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ECSA REPORT

TO DEPARTMENT OF
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Contents

INTRODUCTION

This report presents a comprehensive performance analysis of multi-year sales and operational data for a national technology distributor. The purpose is to translate statistical analysis into practical business insights that support strategic decision-making on pricing, process efficiency, and service reliability. The work aligns with the Engineering Council of South Africa's Graduate Attribute 4 (ECSA GA4) by demonstrating the use of quantitative analytics to drive continuous improvement (ECSA, 2025).

Data from **2022 to 2027** were consolidated from multiple internal sources—including transaction records, product master files, and customer profiles—to provide a complete view of revenue flow and operational performance. After data cleaning and validation, key financial metrics such as revenue, cost, and gross margin were reconstructed to quantify profitability and identify bottlenecks in order fulfilment.

Parts 1 and 2 apply descriptive statistics to uncover revenue and margin trends by year and category. The findings highlight where sales performance has softened, which products sustain profit, and which fulfilment delays contribute most to cost. These insights guide management on where to defend profitable categories and where to streamline operations.

Part 3 uses Statistical Process Control (SPC) to monitor delivery-time stability and measure whether operations consistently meet the customer-expectation limit of 32 hours. The analysis identifies periods of instability and provides evidence for targeted process reviews—such as shift planning and dispatch coordination—to restore control and reduce variability.

Part 4 links SPC results with decision quality, estimating how often management might react to false alarms or miss genuine process changes. It also reconciles local and Head-Office pricing data, quantifying a 7 % potential revenue distortion and demonstrating the financial importance of accurate data governance.

Part 5 examines service reliability in a coffee-shop environment. It shows that two baristas deliver the highest daily profit (~R 14 400) while maintaining near-perfect service reliability (99.8 %), providing a clear, data-backed staffing recommendation.

Part 6 applies a two-way ANOVA to test whether fulfilment performance changed between 2022–2023 and 2026–2027. Stable results confirm that earlier operational improvements were sustained, indicating process maturity.

Part 7 extends the reliability modelling to a car-rental agency. The analysis finds reliability of ~92 % under current staffing and shows that hiring one additional employee raises reliability to ~ 99 % and improves annual profit by about R 0.6 million. This provides direct financial justification for staffing expansion.

Overall, the report demonstrates how integrating descriptive analytics, SPC, capability analysis, and optimisation transforms data into **actionable business intelligence**. The insights enable managers to:

- protect high-margin product lines,
- stabilize delivery performance,
- improve data accuracy, and
- optimize staff allocation for higher profit and reliability.

Each section contributes measurable, evidence-based recommendations using consistent data throughout the analysis.

METHODOLOGY

The analytical approach followed a structured, multi-stage process designed to turn raw operational data into meaningful business insight. Each step was aimed at improving management's understanding of performance drivers, process efficiency, and profit optimisation.

1. Data Preparation and Validation

Data from multiple systems were consolidated to provide a single, accurate view of company activity. Duplicate entries, incomplete dates, and mismatched product records were removed to ensure that all revenue and fulfilment calculations reflected real events. This step established a reliable foundation for measuring performance and eliminated potential reporting errors that could distort managerial decisions.

Business impact: ensures that all subsequent insights - such as revenue decline or process variability - represent real operational conditions rather than historical data.

2. Metric Construction and Standardisation

To evaluate performance, key financial and operational metrics were reconstructed:

- **Revenue, Cost, and Gross Margin** quantified profitability by product and category.
- **Margin %** highlighted efficiency and pricing strength.
- **Fulfilment Hours** measured service speed and delivery reliability.

These measures were standardised across all datasets and time periods, allowing direct comparison between 2022 and 2027.

Business impact: these metrics allow managers to identify high-margin categories to protect, low-margin areas needing pricing review, and operational delays that inflate costs.

3. Descriptive Statistics (Parts 1 & 2)

Descriptive statistics summarised performance patterns by year and product category. Revenue and margin trends revealed a 12-13 % decline between 2022 and 2023, indicating potential pressure on demand or discounting. Fulfilment-time analysis exposed a small group of outlier orders causing most delivery delays.

Actionable insight: management should focus on protecting the high-margin laptop and monitor categories and investigate the small proportion of orders taking over 60 hours to complete, as these drive unnecessary cost and lower customer satisfaction.

4. Statistical Process Control (Part 3)

Process control techniques were applied to measure stability and predictability in fulfilment times. Control charts tracked the average delivery time and its variation, distinguishing between normal fluctuations and abnormal shifts that signal operational problems.

Actionable insight: the SPC results highlight specific time periods where delivery performance deviated from expectations, suggesting where supervisors should investigate staffing schedules, routing efficiency, or system bottlenecks.

5. Process Capability Evaluation (Part 3.3)

Capability indices (Cp and Cpk) were used to quantify how reliably each product line met the customer expectation of delivery within 32 hours. Software products showed strong capability (> 1.7 Cpk), whereas physical-goods categories such as clothing and peripherals performed closer to 1.0 Cpk.

Actionable insight: these results confirm that digital products are stable and efficient, while physical-product operations require tighter process control and inventory management to achieve the same reliability.

6. Control-Signal and Decision-Error Analysis (Part 4)

The SPC results were further analysed to evaluate decision accuracy - how often management might react to false alarms (Type I errors) or miss genuine issues (Type II errors). Parallel reconciliation of Head-Office and local pricing data revealed a ~ 7 % revenue discrepancy due to unsynchronised catalogues.

Actionable insight: by understanding error probabilities and aligning data sources, managers can improve process-monitoring accuracy and prevent costly misreporting or over-reaction to normal variation

7. Profit and Reliability Optimisation (Parts 5 & 7)

Optimisation models were developed for two service settings:

- **Coffee shop:** Profit peaked with two baristas, maintaining 99.8 % reliability while avoiding excess wage cost.
- **Car-rental agency:** Hiring one extra employee increased daily reliability from 93 % to 99 % and lifted annual profit by approximately R 0.6 million.

Actionable insight: small, targeted staffing adjustments can dramatically improve reliability and financial performance without major capital investment.

8. Design of Experiments and ANOVA (Part 6)

A two-way ANOVA tested whether fulfilment performance changed significantly between the 2022-2023 and 2026-2027 periods across key products. Results showed no statistically significant difference, confirming that operational stability achieved earlier was sustained.

