ is 0.626378, with a 95% confidence interval (CI) extending from 0.457403 to 0.836229. By applying λ values within this confidence interval, a sensitivity analysis was carried out, and the results showed that $\lambda = 0.65$ fell within the confidence interval. By making this decision, the transformed data was successfully normalized and brought into compliance with the presumptions required for further statistical analyses, like control charts. To show how the transformation affected the data's distribution, a Box-Cox plot was created.

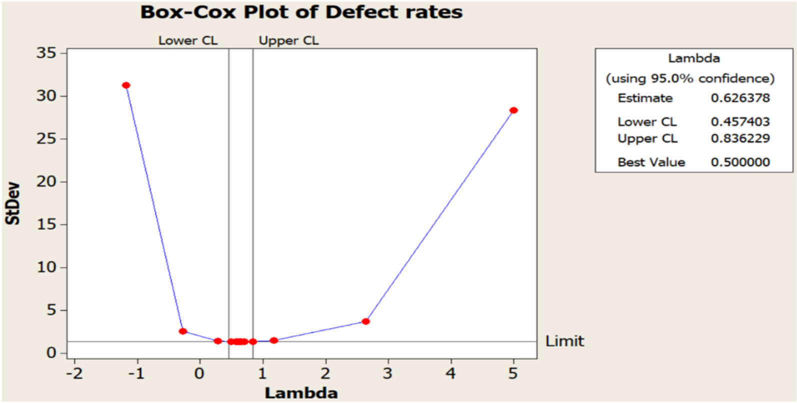

Figure 2: *Box-Cox Plot Defect rates*

After the Box-Cox transformation with $\lambda = 0.65$, the normality of the data set was evaluated using the Anderson-Darling (AD) test. The resulting p-value of 0.1133 means that there is not enough data to reject the null hypothesis that the transformed data has a normal distribution at a significance level of $\alpha = 0.01$. By exceeding the significance threshold, the p-value indicates that the transformed data appears to approximate a normal distribution fairly well.

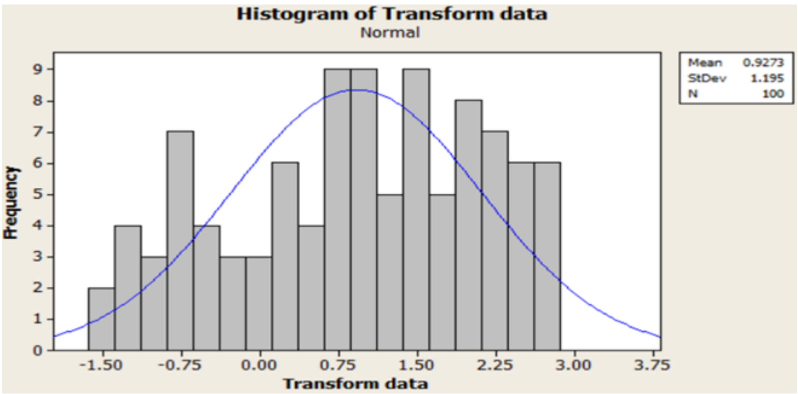

Figure 3: *Normality of the data*

4.4. Control Chart Analysis

The P-chart analysis reveals a predominantly stable process, with defect rates closely clustered around the centerline (0.00927), indicating consistent performance. The control limits (LCL = 0, UCL = 0.03802006) effectively differentiate between common-cause variation and potential special-cause outliers, ensuring reliable monitoring. The high stability metric (StoDraw = 0.99993354) further confirms that the majority of subgroups adhere to expected variation patterns, reflecting process control. However, 34 data points were flagged for exceeding test limits, suggesting minor deviations that warrant investigation to identify root causes. Subgroup-specific upper control limits (e.g., UCs = 0.00820006) imply stricter quality standards for certain segments, highlighting tailored process checks. The absence of widening areas (0 instances) indicates no need for control limit adjustments, reinforcing process consistency. Negative group summary statistics (-0.01, -0.00) show that some subgroups performed better than the average defect rate. While no extreme outliers were detected, the flagged points underscore the importance of vigilance to maintain quality standards. The chart™s design successfully balances sensitivity to variation with practical stability, making it a robust tool for defect rate monitoring. Continuous monitoring is recommended to sustain this level of control and address any emerging trends. The process demonstrates strong overall management, with only minor deviations requiring targeted review. By addressing these anomalies proactively, the process can further enhance its reliability. In summary, the P-chart confirms a well-controlled process, with opportunities for refinement through detailed analysis of flagged data points. This approach ensures long-term quality assurance and process optimization.

