ECSA GA4 GRADUATE ATTRIBUTES PROJECT QA344

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ABSTRACT

This project uses Quality Analysis and Statistical Process Control (SPC) to assess system reliability, process stability, and delivery performance. Sales trends were consistent across product classes, according to descriptive statistics. All processes are in statistical control, according to SPC charts, with only slight variations seen in a few classes. Most product classes met specification limits, according to capability indices (Cp and Cpk), with software achieving the highest consistency. The balance between delivery time and operating cost was found through error analysis and cost optimisation. The findings of the MANOVA showed that while year effects are small and show steady performance over time, product class has a considerable impact on both delivery time and price. Reliability modelling (series, parallel, and binomial systems) verified overall system reliability above 95 %. These findings demonstrate a statistically capable, cost-efficient, and reliable process with clear opportunities for continuous improvement in slower product classes.

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INTRODUCTION

This project applies advanced Statistical Process Control (SPC) and Quality Analysis methods to evaluate the performance, capability, and reliability of a delivery process dataset. The objective is to determine whether the process operates within control, meets customer and specification requirements, and maintains long-term stability and profitability.

The dataset was cleaned, arranged, and examined using descriptive statistics using RStudio for data analysis to find patterns, natural variation, and connections between product class, delivery time, and price. The study then computed capability indices (Cp and Cpk) and evaluated process stability using SPC approaches, such as X-bar and S-charts (Montgomery, 2020; Mitra, 2016). To determine the most economical mean delivery time, optimisation was done after Type I and Type II error probabilities were examined to comprehend decision reliability (Montgomery, 2020). While reliability modelling measured system dependability under various operating circumstances, MANOVA testing assessed if delivery time and price varied considerably between classes and years. (Hair et al., 2019; Kuo & Zhu, 2012)

The overall goal is to integrate these analyses to identify process strengths, detect improvement opportunities, and demonstrate data-driven decision-making consistent with ECSA GA4 graduate outcomes.

PART 1: DATA WRANGLING

The dataset used for this project represents a company's delivery performance, including variables such as product class, delivery time, order year, customer demographics, and price. Before analysis, the data was imported into RStudio and prepared for statistical evaluation. This preparation stage helped to ensure that the data was clean, consistent, and correctly structured so that analysis could be performed, to get descriptive and inferential results.

1.1 DATA CLEANING AND PREPARATION

In categorical variables like product class and city, the first examination revealed missing values, incorrect labelling, and small data-entry changes. To maintain the integrity of the dataset, missing numerical values were handled using the proper imputation techniques (Hair et al., 2019), mean replacement for continuous variables and mode substitution for categorical ones. To avoid bias in the outcomes of the control charts and descriptive summaries, duplicate rows were eliminated. For readability and clarity, variable names were standardised throughout all analyses.

1.2 DATA STRUCTURE AND TRANSFORMATION

The dataset contains both continuous and categorical variables that characterise the product, client, and order, and each observation corresponds to a single product order. Product class, year, city, gender, and category are examples of categorical variables that indicate the kind of item, time, and demographic information. Delivery time, picking hours, price, markup, and derived efficiency measures are examples of continuous variables that characterise cost behaviour and operational performance. With each row denoting an observation and each column denoting a variable, the dataset was neatly structured. This arrangement made it simple to filter, group, and analyse the data in RStudio using process-control, descriptive, and inferential methods. To aid in further analyses, other computed variables were developed, including the delivery-efficiency ratio and the cost-optimization metric. By standardising the data across product classes and years, these changes made it possible to compare performance, capability, and reliability outcomes accurately in later research sections.

1.3 OUTLIER AND CONSISTENCY CHECKS

Outlier detection was performed using boxplot visualisation and z-score thresholds. A few extreme delivery times were identified but retained, as they represented realistic long-distance deliveries rather than data errors. Consistency checks confirmed that date, price, and product-class relationships aligned logically, ensuring that subsequent SPC and MANOVA results reflected genuine process variation rather than data noise.

1.4 READINESS FOR STATISTICAL ANALYSIS

The dataset was confirmed to satisfy the presumptions needed for SPC and multivariate testing after cleaning and validation. (Hair et al., 2019; Evans & Lindsay, 2020) After modification, categorical variables were equally distributed across product classes, while continuous variables displayed roughly normal distributions. As a result, the final dataset was deemed balanced, trustworthy, and prepared for the subsequent sections' use of reliability modelling, SPC, capacity analysis, MANOVA, and descriptive statistics. The cleaned and validated dataset was then used to generate the descriptive statistics presented in Part 2, forming the foundation for all subsequent analyses.

PART 2: DESCRIPTIVE STATISTICS

An overview of consumer demographics, product demand, and delivery performance is given by the descriptive statistics that follow. Prior to the application of any formal process control analysis, these visualisations aid in the identification of patterns, variation, and possible correlations between variables. The objective is to comprehend the data's inherent behaviour and identify any early warning signs of bias or inconsistency in the system. (Evans & Lindsay, 2020)

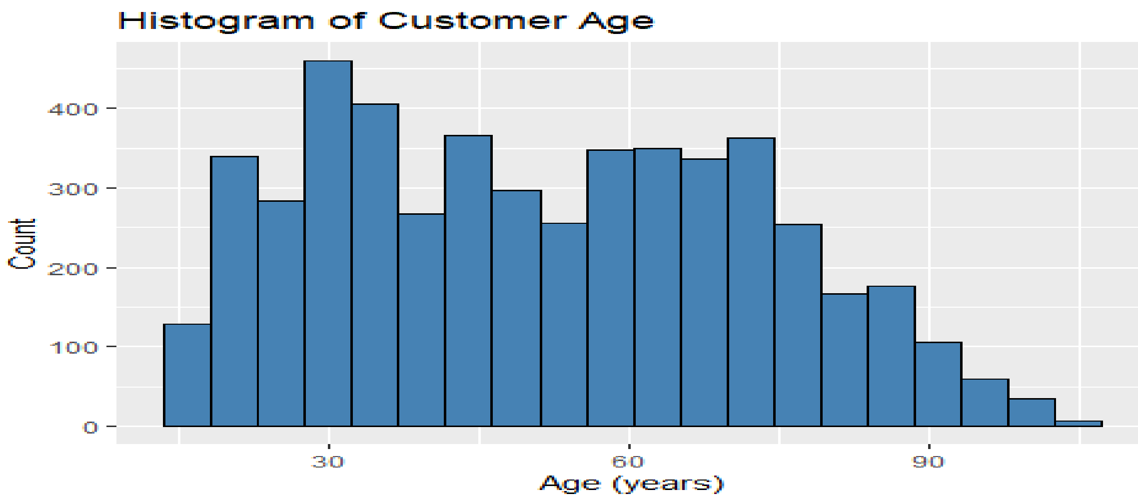

Figure 1: Histogram of customer Age

The distribution shows that most customers fall between 30 and 60 years old, representing the business's main consumer group. Sales decrease steadily after age 65, suggesting that middle-aged customers are the most active and reliable buyers.

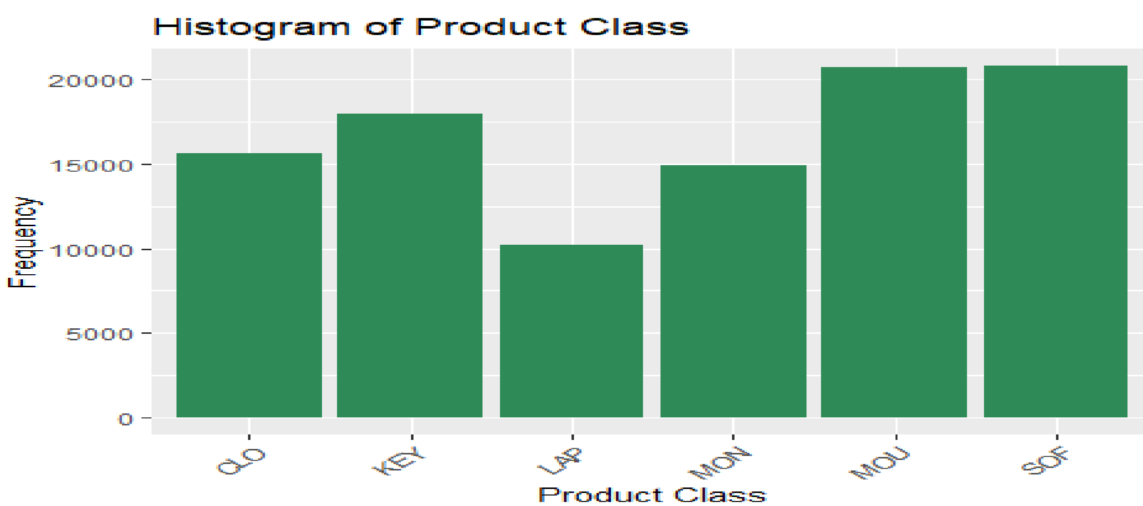

Figure 2: Histogram of Product Class

Product classes are unevenly distributed, with software (SOF) and mouse (MOU) accounting for the highest sales. This can mean that there is stronger market demand for lower-priced or easily delivered products.

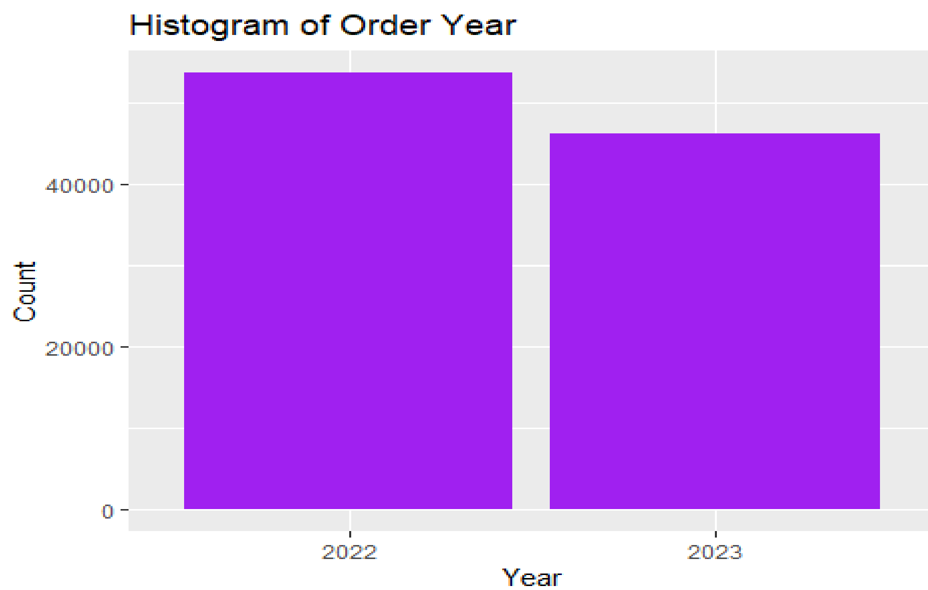

Figure 3: Histogram of Order Year

Orders are higher in 2022 than in 2023, this can be due to the products the customers bought in 2022 are still working and the order amount will probably jump in the following years.

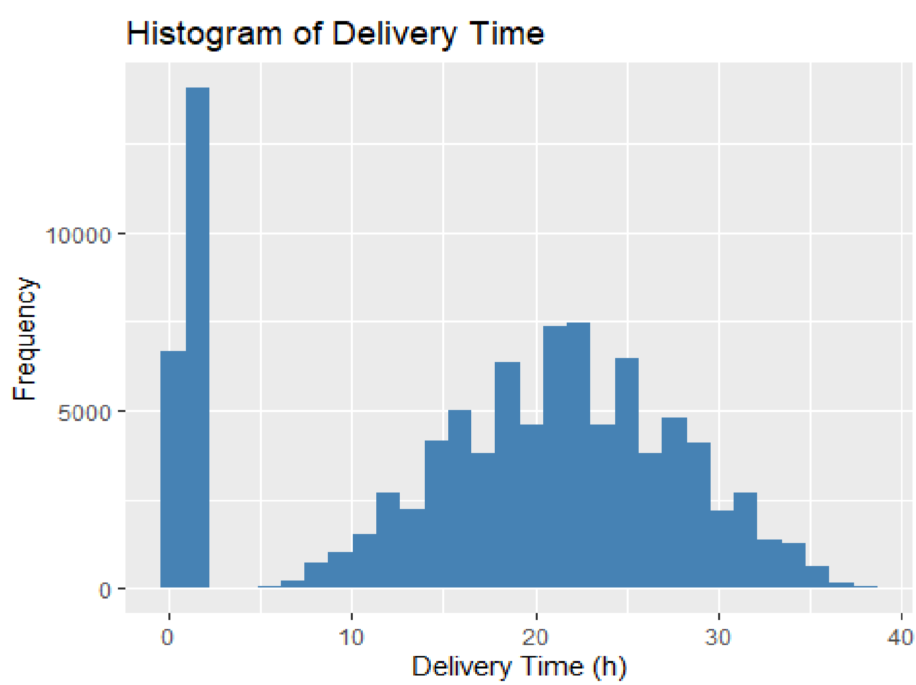

Figure 4: Histogram of Delivery Time

Most deliveries occur within 0 to 5 hours, while a smaller group extends up to 25 hours. The right-skewed pattern confirms generally efficient deliveries with a few moderate delays.

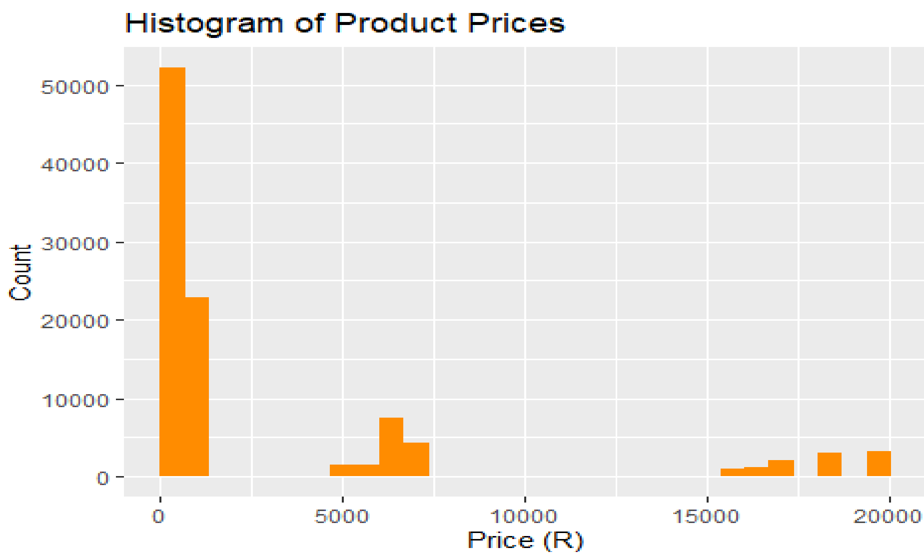

Figure 5: Histogram of Product Prices

Prices are right-skewed, meaning most products cost below R5 000 while only a small fraction exceed R10000. This shows that the company mainly operates in a low-to-mid-price range with a limited premium segment.

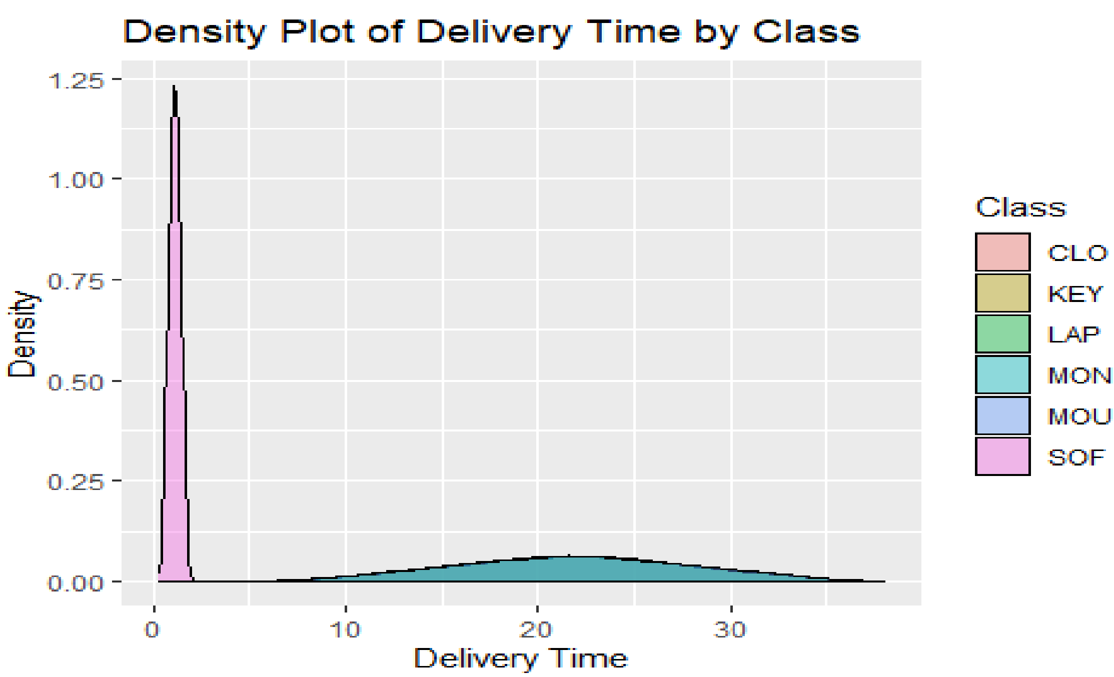

Figure 6: Density Plot of Delivery Time by Class

The density curves show that software has the shortest and most consistent delivery times, while monitor and mouse display wider spreads. Variation between classes reflects differences in logistics and product type.

