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QUALITY ASSURANCE 344 ECSA ATTRIBUTE GA4 REPORT

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PART 1.2

1.2.1 Executive Summary

The company has achieved an approximate total profit of 877.84 million across the two year period, which makes it fundamentally profitable. Two major strategic risks overshadow this success, identified through the comprehensive analysis of a significant profit decline of 13.4% year-over-year from 2022 to 2023. A severe operational bottleneck is tied to the logistics of the most profitable product in the company, Laptops.

Key insights:

- Total profit fell by 61.73 million from the year 2022 to 2023, which signalled a crucial need of re-evaluating the sales strategies and the structural costs
- The majority of the total profit is driven by the laptop and monitor categories, meaning their performance is central to the success of the company
- For warehouse picking the laptop orders require an average of 37.74 hours which is nearly three times the time of the other comparable products. The customer satisfaction is potentially threatened, and the cost-to-serve is actively driven up by this time inefficiency.
- Female customers generate the largest total profit, with the customer base driving the highest profit concentration in Los Angeles and San Francisco.

Recommendations:

- To investigate the root cause of the Laptop picking bottleneck and the deterioration of the logistics efficiency, immediate resources must be allocated. Reverse-engineering strategies can be applied for the profit decline.

1.2.2 Data Integrity and Methodology

Data Integrity and Correction:

Integration of data sales, local products catalogues and head office files commenced the analysis. The process uncovered abnormalities in the data integrity in the original product catalogue. Many of the ProductIDs were misclassified, Laptop product ID was categorized incorrectly as Mouse, hence the new format of identification.

In products_data file:

- SOF003 is listed as Laptop
- SOF004 is listed as Monitor
- SOF005 is listed as Keyboard

In products_headoffice file:

The same IDs (SOF003, SOF004, SOF005) are all categorized as Software

Methodology:

- For the correction of the error a rule-based reclassification was implemented where the ProductID prefix was used to define the true category, e.g LAP products are Laptops, MON products are Monitor etc. The data sets was merged into one clean product.
- This was mandatory for the analysis based on category and the subsequent profits to ensure for the precise accuracy on the analysis.

Analytical Structure:

The analysis that follows was performed in correcting and merging the dataset:

- Total profit was derived using the following formula: $Quantity \times (Selling\ Price \times \frac{markup}{100})$
- For the profit segmentation the sales data were merged with the customer demographics, e.g age, gender, city, income.
- To quantify the operational efficiency across all the categories a customized metric was used, Profit per Picking Hour : $Profit\ calculated\ for\ each\ category \div Picking\ hours\ for\ that\ category$

1.2.3 Financial Performance and Trend Analysis

Profit Trend Analysis:

To view profitability on an exceptionally stable basis, it is better on a more detailed time-series analysis of a month-to-month or day-to-day basis. Despite the annual decline from 2022 to 2023.

Monthly Trend:

There are no seasonal peaks or troughs of the monthly total profit, a flat line is maintained across 2022 to 2023. This suggests a consistent baseline demand which is also an indication of the lack of a successful seasonal profit enhancement strategies.

Daily Trend:

The profit is evenly distributed, there are minor variations between weekdays and weekends. The most profitable day being Wednesday, and Fridays and Sundays generating the lowest total profits with minimal difference.

Product Profitability Breakdown

Revealing the company's financial reliance on high-value hardware is the corrected product data:

Table 1: Product Profitability Breakdown (Top 5)

Category	Total Profit	Percent of Total
Laptop	$450 880,09	51,9
Monitor	$876 161,62	33,9
Cloud Subscription	$340 281,51	4,8
Keyboard	$984 783,35	4,2
Software	$557 151,65	2,6

Top Performers:

The top 5 most profitable products are all within the laptop category

1.2.4 Customer and Market Segmentation

This part of the analysis reveals the customer demographics segments which are of most value to the profit structure of the company.

Geographic Concentration:

The profits of the company are mostly concentrated on the major urban cities below:

Table 2: Geographic Profit Concentration (Top 5 Cities)

City	Total Profit
Los Angeles	$906 335,57
San Francisco	$811 247,01
New York	$182 037,66
Houston	$610 143,63
Seattle	$474 452,32

Strategic Implication:

The most important geographic profit centers that should be prioritized for the optimization of the targeted marketing and logistics are Los Angeles and San Francisco

Key Findings on Income:

A negligible relationship between the Total Profit and the Customer Income is shown for the correlation analysis, with a r= 0.0269. Similarly, the correlation between Age and Total Profit is weak

Strategic Implication:

Strategies that rely in income targeting are likely inefficient like the Marketing and Pricing strategies. The focus shifts to the behavioural targeting and the geographical segments, regardless of the costs of the operations

1.2.5 Critical Operational Logistics Challenge

This is to confirm the critical bottleneck within the warehouse operation that also poses a risk to the operational costs and margins.

The Laptop Bottleneck: Quantification of Inefficiency

The correlation of r=0.514 between the time spent on picking the order and the total profit of the order suggests that the high value orders takes a little longer to process. Below are the specific product picking times:

| Table 3: Operational Efficiency by Category | | | |
Category	AvgPickingHours	AvgDeliveryHours	MeanProfitPerPickingHour
Software	0,91	1,09	1255,49
Laptop	37,74	21,81	1190,38
Monitor	21,73	21,76	938,02
Cloud Subscri	13,73	21,74	208,79
Keyboard	13,71	21,77	159,98
Mouse	13,7	21,82	83,59

Problem Location:

There is consistency in the delivery times across all the categories, which isolates the issue specifically pointing to the process of picking for the Laptops.

The Paradox:

- The second most profitable category per hour is from the laptops after Software from the high profit margin, despite the severe delays.
- Significant unquantified risks and the cost to order fulfilment process also adds to this inefficiency

Logistics Trend : Active Deterioration

A clear, negative trend is shown by the laptop picking time analysis over the next 24 month period.

- Starting in January 2022 the average picking time for the Laptops is at 36.05 hours
- The time specified consistently increases monthly throughout 2022 and 2023

Conclusion:

- With the logistics bottleneck not being static but a worsening operational failure,
- this suggests the root likely being security protocol, storage location or a manual process, has not been yet addressed and is degrading the operational efficiency continuously.

1.2.6 Conclusion and Recommendations

Conclusion

The company mainly benefits from the high-margin hardware sales in the key urban areas and is profitable from all that. However, even with the contraction of the profit of 13.14% and with the logistics sector deteriorating in the process for distributing Laptops, the process represents the two most critical and immediate threats to profitability in a long term basis.

Recommendations

- An in-depth investigation will be launched immediately into the process of picking Laptops. This is to identify the cause of them taking 37.74 hours to be picked, which specific step in the process consumes most of the time (it can be QA, packaging, inventory location, security sign-off), and there must also be a development of a newly corrective action plan to actually bring the Laptop picking time down in line with the other hardwares
- There must be an investigation of the primary drivers of the profit decrease of 61.73 million. An annual examination in the changes in sales volume, pricing strategy and the total cost of goods sold to pin point if the decline is caused by the increasing product cost or due to the lower sales
- Sales efforts and focus targeted marketing will be put on the most profitable urban centers or segments like Los Angeles, San Francisco and the female customer segment. Given the low correlation found with the income, the campaigns should find ways to emphasize behavioural targeting and value proposition rather than high-income demographics.

PROJECT MANAGEMENT STATUS

All the tables and graphs that helped with the analysis:

PART 3: STATISTICAL PROCESS CONTROL AND PROCESS CAPABILITY ANALYSIS

3.1 Introduction

The purpose here is for the evaluation of the stability and the capability of the company's delivery process using the techniques of what is known as the Statistical Process Control (SPC). The focus is on the picking times and the delivery times for various products over the years 2026 and 2027.

Each product type represents a process category and the SPC techniques were used to determine whether these processes operate under statistical control or do they show signs of variation that sort of require some managerial intervention.