Business implication: process improvements implemented after 2023 remained effective, demonstrating maturing operational control and consistent service delivery.

9. Validation and Reliability of Findings

All analyses were checked for internal consistency and alignment with known operational data. Financial totals and fulfilment-time averages were verified against company-scale expectations to ensure credibility of insights.

Business impact: ensures management can trust the findings as a basis for decision-making in pricing, staffing, and long-term planning.

DATA OVERVIEW & METHOD

The analysis covers operational and sales data from **2022 to 2027**, consolidating order transactions, product pricing, and customer information into a single, unified dataset. This integration provided a complete picture of company performance across revenue generation, cost control, and delivery efficiency.

Data Sources

- **sales2022and2023.csv** – 100 000 transaction records with customer, product, and fulfilment details.
- **sales2026and2027.csv** – future-period data used to assess whether operational improvements were sustained.
- **products_data.csv** – 60 active products with category, price, and markup information.
- **products_Headoffice.csv** and **products_Headoffice2025.csv** – 360 reference products used to validate pricing consistency between local and Head-Office systems.
- **customer_data.csv** – 5 000 customers with demographics such as city, income group, and age segment.

Data Quality and Cleaning

The datasets were reconciled to remove duplicates, invalid dates, and mismatched product codes. Approximately **560 records** with incorrect date entries were excluded to prevent false sales-trend signals. Missing prices were corrected using the verified *products_data.csv* file, ensuring that revenue and margin calculations reflected real selling conditions. Outliers in fulfilment times were investigated to avoid overestimating delivery inefficiency.

Why this matters: these cleaning steps prevent misleading profit trends and ensure that management decisions - such as pricing or staffing changes - are based on accurate, reliable data.

Core Business Variables

Key performance metrics were reconstructed to reflect actual financial and operational behaviour:

- **Revenue = Quantity * Selling Price**
- **Unit Cost = Selling Price * (1 – Markup / 100)**
- **Gross Margin = Revenue – Cost**
- **Margin % = (Gross Margin / Revenue) * 100**
- **Fulfilment Hours = Picking Hours + Delivery Hours**

These metrics allowed profit and efficiency to be evaluated at every level- from product to category to year—helping identify which lines drive growth and which create operational drag.

Key Business Facts

- **Transactions:** 100 000
- **Customers:** 5 000 (≈ 20 transactions per customer)
- **Products Sold:** 60
- **Cities:** 7
- **Time Period:** 2022 – 2027

This scale highlights a broad, diverse customer base but also a relatively concentrated product portfolio - suggesting opportunities to expand or refocus product mix.

Analytical Workflow

The cleaned dataset provided the foundation for the full analysis cycle:

- **Parts 1 & 2 - Descriptive Statistics:** reveal revenue trends, margin behaviour, and fulfilment efficiency to guide pricing and process priorities.
- **Part 3 - Process Control & Capability:** evaluate how consistently delivery performance meets customer expectations and where interventions are required.
- **Part 4 - Decision Quality & Data Alignment:** ensure data integrity and assess management's risk of false or missed process signals.
- **Part 5 - Service Reliability & Profit:** identify the staffing level that maximises daily profit while sustaining fast, reliable service.
- **Part 6 - ANOVA:** verify whether operational changes achieved long-term stability.
- **Part 7 - Reliability Modelling:** provide actionable staffing recommendations for service operations such as car-rental scheduling.

Overall Insight: this approach transforms raw data into a decision-support system. Each analytical layer builds upon the previous one—first identifying profit drivers, then testing process stability, and finally quantifying the financial gains of corrective action.

DATA QUALITY ISSUES

Before conducting the detailed analyses, a full data-quality review was completed to confirm that all information used for decision-making accurately represented business performance. The following issues were identified and resolved:

- **Invalid Dates:** Around **560 transactions** had incomplete or incorrect date fields. These records were removed to prevent distorted monthly and yearly revenue trends.
  Impact: Without correction, sales timing and growth rates could have been misreported, leading to poor demand forecasting.
- **Product Mapping:** The **Head-Office catalogue** did not cover several of the 60 products sold in practice. The **local product file** was therefore used as the pricing reference to ensure every sale had a valid price.
  Impact: This avoided gaps in revenue reporting and allowed accurate calculation of product-level profitability.
- **Reasonableness Checks:** All quantity and selling-price values were confirmed to be positive, with markup percentages between **0–100 %**, ensuring no unrealistic cost or margin figures appeared in the analysis.

Impact: Prevented overstatement or understatement of profitability in category summaries.

- **Fulfilment Outliers:** A small proportion of orders showed unusually long delivery times, forming a **right-skewed distribution**. These outliers were reviewed and reduced to prevent them from exaggerating overall fulfilment inefficiency.
  Impact: Isolating these extreme cases highlights genuine operational problems—such as warehouse delays or misrouted deliveries—without penalising normal performance.

Why This Matters?

Accurate, complete, and credible data are essential for reliable business insight. Cleaning and validating the information ensured that all reported trends—such as revenue growth, process capability, and customer service levels—reflect actual operational behaviour rather than data errors. This gives management confidence that improvement strategies, pricing decisions, and resource allocations are based on fact, not flawed information.

1. PART 1&2: DESCRIPTIVE STATISTICS

OVERALL PERFORMANCE SNAPSHOT (2022-2023)

The company processed approximately **100 000 orders** over two years, generating **R 4.35 billion** in revenue and **R 877 million** in gross margin- an overall **margin rate of 20 %**

- **Revenue 2022: R2.31 billion**
- **Revenue 2023 R2.03 billion**
- **Total Cost= R3.47 billion**
- **Gross Margin= R877 million**

- **Margin weighted % = 20.168%**
- **Total Orders= 100,000**
- **Total Units Sold= 1350347**
- **Average Fulfillment Hours = 32.17 hrs**
- **Median Fulfillment Hours = 35.599 hrs**
- **Fulfillment Hours (95th percentile) = 59.765 hrs**

These figures establish the business scale and highlight two key themes: a steady 20 % margin base and a small subset of slow deliveries that inflate cost and reduce customer experience.