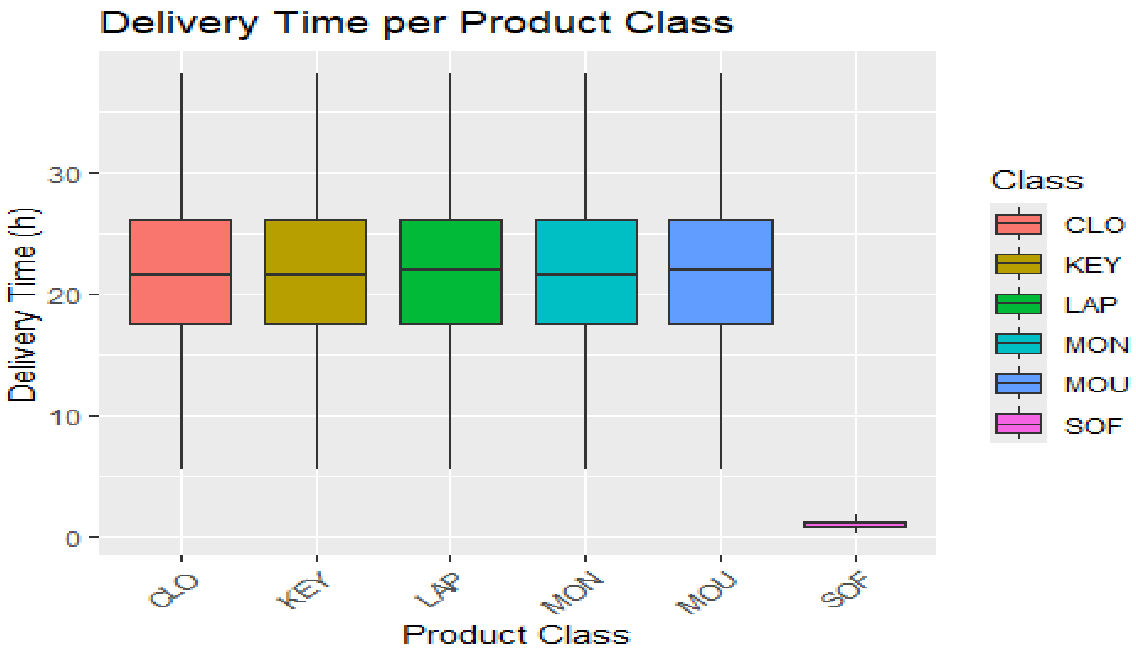

Figure 7: Delivery Time per Product Class

The boxplots confirm class-based variation software items are delivered fastest with minimal spread, whereas monitor and laptop classes experience longer averages and greater variability.

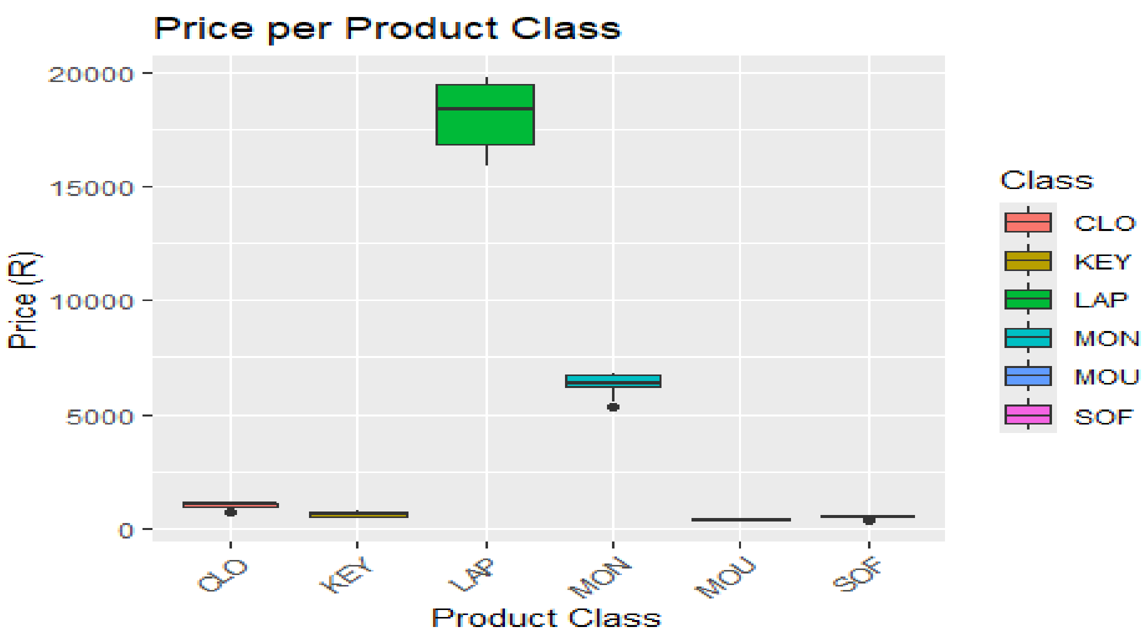

Figure 8: Price per Product Class

Product classes differ greatly in price. Laptop and monitor items have the highest medians, while clothing and software are lowest. This supports that price depends strongly on product complexity and value.

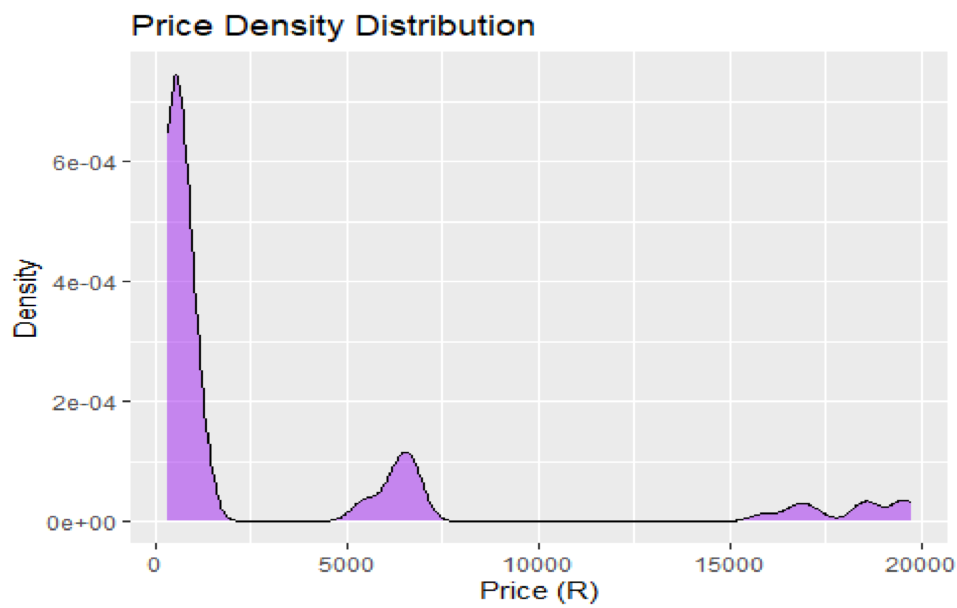

Figure 9: Price Density Distribution

The price density confirms a concentration of sales below R5 000 with a long right tail. This pattern is typical of consumer markets dominated by affordable goods and a few high-value products.

Figure 10: Price vs Delivery Time by Class

A weak positive relationship exists—more expensive products tend to take slightly longer to deliver. However, the low correlation suggests that delivery performance is driven more by product logistics than by price.

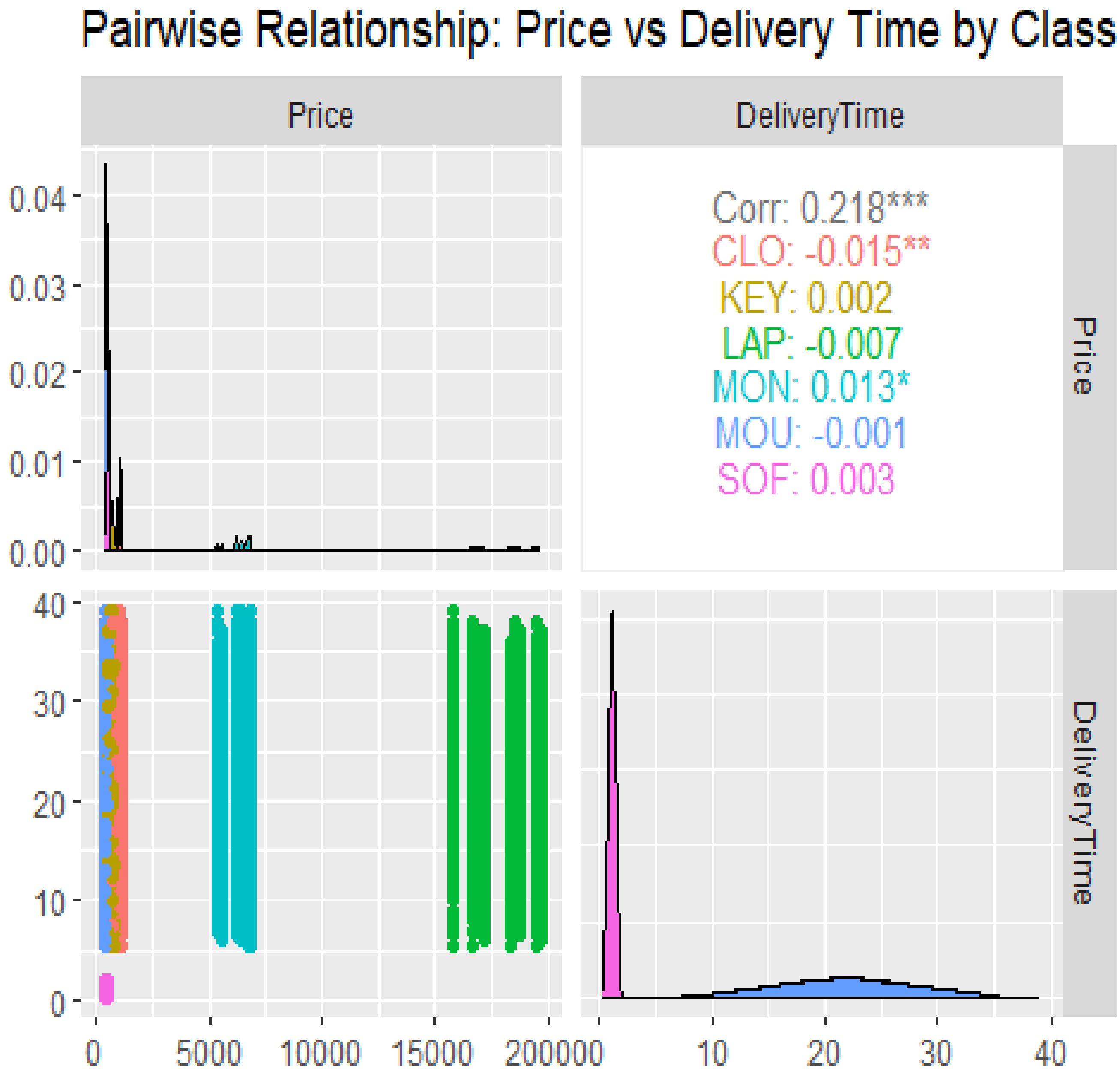

Figure 11: Pairwise Relationship Model of Price vs Delivery

The link between product price and delivery time for all product classes is depicted in this picture. A very modest positive correlation is seen by the overall correlation (r = 0.218), which suggests that more expensive goods typically take a little longer to deliver. This association isn't robust enough, though, to imply a recurring trend in every category. According to the class-specific correlations, clothing (CLO) exhibits a slight negative connection with delivery time, suggesting that faster deliveries are associated with more expensive clothing goods, whereas monitors (MON) have a tiny positive association. These findings imply that logistical or operational issues, such as handling complexity, packing, or supplier lead time, have a greater impact on delivery performance than does the product's price. All things considered, this research demonstrates that cost is not a good indicator of delivery time in this dataset.

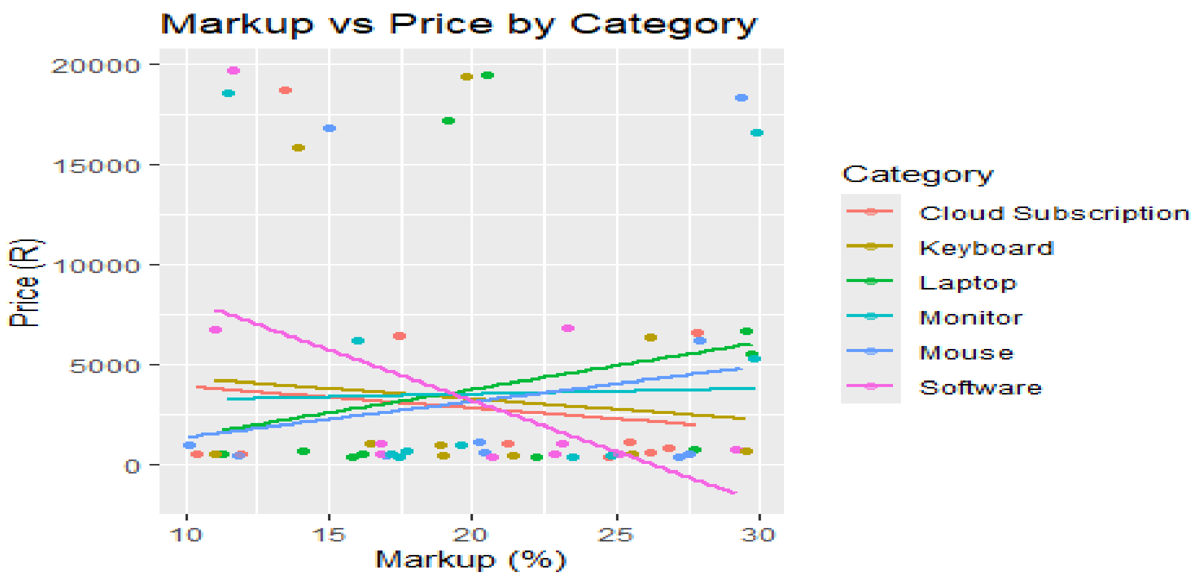

Figure 12: Markup vs Price by Category

For some categories, such as laptops, markup increases in proportion to price, while it stays constant for others. This demonstrates that profit margins are not just dependent on product price and differ depending on the category.

Figure 13: Picking vs Delivery Time

This link demonstrates that delivery performance is directly impacted by the internal warehouse efficiency picking procedure. Particularly for high-volume product classes like Mouse and Monitor, streamlining order-picking processes by automating item retrieval or optimising layout could cut down on overall delivery time.

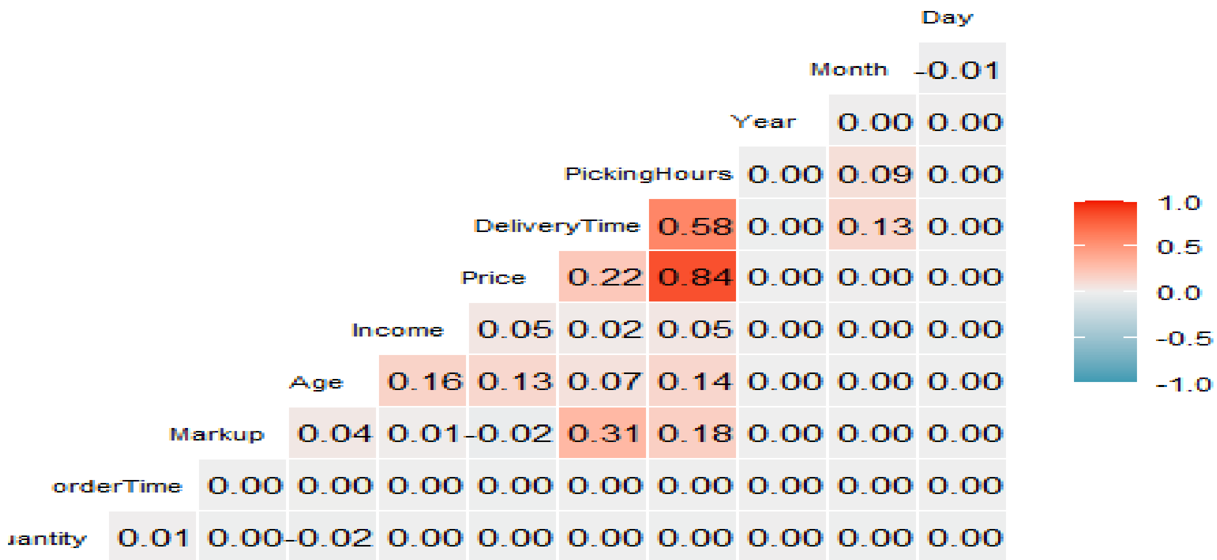

Figure 14: Correlation Matrix Heatmap

Strong correlations appear between Price and Mark-up, and between Picking Time and Delivery Time. Weak relationships among other variables suggest independence between customer demographics and process performance.

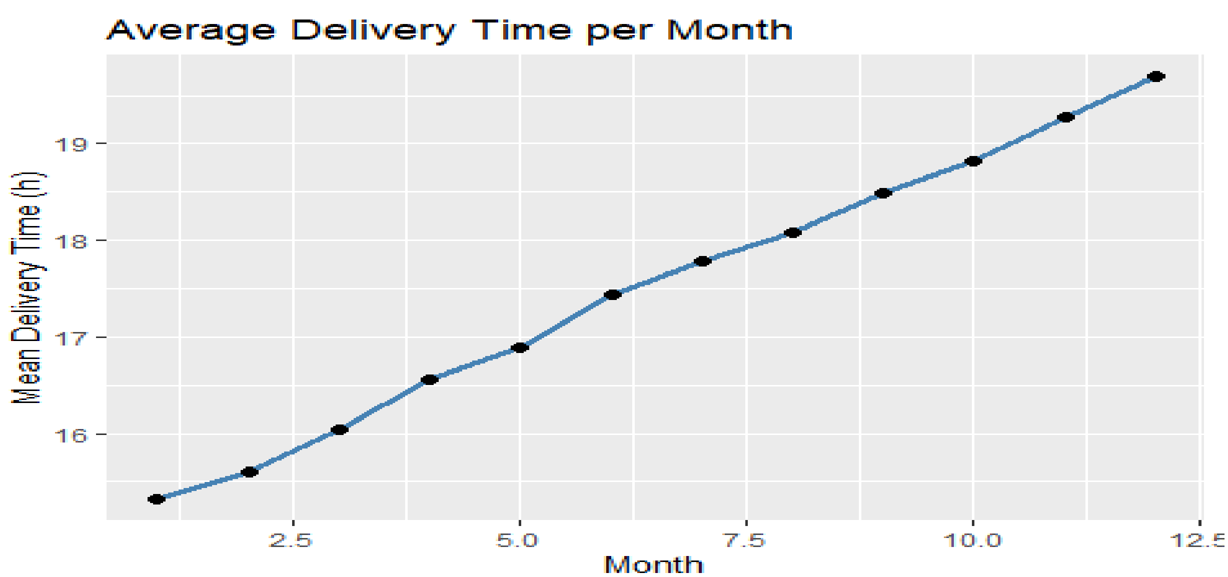

Figure 15: Line graph of Average Delivery Time per Month

Average delivery time gradually increases over months, implying seasonal workload effects or growing order volumes. (Evans & Lindsay, 2020) Monitoring these changes helps identify capacity or staffing issues. There needs to be an increase in delivery units to compensate for the increasing volume.