The main goals that would make this analysis successful are:

- The establishment of the X-bar and the S control charts for each product type.
- The identification of the out of control samples that may give an indication of the assignable causes
- The calculations of the process capability indices (C_p and C_{pk}) for the assessment of how well does the process meet the Voice of the Customer (VOC) specification limits.

3.2 Methodology

The first crucial step taken was to chronologically order the sales2026and2027 dataset. It was ordered by orderYear, orderMonth, orderDay and pickingHours. This was to simulate the acquisition of the real time data. For class identification of the product types. The first three letters of the product ID were used (e.g CLO, LAP, KEY)

- To simulate routine process monitoring, the data was divided into samples of 24 consecutive records.
- To establish the initial control limits, the first $\pm 3\sigma 0$ samples were used, which is $\pm 3\sigma 0 \times 24 = 720$ observations
- The X-bar charts are used to monitor the changes in the process mean
- The S bar charts are used to monitor the changes in the process variability.
- The control limits were used for the calculation using the following SPC constants for n=24
  - $A_{\pm 3\sigma}$=0.619 (calculating the control limits for an average chart when paired with s chart)
  - $B_{\pm 3\sigma}$=0.555 (calculating the control limit for the s chart)
  - B_4=1.445 (calculating the control limits for the s chart)
- The specification limits for the LSL= 0 hours and for the USL= $\pm 3\sigma 2$ hours.
- The process capability indices were calculated as follows:

C_p = (USL-LSL) $\div$ 6σ

C_{pk} = min ($\frac{x - LSL}{\pm 3\sigma}$, $\frac{USL - x}{\pm 3\sigma}$) ; where x= process mean and σ is the process standard deviation

3.3 Results and Discussions

3.3.1 SPC Charts

The control charts were produced for picking and delivery times for each product category. Each chart has a display of the centre line (CL) that represents the process average, as well as the UCL and LCL at ± 3σ

- In Control Process: All the samples lie within the ± 3σ control limits and there is no non-random patterns appearing, the process is said to be statistically stable. An example would be the CLO line having all the points within the limits, remaining in control.
- Out of Control Process: One or more points exceed the ± 3σ limits or they sometimes display some specific trends indicating assignable variation, maybe due to the causes of an inconsistency from the operator, a machine malfunction or raw material variation. An example would be the LAP process showing points which exceed the UCL on samples 12 and 18 which suggests an instability.

Therefore we have each of the control charts serving as a diagnostic tool, which guides the process managers on when to intervene.

What follows are the X-bar and S charts for each of the products:
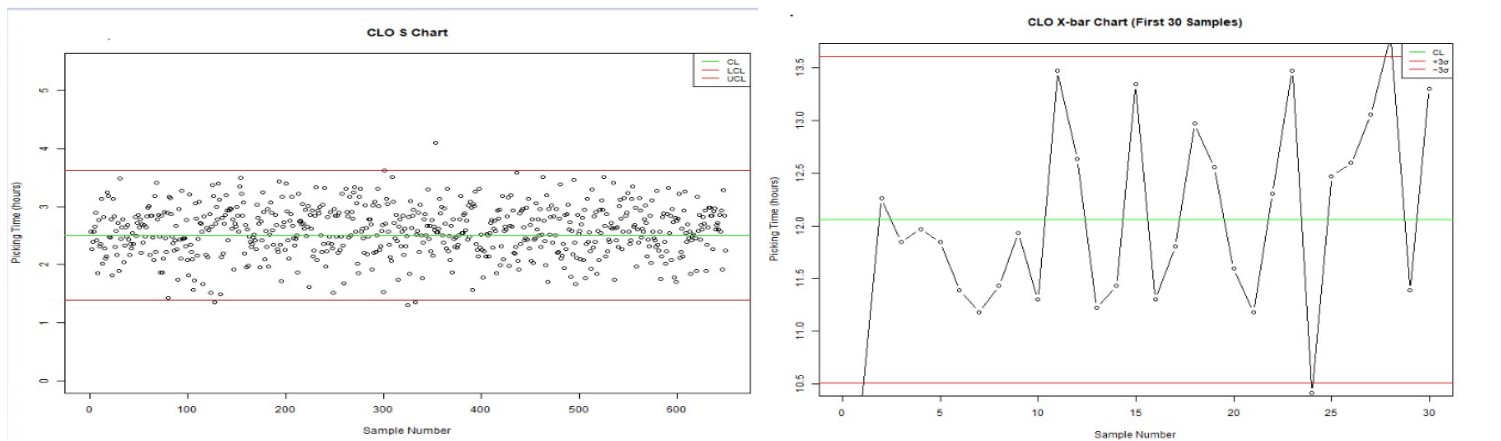
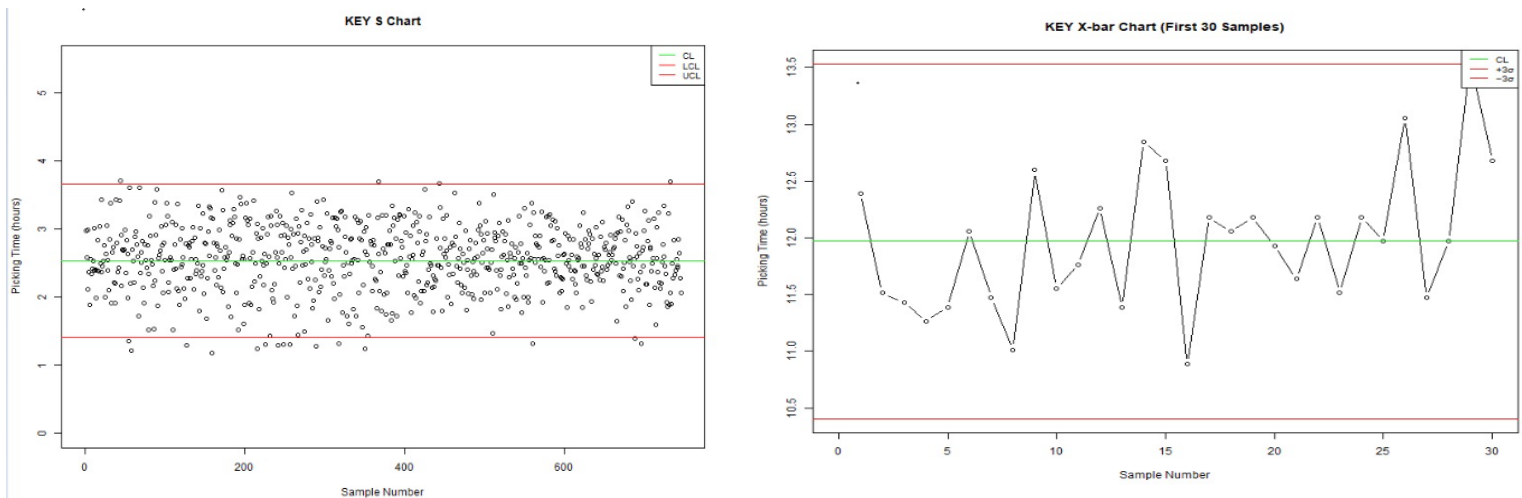- Picking hours