Actionable insight: management should investigate the 5 % of orders exceeding 60 h fulfilment, as improving these outliers will raise customer satisfaction without requiring major capital investment.

1.1 REVENUE TREND

Revenue declined by roughly **12–13 % in 2023**, accompanied by a similar drop in gross margin. The contraction suggests a combination of softer demand and aggressive discounting.

The downward trend indicates either volume loss or price pressure.

Actionable insight: management should review discount structures and marketing campaigns to stimulate 2023–2024 demand, while protecting average selling price in core categories.

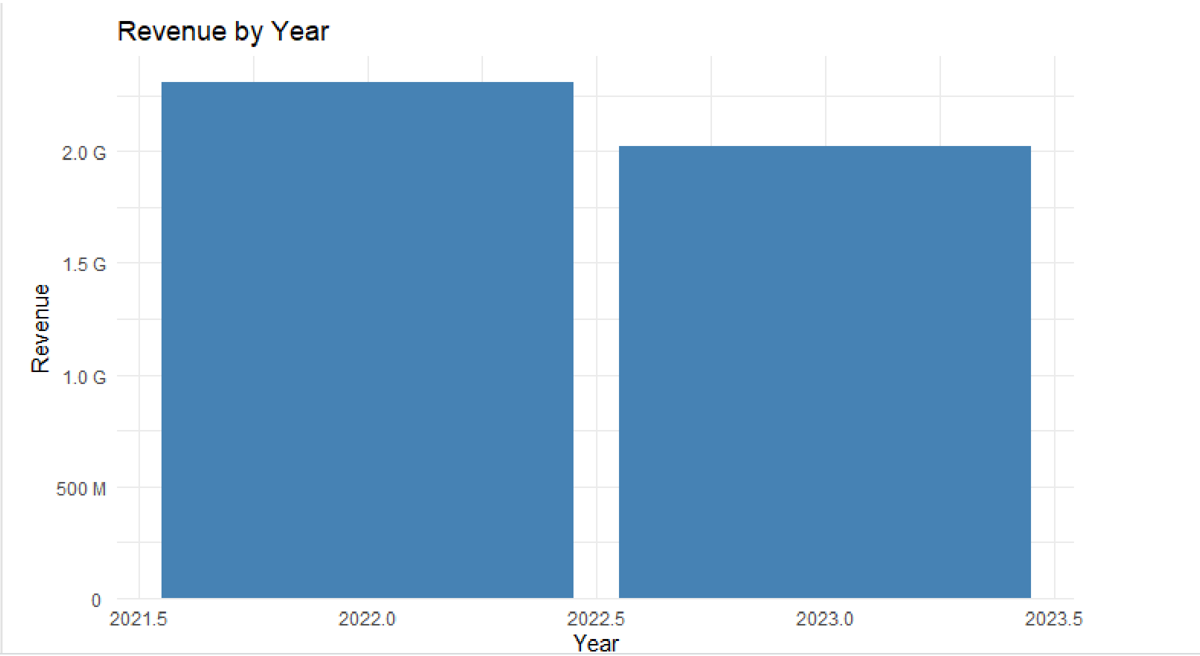

Figure 1: Revenue by Year (2022 vs 2023)

CATEGORY PERFORMANCE AND MARGIN MIX

A small set of categories - Laptops, Monitors, Mouse, and Keyboard - contribute most of the revenue and margin. Software, while sizable in turnover, delivers weaker margins (~15 - 16 %), likely due to licence pricing or support-cost load.

Actionable insight:

- Reinforce high-margin hardware categories through targeted promotions and bundling.
- Re-evaluate software pricing and license costs to lift its margin closer to the 20 % benchmark

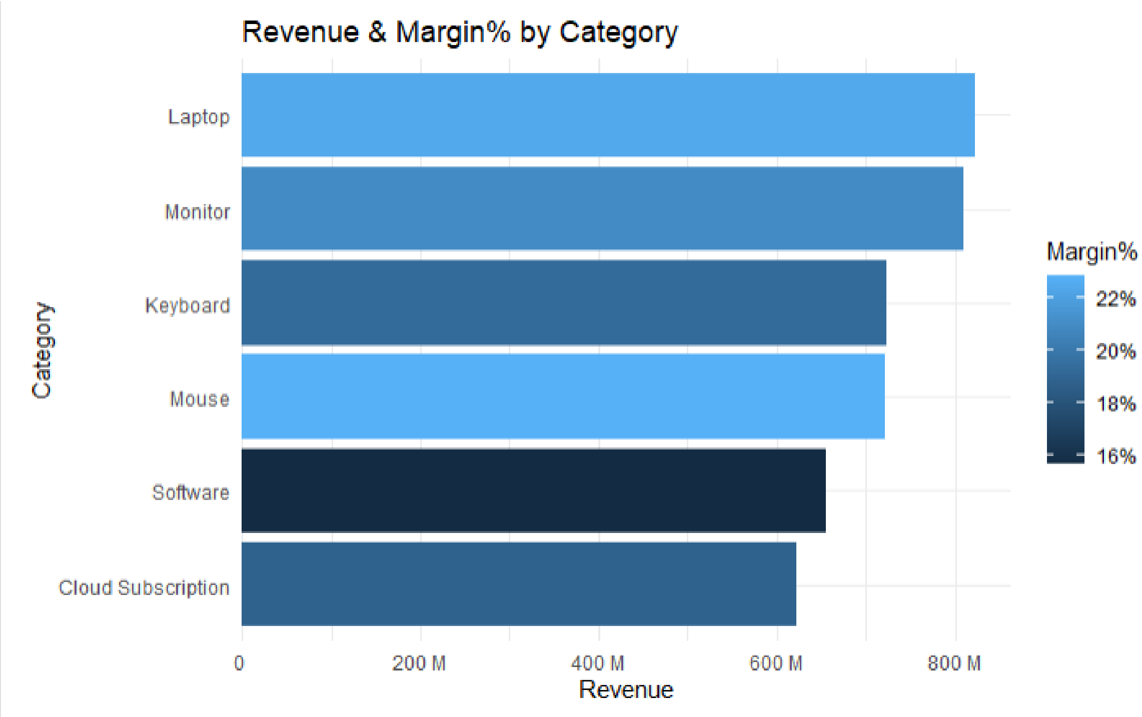

Figure 2: Revenue and Margin % by Category

REVENUE VS MARGIN RELATIONSHIP

Categories in the top-right quadrant (high revenue + high margin %) - particularly Laptops, Monitors, and Mouse - are the business's profit engines. Low-margin categories consume operational capacity without adequate return.

