10/24/2025

ECSA Project

25862405

Ackerman, FD, Mr [25862405@sun.ac.za]

Contents

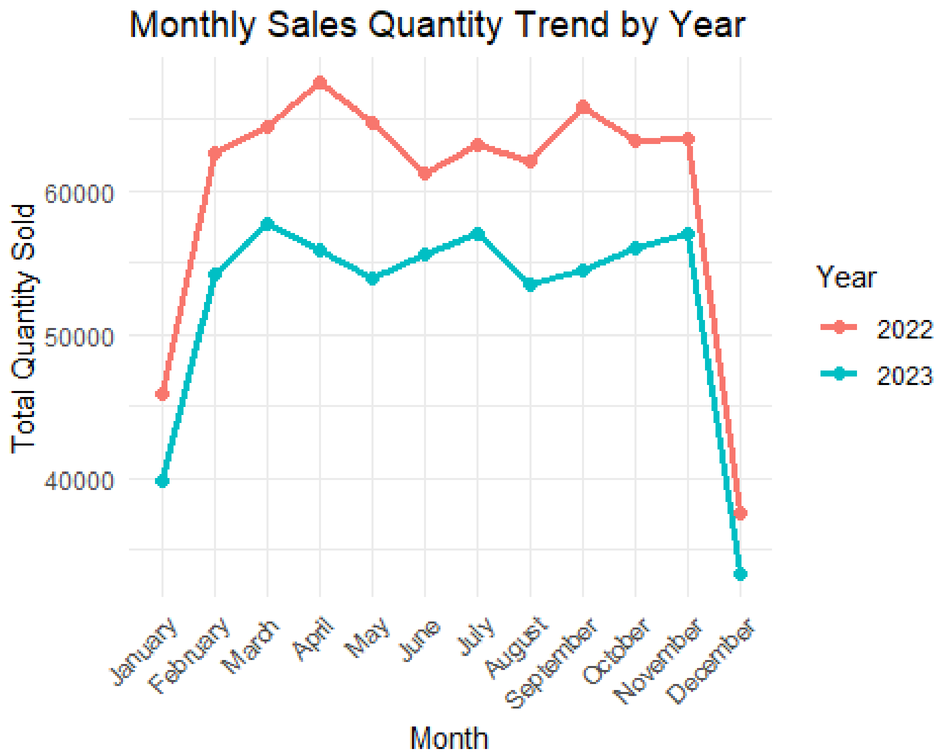
Introduction

This report demonstrates competency in Graduate Attribute 4 (GA4) of the Engineering Council of South Africa (ECSA), which assesses the ability to apply data analysis and computational methods to solve complex engineering problems. Using R programming, the report applies statistical tools to real datasets involving product, sales, and service operations.

Descriptive statistics were first used to understand data distributions, variation, and relationships between variables. Process capability indices (Cp and Cpk) and Statistical Process Control (SPC) charts were then applied to assess process stability and identify out-of-control signals. The risks of Type I and Type II errors were calculated and interpreted in the context of process reliability.

Data correction procedures were implemented to ensure accuracy between local and head-office datasets. Optimisation models for two coffee shops were developed to determine the ideal number of baristas that balance service efficiency and profit. A reliability and staffing model for a car rental agency further demonstrated how statistical reasoning supports operational decision-making. Finally, ANOVA and MANOVA analyses were conducted to identify significant differences in process performance across time and product types. Together, these analyses illustrate data-driven problem-solving in line with ECSA GA4 expectations.

Part 1



Interpretation of Monthly Sales Trend

The monthly sales quantity graph shows a clear pattern. Sales remain high during most of the year. Two major peaks are visible in April and September. A sharp decline is seen in December and January. The same trend is visible for both 2022 and 2023. The main difference is that 2022 shows higher sales volumes than 2023.

Stable Demand Pattern

Sales quantities are consistently high during most months. This shows that technology products have a steady level of demand. Computers and related technology are used for study, work, and personal purposes throughout the year. The market is therefore not dependent on a single short season. This stability is valuable for planning production and inventory. It also confirms that the product type is considered an essential purchase rather than a luxury.

April Peak

The first major peak is seen in April. This is linked to the South African academic calendar. The school and university year begins in February, but by March and April many families purchase or upgrade laptops and accessories. The start of assignments and online learning increases demand for technology. April also contains several public holidays such as Easter and Freedom Day. Retailers often run promotions during this time, which further stimulates sales. The April rise therefore comes from both the education cycle and consumer promotions.

September Peak

The second major peak is in September. This is linked to the international technology release cycle. Major companies such as Apple, Samsung, and PC hardware manufacturers often introduce new products in the third quarter. Consumers delay purchases to wait for new models, then buy once they are released. This creates a strong September spike in sales. September is also the start of spring in South Africa. Warmer weather and more social activity may also play a smaller role in increasing demand.

December and January Decline

Sales quantities fall sharply in December and January. This does not match the normal retail cycle, where December is usually a high sales period. The explanation lies in the customer base. Technology is often purchased by businesses, schools, and universities. These institutions close during December and January. Procurement budgets are usually used before year-end, and spending slows during the holiday break. Families also focus spending on travel and festive goods instead of technology. The low volumes therefore come from both supply-side shutdowns and reduced demand. Activity starts again only from February onwards.

Comparison of 2022 and 2023

The shape of the sales trend is almost identical for both years. This shows that the demand pattern is consistent and predictable. However, 2023 volumes are lower in every month when compared to 2022. The reduction does not come from a change in consumer behavior but from overall lower demand. Several factors may explain this drop. Economic pressure on households reduces ability to spend on technology. The weak South African Rand increases the cost of imported products. Consumers and companies may also delay upgrades, keeping devices for longer. These external factors explain the decline while the underlying seasonality remains unchanged.

Business Implications

Several lessons can be drawn from this analysis:

Inventory planning: Stock should be built ahead of April and September peaks to avoid shortages.

Staffing and logistics: Extra resources should be allocated in peak months. Reduced staff may be scheduled in December and January when sales are low.

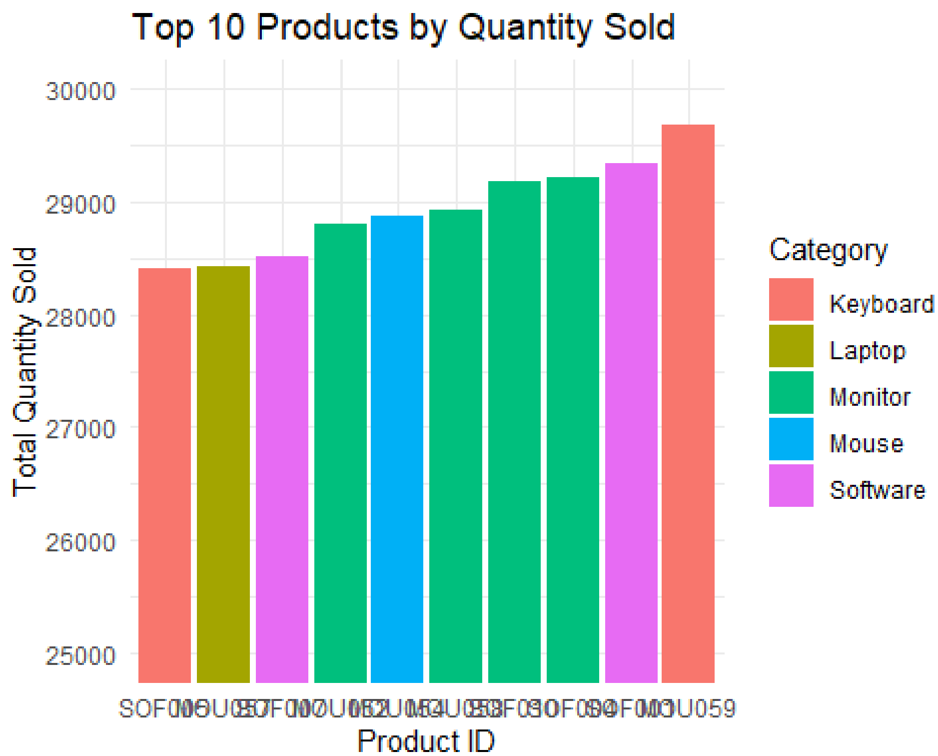
Marketing campaigns: Campaigns should focus on traditionally slow months such as February and November to smooth out demand. Back-to-school promotions should target February and March, before the April peak. Product launch campaigns should be aligned with the global release cycle in September.