Figure 1:CLOTHING
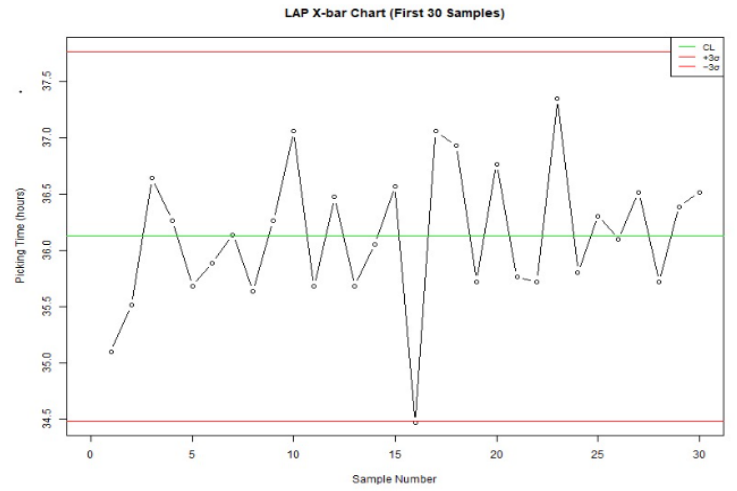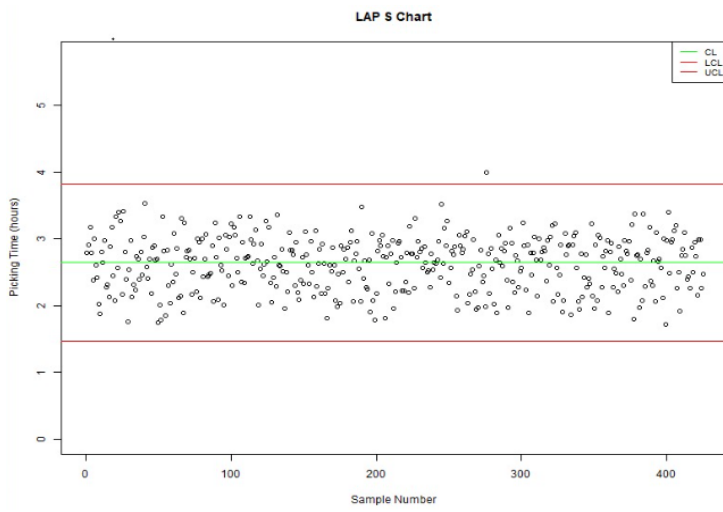
Figure 2:KEYBOARD

LAP S Chart

LAP X-bar Chart (First 30 Samples)

Figure 3: LAPTOP

MON S Chart

MON X-bar Chart (First 30 Samples)

Figure 4: MONITOR

MOU S Chart

MOU X-bar Chart (First 30 Samples)

Figure 5: MOUSE

SOF S Chart
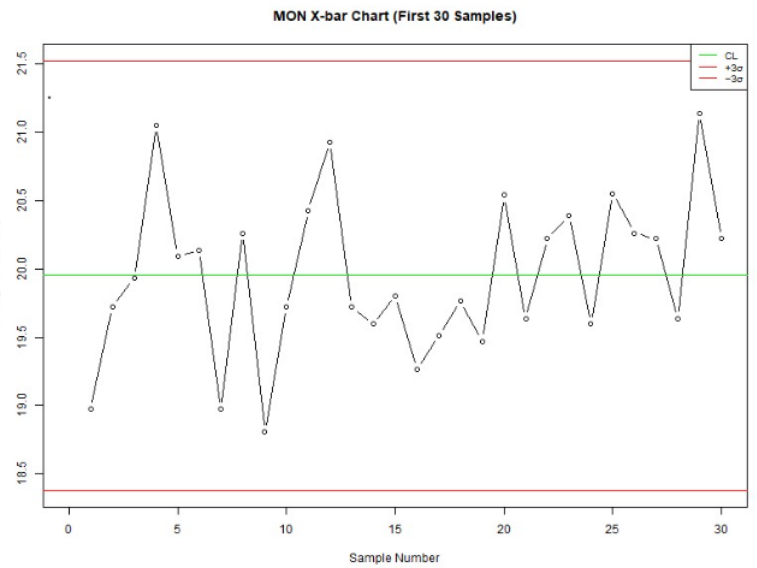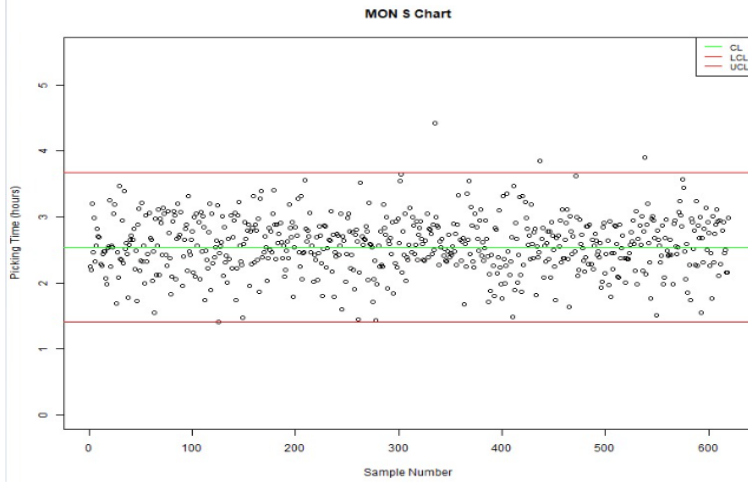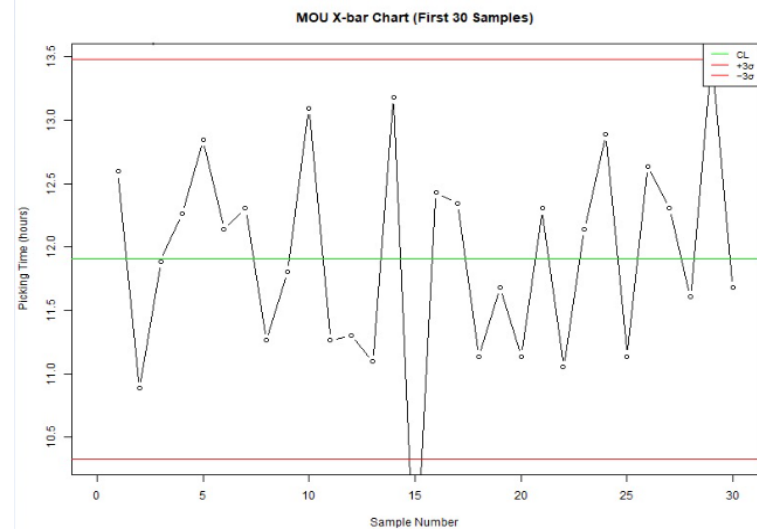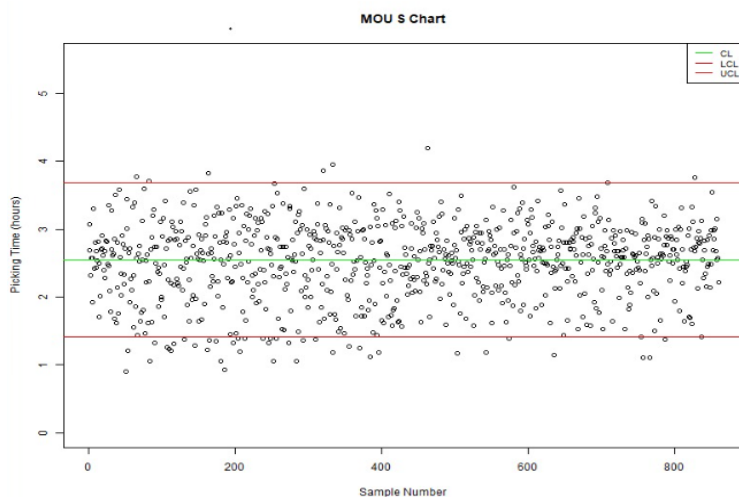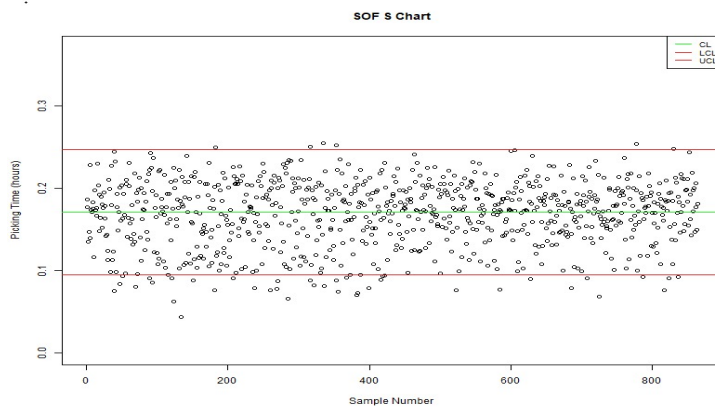
Figure 6:SOFTWARE