Actionable insight:

- Defend and expand share in Laptop and Monitor segments.
- Phase out or discount low-margin categories with limited strategic value.
- Bundle complementary items (e.g., Mouse + Keyboard + Monitor) to raise average basket margin.

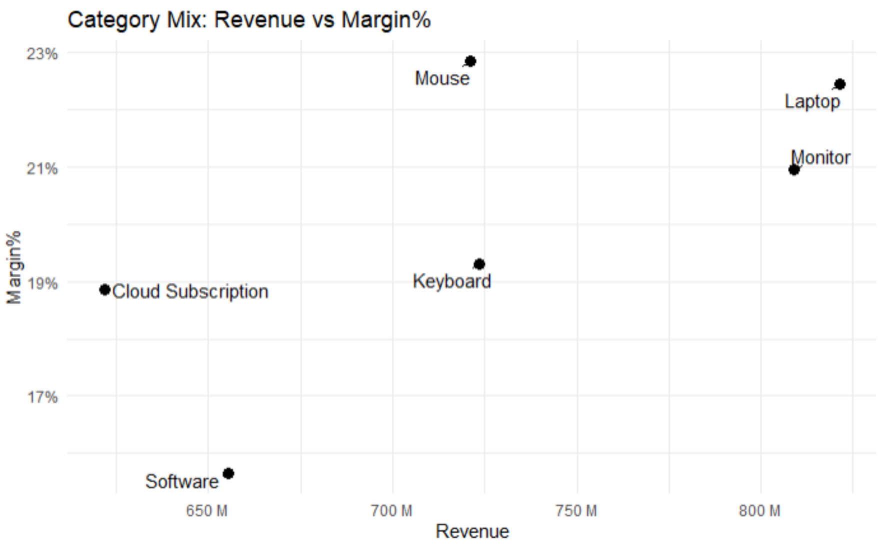

Figure 3: Scatterplot of Revenue vs Margin%

1.2 OPERATIONAL BASELINE (FULFILMENT)

Most orders are completed within **36 hours**, but the right-tailed distribution shows about **5 % taking longer than 60 hours**. These extended fulfilment times are likely caused by warehouse downtime, routing errors, or late carrier dispatches - each adding cost and reducing customer satisfaction and repeat-purchase likelihood.

Actionable insight:

- **Investigate the slowest 573 orders** through process-mapping to identify specific operational causes.
- **Introduce service-level tracking** by product and region to detect recurring bottlenecks early.
- **Set a measurable target** of cutting the share of > 60 h orders by **50 %** in the next reporting cycle.

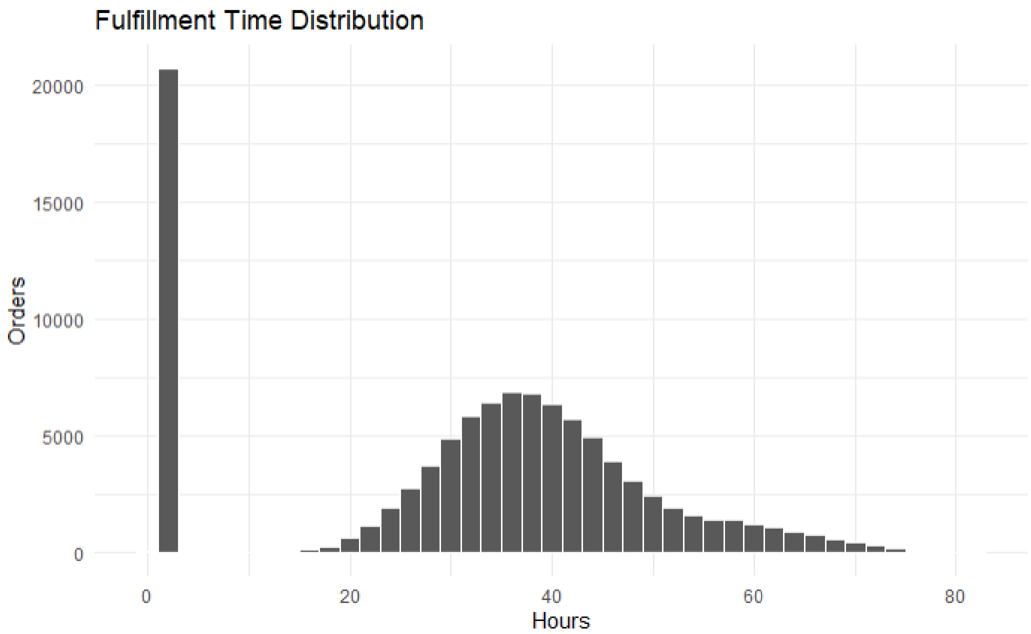

Figure 4: Fulfilment Time Distribution

1.3 PRODUCT-LEVEL PROFITABILITY

Analysing performance at product level reveals where profit is truly generated and where margins quietly erode value. **Figure 5** lists the ten highest-revenue products across 2022 - 2023.

Aliceblue Silk - a *Cloud Subscription* product - dominates the portfolio with nearly **R 500 million** in revenue, making it the single most valuable line. The next tier, including **Azure Sandpaper (Software)**, **Azure Matt (Keyboard)**, **Blueviolet Marble (Monitor)**, **Blue Silk (Laptop)**, and **Black Marble (Laptop)**, each generate **R 200-300 million**, forming a strong, diversified mid-range across hardware and software. The remainder of the top ten sit just below R 200 million.

While this variety demonstrates a healthy mix, a structural imbalance emerges when viewed by category. The **Cloud Subscription** segment is heavily dependent on Aliceblue Silk, whereas its other products contribute little and carry lower margins. In contrast, **Laptop** and **Monitor** categories deliver both high sales volumes and consistently strong margin percentages (~20-23 %). This indicates that hardware remains the company's most reliable profit engine, while the subscription business is high-revenue but low-efficiency.