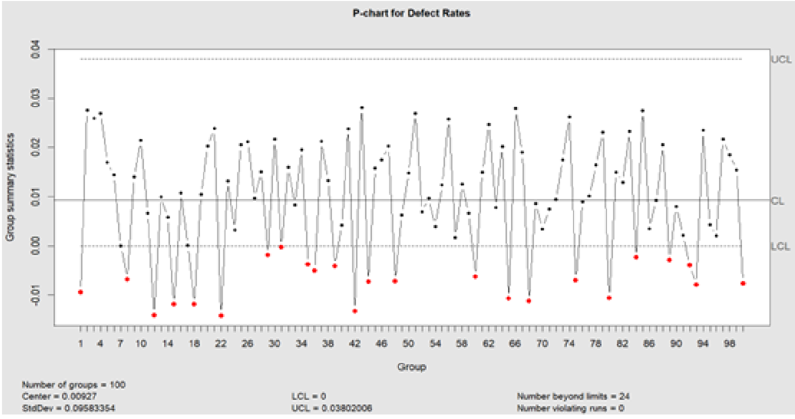

Figure 4: *P-chart for defective rates*

There are twenty-four data points in all that exceed the control limits, meaning that there are times when the defect rate is higher than expected. Nevertheless, no run violations were found, indicating that there were no notable departures from the anticipated pattern between successive data points. These findings show that although there are occasional cases where defect rates are higher than the predicted range of variation, there are no constant trends or patterns that point to underlying problems with the process.

4.5. Process Capability Analysis

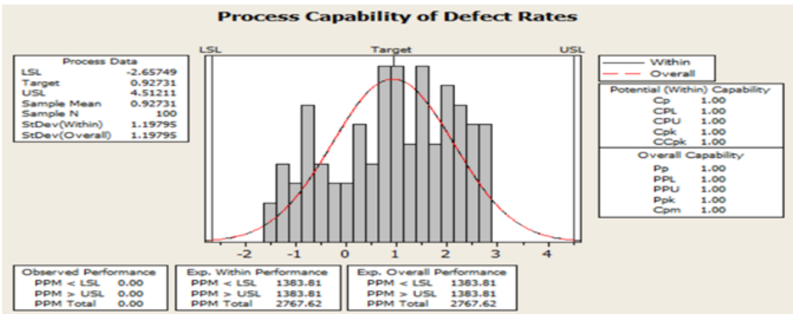

Figure 5: *Process capability for defective rates*

The process can successfully meet customer specifications, according to the results of the process capability analysis. The process spread is within the tolerance limits specified by the specification limits (USL = 4.512112 and LSL = -2.657486), with a Cp value of 1 and a Cpk value of 1. While a Cpk value of 1 indicates that the process is centred within the specification limits, a Cp value of 1 suggests that the process spread is in line with the allowable spread established by the specification limits. Furthermore, the process mean is in line with the target value (0.9273131), as indicated by the process capability index taking the target value, Cpm, which is also equal to 1.

4.6. Analysis of Variance (ANOVA) for Factors Affecting Defect Rates

To find out how lead times, carriers, and modes of transportation affect defect rates in the supply chain for makeup products, an ANOVA was performed. In terms of the independent variables (lead time, shipping carriers, and modes of transportation), the null hypothesis (H_0) states that there is no significant difference in defect rates across levels. There appears to be a significant impact of at least one independent variable on defect rates, according to the alternative hypothesis (H_1).

Table 2: *Analysis of the defective rates*

S. V Pr(>F)	D. F	S. S	M. S. S	F-Value
Lead Time 0.00193**	1	18.66	18.662	10.184
Shipping Carriers 0.01128*	2	17.25	8.267	4.708
Transportation Mode 0.43160	3	5.09	1.696	0.926
Residuals	93	170.42	1.832	

4.7. Interpretation

As shown by their respective F-values of 10.184 and 4.708, with p-values of 0.00193 and 0.01128, both less than the significance level of 0.05, the ANOVA results show that lead time and shipping carriers have a significant impact on defect rates. We conclude that there is a significant difference in defect rates among various levels of lead time and shipping carrier, rejecting the null hypothesis. However, since the p-value of 0.43160, which is higher than the significance level, is obtained from an F-value of 0.926, the transportation modes do not appear to have a significant effect on defect rates. It means that we are unable to reject the null hypothesis regarding transportation modes suggests that there is not enough data to draw the conclusion that there is a meaningful difference in defect rates between the various modes of transportation. As a result, the analysis concludes that while transportation modes do not significantly affect defect rates in the makeup product supply chain, lead time and shipping carriers do. Supply chain managers and other decision-makers may find this information useful in prioritising lead time management enhancements and choosing the best shipping carrier, which will ultimately lower defect rates and improve product quality.