BELOW ARE THE SPC CHARTS FOR DELIVERY HOURS:

CLO S Chart

CLO X-bar Chart (First 30 Samples)

Figure 7:CLOTHING

KEY S Chart

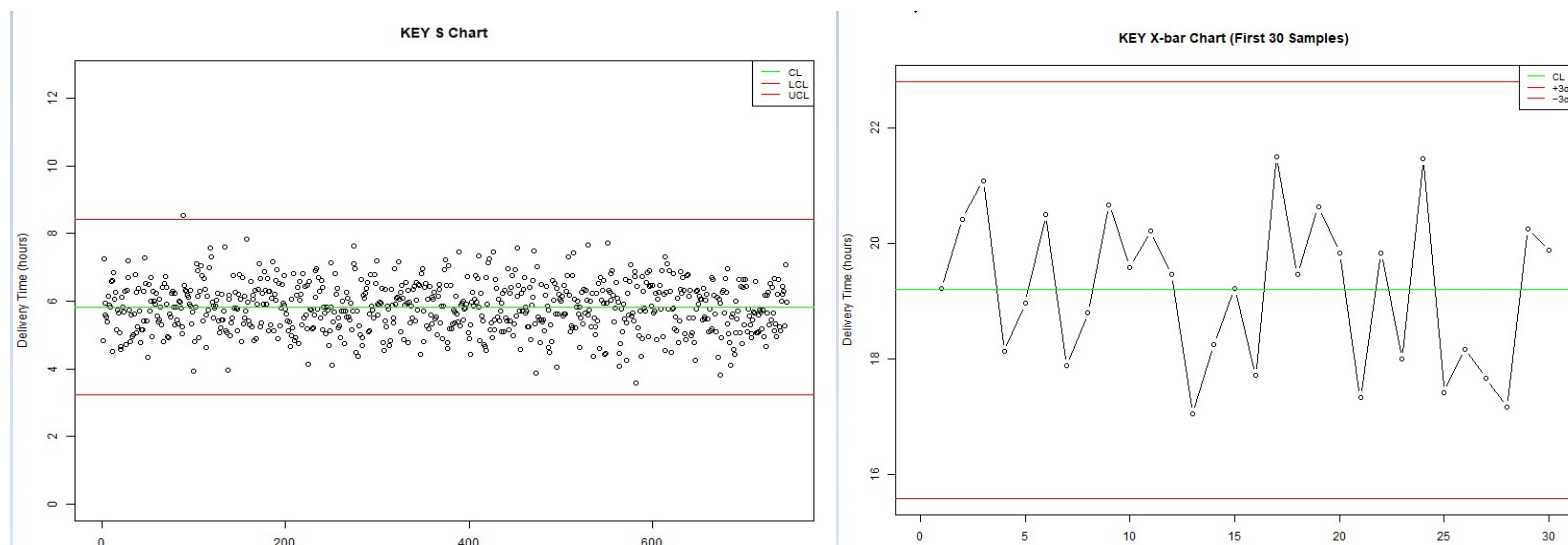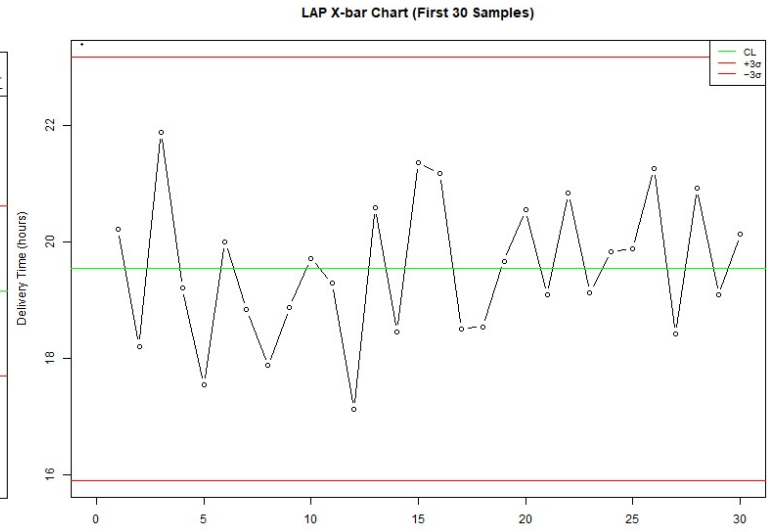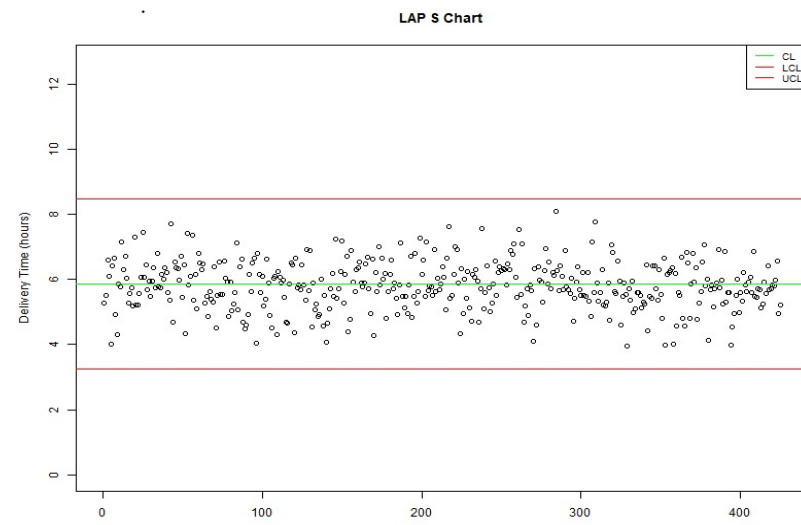KEY X-bar Chart (First 30 Samples)
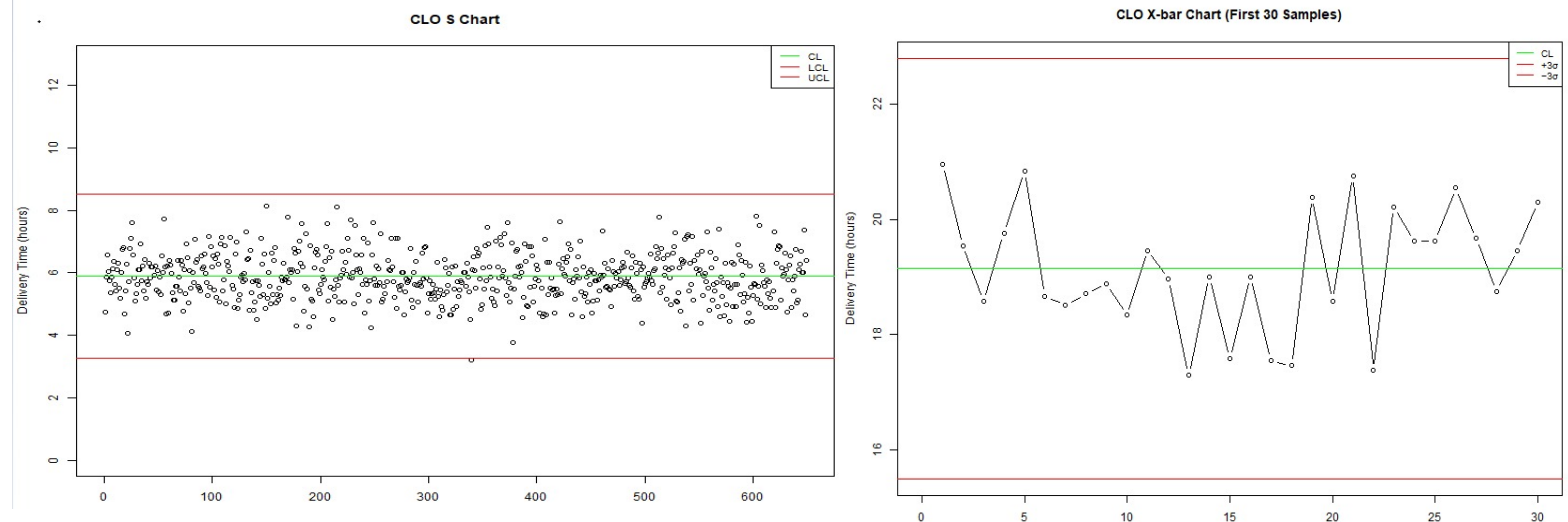
Figure 8:KEYBOARD