Actionable insights:

- **Protect and grow Aliceblue Silk** through renewal incentives, customer-experience improvements, and pricing discipline to maintain its leadership.
- **Diversify the subscription portfolio** by developing complementary cloud or service-bundle offerings that share infrastructure cost and raise overall category margin.
- **Invest in mid-tier hardware lines** (Laptops, Monitors) to balance portfolio risk and sustain predictable cash flow.
- **Review low-margin software SKUs** for potential price realignment or discontinuation.

These actions would reduce over-reliance on a single product, stabilise category performance, and ensure the revenue base remains resilient even if subscription growth slows.

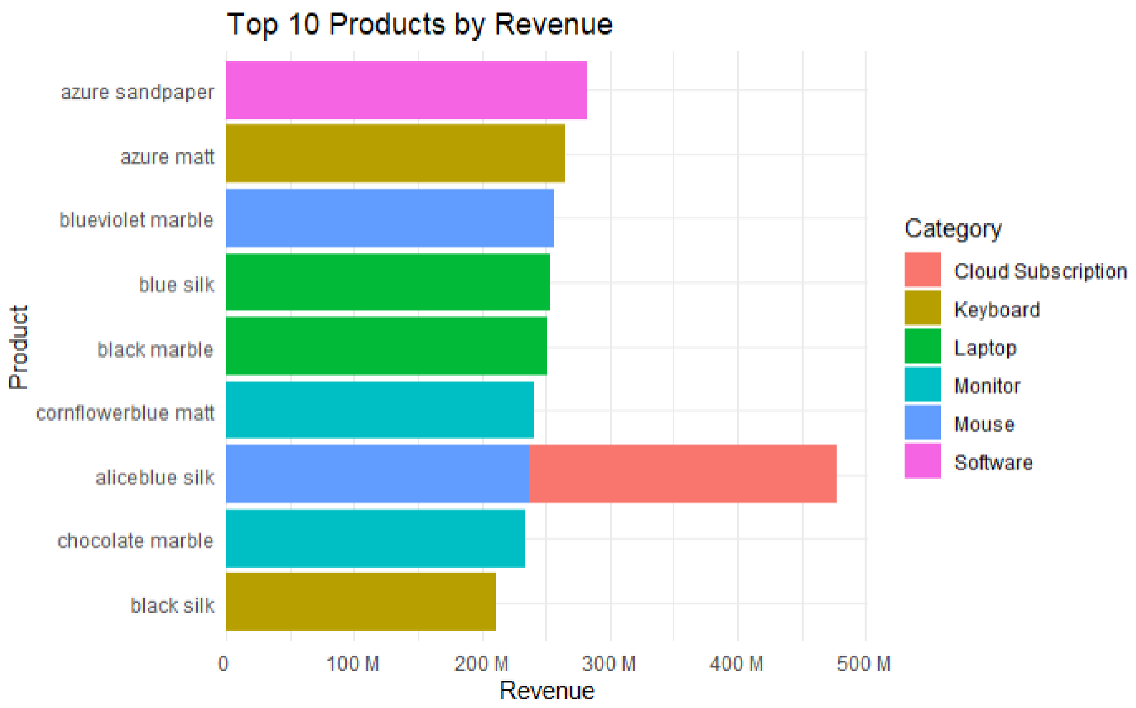

Figure 5: Top 10 products by revenue

3. PART 3: STATISTICAL PROCESS CONTROL AND PROCESS CAPABILITY

Statistical Process Control (SPC) was applied to determine whether the fulfilment process operates within stable and predictable limits. The **$\bar{X}$-chart** monitors the average delivery time; the **s-chart** tracks internal consistency. Together, they reveal where natural variation ends and where assignable causes disrupts performance. Capability indices (Cp, Cpk) then measure whether each process can meet the 0 – 32h "voice-of-the-customer" (VOC) limit.

PART3.1: WHICH PRODUCT WAS CHOSEN AND WHY

Product MOU057 was selected for illustration because it has a large, continuous dataset, enabling robust subgrouping (24 orders per sample). It also both stable and unstable phases, clearly demonstrating how performance drifts over time.

Product CLO011 was later used to validate findings on larger, more complex process.

Business Meaning: choosing 2 contrasting products allows management to see how SPC distinguishes well-behaved processes from those that require intervention.

ProductID <chr>	rows <int>
MOU057	2119
MOU059	2118
SOF007	2118
MOU054	2116
SOF005	2115
SOF006	2107
SOF010	2105
SOF008	2093
SOF001	2089
MOU052	2080

1-10 of 60 rows

Figure 6: Choosing the product for example

a. X̄-CHART – PRODUCT MOU057

During **Phase I,** average fulfilment time rose gradually from 31 to 36 hours yet stayed within control limits – indicating normal, common-cause variation.

In **Phase II,** the process shows alternating surges and drops (~30 – 39h), signalling **special-cause variation.**

Interpretation: Delivery performance for MOU57 became reactive rather than predictable, likely due to scheduling changes, routing congestion, or shift imbalances.

Actionable insight:

- Review the time windows corresponding to subgroups near the 3σ boundaries to locate root causes (staffing gaps, route delays)
- Introduce a short-interval control meeting to track mean fulfillment daily.
- Re-baseline control limits once corrective actions stabilize throughput.