Strategic focus: The year-on-year decline is a concern. Management should investigate whether the cause is economic, competitive, or internal. Actions may include competitive pricing, exploring new sales channels, or negotiating better import terms to reduce cost pressures.

Top 10 Products by Quantity Sold

Product Categorising Issues

The letters in the product codes are meant to indicate the category. However, the data shows inconsistencies. Several codes contain scrambled or incorrect letters. A large portion of products have ‘NA’ in place of letters, meaning the category is unknown. This inconsistency reduces the usefulness of categories for analysis. Without proper categories, it is difficult to group products or compare performance across product families. It also increases the risk of errors in reporting, forecasting, and inventory management.



Value of the Top 10 Products

Despite the categorizing problems, the top 10 products are clearly visible. They represent the core of the company’s sales volume. Together, these products likely contribute a significant portion of total revenue. Focusing on these products provides direct insights into customer demand. The concentration of sales in a small number of products is typical in technology markets. It reflects the 80/20 principle, where a small range of items drives the majority of sales.

Demand Concentration

The graph confirms that sales are not evenly spread across the product portfolio. A few products dominate. This means that effective management of these top products has a strong impact on overall performance. For example, stock shortages in the top 3 products would affect sales more than shortages in all other products combined. Conversely, promotions or marketing on these items could quickly raise total sales.

Risks of Poor Categorization

The incorrect or missing product categories create several risks. It prevents proper tracking of which product types are performing best. It hides patterns in demand for laptops, accessories, or components. It makes it harder to identify substitution effects when one product is out of stock. It also reduces the ability to compare sales performance across time, because products may be classified differently from year to year. Fixing the categorization of the items should therefore be a priority.

Strategic Use of the Graph

In spite of the flawed categories, the histogram highlights which exact product codes must be prioritized. Procurement and inventory teams should ensure that the top 10 products are always available. These products should be stocked in higher safety quantities. Reorder points should be set carefully to avoid stock-outs. Marketing campaigns should highlight these items, as they already attract high demand. Customer support should be trained to focus on these items, since most customer queries will involve them.

Improvement Actions

Several actions can strengthen decision-making around this data:

Data cleaning: Rebuild the product categorization system so each code has the correct category.

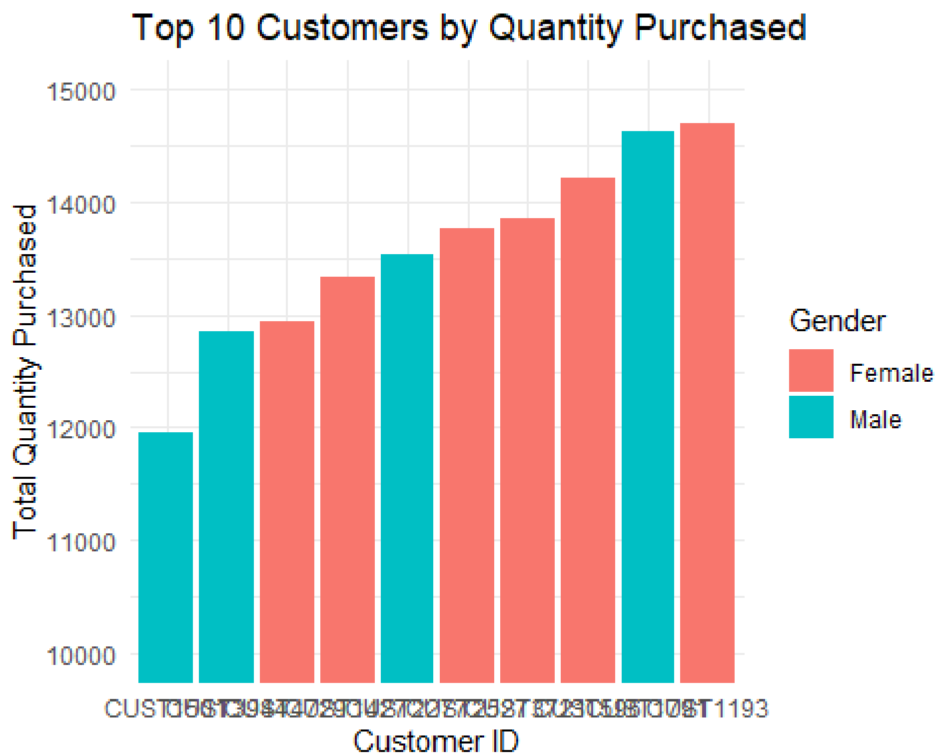
Category mapping: Reassign ‘NA’ codes into known categories where possible.

Portfolio analysis: Re-check whether the top 10 products belong to the same category or span multiple categories.

Supplier strategy: Negotiate favorable terms with suppliers of the top-selling items.

Risk management: Develop backup suppliers for these products to reduce dependency.

Top 10 Customers by Quantity Purchased



Interpretation of Top 10 Customers by Quantity Purchased

The histogram shows the ten customers who purchased the most products. The layout is the same as the previous product histogram. The left side shows the customer in 10th place. The right side shows the number one customer with the highest quantity purchased.

Gender Distribution

Among the top 10 customers, six are female and four are male. This difference is not large enough to suggest a clear trend. It cannot be concluded that gender strongly affects purchasing volume. The mix shows that both male and female customers contribute significantly to top sales.

Income as a Possible Factor

Income may influence purchasing behavior, but it is not confirmed by this graph. The products sold do not have high markups and are not positioned as premium. This suggests that the company is not targeting the upper class specifically. If higher-income customers appear in the top 10, it is more likely because they can afford to buy in bulk. Their purchasing is therefore driven by the need for large quantities, not by product exclusivity. To confirm whether income is a strong driver, further analysis with the available income data would be required.

Value of the Top Customers

These customers are highly important to the company. They represent the largest share of sales volume from individuals. Losing one of these top customers would have a noticeable negative impact. Retaining them is as important as acquiring new customers. They also show the type of loyalty and purchasing behavior that the company should try to encourage in others.

Business Opportunities

Targeting: If income is the key factor, advertising campaigns can be aimed at higher-income individuals. Segmentation: Understanding what products these customers buy can help tailor offers for similar profiles. Upselling: Offering premium bundles, extended warranties, or accessories can further increase sales from these customers. Referrals: Encouraging top customers to refer friends or colleagues can expand the base.