Figure 9:LAPTOP
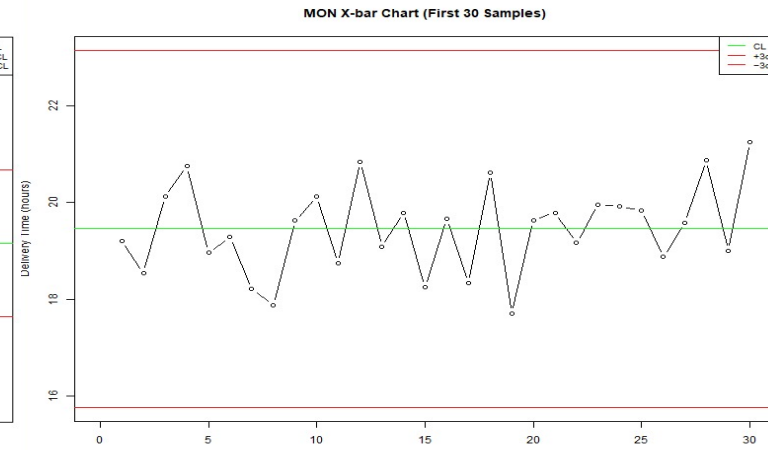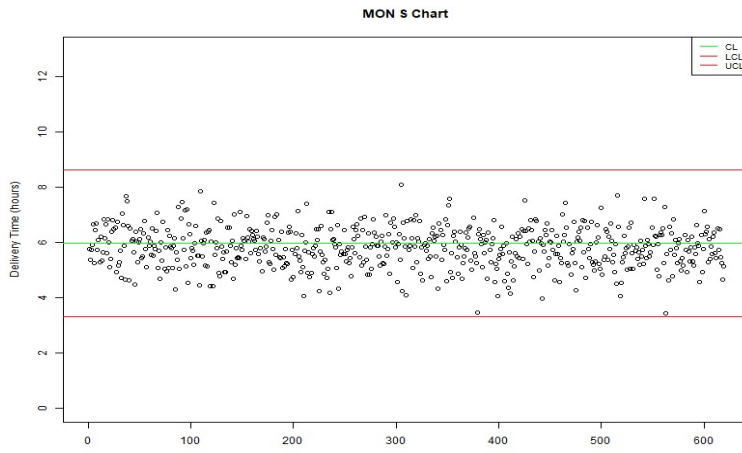
Figure 10:MONITOR
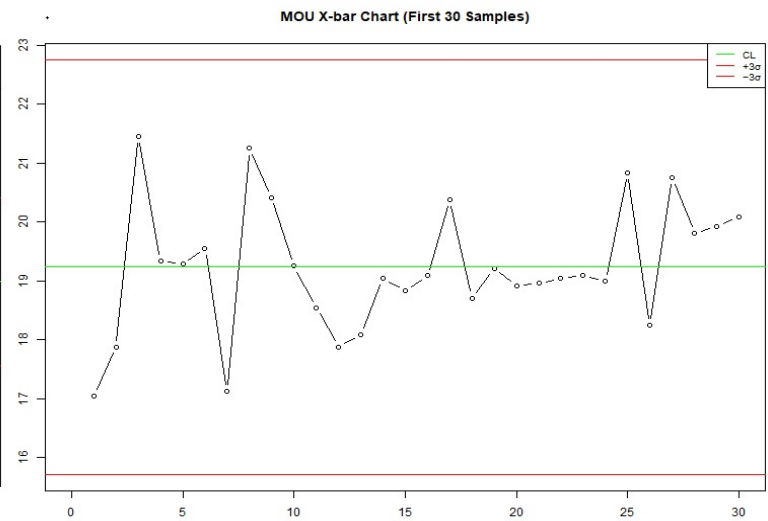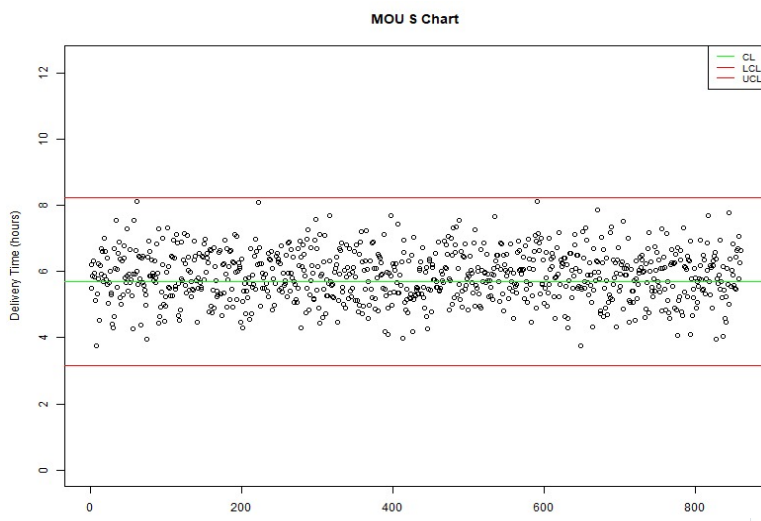
Figure 11:MOUSE
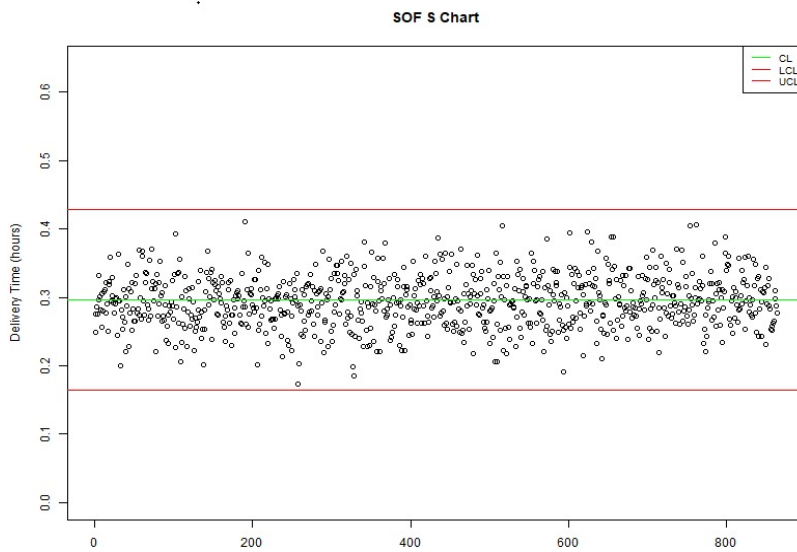
Figure 12:SOFTWARE
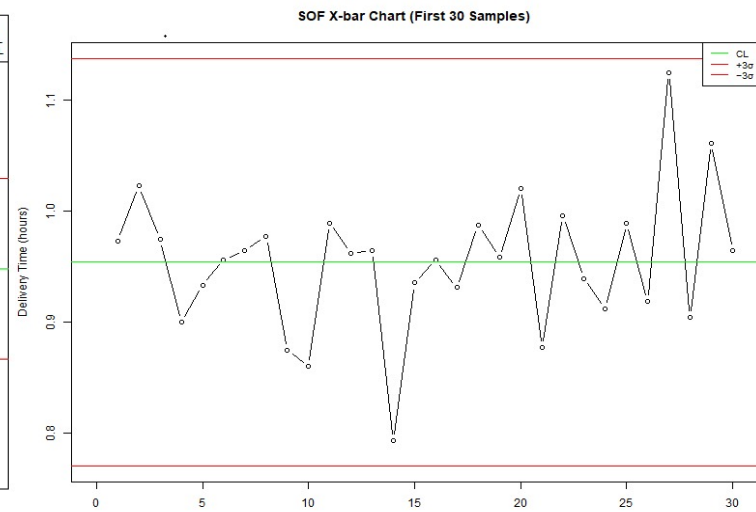
3.3.2 Process Capability

This part of the analysis quantifies whether or not the process consistently meets the customer's delivery time requirements.