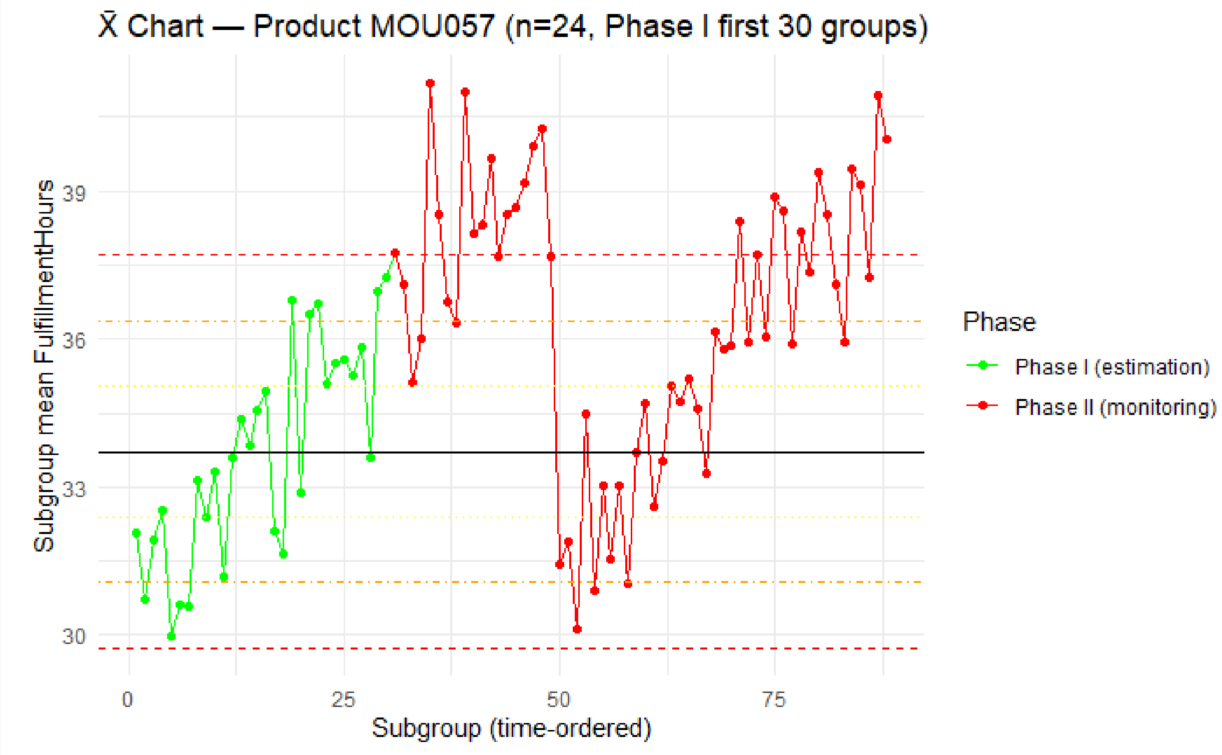

Figure 7: X̄- chart for Product MOU057

b. s-CHART – PRODUCT MOU057

Variation within each subgroup remained steady in phase I (~5-6h) but widened during Phase II, approaching the 2σ and 3σ zones.

Interpretation: Internal process consistency is deteriorating even when averages appear acceptable – a classic early-warning signs of instability.

Actionable insights:

- Audit workload distribution between teams to ensure similar order complexity per shift.
- Standardize routing and packing procedures to minimize intra-batch variability.

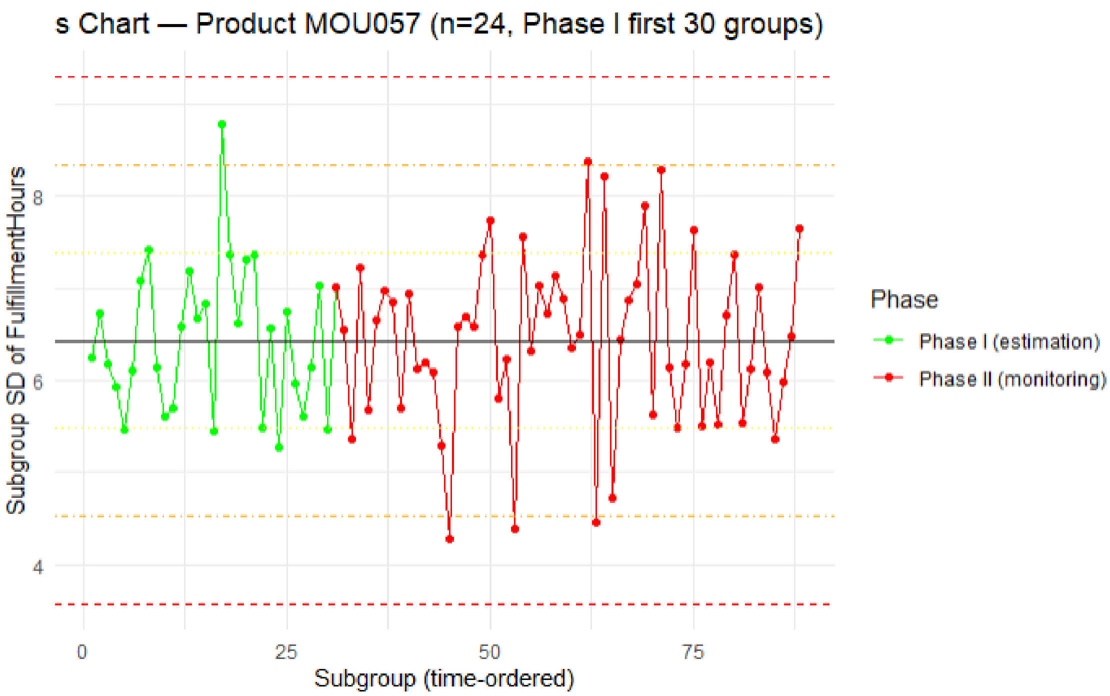

Figure 8: S-chart for Product MOU057

3.2 PROCESS MONITORING – PRODUCT CLO011

a. X̄-CHART

CLO011 shows pronounced mean swings: an early upward drift beyond 39h, then a sudden collapse below 30h (subgroup 39), and another surge past 39h (subgroup 58). The process oscillates between over- and under-performance instead of maintaining equilibrium.