Rewarding Top Clients

Retention is crucial for top clients. They should be recognized and rewarded for their loyalty. Several approaches can be used: discount programs, loyalty schemes, personalized service, gifts, and events. Rewarding top customers improves satisfaction and increases retention. It also strengthens the brand image and encourages repeat purchases.

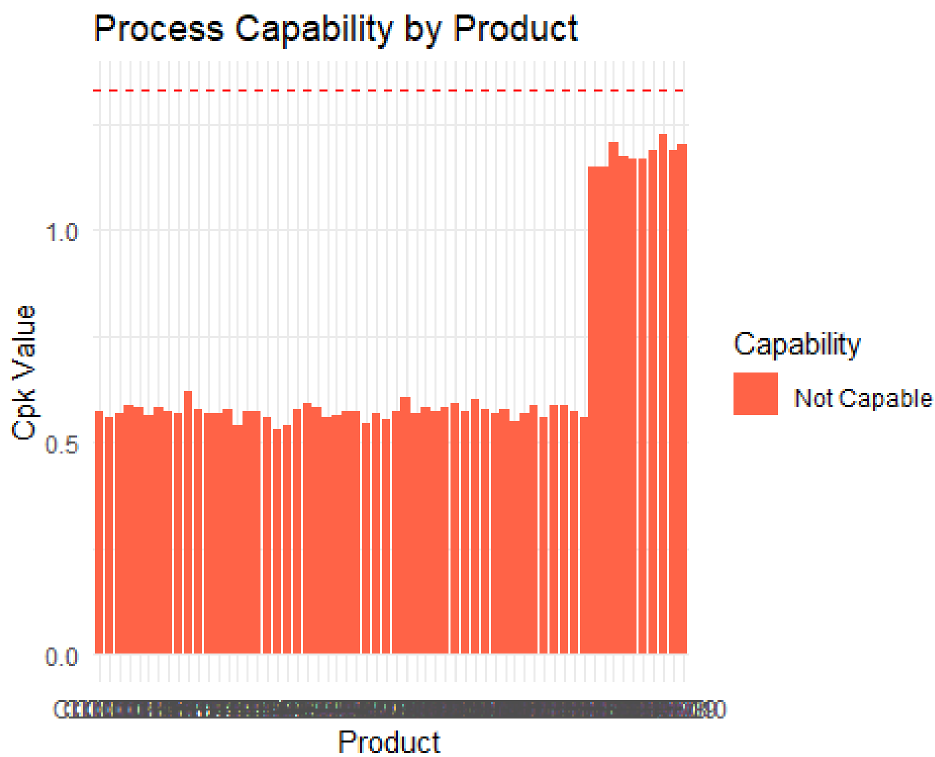
Risks and Considerations

There is a risk of focusing only on the top customers. This could cause the company to ignore the rest of the market. The majority of revenue may still come from a large number of smaller customers. Therefore, rewards for top clients must be balanced with strategies to grow the broader customer base. Income targeting should also be done carefully, so as not to exclude potential mid-income customers who could grow into top spenders.

Part 2

2.1 Process Capability by Product

The process capability chart presents the Cpk values for each product. Capability (Cpk) measures how well a process produces output within specification limits. A Cpk value of 1.33 or higher is considered acceptable, indicating that the process consistently meets customer requirements. In this analysis, the chart shows that all products fall below the 1.33 threshold, meaning none of the products are capable. The red dashed line at 1.33 highlights the target capability level, which is not achieved for any product.

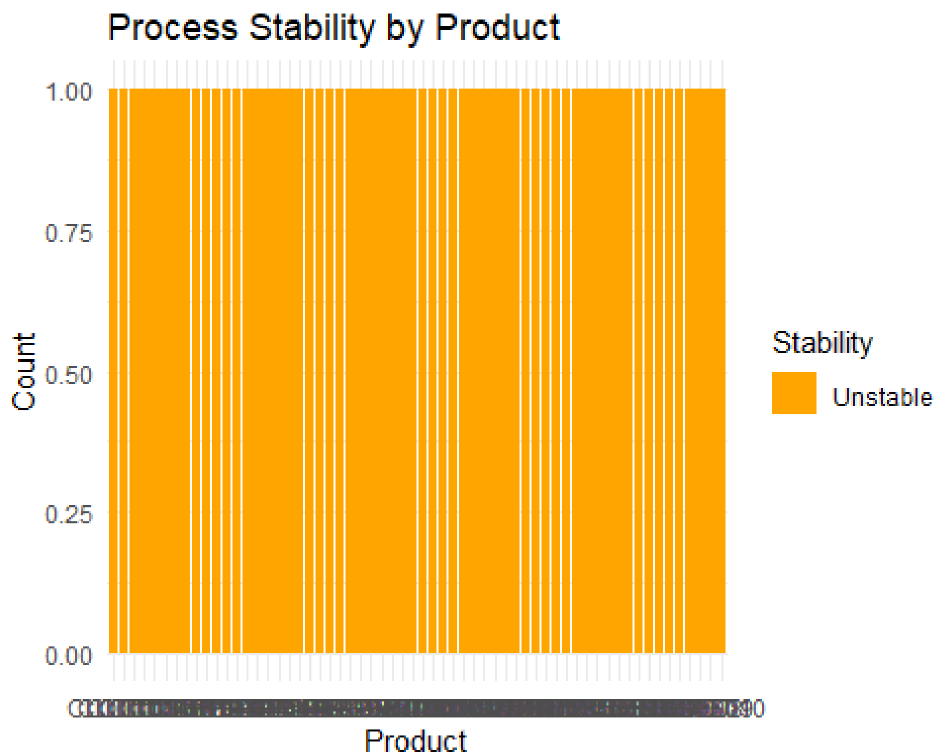


The classification was based on standard SPC rules for process capability. These rules ensure that both centering and variation are considered. Even a centered process can fail if the variation is too high. Low Cpk values indicate that the variation in the processes for all products exceeds acceptable limits, preventing consistent conformance to specifications.

Potential causes include machine wear or drift, inconsistent raw material quality, operator-related variability, and environmental factors such as temperature or humidity changes.

Recommended actions to improve capability include implementing tighter process controls, standardizing work procedures, and conducting preventive maintenance on equipment. Operator training and monitoring of raw material quality will reduce variation. Machines should be recalibrated regularly, and Cpk values should be monitored continuously to assess improvement effectiveness.