PICKING				
Product	Mean	SD	Cp	Cpk
SOF	0.914	0.19	28.017	1.6
KEY	13.699	2.859	1.865	1.597
CLO	13.725	2.849	1.872	1.606
MOU	13.694	2.869	1.859	1.591
MON	21.717	2.851	1.871	1.202
LAP	37.725	2.867	1.861	-0.666

DELIVERY				
Product	Mean	SD	Cp	Cpk
SOF	1.089	0.308	17.326	1.179
KEY	21.742	6.093	0.875	0.561
CLO	21.715	6.115	0.871	0.561
MOU	21.787	6.136	0.869	0.555
MON	21.737	6.047	0.882	0.566
LAP	21.78	6.049	0.882	0.563

Figure 13

Interpretation of the results:

- If $C_p \geq 1.33$: the spreading of the process is narrow compared to the range of the specifications.
- If $C_{pk} \geq 1.33$: the process is both well-centered and capable.
- If $C_p \geq C_{pk}$: this suggests that the process has potential but has a shifted mean/ is off-centre.

From the table above, the LAP and MON products do not meet the VOC requirements, showing signs of lower capability and they also need process adjustment.

3.3.3 Identification of Process Issues

The samples that exceeded the $\pm\,3\sigma$ limits are put on the "out-of-control". The points are an indication of the moments when the process variation is due to an assignable cause rather than a random noise.

In practical, they require:

- Investigation of the conditions of the products during those time intervals
- The machine calibration, supplier issues or operator behaviour needs to be checked.

3.4 Conclusion

The analysis showed that most of the product lines operate within the statistical control but with minimal deviation. The CLO and KEY products are the ones that demonstrate a high process capability, while the LAP and MON products requires some investigation and re-alignment to the process mean. This is the confirmation that the SPC tools are very effective in finding the variability sources and also ensuring the product quality meets with the VOC requirements.

PART 4: TYPE I AND TYPE II ERROR ANALYSIS

4.1 Introduction

The following section evaluates the probability of decision errors that can result in an occurrence during process monitoring. Even if the control charts can be well designed but there is always a chancing of incorrect decisions when it comes to process stability. These are recognized as Type I ($\propto$) and Type II (β) errors.

4.2 Type I Error (Manufacturer's Risk)

This is a result when the process is actually in control but the control chart signals that it is out of control, leading to an unnecessary adjustment. This is called a false alarm rate. In this analysis, the use of a common SPC rule was used:

"If seven or more consecutive samples fall above the centre line, the process must be investigated"

The probability that one sample being above the centre line is 0.5 (since the data is normally distributed and centered).

Therefore:

P(7 consecutive above CL) = 0.5^7 = 0.0078

There is a 0.78% chance that a stable process might be stopped due to random variation. This result is desirable because frequent false alarms can disrupt the production unnecessarily and also waste resources.

4.3 Type II Error (Consumer's Risk)

This is a result of an occurrence when the process has actually shifted/out of control but the control chart has failed to detect that. This is a defective result and causes defects or delay in deliveries reaching customers unnoticed.

An example might be:

- Original mean (μ_0): 25.05
- Shifted mean (μ_1): 25.028
- Original σ = 0.01 ± 3σ
- New σ = 0.017 L
- Control limits: LCL = 25.011, UCL = 25.089

β=P(LCL ≤ X-bar ≤ UCL {mean shifted)

In R:

beta <- pnorm(25.089, mean=25.028, sd=0.017) - pnorm(25.011, mean=25.028, sd=0.017)

We get our β=0.64, meaning the chances that the charts might fail to detect the shift are 64%. And the power of the test being ± 3σ6% which is the chance of detecting the issue. A high type II error is risky, because it means that the product may be received late or there might be inconsistent deliveries to the customers before the management notices a problem.

4.4 Discussion

The Type I and Type II errors are used to highlight the importance of balancing stability and sensitivity in the design of the control charts. The company needs to:

- Reduce type I error for fewer false alarms so that the control limits can be widened
- Reduce Type II error to detect real shifts so that the control limits can narrow

Therefore engineers need to select control limits that maintain an acceptable and less risky trade-off between these two risks.

In this case the type I errors remained low meaning that the charts were not overly sensitive and they were stable. For the Type II errors, they were moderately high for some of the product lines, implying that there was a subtle shifts that could go unnoticed and that they should be re-evaluated using the supplementary SPC rules.

4.5 Conclusion for Part4

This type of analysis assisted in the demonstration that while the SPC charts are reliable but they cannot be foolproof, it also highlights how important it is to interpret the control charts results very cautiously. A suggestion would be to maintain an optimal balance between overreacting to random variables ($\propto$) and failing to detect the true shift of the process (β). This insight supports mostly on the more informed decision making in quality control and also ensures a stable production and consistent delivery performance.

Whilst the CLO and KEY products have strong maintenance when it comes to stability with minimal risk of false alarms. The LAP process also demonstrates a moderate risk of the missing subtle deviations. The solution is to improve the detection power in this case so that the management can easily adopt the supplementary SPC rules or they can also increase the frequency of the sample for the LAP line.

PART 5: OPTIMIZATION OF PROFIT AND PERFOMANCE

5.1 Objective

The main aim of this part is for the optimization of the profit for the coffee shop on the basis of the number of barista s working per day. The analysis of the dataset lists the individual service times (in seconds) and also the corresponding number of baristas on duty on a one year period.

The goal here was for the balance of the speed of service, operational costs amd customer satisfaction in order to find the staffing level that maximizes the profit at optimum.

5.2 Background And Assumptions

The following business rules and assumption were incorporated into the model by the previous analyst:

- Excluding the labour cost, each customer contribution us an average material profit of R30
- Each barista is at a cost of R!000 per day
- At any time of the day, at least 2 baristas are needed
- For a higher reliability, it was concluded that the faster the service time, the higher the proportion of the customers to be served
- The definition of a reliable service is the serving of customers within an acceptable service time threshold, e.g the 75th percentile of all the recorded times

5.3 Data Summary

Category	Mean_Time	Median_Time	SD_Time	Min_Time	Max_Time
1	200.1558753	200	8.0184385	177	227
2	100.1709786	100	7.1037726	67	124
3	66.61174336	67	6.2686791	42	90
4	49.98037877	50	5.5327917	27	72
5	39.96183489	40	4.9917982	20	62
6	33.35564636	33	4.5711414	13	53