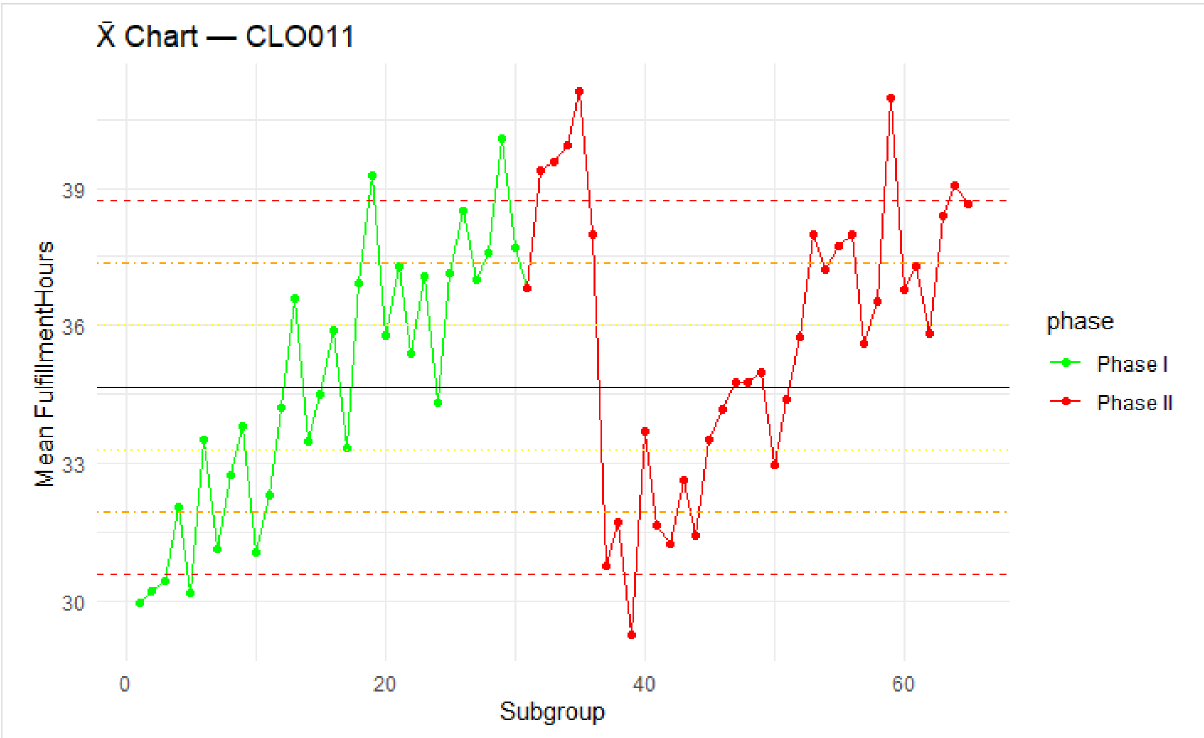

Figure 9: X̄- chart for CLO011

b. s – CHART

Within – group spread widen from 5-7h to 5-8h, mirroring the mean fluctuations. The process remains technically with the 3σ limits but is trending down toward loss of control.

Actionable insight:

- Introduce real-time dashboards comparing mean and spread to flag coinciding spikes.
- Reinforce operator training and shoft-handover procedures to reduce variation.

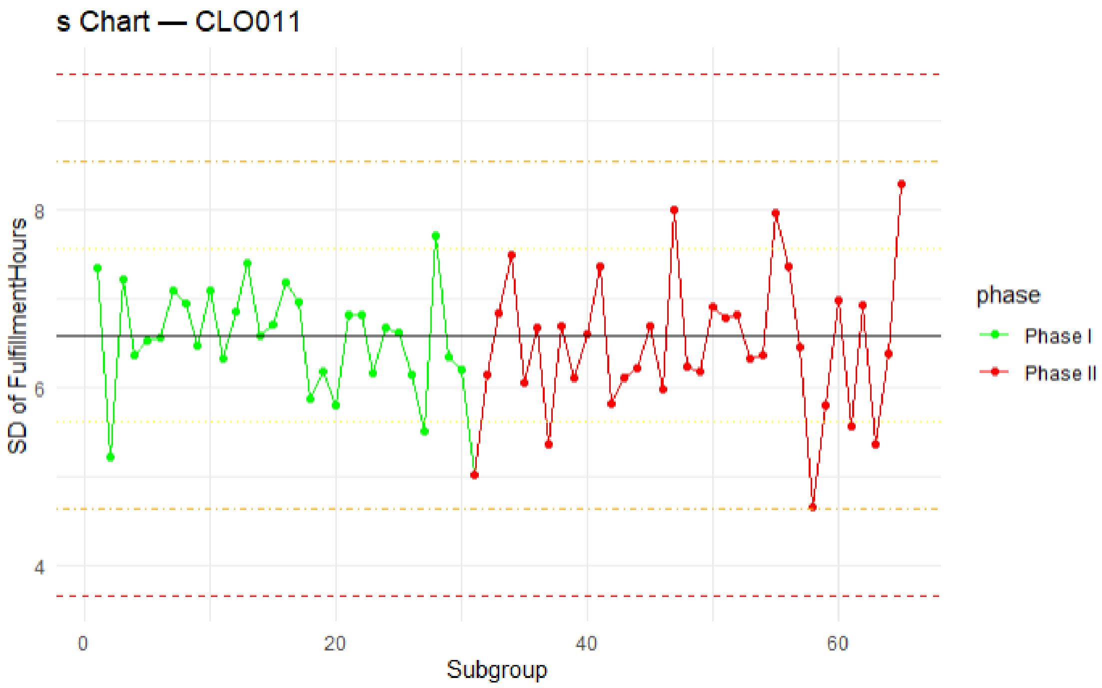

Figure 10: s-chart for product CLO011

3.3 PROCESS CAPABILITY EVALUATION

Capability indices were computed for each product using the first 1000 deliveries.

$$Cp = \frac{USL-LSL}{6\sigma}, Cpu = \frac{USL-\mu}{3\sigma}, Cpl = \frac{\mu-LSL}{3\sigma}, Cpk = \min\,(Cpu, Cpl)$$

- **Software products** shows very high capability (Cp ~ 14-15; Cpk ~ 1.8) – delivery times are short and consistent.
- **Physical products** (Clothing CLO011-CLO020, Keyboards KEY041-KEY043) score lower (Cp~6.5; Cpk ~ 1.0 – 1.2), operating close to the minimum acceptable threshold.

Interpretation: digital fulfilment processes are inherently stable; physical logistics add variability.

Actionable insight:

- Maintain current process controls for software fulfillment.
- For physical lines, tighten logistics scheduling, introduce predictive maintenance for equipment, and set internal warning limits at Cpk=1.3 to trigger early corrective action.