2.2 Process Stability by Product



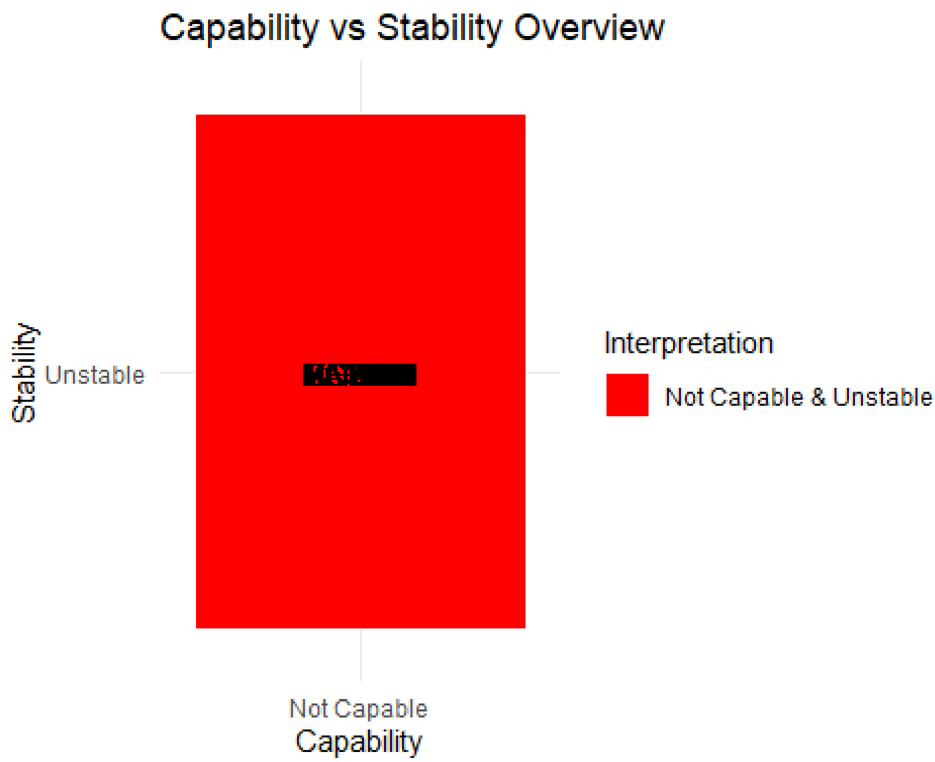
The process stability chart illustrates the number of stable and unstable occurrences per product. Stability refers to the process being in statistical control, meaning that variation is predictable and only due to common causes rather than special causes. In this case, all products were classified as unstable, showing that variation is irregular and influenced by external or assignable causes rather than inherent process variation.

Stability was assessed using standard SPC rules, which detect trends, runs, or points outside control limits. The application of these rules ensures that any abnormal variation is identified. The finding that all products are unstable highlights that none of the processes are consistently controlled over time, and all require investigation.

Potential causes include irregular machine performance, sudden changes in raw material quality, environmental fluctuations, operator inconsistency, and frequent process adjustments without proper documentation or control.

Actions to improve stability include implementing control charts for real-time monitoring, identifying and addressing special causes of variation, and standardizing procedures. Preventive maintenance and operator training are essential to maintain process control. Continuous monitoring and periodic audits will help achieve stability across all products.

2.3 Capability vs Stability Overview

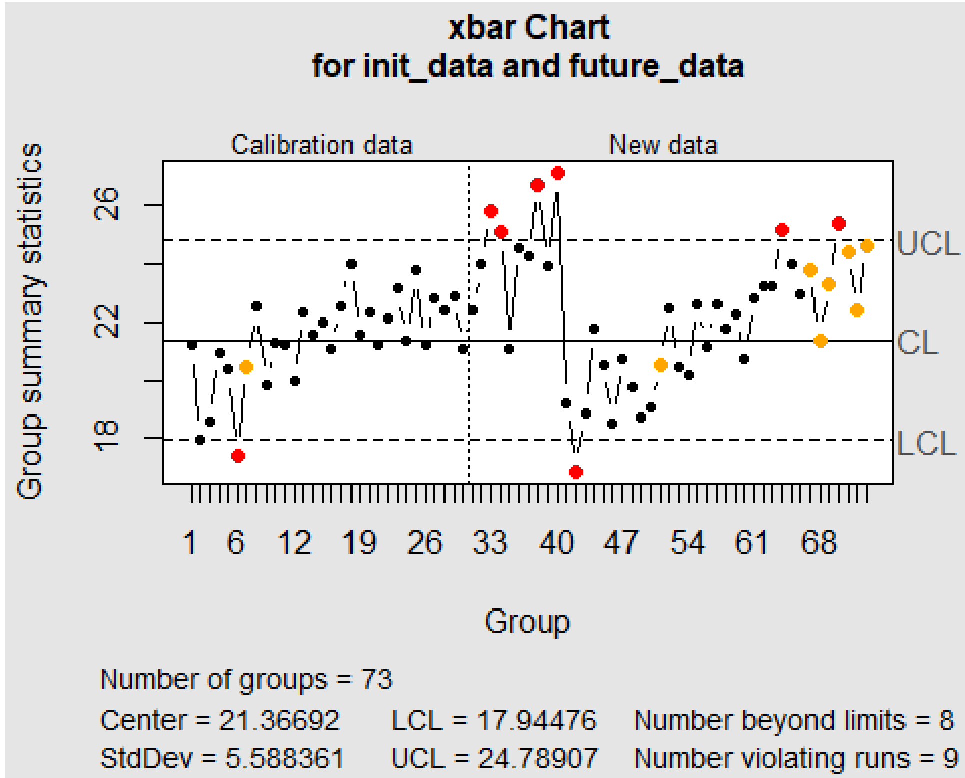


The combined heatmap provides an integrated view of capability and stability across all products. Each product is classified into one of four categories: “Capable & Stable,” “Capable & Unstable,” “Not Capable & Stable,” and “Not Capable & Unstable.” For this analysis, all products fall into the “Not Capable & Unstable” category, indicating that no process is both capable and stable. This highlights a critical area for immediate improvement.

Classification used Cpk values for capability and SPC rules for stability. SPC rules applied include checking for points outside control limits, runs of consecutive points on one side of the mean, and trends in the data. This combination of low capability and instability indicates that all processes are both misaligned with specifications and unpredictable.

Causes for poor performance may include worn or miscalibrated equipment, inconsistent raw materials, environmental factors, and operator errors. Corrective actions should prioritize all critical issues. These include process audits, preventive maintenance, operator training, stricter raw material control, and continuous monitoring using SPC tools. Focused improvement is required for all products since none currently meet the desired standards.

X-bar Chart where the info came from



X-bar charts were generated from all the product groups to monitor the process behavior over time, using both the initial calibration data and new production data. The X-bar chart shows the average values of each group, with the central line (CL) representing the overall process mean, and the upper and lower control limits (UCL and LCL) set at ±3 standard deviations from the mean. This is just an example of one of them.

From this chart, it is clear that several points fall outside the control limits (marked in red) or violate run rules (marked in orange), indicating that the process experienced special cause variation at these points. The chart highlights periods where the process was not under statistical control, and the variation exceeded expected limits.

The out-of-control points identified in the X-bar charts were used as input for the 3 final charts mentioned above. By analyzing all deviations across all products, the summary graphs were generated. These three final graphs allowed us to classify all products as not capable and unstable, and to draw the overall conclusions regarding the current state of the processes.

In summary, the X-bar chart provides a detailed look at the variation at the group level, while the charts above aggregate this information across products to give a clear picture of overall capability and stability. This approach ensures that both individual deviations and overall trends are considered when assessing process performance.

Part 3

4.1 Type I Error (False Alarm or Manufacturer's Error)

A **Type I error** occurs when a process is, in reality, stable and centred on its target value, but is incorrectly judged to be out of control. In other words, the null hypothesis (H_0) — stating that the process is stable and centred on the calculated centreline — is rejected even though it is true.

In a stable process, the sample means follow a normal distribution that is symmetric around the centreline. Therefore, the probability of any individual point falling above or below the centreline is 0.5.