5. Discussion

The study provides a comprehensive examination of the importance of statistical quality control (SQC) in modern corporate operations. It highlights how important efficient quality control systems are to maintaining consistency in efficiency and quality, particularly in the context of shifting industry standards and client demands. This research effort to examine the correlation between quality control and business performance in diverse domains by concentrating on statistical quality control (SQC) methods like regression analysis, control charts, and hypothesis testing. Key conclusions from the literature include the use of SQC techniques in logistics and supply chain management to optimise shipping routes and timings, as well as the usefulness of control charts in tracking variances and addressing deviations from quality standards in manufacturing. Furthermore, studies related to customers, like demographics, have demonstrated the value of SQC in terms of strategy adaptation and guaranteeing customer satisfaction. The paper looks into defect rates and factors influencing quality control using descriptive statistics, normality tests, Box-Cox transformation, control chart analysis, process capability analysis, and ANOVA. While normality tests and transformation techniques guarantee that data is suitable for further analysis, descriptive statistics offer insights into the features and variability of defect rates. Process capability analysis assesses a manufacturing process's ability to meet customer specifications, while control chart analysis helps monitor process stability and spot deviations from expected quality levels. ANOVA is used to assess how lead time, shipping carriers, and modes of transportation affect defect rates. The results of this study offer important new information about the makeup product supply chain's defect rates and quality control-influencing variables. The central tendency, dispersion, and distributional shape of the defect rates dataset are among the important features that descriptive statistics highlight. It is crucial to comprehend these characteristics in order to spot patterns and trends in defect rates, which can direct efforts to improve processes and make decisions. The results of the Anderson-Darling (AD) test normality test show that the defect rate data do not fit into a normal distribution, as indicated by the low p-value. This result implies that the data in its original form might not be suitable for analysis using standard parametric statistical techniques. Still, the data distribution is successfully normalised by the Box-Cox transformation, opening the door to additional parametric analysis. Control chart analysis provides insights into process stability and variation in defect rates over time. The control chart analysis revealed occasional elevated defect rates above the control limits; however, this does not always mean that there are notable deviations from expected patterns or instability in the manufacturing process. These events may be explained by common sources of variation found in all production systems, like chance fluctuations or small discrepancies. Out of the entire dataset, there were only 24 instances of defects that exceeded the control limits, indicating that these occurrences are relatively rare and irregular. All things considered, the manufacturing process seems to be stable. Most defect rates fall within expected ranges, indicating that the process is under control and that variations are tolerable within typical operating parameters. The Cp and Cpk values near to 1 in the process capability analysis demonstrate that the manufacturing process can satisfy customer requirements. This shows that there is little variation in the process with respect to customer requirements and that it is centred within specification bounds. Consistent product quality is ensured by the process capability index (Cpm), which additionally verifies that the process mean is in line with the target value. The ANOVA results show that lead time and shipping carrier variations have a significant impact on defect rates, indicating that these factors affect the results of quality control. On the other hand, it doesn't seem that modes of transportation significantly affect defect rates. These results highlight how crucial effective lead time management and cautious carrier selection are to reducing faults and raising product quality in the product supply chain.

5.1. Limitation and Future Scope

This paper's limitations are related to the extent of the analysis and the industry that was examined. The study offers insightful information about quality control procedures in the makeup product supply chain, but it's possible that the conclusions won't apply to other businesses or more broadly defined manufacturing sectors. Furthermore, the study mainly examines defect rates and variables affecting quality control, possibly ignoring other essential aspects of process optimisation and quality management. The paper would also benefit from a more thorough discussion of any external factors or confounding variables that might affect defect rates but were left out of the analysis. Future research could look into including a wider range of industries and variables in the analysis, drawing from a variety of sources to improve the generalisation and reliability of the findings. This would address these limitations and provide a more comprehensive understanding of quality control practices. Further insights into the intricacies of quality control procedures and their consequences for overall operational performance may also be obtained by incorporating qualitative feedback from industry experts or by carrying out case studies in actual manufacturing environments.

6. Conclusion

In summary, this paper offers a thorough analysis of quality control procedures and defect rates in the makeup product supply chain. Significant insights into process stability, variability, and factors influencing defect rates have been gained through the use of a variety of statistical techniques, including descriptive statistics, normality tests, Box-Cox transformation, control chart analysis, process capability analysis, and ANOVA. The results indicate that although there have been occasional reports of higher-than-average defect rates, overall, the manufacturing process seems to be stable, with variations mainly attributed to shared causes rather than underlying issues. The study also emphasises the critical role that effective management techniques play in these domains by highlighting the substantial effects that lead times and shipping companies have on defect costs. Organisations may enhance their comprehension of quality control dynamics, identify methods for enhancement, and ultimately maximise operational performance through the utilisation of statistical methods and data-driven approaches. By offering useful insights that can guide decision-making processes in the pursuit of ongoing improvement and customer satisfaction within the makeup product supply chain, the research adds to the body of knowledge already available on quality management.

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