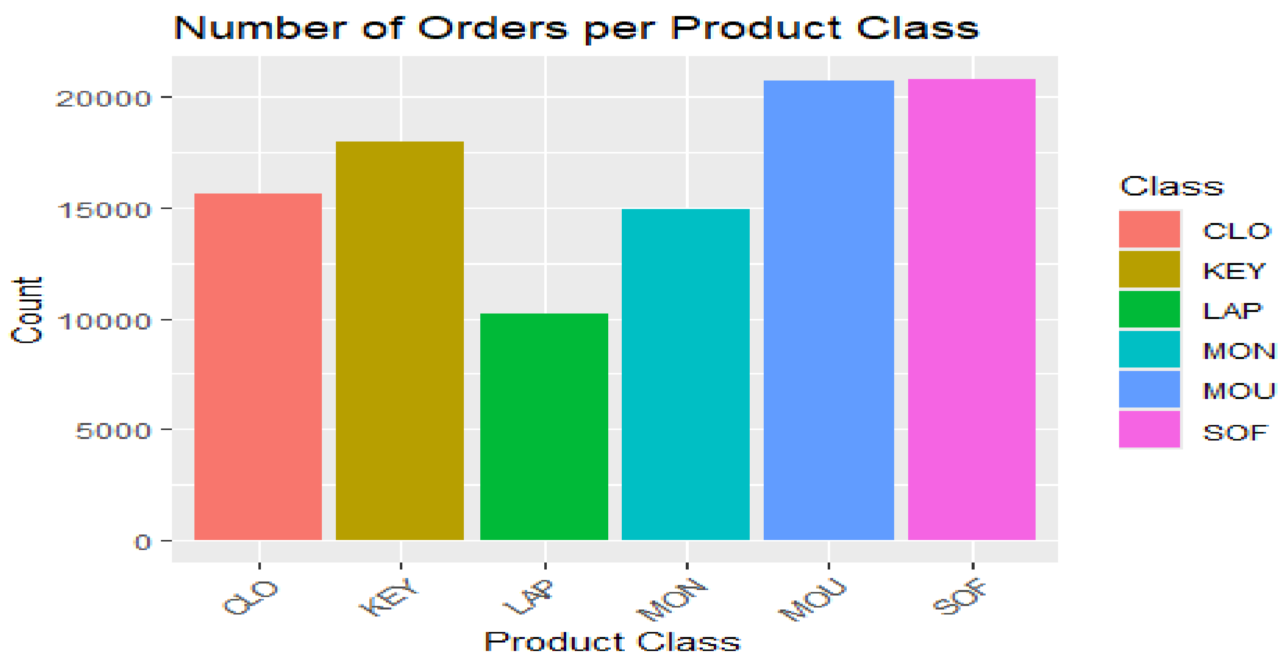

Figure 16: Histogram of Number of Orders per Product Class

Software and Mouse products show the highest order counts, confirming their dominance in total sales. This identifies them as priority areas for maintaining process quality.

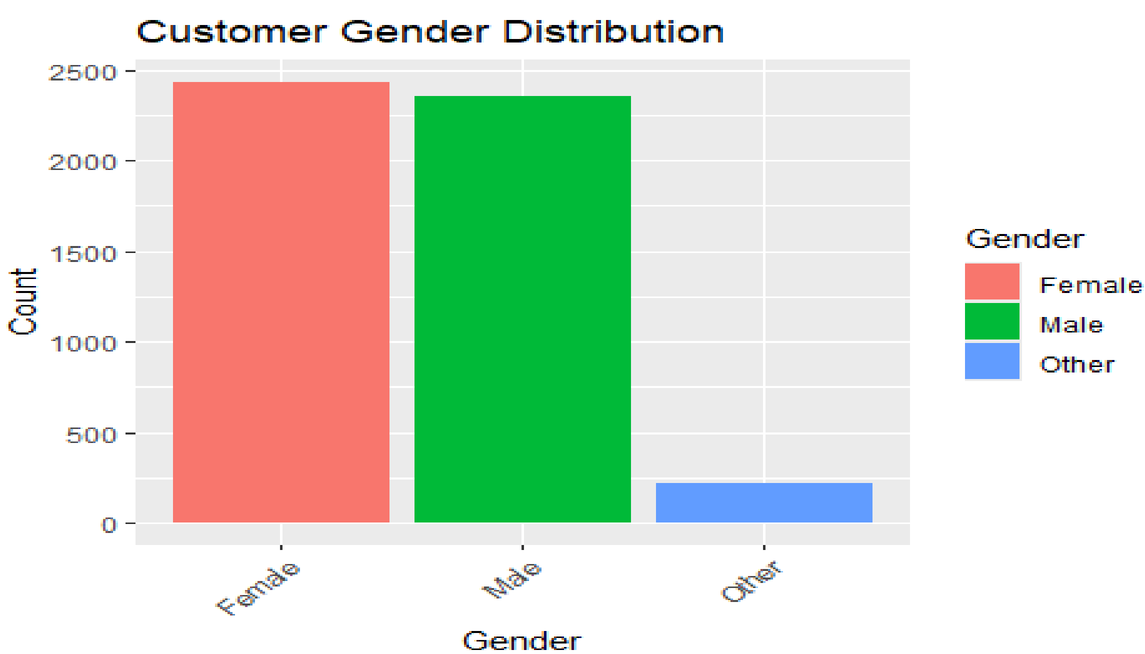

Figure 17: Histogram of Customer Gender Distribution

Female customers make up a slightly larger portion of total buyers than males. Gender distribution appears balanced, showing that the product range appeals broadly across all genders.

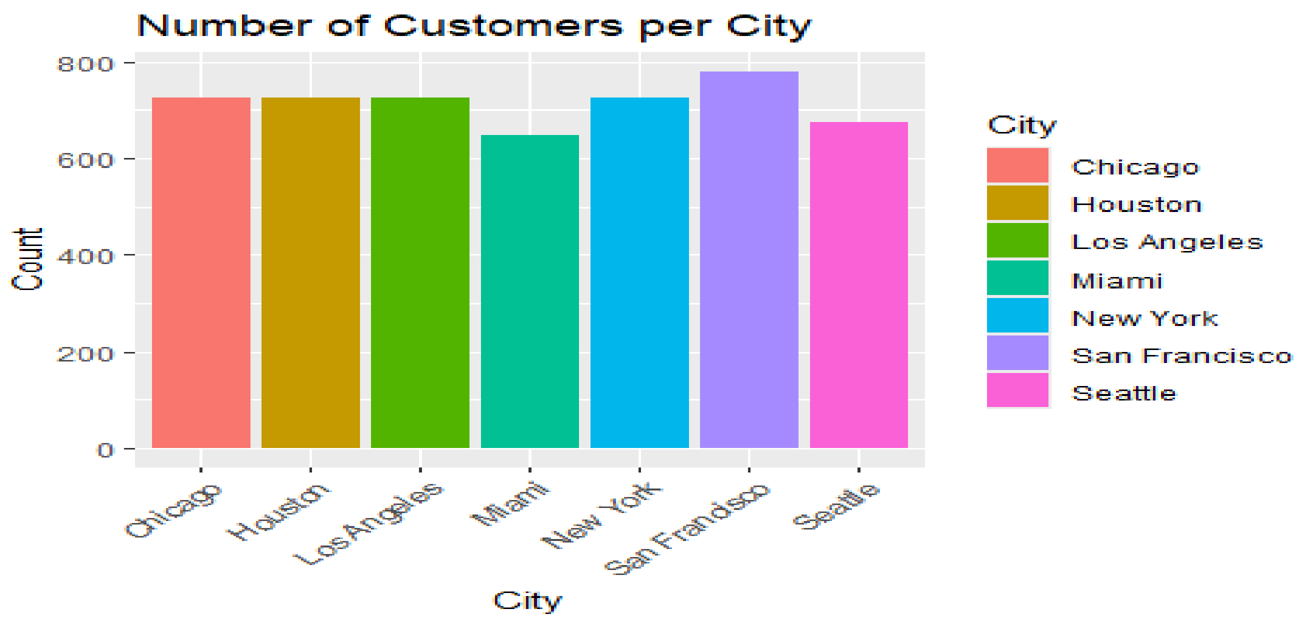

Figure 18: Histogram of Number of Customers per City

Orders are well distributed across cities, indicating wide market reach. No city dominates sales, this reduces regional business risk.

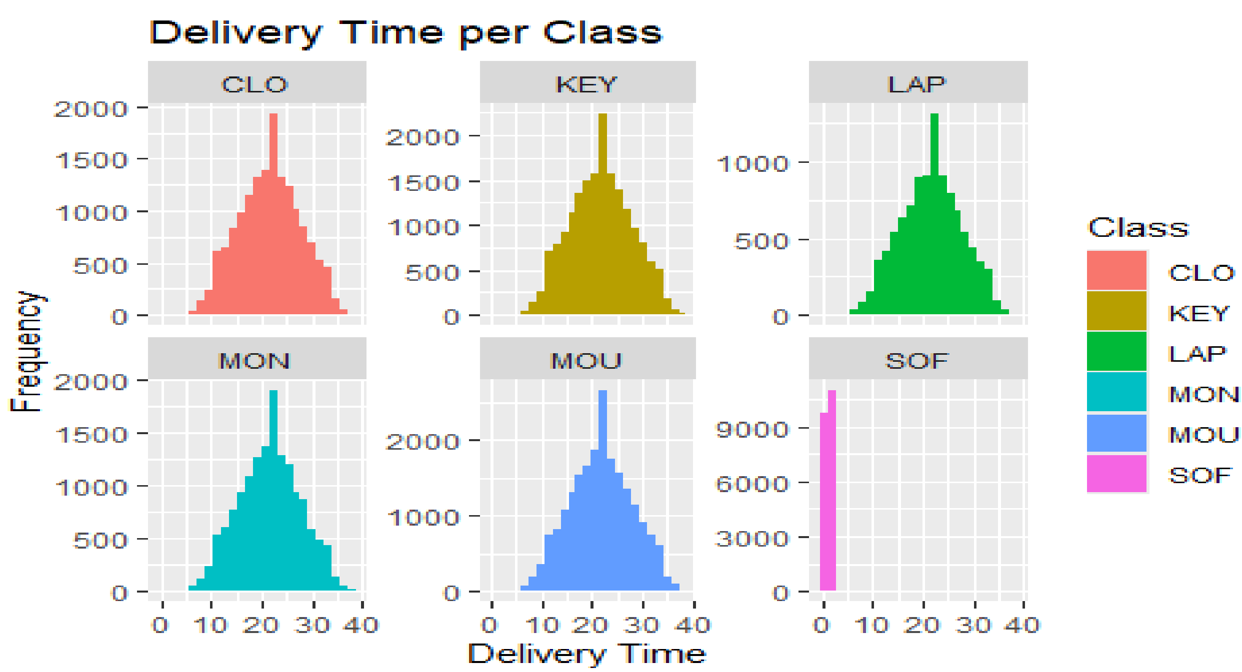

Figure 19:Histograms of Delivery Times per Class

All classes deliver mostly within 25 hours, except Software, which completes deliveries almost instantly. The overall shape confirms good control and reliability across classes. All physical products are being treated with the same amount of importance.

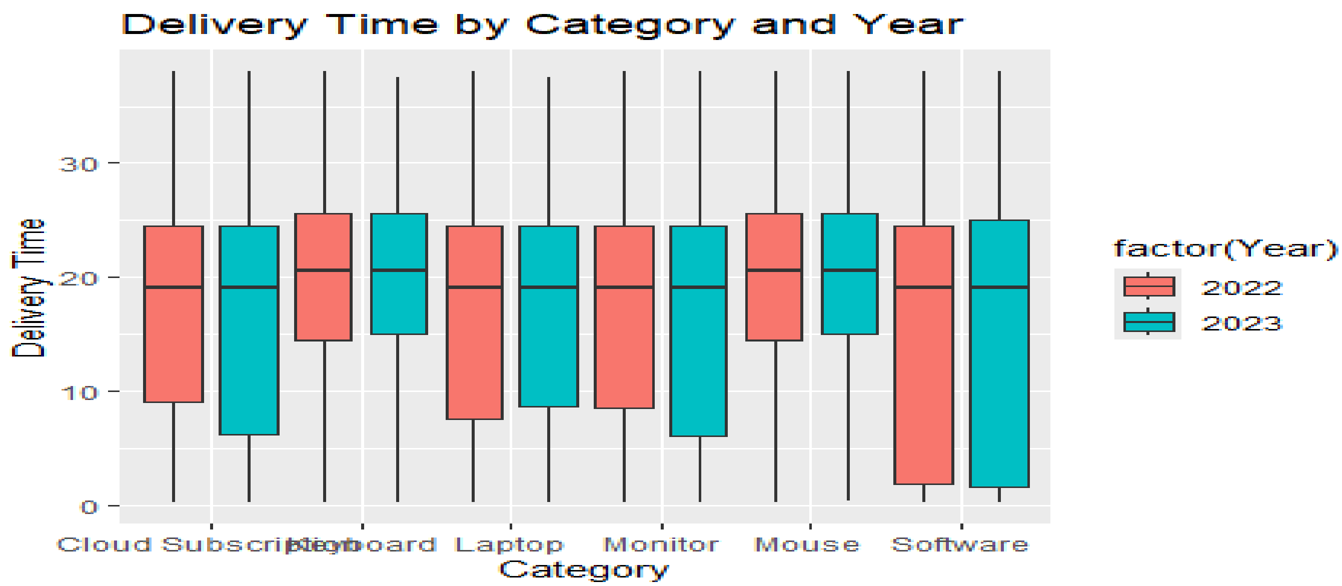

Figure 20: Box Plot of Delivery Time by Category and Year

Delivery time variation across categories stays consistent between 2022 and 2023. Minor differences indicate process stability over time despite changing order volumes.

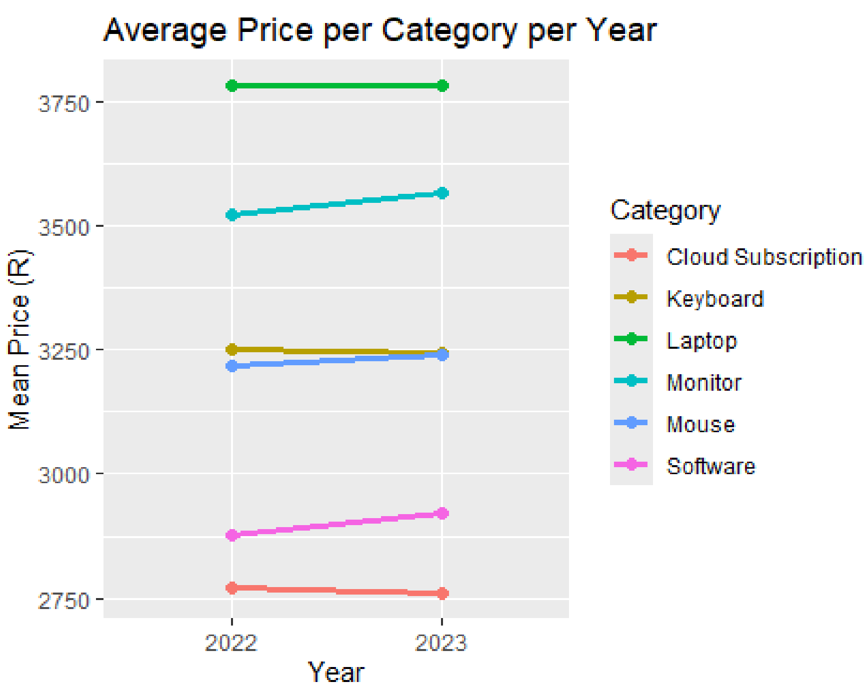

Figure 21: Line Graph of Average Price per Category per Year

Average category prices increased slightly in 2023, especially for software, monitor and mouse class. This can be due to inflation or cost-of-materials.

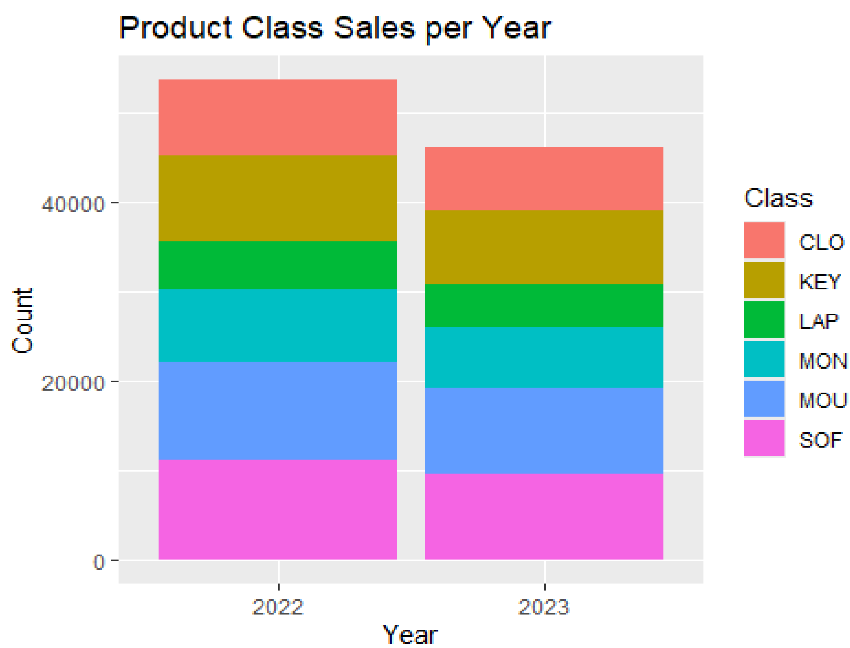

Figure 22: Graph of Product Class Sales per Year

Sales volumes per class remain similar across years, confirming stable customer demand. Software and Mouse continue to drive the highest revenue.