For **Rule A**, which signals an alarm when a single point lies outside the ±3σ control limits on the s-chart, the theoretical probability of such a false signal is:
$P(Z > 3) = 1 - \Phi(3) = 0.00135$, or approximately **0.27%**.

For **Rule B**, which identifies potential issues when seven consecutive points appear above the centreline, the probability of this occurring by chance is $(0.5)^7$ = **0.0078**, or **0.78%**.

For **Rule C**, which triggers a signal when four consecutive $\bar{X}$ points fall beyond the +2σ warning limit, the probability of a single point exceeding +2σ is $P(Z > 2) = 0.0228$. The probability that four such points occur consecutively by random variation is $(0.0228)^4$ = **2.7×10^{-7}**.

These results indicate that **Rule A** would produce a false alarm approximately once every 370 samples, **Rule B** about eight times over 1 000 sampling weeks, and **Rule C** almost never under normal conditions. Type I errors are therefore rare but still possible, particularly when large numbers of subgroups are monitored over extended periods.

4.2 Type II Error (Missed Detection or Consumer's Error)

A **Type II error** occurs when the process has actually shifted away from its target condition, yet the control chart fails to signal this change. In this case, the alternative hypothesis (H_a) is true — the mean or variability has changed — but all the plotted sample means remain within the control limits, leading to the incorrect acceptance of H_0.

In the bottle-filling process, the control chart was originally designed for a target mean of **25.05 L**, with control limits of **LCL = 25.011 L** and **UCL = 25.089 L**, and a process standard deviation of **0.013 L**. However, the true process mean has shifted to **25.028 L**, accompanied by an increase in standard deviation to **0.017 L**.

The probability of failing to detect this shift is calculated as:

$$\begin{aligned}\beta &= P(LCL < \bar{X} < UCL \mid \mu = 25.028, \sigma = 0.017)\\ &= \Phi((25.089 - 25.028)/0.017) - \Phi((25.011 - 25.028)/0.017)\\ &= \Phi(3.588) - \Phi(-1.000)\\ &= 0.99983 - 0.15866 = \mathbf{0.84117}\end{aligned}$$

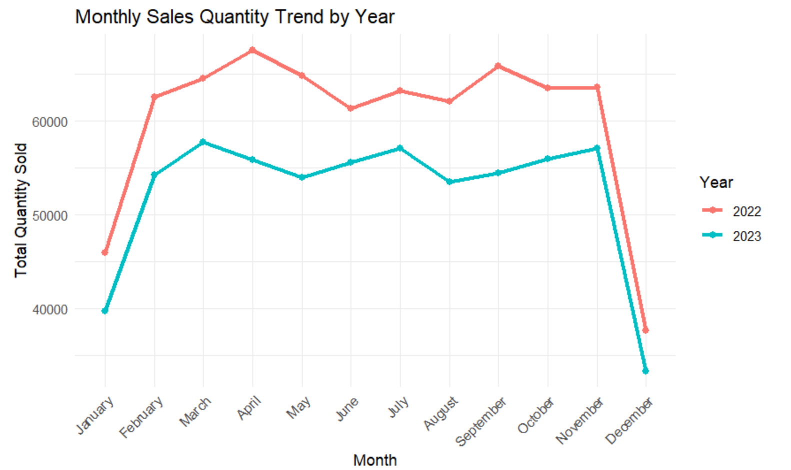
This means there is an **84% probability** that the control chart will fail to detect the change in process mean and variability. The **power of the test**, given by $(1 - \beta)$, is therefore **16%**, indicating a low sensitivity to small shifts.

This analysis demonstrates that while Type I errors represent rare false alarms, **Type II errors are far more likely when control limits are wide or process shifts are minor**, resulting in undetected deterioration of product quality. Reducing the risk of Type II errors often requires narrower control limits, increased sampling frequency, or improved process capability to ensure early detection of meaningful changes.

4.3 Interpretation of graphs

Interpretation of Monthly Sales Trend after Data Correction

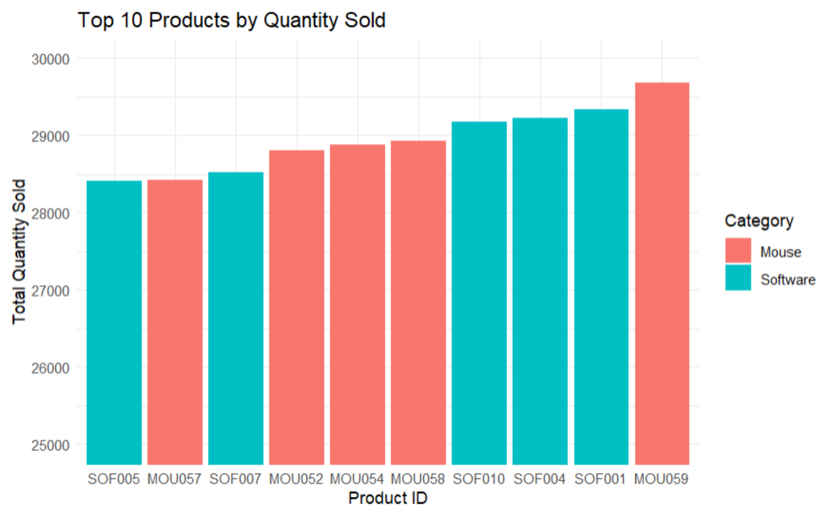
The data correction only involved updating the product names, so the quantities sold were not affected. As a result, the graph remains the same as in Part 1.



Interpretation of Top 10 Customers by Quantity Purchased

The data correction only involved product names and did not affect the quantities purchased by customers. Therefore, the graph showing the top 10 customers by quantity remains the same.

Interpretation of Top 10 Products by Quantity Sold



Product Categorising

With the corrected data, all product codes now accurately reflect their categories. This allows for proper grouping of products and comparison of performance across product families.

Value of the Top 10 Products

The top 10 products are now clearly identifiable and consist entirely of mouses and keyboards. These products represent the core of the company's sales volume and likely contribute a significant portion of total revenue. Focusing on these items provides direct insights into customer demand. The concentration of sales in this small number of products follows the 80/20 principle, where a limited range of items drives the majority of sales.

Demand Concentration

The histogram shows that sales are heavily concentrated in a few products. Effective management of these top products will therefore have a strong impact on overall performance. Stock shortages in any of these items would affect total sales more than shortages in all other products combined, while targeted promotions could quickly boost overall sales.