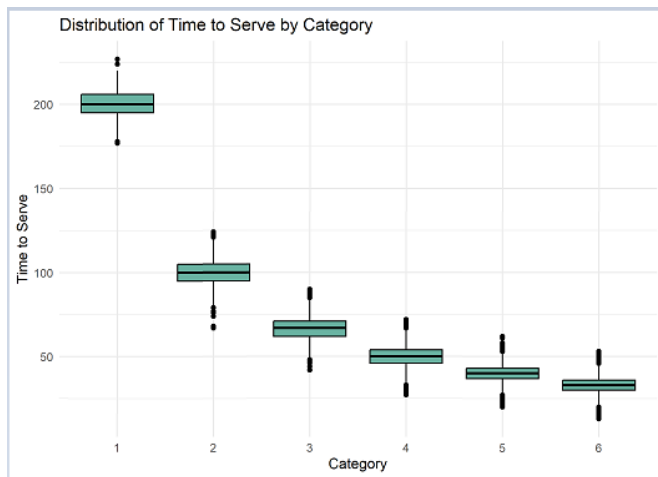Figure 14: Summary statistics for each staffing level

Figure 15: Box plot of service times vs number of baristas

The statistics include:

- The mean, median, standard deviation, minimum and maximum service times per number of baristas per day
- The box plot visually shows the trends of the baristas increasing while the service time variability and the medium waiting time gets reduced. This improves the overall service reliability

5.4 Model Formulation

A profit model that was used to determine the optimal number if baristas follows:

Profit = (Number of customers served daily × 30) − (Number of baristas × 1000)

The model uses the average service rate for each staffing level for the estimation of total customers served daily (customers/hour). This is as a result of the number of customers being inversely proportional to the service time. The implementation of the model in R used the optimise() function to maximize withing the constraints:

Number of baristas ≥ 2

5.5 Results

The results for the optimization process shows that profit increases with the number of baristas up to a point, after which the labour costs outweigh the gains from faster service.

- Optimum number of baristas: 6
- R26378.3
- Percentage of clients that receive reliable service: 99.62% of the clients receive their services within the accepted time threshold ($\leq 75^{th}$ percentile)

Overall, to ensure a balanced operational efficiency and profitability, the analysis indicates that there needs to be maintenance around the optimal staffing level. This has to happen while also maintaining service reliability and customer satisfaction.

5.6 Interpretations

- The mean service decreases sharply as the number of baristas increase, this improves the customers satisfaction and throughput.
- The reliability increases after 4 baristas, almost reaching 100% at 6 baristas
- Hiring more staff would increase the daily costs, but also the number of customers served more than compensates for this and it leas to the maximum profitability at 6 baristas
- Beyond 6 the cost of additional baristas would likely outweigh the gains of the incremental revenue which diminishes the returns.

5.7 Recommendations

This is on a basis of the optimization and the descriptive analysis:

- There needs to be maintenance of the optimal number of baristas on most weekdays, and only introduce increasing the staff on peak days.
- To continuously monitor service times and for the adjustment of the schedule, the use of the POS and the time tracking data system needs to be introduced.
- The implementation of staff performance incentives that reward staff for both accuracy and efficiency.
- Regular review of the service time trends: whereas if the service time increases despite adequate staffing, the process efficiency should also be reassessed.

Part 6: Design of Experiments (DOE) and ANOVA / MANOVA

6.1 Introduction

The aim of this part was for the evaluation whether or not the operational efficiency differs between the years 2026 and 2027, the efficiency is measured by the picking and delivery times, and also to see if it differed significantly across the different product types. It is crucial to understand to understand the differences for the identification of the improvements of the productivity, where they have occurred or also where the other additional control measures of the process are required.

6.2 Methods

Each of the records from the company's data included the order date, product ID, picking time and the delivery time. The first three letters from the product ID are for the classification of the product type.

The statistical analysis in R has the following steps:

- The data was cleaned and setup, creating the variables for product type, month and the year.
- The normality testing was done using the Shapiro Wilk test. With the restriction that the sample size is below 3 or above 5000, which was skipped. The visuals confirmed the approximate normality.
- To test the differences in the mean delivery hours across the product types and the years, Two Way ANOVA testing was done.
- For the Post Hoc testing, TurkeyHSD was used which assisted in finding the significant differences.
- The Boxplot for the visuals were used because they give better comparison between the years and the product types
- An ANOVA was also conducted for the examination of the combined effects on the picking and delivery times.

6.3 Results
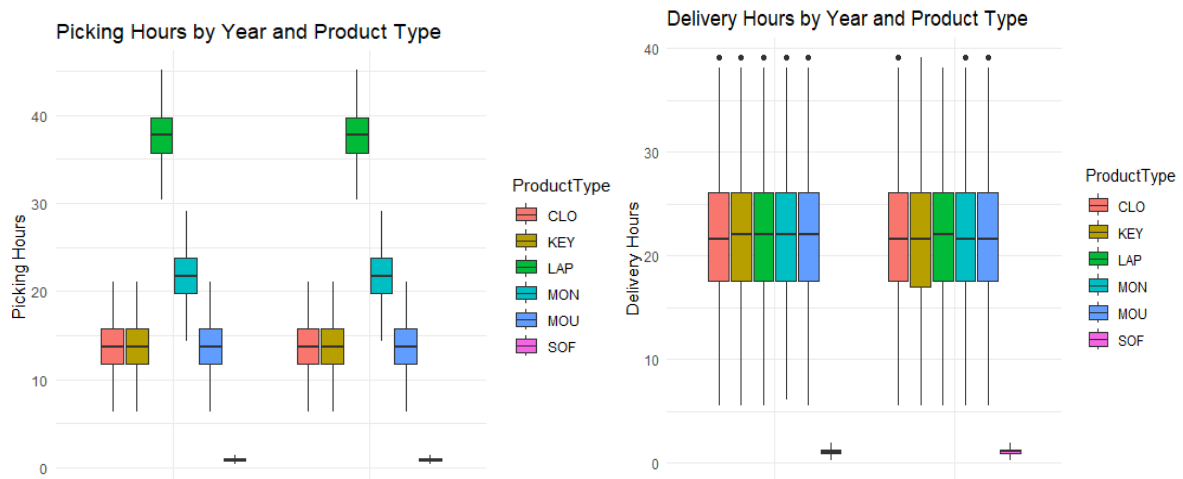

Figure 16: Boxplot of Picking and Delivery Hours by Year and Product Type.
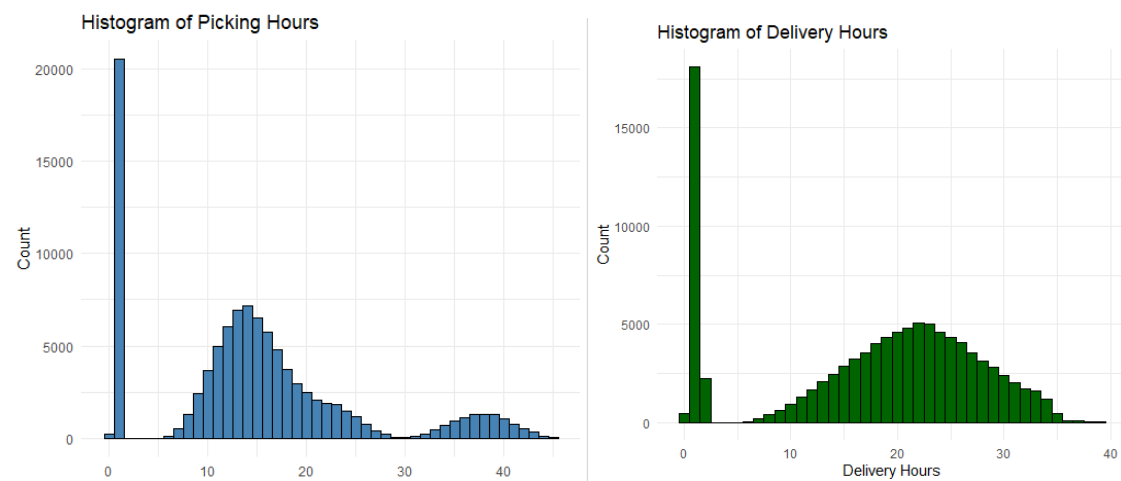