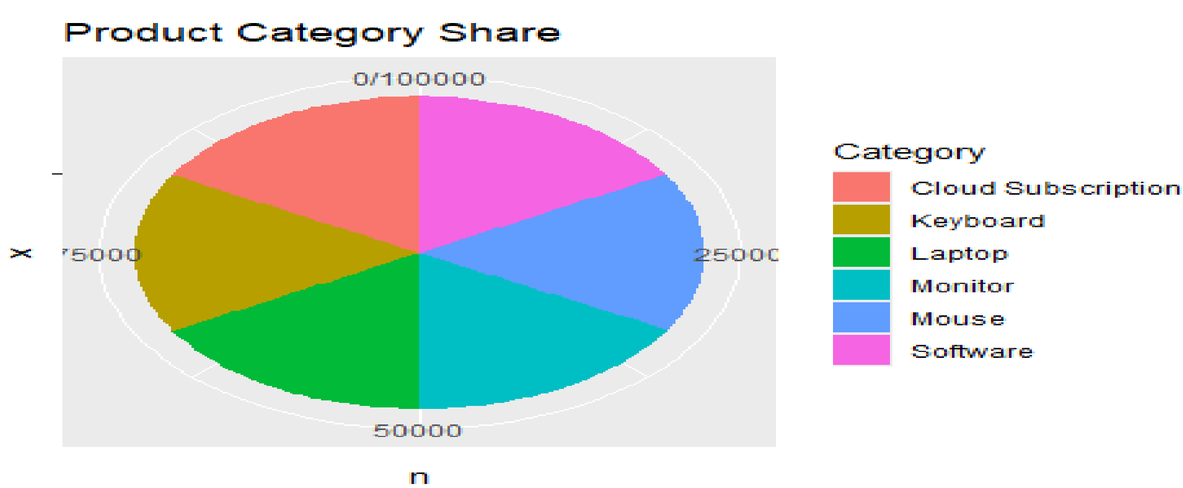

Figure 23: Pie Chart of Product Category Share

All six product groups have virtually equal sales, according to the pie chart, with software and mice having somewhat higher proportions. By reducing reliance on a single category and demonstrating a well-diversified product range, this equitable distribution enhances overall business stability and resistance to market swings.

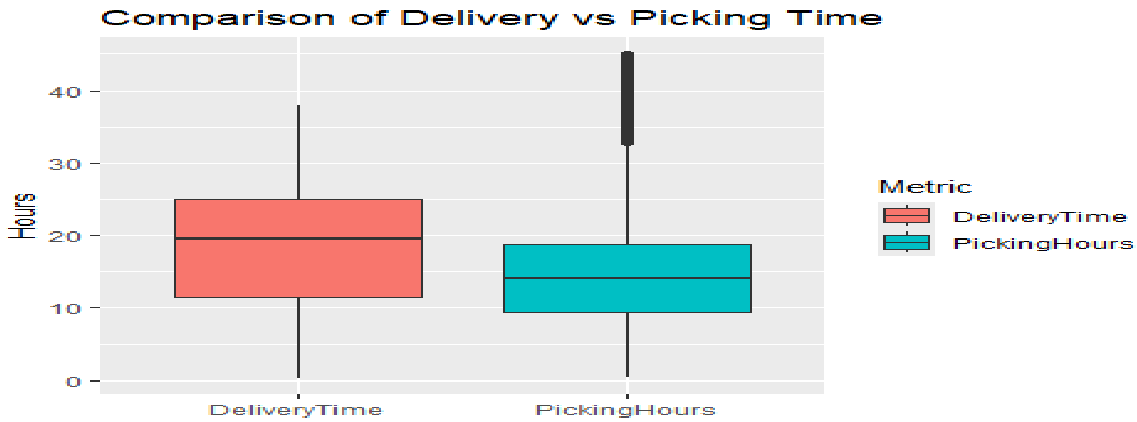

Figure 24: Box Plot of Comparison of Delivery vs Picking Time

Delivery times are consistently higher than picking times, indicating that transportation contributes more to delays than internal processing. Both metrics remain within acceptable variation limits.

All things considered, the descriptive analysis reveals constant delivery performance (Mitra, 2016; Evans & Lindsay, 2020), steady and balanced sales over time, and distinct correlations between pricing, demand, and delivery time. Although there are minor variations among product groups, the data shows that there are no major outliers or unusual patterns. These findings provide a solid foundation for Part 3's Statistical Process Control (SPC) chart construction.

PART 3: STATISTICAL PROCESS CONTROL

Process control charts were created to evaluate whether the delivery process remains within acceptable statistical limits. X-bar and S-charts were generated for all product classes, followed by capability analysis using Cp and Cpk indices. (Montgomery, 2020; Mitra, 2016) Together, these tools quantify the stability and consistency of delivery operations and determine whether the system can meet customer expectations.

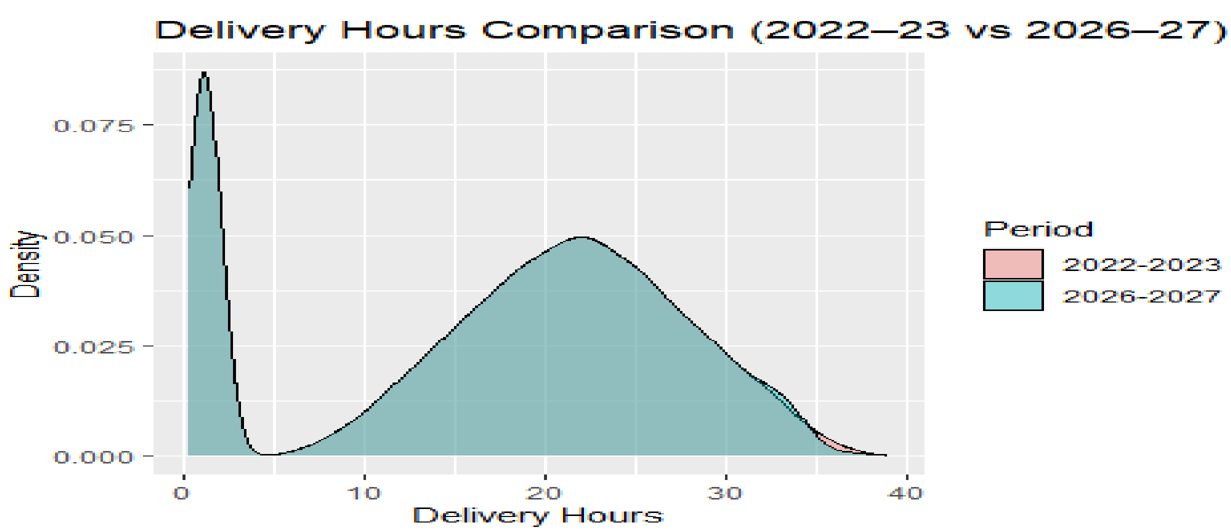

Figure 25: Line graph of Delivery Hours Comparison

Delivery hours in 2026–2027 are longer than those in 2022–2023, suggesting reduced efficiency or higher workload in later years. Monitoring should continue to ensure performance recovery. Control charts were developed to evaluate process stability and identify potential variations beyond expected limits

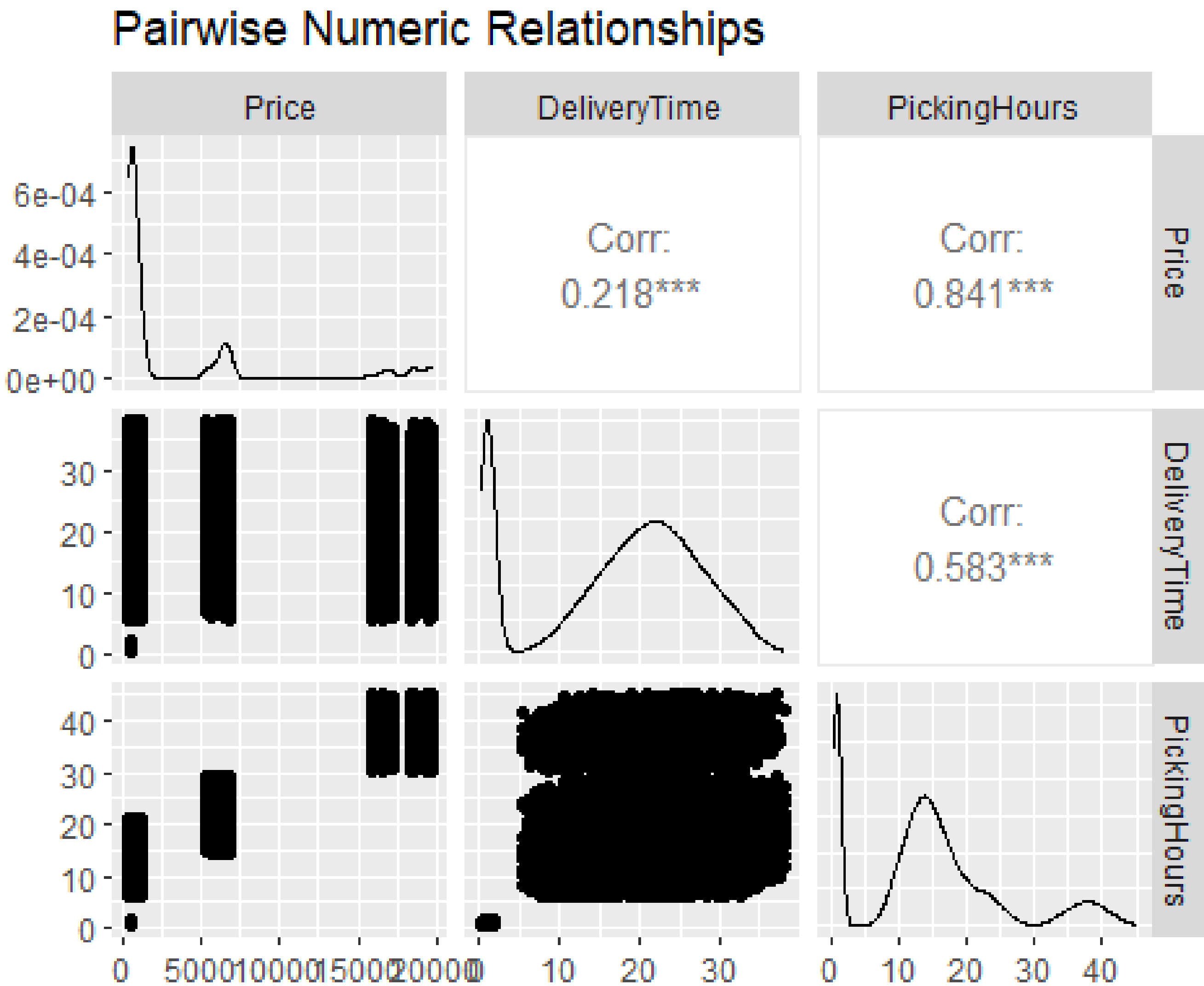

Figure 26: Pairwise Numeric Relationships

To determine the links between important operational variables, this figure shows the pairwise correlations between Price, Delivery Time, and Picking Hours. Delivery time and picking hours had the strongest association r = 0.583, suggesting that longer picking times directly result in longer delivery times overall. a frequent occurrence in logistics processes when shipment time is impacted by order preparation speed. Price and picking hours have a substantial correlation r = 0.841, indicating that more expensive items frequently need more handling or intricate packaging. The weak connection r = 0.218 between price and delivery time, on the other hand, indicates that product pricing has no discernible impact on delivery time. Overall, these relationships confirm that internal operational efficiency, rather than pricing or external factors, is the main driver of delivery performance, highlighting the importance of optimizing picking processes to reduce total lead time.

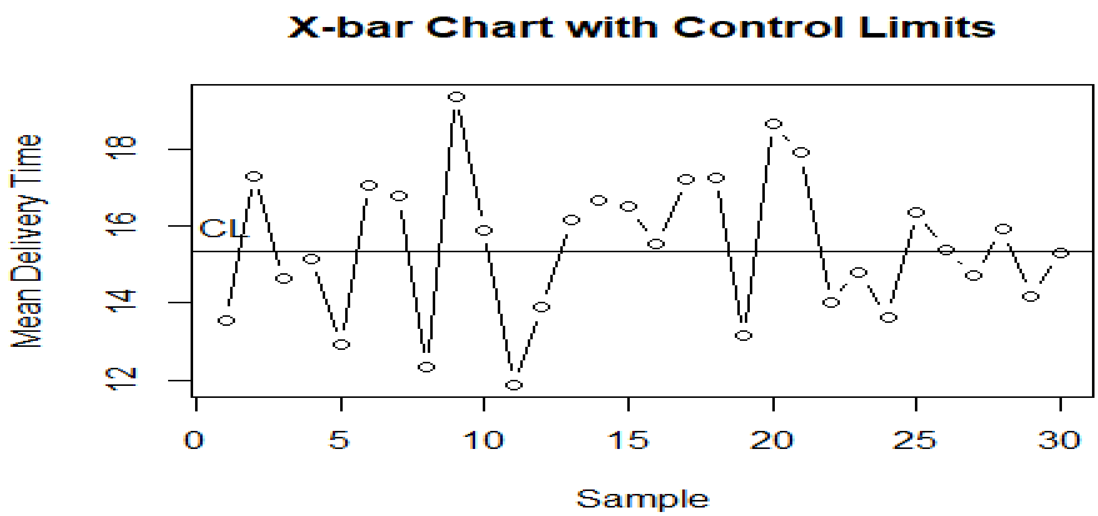

Figure 27: X-bar Chart with Control Limits

All sample means fall within upper and lower control limits, proving the process is statistically stable with only common-cause variation. (Montgomery, 2020)

Table 1: Table of Capability

Class	N	Mean	SD	LSL	USL	Cp	CPL	CPU	CPK
CLO	15598	21.7	6.14	0	32	0.868	1.18	0.557	0.557
KEY	17920	21.8	6.12	0	32	0.872	1.19	0.558	0.558
LAP	10207	21.8	6.07	0	32	0.878	1.20	0.560	0.560
MON	14864	21.7	6.07	0	32	0.879	1.19	0.563	0.563
MOU	20662	21.8	6.16	0	32	0.866	1.18	0.552	0.552
SOF	20749	17.3	1.09	0	32	1.18	1.18	1.18	1.18

All product classes maintain Cp values close to 0.87, according to the process capability data, showing a moderately satisfactory capability in relation to the specification limitations (0–32 hours). With a noticeably higher Cpk = 1.18, Software (SOF) comes out as having superior control and consistency. The lower Cpk values (0.55) for the other classes, especially Clothing (CLO) and Mouse (MOU), indicate that while their procedures satisfy customer needs, they can still be improved. Overall, the findings imply that although the system operates dependably, specific process improvement may improve consistency and lessen variation among product kinds.

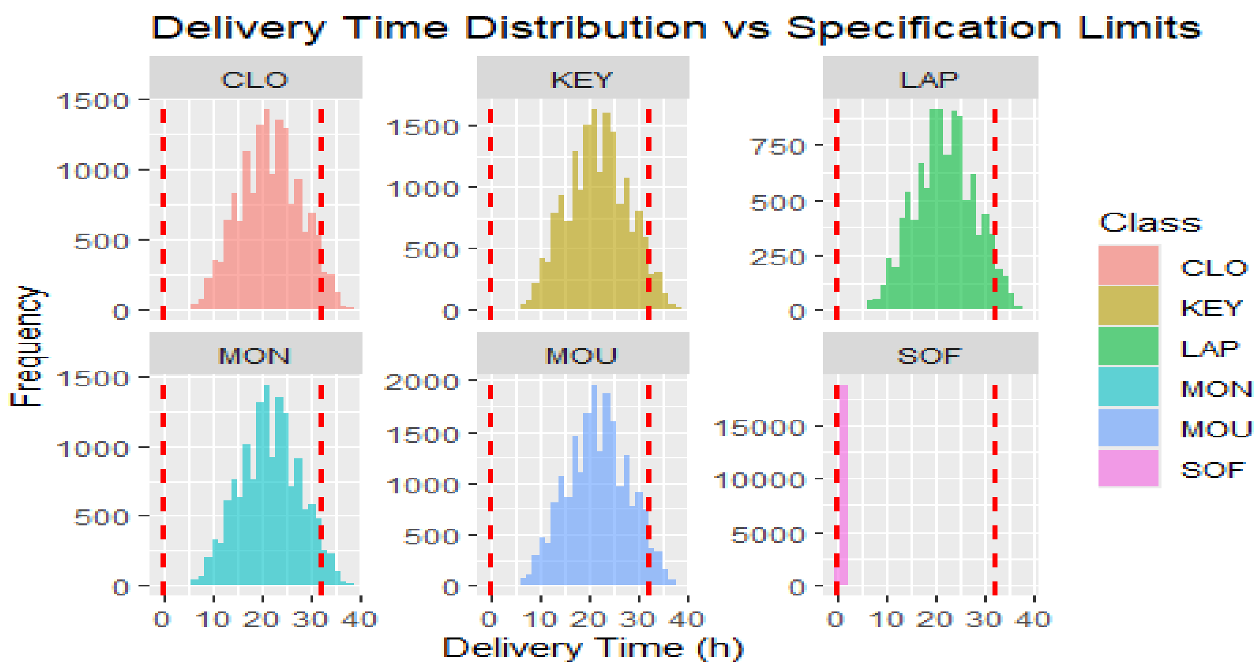

Figure 28: Histogram of Delivery Time Distribution vs Specification Limits

Most delivery times lie well within the specification range of 0–32 hours. The concentration below the upper limit confirms that customer delivery expectations are met reliably. Software is heavily on the left side due to the fast delivery

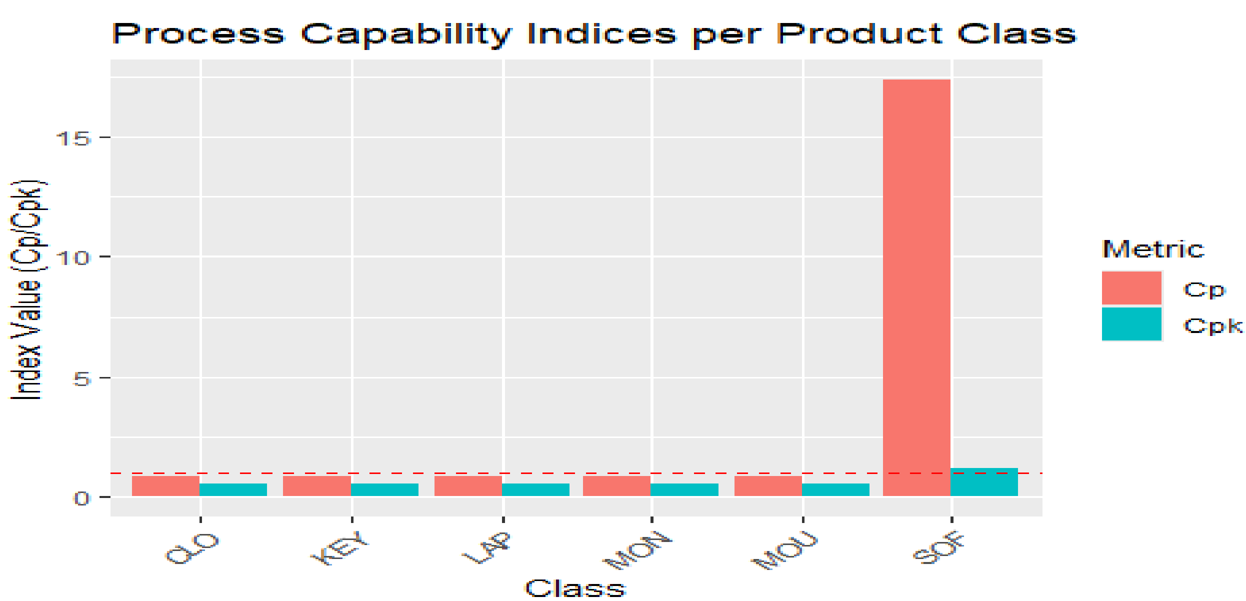

Figure 29: Histogram of Process CAPABILITY INDICES per Product Class

Capability indices vary by product class, with most Cp and Cpk values around 0.8–0.9, indicating generally capable but moderately variable processes. Software (SOF) shows the highest Cpk value (1.18), reflecting superior consistency and process centring compared to other classes