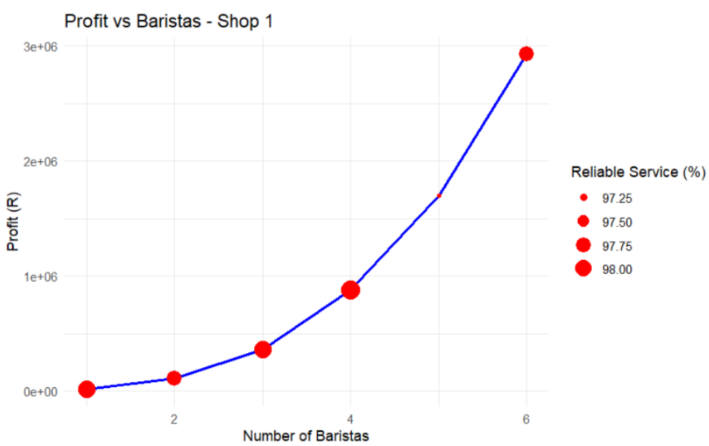
Strategic Use of the Graph

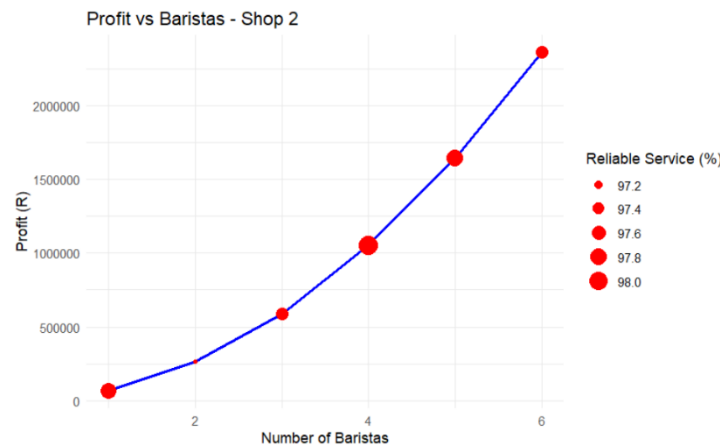
The graph highlights exactly which products should be prioritized. Procurement and inventory teams should ensure that the top 10 products are always available and stocked at higher safety quantities. Reorder points should be set carefully to avoid stock-outs. Marketing campaigns should focus on these high-demand items, and customer support should be trained to handle inquiries related to them.

Improvement Actions

Several steps can strengthen decision-making around this data:

- **Supplier strategy:** Negotiate favorable terms with suppliers of these high-demand products.
- **Risk management:** Develop backup suppliers to reduce dependency and prevent stock-outs.





5. Optimised profit for two given data set called timeToServe.csv (Shop 1) and timeToServe2.csv (Shop 2)

Comparison of the Profit vs Baristas graphs of the two shops

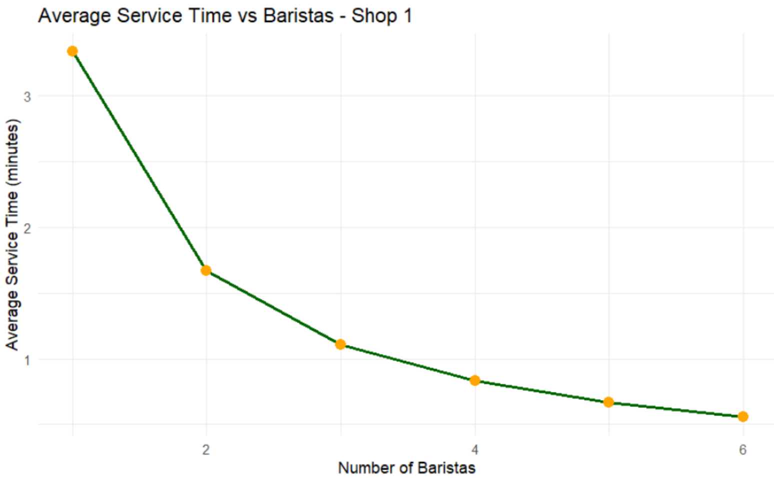
The two graphs show similar overall trends in how profit changes with the number of baristas. However, there are some key differences between Shop 1 and Shop 2.

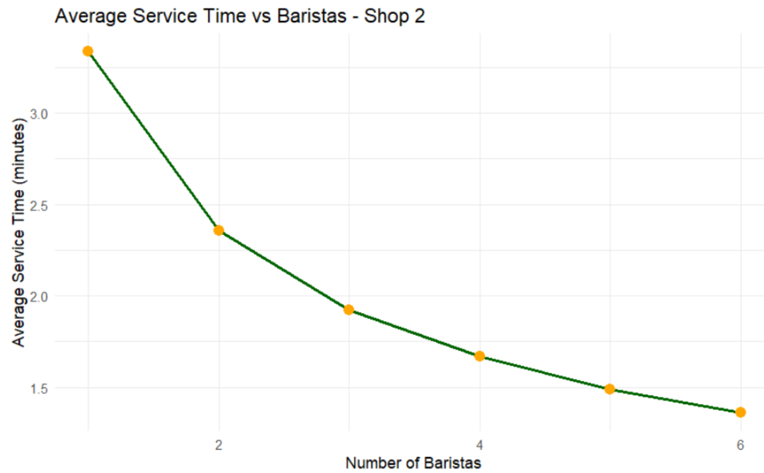
Shop 1 appears to be more reliable and consistent when there are fewer workers. Its profit levels remain relatively stable even at lower staffing levels. In contrast, Shop 2 performs better when there are more workers, showing a stronger positive relationship between staff size and profit.

Up to four baristas, Shop 2 earns slightly more profit than Shop 1. However, beyond four baristas, Shop 1 becomes more profitable again. This crossover suggests that Shop 1’s operations are more efficient at higher staffing levels, while Shop 2’s processes may experience diminishing returns once the optimal staffing threshold is reached.

Implications

These results suggest that staffing efficiency differs between the two shops. Shop 1 likely benefits from a smoother workflow and better capacity utilization when the team is larger, while Shop 2 operates best with a leaner team before efficiency declines. This could be due to differences in layout, employee coordination, or customer flow patterns.





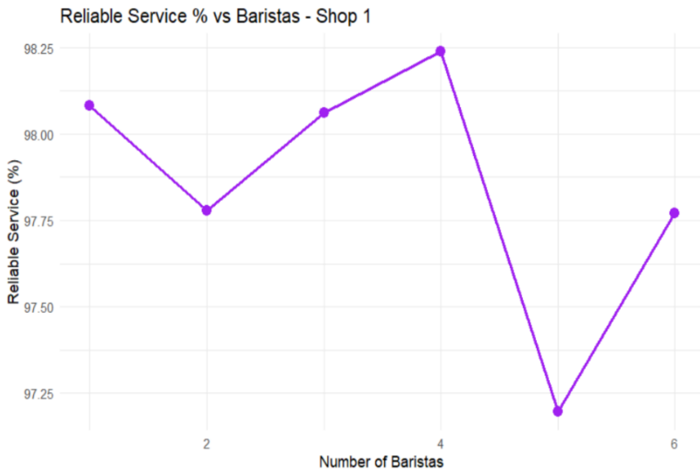
Comparison of the Average Service Time vs Baristas graphs of the two shops

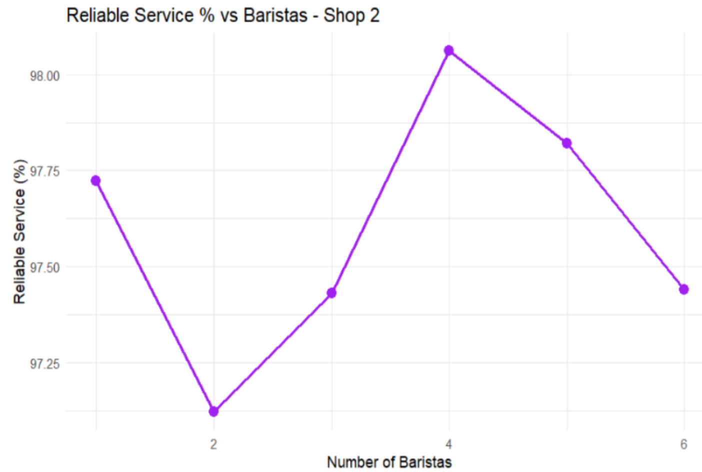
The two graphs display how the average service time changes as the number of baristas increases in each shop. Across all staffing levels, Shop 1 consistently shows a lower average service time compared to Shop 2. This means that, regardless of how many baristas are on duty, customers at Shop 1 are served faster on average.