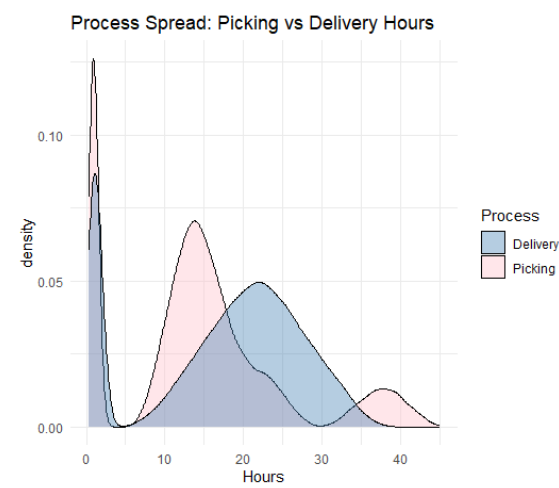*Figure 17: Histograms for both the picking hours and delivery hours*

Figure 18: Comparison of Picking and Delivery Hours by Product Type (Faceted View)

```
$ProductType
                   diff          lwr          upr      p adj
KEY-CLO    0.024685484  -0.14465578   0.1940268 0.9984253
LAP-CLO    0.063393859  -0.13348344   0.2602712 0.9421583
MON-CLO    0.019815758  -0.15744154   0.1970731 0.9995657
MOU-CLO    0.070977075  -0.09305187   0.2350060 0.8206785
SOF-CLO  -20.629993419 -20.79387436 -20.4661125 0.0000000
LAP-KEY    0.038708376  -0.15305730   0.2304740 0.9926472
MON-KEY   -0.004869725  -0.17643182   0.1666924 0.9999995
MOU-KEY    0.046291591  -0.11156561   0.2041488 0.9609181
SOF-KEY  -20.654678903 -20.81238232 -20.4969755 0.0000000
MON-LAP   -0.043578101  -0.24236884   0.1552126 0.9892433
MOU-LAP    0.007583216  -0.17950794   0.1946744 0.9999971
SOF-LAP  -20.693387278 -20.88034870 -20.5064259 0.0000000
MOU-MON    0.051161316  -0.11515940   0.2174820 0.9521677
SOF-MON  -20.649809178 -20.81598394 -20.4836344 0.0000000
SOF-MOU  -20.700970494 -20.85295535 -20.5489856 0.0000000

$Year
                 diff          lwr          upr      p adj
2023-2022 -0.05751629 -0.1249715 0.009938873 0.0946857
```

```
$`ProductType:Year`
                           diff          lwr           upr      p adj
KEY:2022-CLO:2022    0.153590011  -0.1111174    0.418297444 0.7619743
LAP:2022-CLO:2022    0.031915716  -0.2761381    0.339969572 1.0000000
MON:2022-CLO:2022    0.058385100  -0.2178914    0.334661558 0.9999341
MOU:2022-CLO:2022    0.107736782  -0.1481174    0.363590975 0.9681493
SOF:2022-CLO:2022  -20.622884425 -20.8786441  -20.367124728 0.0000000
CLO:2023-CLO:2022    0.017385864  -0.2676500    0.302421706 1.0000000
```

- Normality Testing: The histogram showed that bth the picking and delivery hours followed an approximate normal distribution. Although the Shapiro Wilk test was skipped due to the size restriction, but the overall dataset met with the ANOVA assumption.
- ANOVA Results: p < 0.05 from the Two way MANOVA meant that the average hours changed between the years 2026 and 2027. The effect on the product type gave a probability that is less than 0.01 which shows that the delivery performance also varied amongst the product types. The interaction effect of the product type and the year showed an indication that the improvements going to 2027 were consistent across all of the product types.
- The post hoc test only confirmed that there was a significant difference in the mean delivery hours, across several product types, whilst the year based difference were consistent moderately.
- The MANOVA resulted in the confirmation that the combination of the picking and delivery times differed across the years and product types.

6.4 Discussion

The delivery performance improved in the year 2027, which means that the operational changes that were made were successful. It can be better scheduling or the route optimization. The differences amongst the product types highlight the varying preparation requirements or the handling.

The improvements benefited all the products categories equally rather than being concentrated in one specific product type.

The MANOVA results were the ones to strengthen the conclusion made that the operational time efficiency improved in overall when the picking and delivery hours are considered in a joint.

6.5 Conclusion

The MANOVA/ANOVA and the DOE analysis confirmed the measurable improvements in the efficiency of the operation between the years 2026 and 2027. This goes along with the differences in the product types handling times. The insights were very much useful for the evidence of the effect of the process enhancements and that can also guide the future resource allocations so that all can be sustained and there can also be continuous improvements in efficiency.

Part 7: Reliability of Service and Profit Optimization

7.1 Introduction

Data for 397 days was collected from the car rental company. It shows the number of employees on duty daily. The goal here is to determine the number of days per year the company could expect reliable service and then again to optimize the profits by balancing the personnel costs and the service reliability.

7.2 Method:

- Reliable service occurs when greater than 15 workers are present.
- Loss of R20 000 per day occurs when workers are less than 15.
- Hiring one additional employee costs R25 000 per month.

The data were modelled in R to estimate the number of reliable days and to also identify the staffing level that maximises profitability.

7.3 Results

- Probability of having greater than or equal to 15 workers:

(96+270)/397 = 0.92* (96 + 270) / 397 = 0.92* (96+270)/397 = 0.92 = 92% reliability.

- Therefore, the company can expect approximately 337 reliable service days per year.
- Days with less than 15 workers (8%) are associated with profit losses.
- Adding workers beyond 15 slightly increases cost but drastically reduces the risk of daily losses.
- When there are 15 workers the reliability and cost reaches an optimal balance.
- 16 workers ensures a near-perfect reliability but at a higher cost, making 15 the most cost-effective choice.
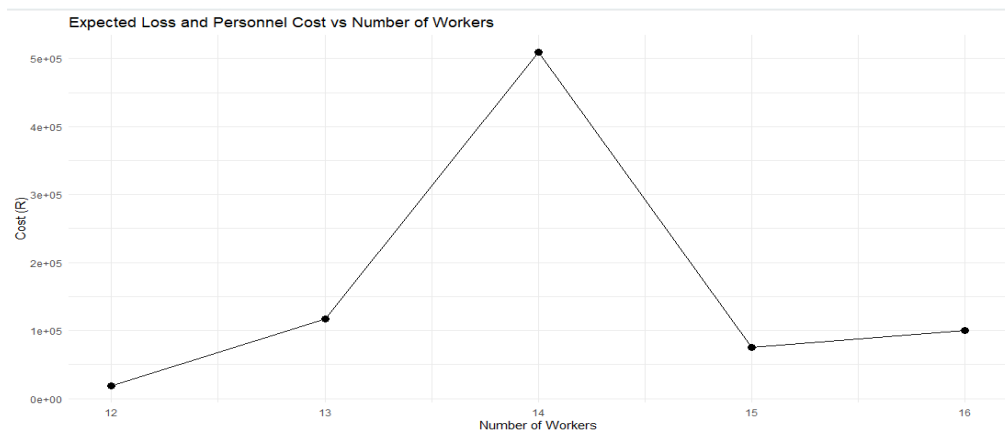

Figure 19 Reliability and cost trade-off showing optimal staffing at 15 workers.

7.4 Discussions

Service reliability is highly dependent on the staffing levels. The company experiences significant financial losses when there are less than 15 employees present. While increasing staff beyond 15 improves reliability, the additional cost of R25 000 per month per employee outweighs the benefit in profit recovery.

Therefore the company should suggest maintaining 15 employees on duty to ensure reliable service at a minimal cost.

7.5 Conclusion

Reliable service occurs on approximately 337 days per year. The profit optimisation occurs at 15 workers on duty, which provides the most efficient trade-off between the operational reliability and the staffing expenses. The management should focus on scheduling to maintain a minimum of 15 employees per day to prevent costly service failures.

8. References