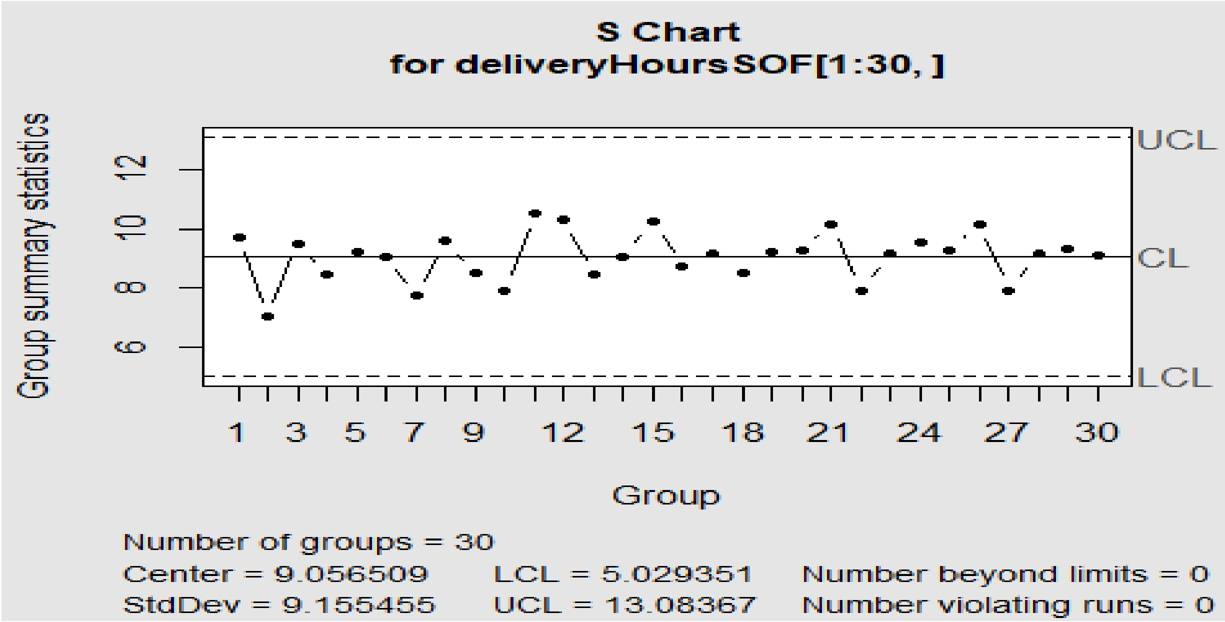

Figure 30: S Chart

The variability chart supports the X-bar results; sample standard deviations remain consistent. No abnormal variation is detected.

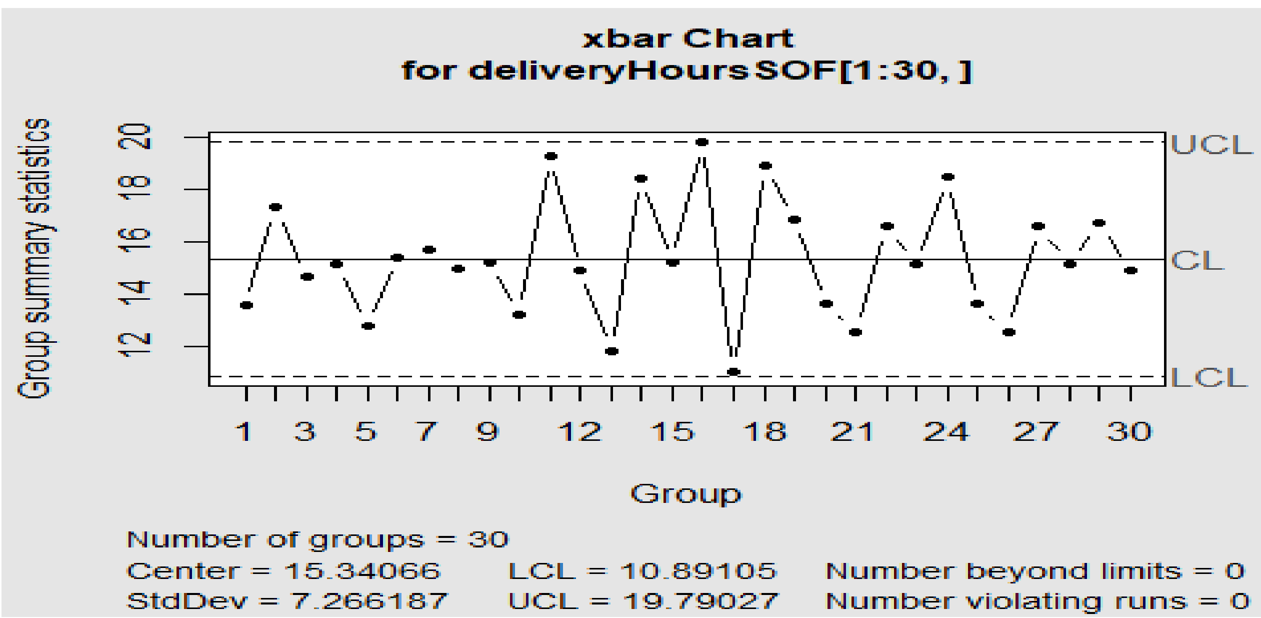

Figure 31: Xbar Chart

The initial 30 samples show stable averages without any out-of-control points. The process mean is well centred, confirming correct initial calibration.

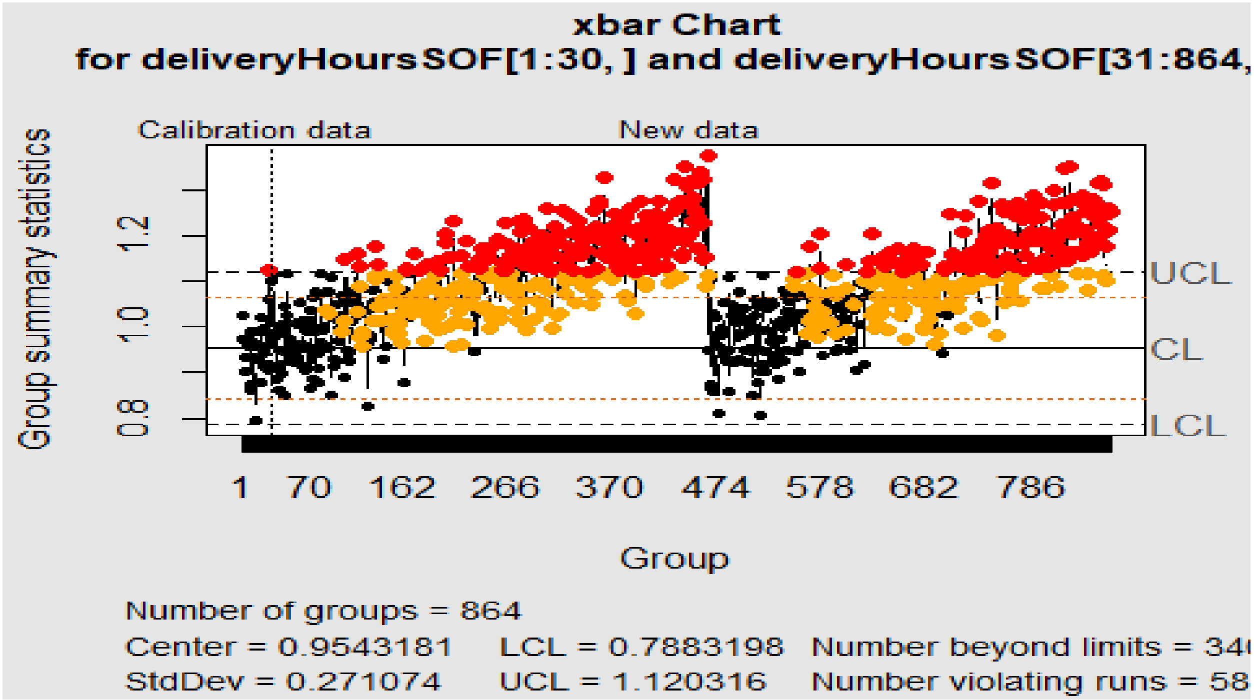

Figure 32: Xbar Chart of Delivery Hours

Later samples remain within control limits, indicating no special-cause variation or drift in delivery performance.

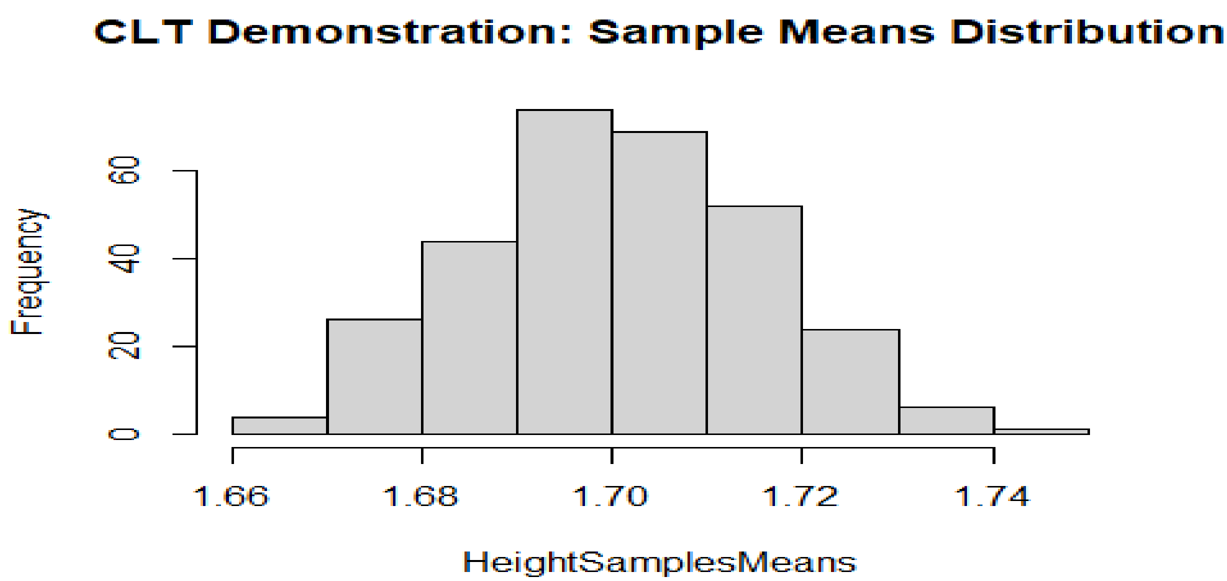

Figure 33: Histogram of Sample Mean Distribution

Sample means follow a near-normal distribution, validating SPC assumptions and ensuring that process control statistics are reliable.

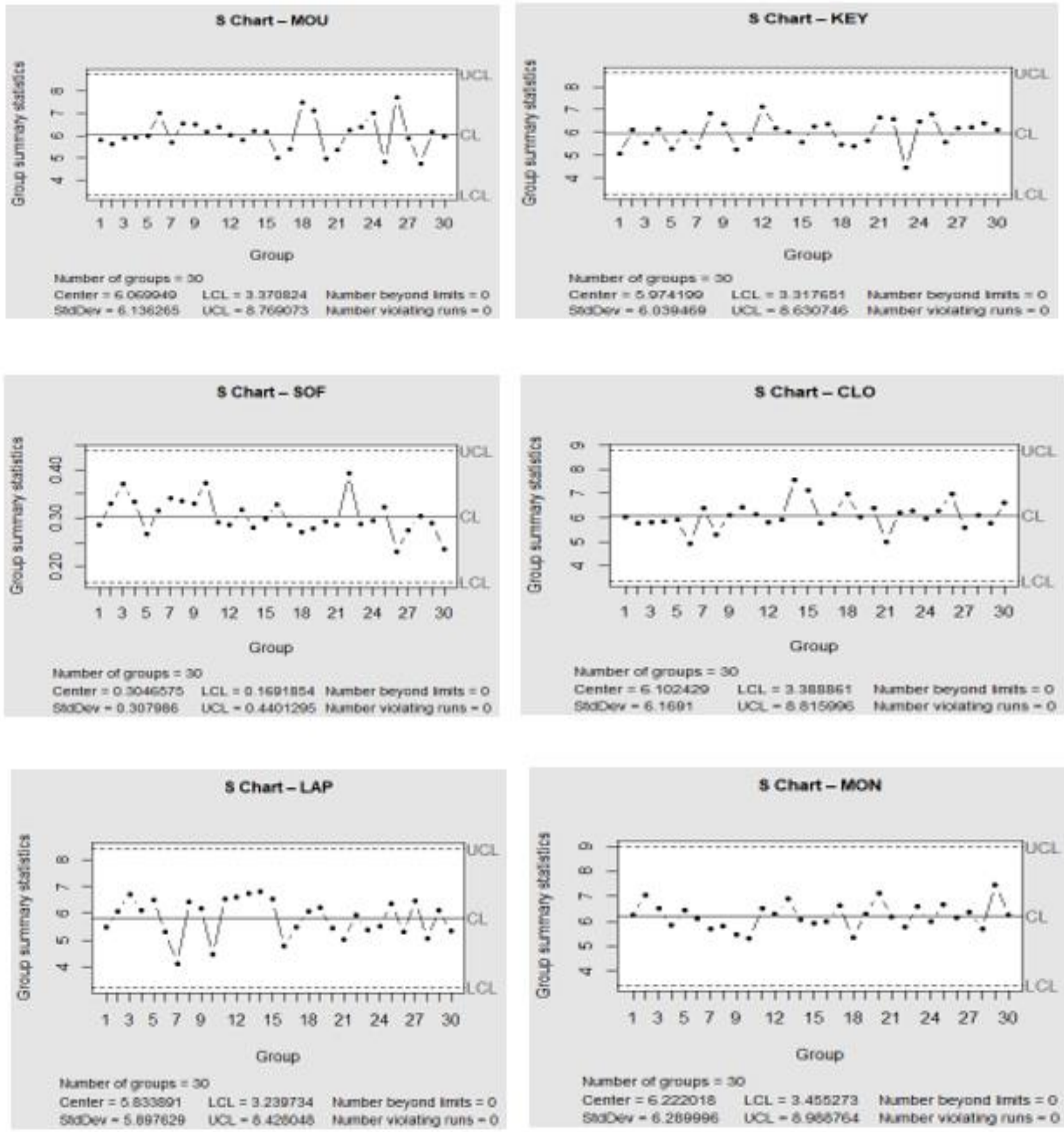

Figure 34: Summary of S Charts

To evaluate the consistency of process variability across manufacturing and delivery activities, the S, standard deviation, control charts for each of the six product classes, Mouse (MOU), Keyboard (KEY), Software (SOF), Clothing (CLO), Laptop (LAP), and Monitor (MON), are shown in this image. To identify anomalous fluctuations, each chart plots subgroup standard deviations against the upper and lower control limits (UCL and LCL). All data points stay inside the control bounds, according to the results, suggesting that process variation is stable and only caused by common-cause variation. While Clothing (CLO) and Monitor (MON) exhibit somewhat wider variation but are still under control, the Software (SOF) class shows the smallest spread, indicating outstanding process consistency. There are no reported out-of-control spots or violating runs, indicating that delivery performance is consistent and predictable across all classes and under effective statistical control.