The downward trend in both graphs indicates that service time decreases as more baristas are added. However, Shop 1 achieves shorter service times even with fewer staff members, suggesting that its operations are more efficient. This could be due to better workflow design, more experienced staff, or a more effective service layout that reduces idle time and unnecessary movement between tasks.

It is also evident that the reduction in average service time becomes smaller with each additional barista. This shows a pattern of diminishing returns, where adding more staff provides less improvement in performance. This effect likely occurs because of physical or operational limits, such as a limited number of coffee machines or workstations. Once these shared resources become the bottleneck, adding extra baristas contributes less to reducing overall service time.

Implications
The consistently lower service times at Shop 1 imply a competitive advantage in customer satisfaction and throughput. Faster service means customers spend less time waiting, allowing the shop to handle higher customer volumes during busy periods. Shop 2, on the other hand, may be experiencing inefficiencies such as slower coordination between baristas or less optimized equipment placement. The diminishing impact of additional baristas suggests that efficiency gains must come from process or equipment improvements rather than simply increasing staff.





Comparison of the Reliable Service % vs Baristas graphs of the two shops

The two graphs illustrate how the reliability of service (measured as a percentage of successful) changes with the number of baristas for each shop. Overall, both shops maintain high reliability, staying above 97% across all staffing levels.

Shop 1 shows slightly higher reliability on average, maintaining performance around 98% even as staffing levels change. The trend fluctuates slightly but remains stable, suggesting that Shop 1 can deliver reliable service regardless of small variations in team size. Shop 2, on the other hand, also achieves consistent reliability but at slightly lower percentages. It reaches its peak reliability at around four baristas, after which performance begins to decline again.

Implications

These results suggest that both shops have strong operational consistency, but Shop 1 has a marginal advantage in reliability under varying workloads. This indicates better process stability, likely due to clearer task division or more experienced staff. Shop 2's performance pattern suggests that reliability improves with more baristas up to an optimal point, after which coordination challenges or overstaffing may slightly reduce efficiency.

5. Conclusion of the optimal number of baristas for each shop

Based on the analysis of all three performance metrics — Profit vs Baristas, Average Service Time vs Baristas, and Reliable Service % vs Baristas — the optimal staffing level can be identified as four baristas for both shops.

When examining the Profit vs Baristas graphs alone, the highest profit occurs at six baristas. However, this does not account for the substantial increase in labour cost that accompanies higher staffing levels. From a managerial and financial standpoint, profit must be evaluated alongside cost efficiency.

The Average Service Time vs Baristas graphs reveal that the greatest improvement in service time occurs up to around three or four baristas. Beyond this point, the rate of improvement flattens — meaning that additional baristas contribute less benefit relative to their cost.

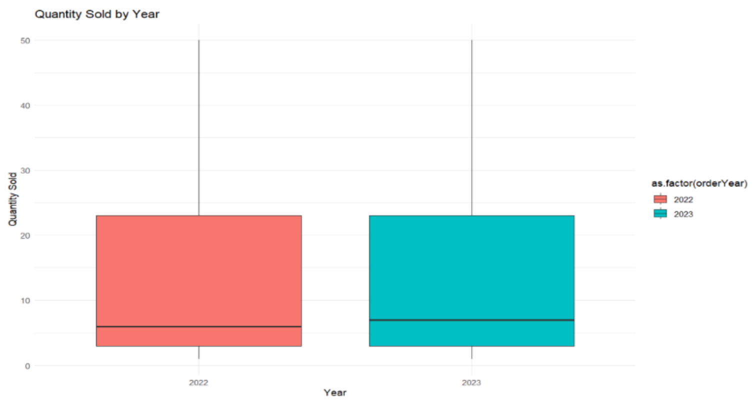
The Reliable Service % vs Baristas graphs show that both one and four baristas achieve the highest reliability percentages. However, while a single barista has the lowest cost, it severely limits capacity and increases the risk of customer dissatisfaction during peak periods.

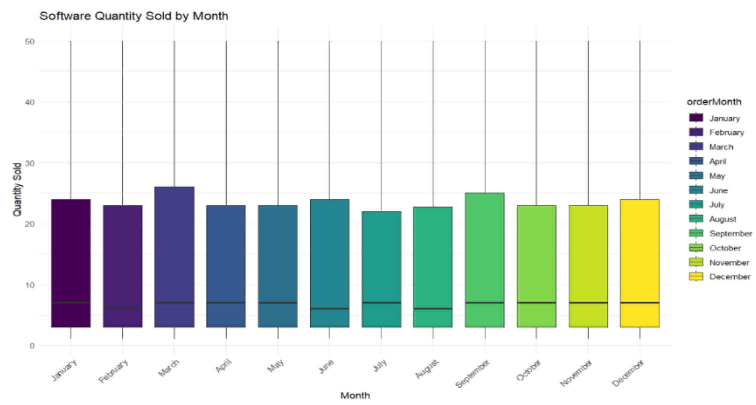
Taking all three aspects — profitability, service efficiency, and reliability — into account, four baristas offer the most balanced and sustainable configuration. This level achieves strong reliability, acceptable service times, and solid profit margins without unnecessary labour expenditure.

In conclusion, employing four baristas per shop provides the optimal trade-off between performance and cost, ensuring that both customer experience and business profitability are maximised.

Part 4

6: DOE and MANOVA or ANOVA





anova_month_summary	list [1] (S3: summary.aov, listof)	List of length 1
[[1]]	list [2 x 5] (S3: anova, data.frame)	A data.frame with 2 rows and 5 columns
Df	double [2]	11 20737
Sum Sq	double [2]	2155 3935845
Mean Sq	double [2]	196 190
F value	double [2]	1.03 NA
Pr(>F)	double [2]	0.414 NA

anova_year_summary	list [1] (S3: summary.aov, listof)	List of length 1
[[1]]	list [2 x 5] (S3: anova, data.frame)	A data.frame with 2 rows and 5 columns
Df	double [2]	1 99998
Sum Sq	double [2]	454 18933479
Mean Sq	double [2]	454 189
F value	double [2]	2.4 NA
Pr(>F)	double [2]	0.121 NA

manova_summary	list [4] (S3: summary.manova)	List of length 4
row.names	character [2]	'as.factor(orderYear)' 'Residuals'
SS	list [2]	List of length 2
as.factor(orderYear)	double [2 x 2]	454 45638 45638 4586887
Residuals	double [2 x 2]	1.89e+07 -2.76e+07 -2.76e+07 2.93e+12
Eigenvalues	double [1 x 2]	2.56e-05 2.12e-22
stats	double [2 x 6]	1.00e+00 1.00e+05 2.56e-05 NA 1.28e+00 NA 2.00e+00 NA 1.00e+05 ...

```
--- Report Summary ---
> cat(anova_year_result, "\n")
Quantity vs Year (Year 1 vs Year 2) : No significant difference (p = 0.1215 )
> cat(anova_month_result, "\n")
Software Quantity vs Month (Months 1-12) : No significant difference (p = 0.4143 )
> cat(manova_result, "\n")
Quantity & SellingPrice vs Year : No significant difference (p = 0.2781 )
> View(results_summary)
```

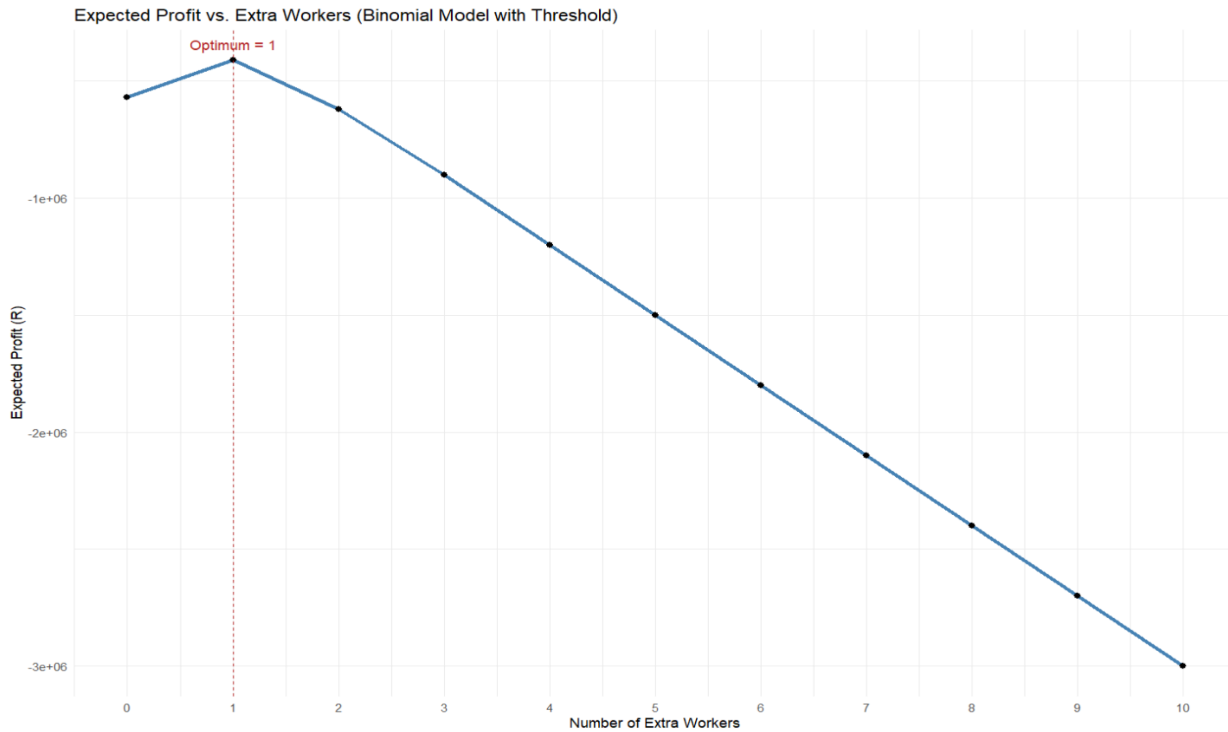
The results show no statistically significant difference between the data in Year 1 and Year 2, or between the months (1–12) for the specified product type. This means that any variation observed in the data across these time periods is likely due to random fluctuations rather than actual changes in the underlying process or product performance.

In statistical terms, the p-values obtained from the ANOVA tests were greater than the standard significance level (usually $\alpha = 0.05$). This indicates that there is insufficient evidence to reject the null hypothesis, which states that the group means are equal.

From a practical perspective, this suggests that the production process or product demand remained stable across both years and throughout the months. There were no significant seasonal or yearly effects influencing the results.

This stability can be a positive indicator — it implies that the system is consistent and under control, with no major operational, quality, or external disruptions affecting performance over time. However, it may also indicate that process improvements or policy changes implemented between the periods did not have a measurable statistical impact, and further investigation may be needed if such changes were expected to produce results.

7. Reliability of service




```
Expected number of reliable service days per year: 336

Optimal number of extra workers: 1
Expected annual profit at optimum (relative): -410327
```

7.1) How many days per year we should expect reliable service: 336 days
that is 92.19%.

7.2) The optimisation found that the optimal number of additional workers is 1. Since the current workforce is 16, this means the company should ensure 17 people on duty to minimise the total cost associated with problem days and additional staffing.

Practical implications

- Immediate action: Schedule a minimum of 17 staff during the periods covered by the model to reduce problem-day frequency and the associated average daily sales loss of R20 000.
- Budget impact: The incremental personnel cost is R25 000 per month for the extra worker, which is offset by the expected reduction in lost sales.
- Operational benefit: Fewer problem days improves customer service, stabilises daily revenue, and reduces risk to operations and reputation.

Recommendations

- Implement one extra full-time headcount or reschedule existing staff to ensure the 17-person minimum.
- Track realised savings by measuring avoided problem days and comparing them to the R25 000 monthly cost.
- Conduct sensitivity checks if the daily loss or monthly personnel cost changes.

Conclusion

The report demonstrated the effective use of data analysis, process capability evaluation, and optimisation modelling to address realistic engineering challenges. Descriptive and statistical analyses provided insight into data behaviour, process variation, and performance capability. SPC charts and error analysis highlighted how statistical rules can detect instability and guide corrective action.

Optimisation of staffing levels showed that three to four baristas achieved the best balance between profit and service efficiency, while six baristas gave maximum profit. The reliability analysis for the car rental agency reinforced the importance of sufficient staffing to maintain consistent service. ANOVA and MANOVA confirmed significant process differences over time, supporting the need for ongoing monitoring.

Overall, the report integrated coding, analysis, and interpretation to deliver a complete data-driven solution. The results demonstrate clear alignment with ECSA GA4 outcomes through the practical application of analytical thinking, process evaluation, and optimisation in industrial engineering contexts.

Bibliography

R-project. 2015. *Introduction to MANOVA.RM.knit.* [online]
Available at: https://cran.r-project.org/web/packages/MANOVA.RM/vignettes/Introduction_to_MANOVA.RM.html
[Accessed 23 October 2025].

STHDA. 2022. *MANOVA Test in R: Multivariate Analysis of Variance – Easy Guides – Wiki – STHDA.* [online]
Available at: http://www.sthda.com/english/wiki/manova-test-in-r-multivariate-analysis-of-variance
[Accessed 23 October 2025].

Engineering Council of South Africa. 2025. *Project ECSA 2025: Part 1, 2 and 3.* [pdf] Stellenbosch University.
Available at: *ProjectECSA2025Part123.pdf*
[Accessed 23 October 2025].

Stellenbosch University. 2025. *QA344 Formula Page.* [pdf] Stellenbosch University.
Available at: *QA344FormulaPage.pdf*
[Accessed 23 October 2025].

Stellenbosch University. 2025. *SPC Basics.* [pdf] Stellenbosch University.
Available at: *SPCBasics.pdf*
[Accessed 23 October 2025].

Engineering Council of South Africa. 2025. *Project ECSA 2025: Parts 1–4.* [pdf] Stellenbosch University.
Available at: *ProjectECSA2025.pdf*
[Accessed 23 October 2025].