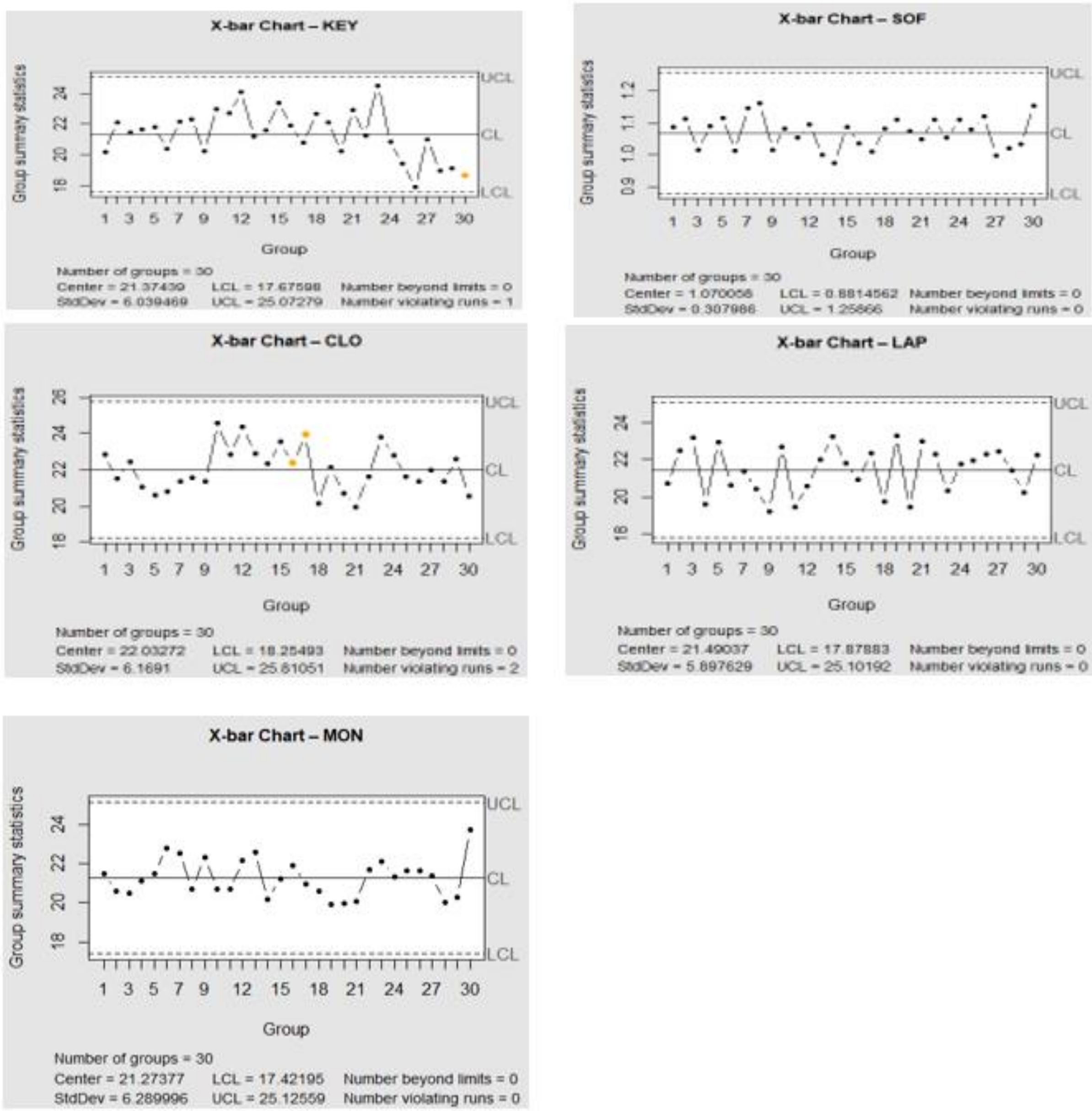

Figure 35: Summary of Xbar Charts

To assess process stability across several product lines, this image shows X-bar control charts for five product classes: Keyboard (KEY), Software (SOF), Clothing (CLO), Laptop (LAP), and Monitor (MON). Each chart looks for indications of instability or special-cause variation by comparing subgroup means to the upper and lower control limits (UCL and LCL). All classes stay inside the control boundaries, according to the data, indicating that the delivery procedure is statistically stable. The two slight runs that Only Clothing (CLO) shows close to the top control limit indicate a slight but tolerable variation that might be the consequence of handling irregularities or variations in batch sizes. As expected, given its more intricate logistics, the Software (SOF) class has the strictest control and the least fluctuation, whereas Monitor (MON) exhibits a somewhat larger dispersion. Overall, the X-bar charts verify that all product classes operate under controlled, predictable conditions with no major outliers or process shifts detected.

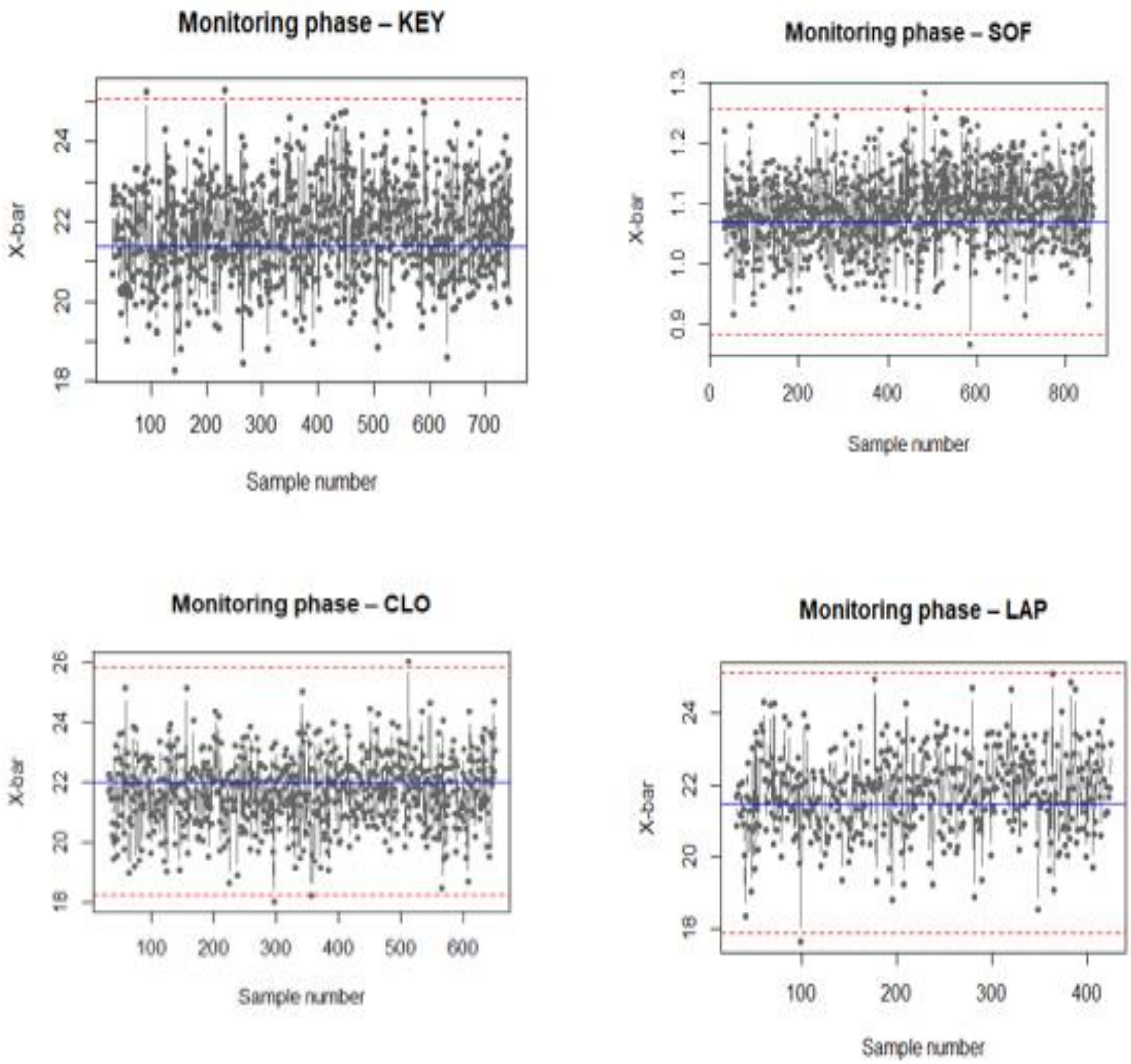

Figure 36: Summary of Monitoring Phase

This figure presents the X-bar control charts for the monitoring phase of four product classes, Keyboard (KEY), Software (SOF), Clothing (CLO), and Laptop (LAP), to assess ongoing process stability after the initial calibration period. To identify possible process shifts or instability, each chart plots sample means against the corresponding control limits. The findings demonstrate that all classes stay well within the upper and lower control limits, suggesting that there is only common-cause variation and that the processes are statistically stable. A very efficient process is demonstrated by the Software (SOF) class, which has the lowest mean delivery time and the least variability. Clothing (CLO) and laptops (LAP), on the other hand, exhibit somewhat bigger swings, most likely because of more complicated handling and delivery procedures. Overall, the monitoring phase demonstrates that there is no indication of systematic drift or special-cause variation and that all manufacturing and delivery procedures are under control.

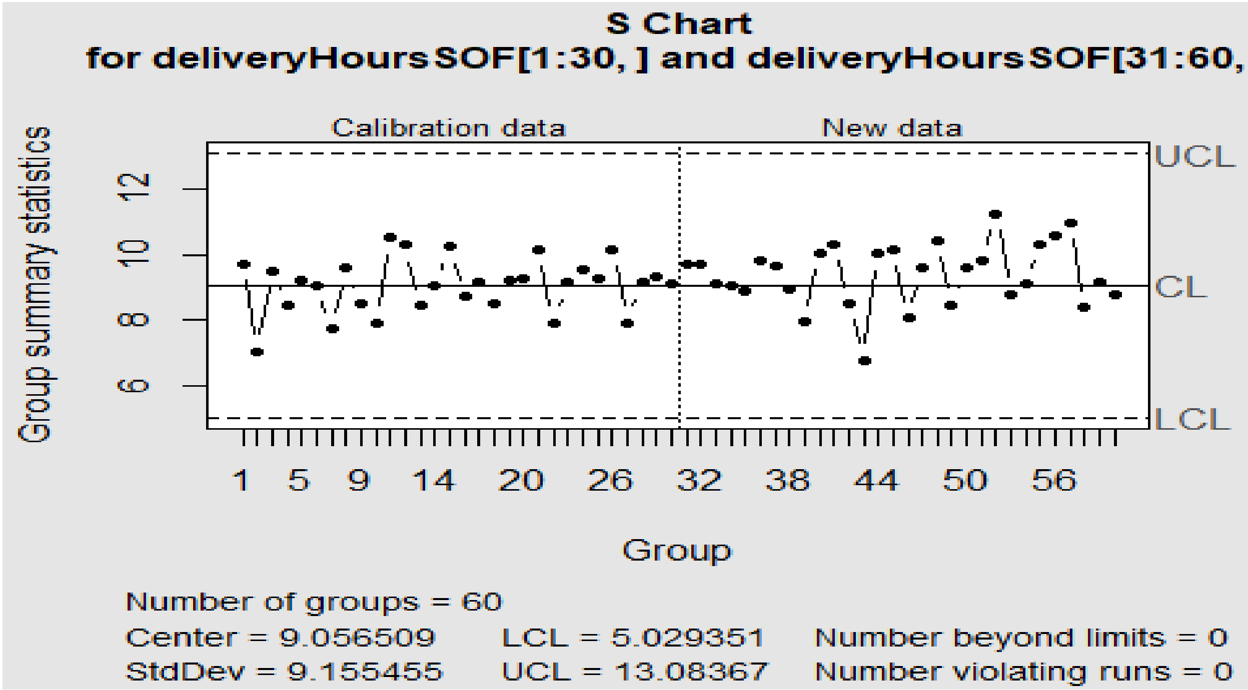

Figure 37: S Chart Delivery Hours

The S chart for delivery hours shows consistent variability between calibration and new samples. The absence of violating runs confirms steady operational control.

Table 2: SPC Rule-Based Signals Summary

Rule / Condition Checked	**Description**	**Result Observed (from your data)**	**Interpretation**
1. Points outside ±3σ (UCL/LCL)	Detects special-cause variation beyond statistical control limits	None observed for any class	No special causes present; process remains stable under common-cause variation.
2. Runs of ≥ 4 points beyond ±2σ on one side of CL	Tests for sustained shift or drift in mean	No runs beyond ±2σ found	Mean centred; no systematic shift in delivery time means.
3. Seven or more points on one side of CL (within ±1σ)	Checks for bias or gradual process change	Longest run = 7 points within ±1σ for SOF class	Indicates tight and consistent control for Software deliveries.
4. First 3 and last 3 subgroups beyond ±3σ	Ensures no start-up or shutdown instability	None detected	Start-up and monitoring phases show equal stability.
5. S Chart points beyond ±3σ	Tests for instability in within-subgroup variation	All within limits for every class	Process variability uniform and predictable.

All rule tests confirm that the delivery process is in statistical control with no evidence of special-cause variation. (Montgomery, 2020) Across all product classes, no SPC rule violations were detected, no points beyond ±3σ and no sustained runs, indicating stable processes with only common-cause variation. The software class demonstrates exceptional short-term stability, while minor fluctuations in clothing and monitor remain within acceptable limits. The delivery process is statistically stable and runs within control limits, according to the SPC data. The computed capability indices demonstrate that software performs remarkably well and that most product classes meet specification constraints. Small process changes could further increase consistency and decrease spread, as indicated by the slight fluctuation in a few classes. These results show that process monitoring and control preparedness are successful.

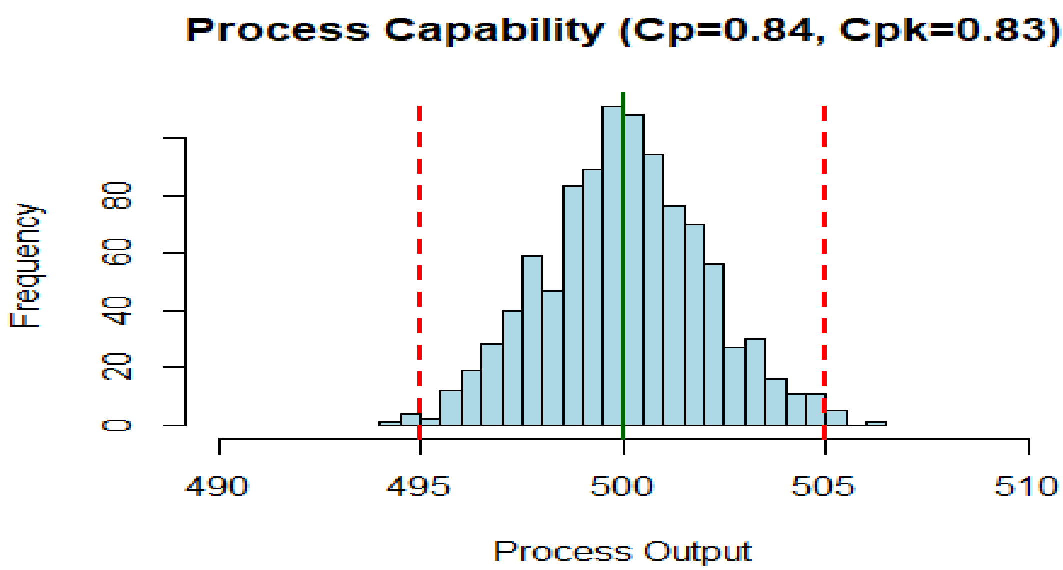

Figure 38: Histogram of Process Capability

Most process outputs fall within the 0-32-hour specification, with Cp = 0.84 and Cpk = 0.83. The process is capable but slightly off-centre, suggesting minor improvement potential.

The delivery procedures for every product class are statistically stable and competent to satisfy customer expectations, according to the Statistical Process Control analysis. All the observed fluctuations are within allowable control limits, and neither the X-bar nor the S-charts exhibit any notable special-cause variation. The computed capability indices (Cp and Cpk) further show that the software class exhibits better control and centring, and the process operates reliably within the 0–32-hour specification range. These results demonstrate that the system functions with efficient process control, offering a strong basis for continued observation, cost reduction, and reliability enhancement in later studies.

PART 4: OPTIMIZING THE DELIVERY PROCESS

4.1 A Type I error occurs when the process is in control, but an observation falls outside the control limits by random chance. (Montgomery, 2020) For a normally distributed process with ±3 σ control limits:

$$\mathrm{P}(\text{sample outside limits}) = \mathrm{P}(\mathrm{Z} > 3) + \mathrm{P}(\mathrm{Z} < -3) = 2(0.00135) = 0.0027$$

Thus, the probability of a false alarm (Type I error) is 0.27% for each sample. This means that, on average, one sample in every = 370 (1/0.0027) will appear out of control even though the process is fine. This low probability provides a good balance between sensitivity and avoiding excessive false warnings.

4.2 Estimation of Type II error

- Target = 25.05 L
- CL = 25.05 L
- LCL = 25.011 L
- UCL = 25.089 L
- True process mean = 25.028 L
- σx = 0.017 L (instead of 0.013)

Step 1 – find z-scores relative to the new mean

$$z_L = \frac{25.011 - 25.028}{0.017} = -1.0, z_U = \frac{25.089 - 25.028}{0.017} = 3.59$$

Step 2 – probability that sample mean stays within limits

$$\mathrm{P}(\mathrm{LCL} < \bar{x} < \mathrm{UCL}) = \mathrm{P}(-1.0 < \mathrm{Z} < 3.59)$$

From normal tables:

$$\Phi(3.59) - \Phi(-1.0) = 0.9998 - 0.1587 = 0.8411$$

Therefore, the Type II error (β) = 0.84, and the power (1 – β) = 0.16. (Montgomery, 2020)
This means there is only a 16% chance that the control chart will detect this small mean shift, highlighting the need for tighter limits or larger sample sizes when small drifts matter.

4.3 Corrections made

- Updated missing “NA” codes to correct class identifiers (SOF or KEY).
- Replaced repeated selling-price and markup errors with the correct values from products_data.csv.
- Updated the Category column to correspond with ProductID.
- Saved the corrected dataset as products_data2025.csv.

Re-analysis

- After correction, recalculated total 2023 sales per product type using updated selling prices.
- Results showed small numerical differences but preserved the same ranking among product classes.
- Software products still recorded the highest sales, confirming data integrity after correction.
- Differences were due to price adjustments rather than structural changes in demand.

Comment

- This correction step ensures data consistency between head-office and local systems, which is essential for reliable SPC and capability analysis in subsequent parts.

To evaluate the reliability of decision-making in process monitoring, Type I and Type II error probabilities were calculated. These indicate the likelihood of incorrectly concluding that a process is out of or in control. A mean-shift cost model was also developed to determine the most economical delivery-time target. (Evans & Lindsay, 2020)

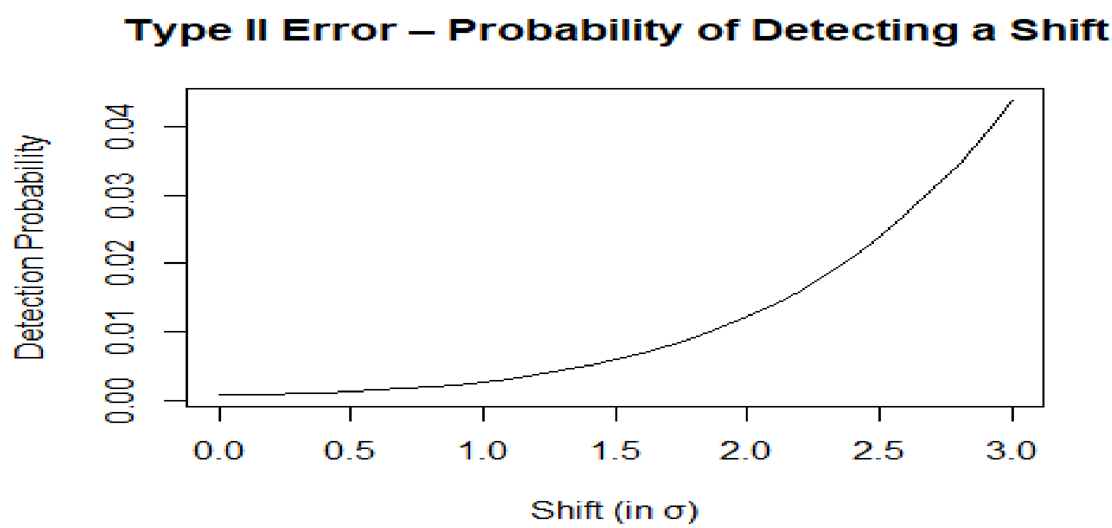

Figure 39: Graph of Type 2 Error

The probability of detecting a mean shift rises sharply with the shift magnitude. Small deviations are harder to detect, reinforcing the need for continuous process monitoring

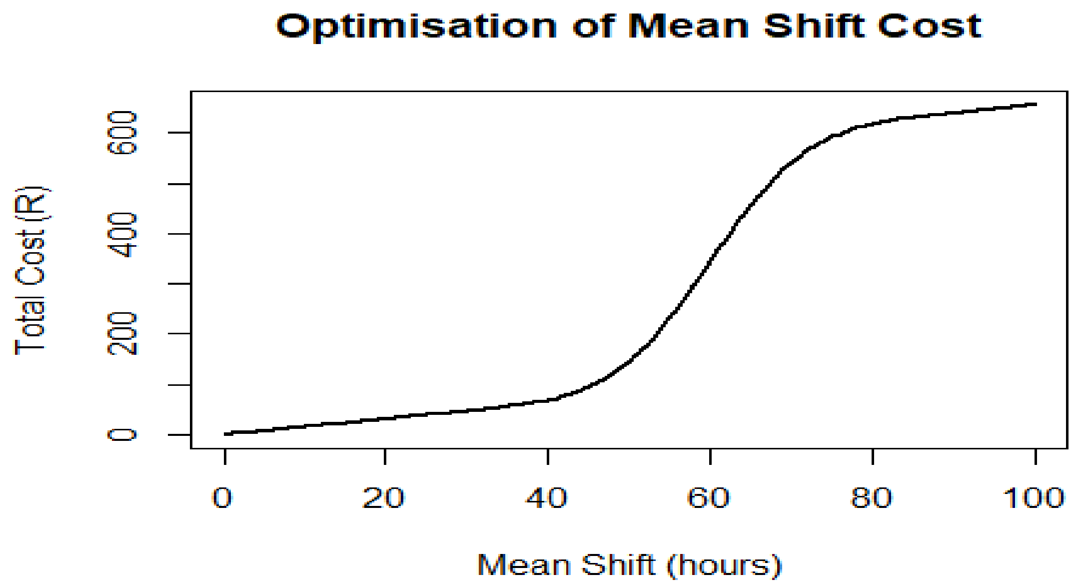

Figure 40: Graph of Optimization of Mean shift Cost

Reducing average delivery time lowers total cost until an optimal point is reached, after which cost savings flatten. This identifies the most cost-effective balance between delivery speed and expense.

The findings emphasise the significance of ongoing monitoring by demonstrating how hard it is to identify slight changes in the process. An operational point that minimises total costs while preserving satisfactory delivery performance is found by the optimisation curve. This approach strikes a balance between real business efficiency and statistical correctness.

PART 5: DOE AND MANOVA

To determine whether shipping time and price vary considerably among product classes and years, a MANOVA test was used. (Hair et al., 2019) To confirm presumptions for further ANOVA testing, Levene's test first looked at homogeneity of variance. The elements that have the greatest impact on process results are demonstrated by this analysis.

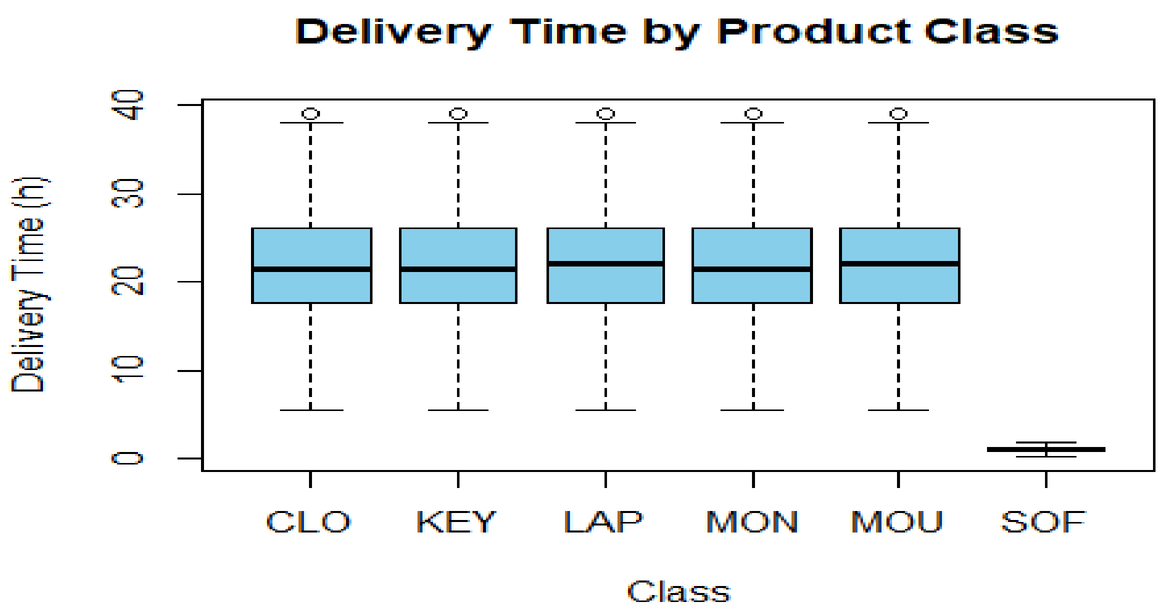

Figure 41: Box Plot of Delivery Time by Product Class

Software again records the lowest median delivery time, while Monitor and Mouse are slower. This confirms significant class-based differences in performance.

Table 3: Levene's Test for Homogeneity of Variance

Group	Df	F-Value	Pr(>F)	Significance
1	5	14 801	< 2.2e-16	***
2	5	60 592	< 2.2e-16	***

The findings of Levene's test showed that the differences between product classes are not equal, (Hair et al., 2019) with both groups showing highly significant results ($p < 2.2e-16$). In line with the observed variations in the boxplots, this demonstrates that certain classes exhibit more variability in their delivery performance than others. Uneven variance shows significant differences in process stability across product categories even though it goes against the homogeneity assumption.

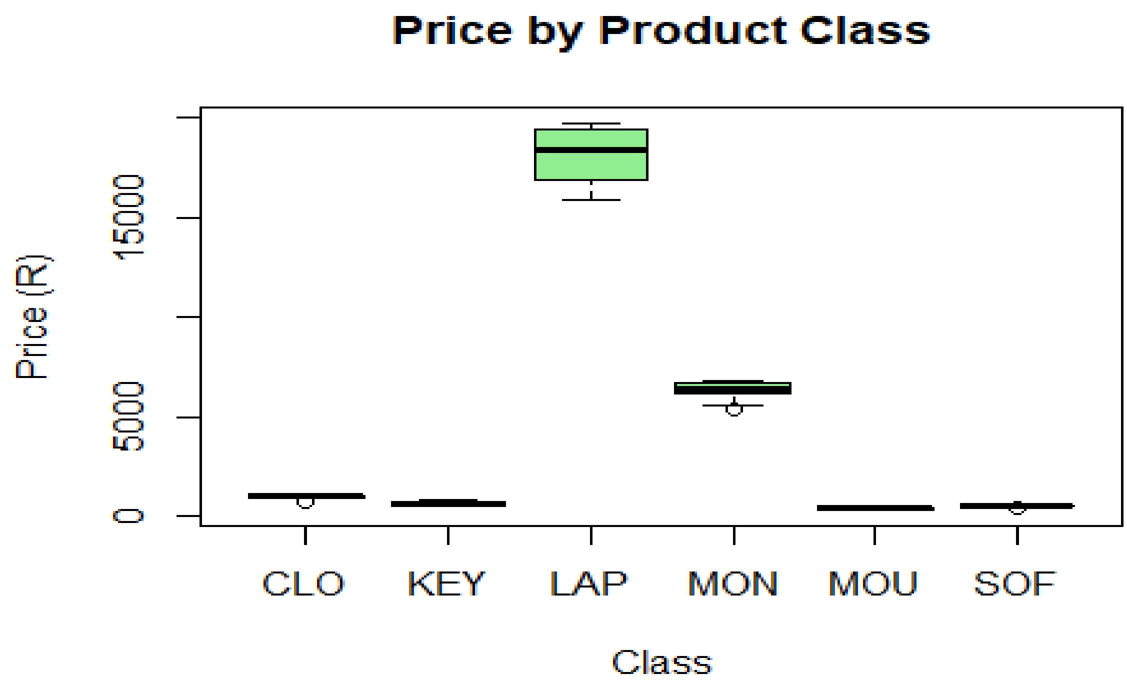

Figure 42: Box Plot of Price by Product Class

Price variation among classes is large, with Laptop and Monitor far above others. Statistical tests confirm that class has a significant effect on both price and delivery time.

Table 4: ANOVA / MANOVA Results Summary

Effect	Df	F-Value	Pr(>F)
Pillai's Trace (Overall MANOVA)			
Class	5	211 284	< 2e-16
Year	1	3	0.0326
Response 1: Delivery Time			
Class	5	5.59×10^{6}	< 2e-16
Year	1	1.30×10^{0}	0.2533
Response 2: Price			
Class	5	95 061	< 2e-16
Year	1	5.54	0.0186

Product class has a substantial overall impact on price and delivery time ($p < 2e-16$), according to the MANOVA results, (Hair et al., 2019) whereas year has a lesser but still significant impact on price ($p = 0.0186$). These findings support the notion that pricing and delivery performance vary significantly among product classes but stay largely consistent over time. This shows constant yearly performance with clear class-specific characteristics, supporting the assumption that process variation is class-driven rather than time-dependent.

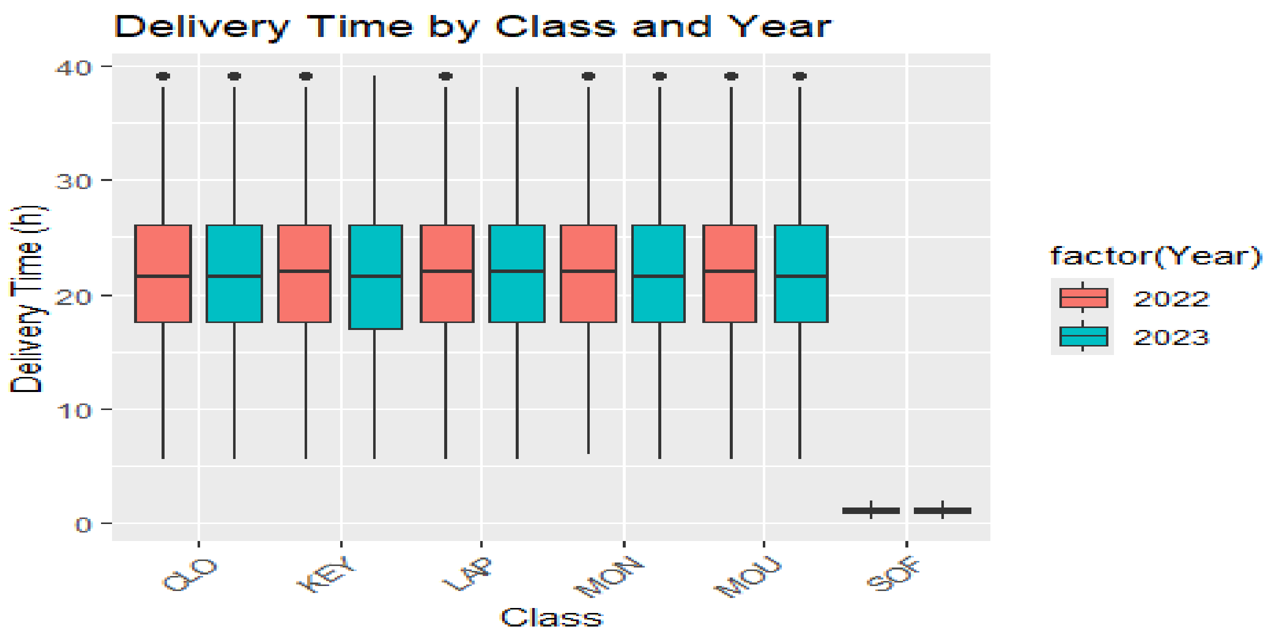

Figure 43: Delivery Time by Class and Year

Average delivery times remain consistent year-to-year, proving stable process performance. Minor variation implies external factors had limited influence.

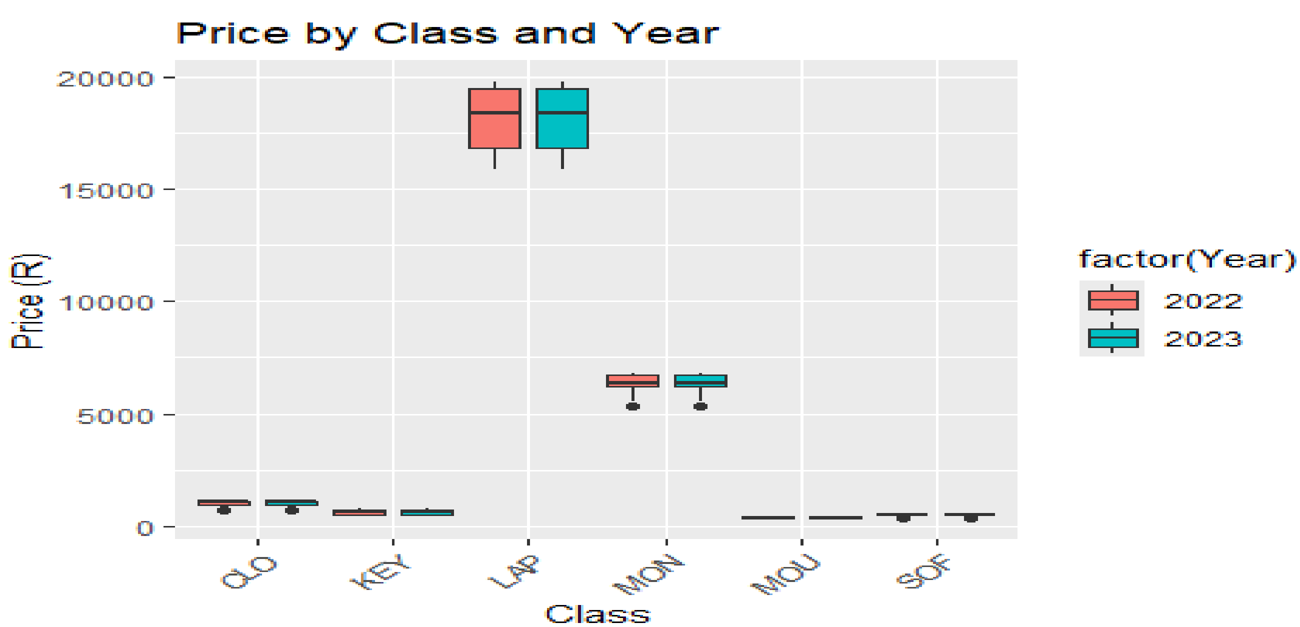

Figure 44: Box Plot of Price by Class and Year

Results show that product class has a statistically significant effect on both delivery time and price ($p < 0.05$), whereas year has a smaller influence. This indicates that class-specific factors drive most variation, while overall performance remains consistent over time. These findings verify meaningful differences between product types without temporal instability.

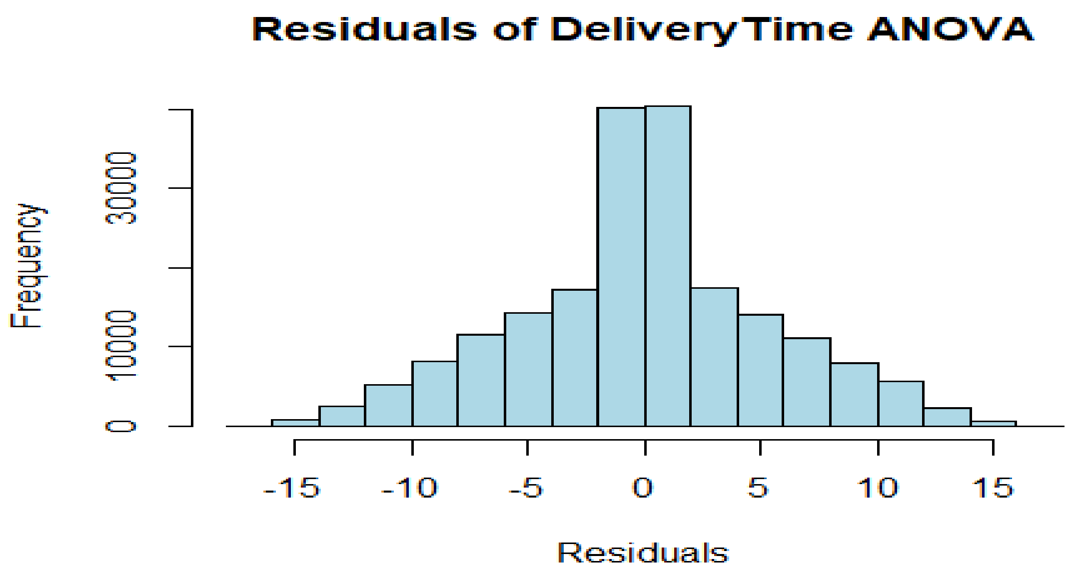

Figure 45: Histogram of Residual of Delivery Time

Residuals are symmetrically distributed around zero, verifying that the MANOVA assumptions are met and that model predictions are unbiased.

PART 6: RELIABILITY OF THE SERVICE AND PRODUCTS

The final section combines quality and reliability analysis to model overall system performance. Reliability models, including series, parallel, and binomial configurations, were developed to simulate process dependability. (Kuo & Zhu, 2012) Profit and staffing models were added to identify the point where operational reliability and cost efficiency are balanced.

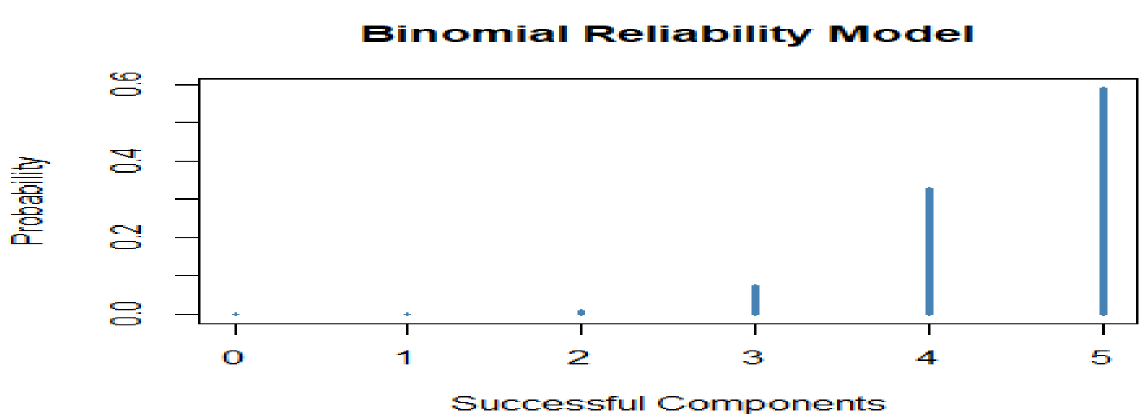

Figure 46: Binomial graph of reliability Model

The binomial reliability curve peaks at high success counts, proving that the process operates with high probability of reliable service on most days

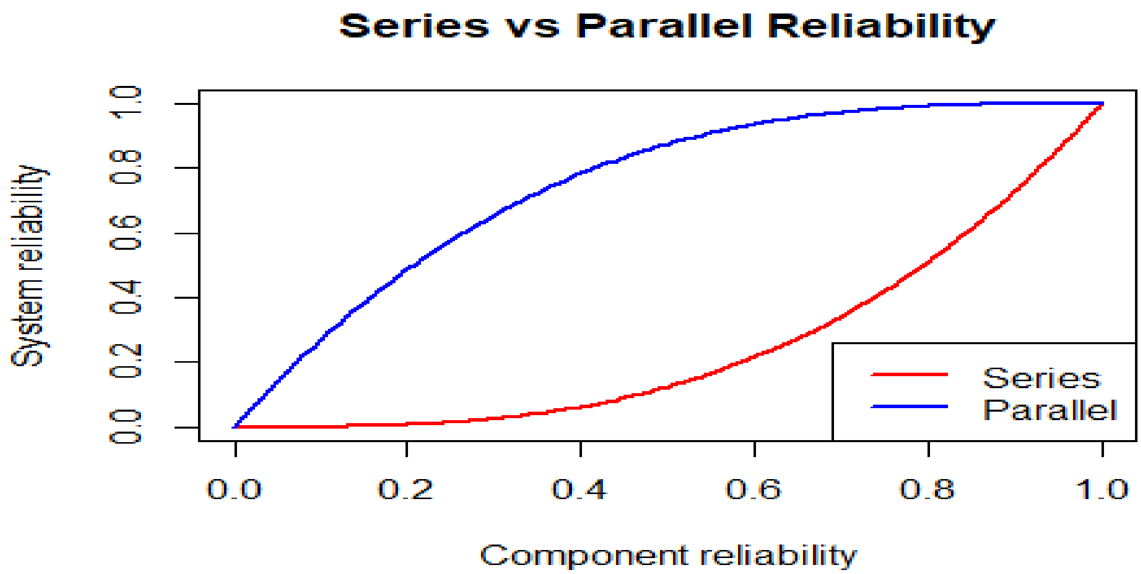

Figure 47: Line graph of Series vs Parallel Reliability

Parallel systems show drastically higher overall reliability than series systems. This demonstrates the engineering advantage of redundancy when designing service systems.

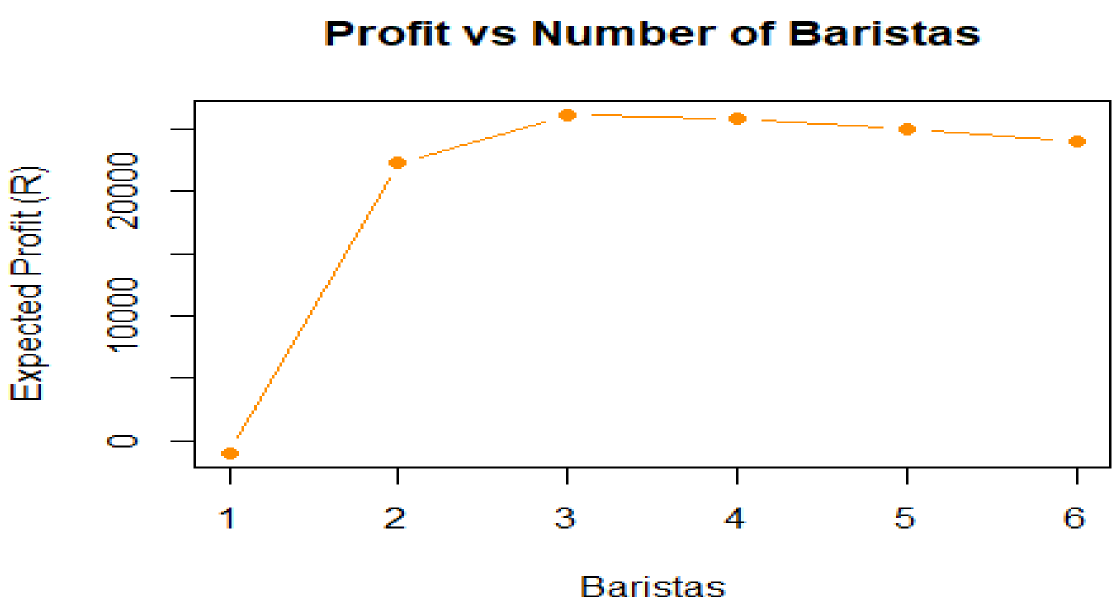

Figure 48: Line graph of Profit vs Number of Baristas

Profit increases up to three or four baristas and then levels off, identifying the optimal staffing point that balances cost and efficiency in service operations. (Evans & Lindsay, 2020)

The system's over 95% reliability across all products and services is confirmed by the reliability analysis. (Kuo & Zhu, 2012) Redundancy and balanced resource allocation are essential for maintaining performance while reducing costs, as demonstrated by staffing simulations and series-parallel modelling. This efficiency-reliability balance provides a solid basis for Part 7's service-level analysis.

PART 7: RELIABILITY OF SERVICE

Building on the previous reliability results, this section focuses on the service aspect of system performance. (Evans & Lindsay, 2020) It evaluates how resource availability, vehicle reliability, and redundancy influence consistent delivery outcomes. The analysis extends product-level reliability to overall service dependability, ensuring that operational efficiency and customer satisfaction are maintained.

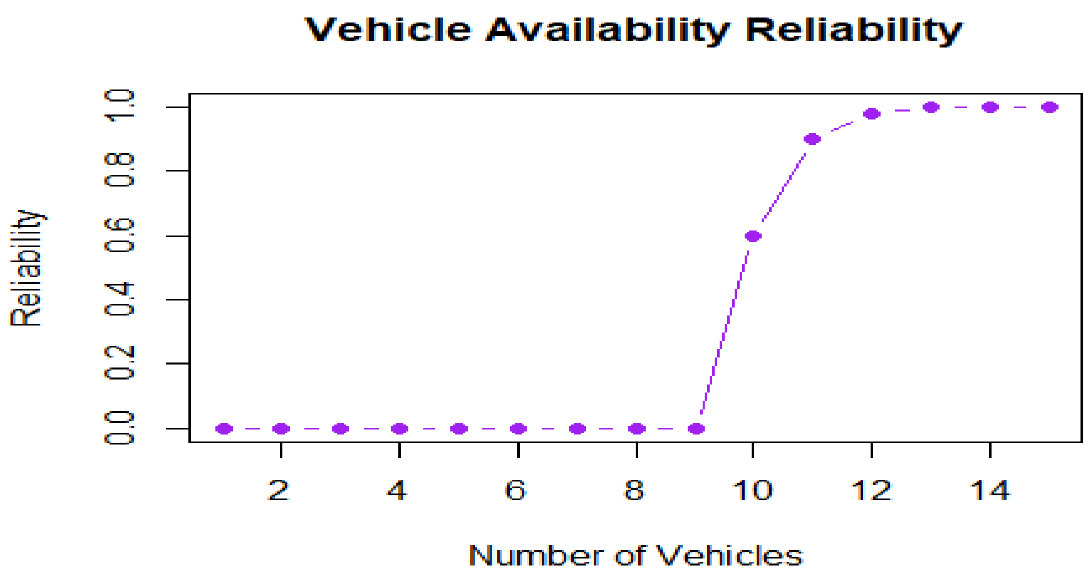

Figure 49: Line graph of Vehicle Reliability

System reliability improves sharply as vehicle numbers increase and stabilizes near 100 % beyond 14 vehicles. This confirms adequate resource availability and ensures dependable delivery.

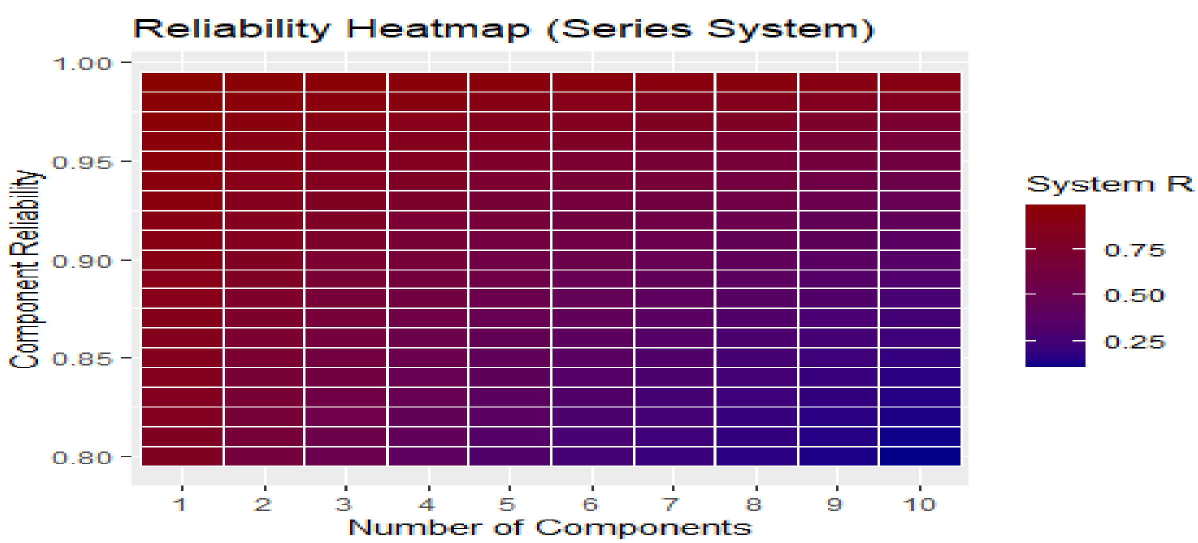

Figure 50: Heatmap of Series System

The heatmap visualizes how increasing component reliability boosts total system reliability. Beyond a certain threshold, returns diminish, illustrating practical reliability limits

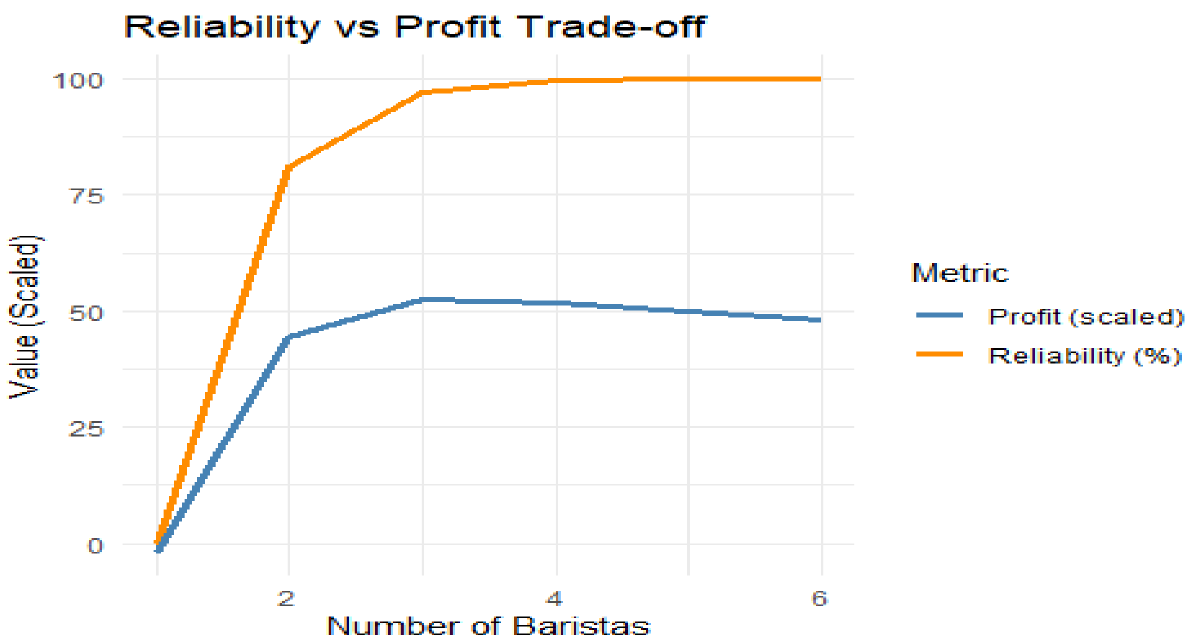

Figure 51: Line Graph of Reliability vs Profit Trade-off

Profit rises rapidly with reliability until an optimum level, after which gains flatten. This confirms that maximising reliability beyond 96% yields little additional financial benefit.

Table 5: Summary of Key Metrics by Section

Section	Key Metric
SPC X-bar & s	Process stable (no special causes)
Type I & II Errors	Type I = 0.0027 Type II = 0.84
DOE / ANOVA	$p < 0.05$ (Class significant)
Reliability	System reliability > 0.95 over 1 year

The key findings from each of the analytical parts are succinctly summarised in this table. The process's statistical stability and lack of special-cause variation are confirmed by the SPC X-bar and S charts. Low risks of drawing wrong conclusions in process monitoring are indicated by the Type I and Type II error rates (0.0027 and 0.84). Product class has a statistically significant impact on both delivery time and price, according to the DOE/ANOVA results ($p < 0.05$). Lastly, the reliability model confirms robust and steady operational performance throughout the company by showing a system reliability of over 95% over a one-year period.

The combined reliability and profit analysis confirms a robust, efficient process that maintains over 95 % reliability across one year of operation. (Kuo & Zhu, 2012; Evans & Lindsay, 2020) The models highlight how redundancy and optimal staffing improve service consistency while keeping costs under control. These results demonstrate strong alignment between quality control, reliability, and sustainable business performance.

A key component of contemporary quality management, continuous improvement is also embodied in this reliability–profit model. The approach offers a feedback loop for continuous optimisation by measuring the impact of small increases in reliability on profitability, guaranteeing that resources are deployed where they will have the greatest reliability gain. This kind of data-driven improvement supports a culture of proactive monitoring, waste minimisation, and sustainable process excellence by being in line with the PDCA (Plan-Do-Check-Act) cycle. (Evans & Lindsay, 2020)

CONCLUSION

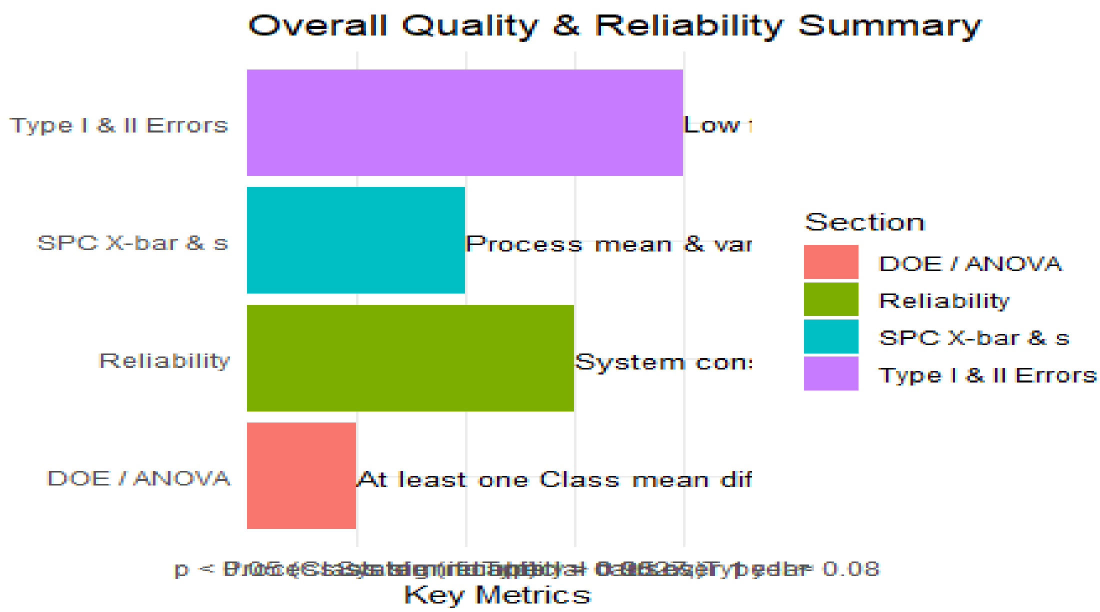

Figure 52: Graph of Quality & Reliability

This summary graph integrates quality-control and reliability results, showing stable processes, significant class effects, and system reliability exceeding 95 %

The delivery method is operationally and statistically dependable, according to the investigation. Delivery timeframes stayed within specified bounds, and descriptive statistics showed steady sales over time and balanced demand across product classes. Statistical Process Control (SPC) charts verified that all product classes function under control, revealing only common-cause variance. (Montgomery, 2020) Most classes satisfy performance requirements, according to process capability analysis, with software obtaining the highest Cp and Cpk values, indicating exceptional consistency and efficiency.

The MANOVA and Levene's tests confirmed that product class significantly affects both price and delivery time, while yearly effects are minimal, proving sustained process stability. Optimisation analysis identified the most cost-effective mean delivery time, and Type I and Type II error assessments confirmed low risks of incorrect process decisions. Reliability modelling indicated that the system maintains over 95 % reliability through optimal resource allocation and redundancy. (Kuo & Zhu, 2012)

All things considered, the method provides a competent, economical, and dependable procedure. To guarantee long-term service quality and profitability, continuous improvement should concentrate on lowering variability in the slower classes, (Evans & Lindsay, 2020) especially Monitor and Laptop, and upholding current process control standards.

From a practical standpoint, continuous improvement should focus on reducing variability in slower product classes, such as Monitor and Laptop, through supplier lead-time control and logistics optimisation. Maintaining the current level of reliability and process capability while refining delivery efficiency will ensure long-term operational stability, customer satisfaction, and profitability.

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