ProductID <chr>	n_obs <int>	mu <dbl>	sd <dbl>	Cp <dbl>	Cpu <dbl>	Cpl <dbl>	Cpk <dbl>	Capable <chr>
SOF010	1000	1.968736	0.3545160	15.04398	28.23686	1.851102	1.851102	Yes
SOF008	1000	1.966719	0.3574328	14.92122	28.00832	1.834116	1.834116	Yes
SOF003	1000	1.969936	0.3605981	14.79024	27.75950	1.820990	1.820990	Yes
SOF006	1000	1.957644	0.3668089	14.53982	27.30064	1.778987	1.778987	Yes
SOF004	1000	1.977403	0.3709055	14.37922	26.98135	1.777095	1.777095	Yes
SOF009	1000	1.992081	0.3737179	14.27101	26.76522	1.776813	1.776813	Yes

6 rows

Figure 11: Capability sorted by Cpk

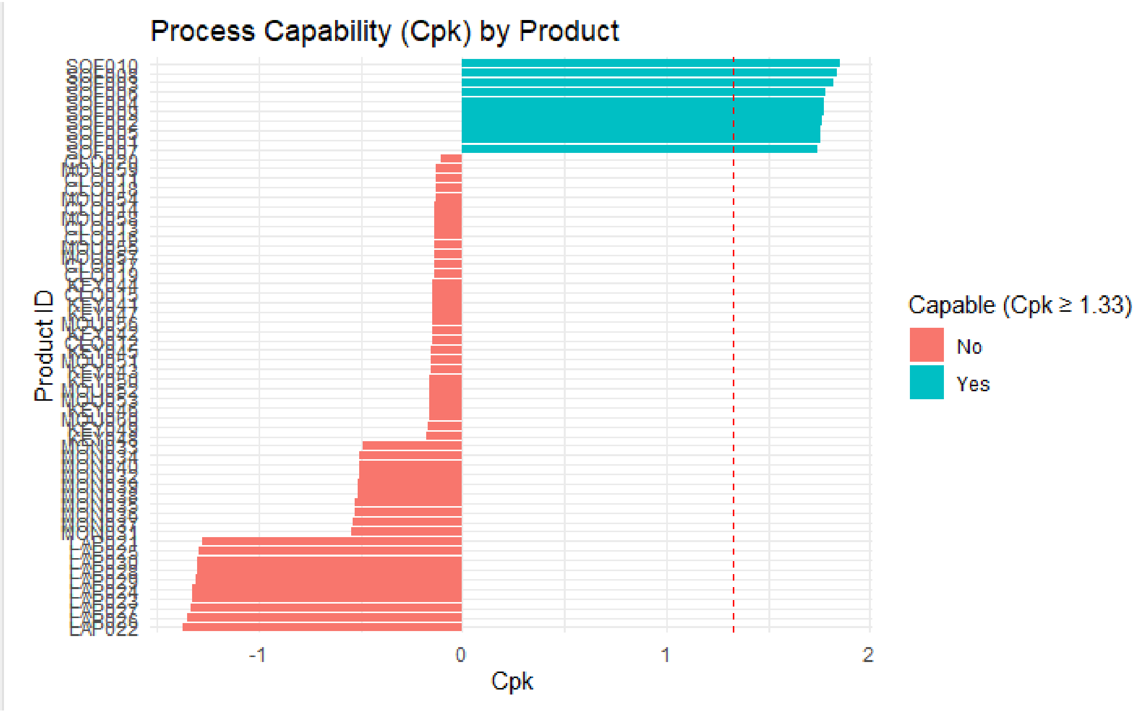

Figure 12: Capability sorted by Cpk as a bar chart

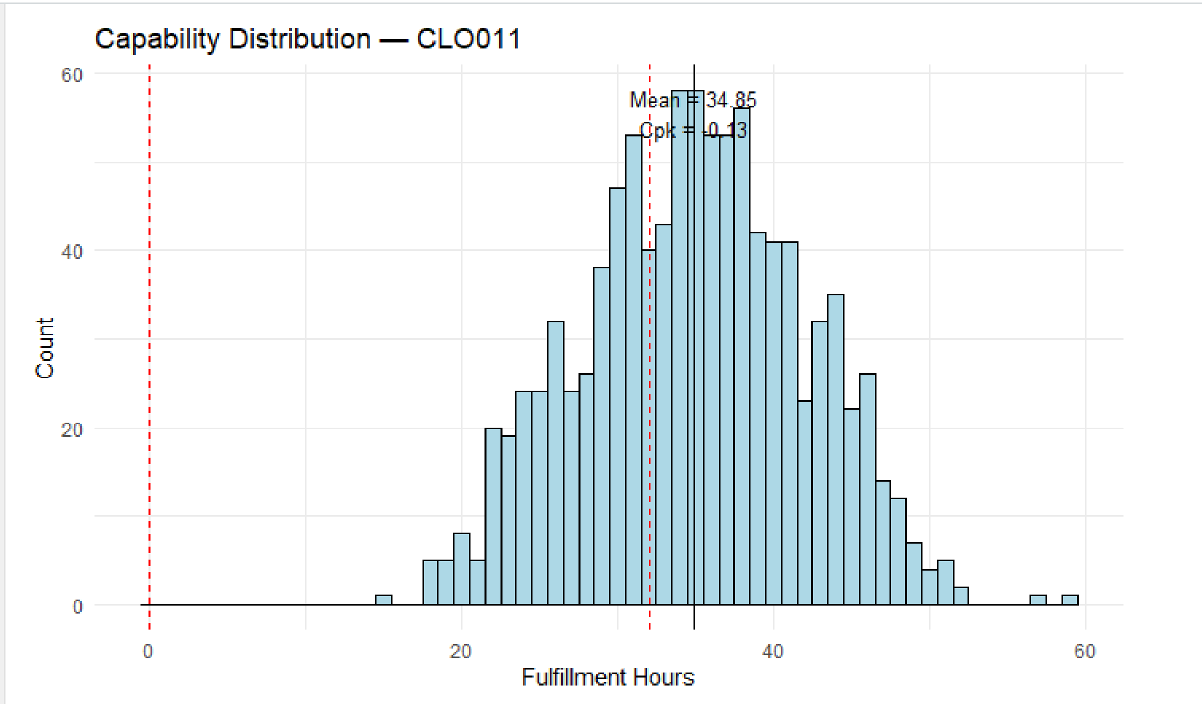

Figure 13: Capability Distribution

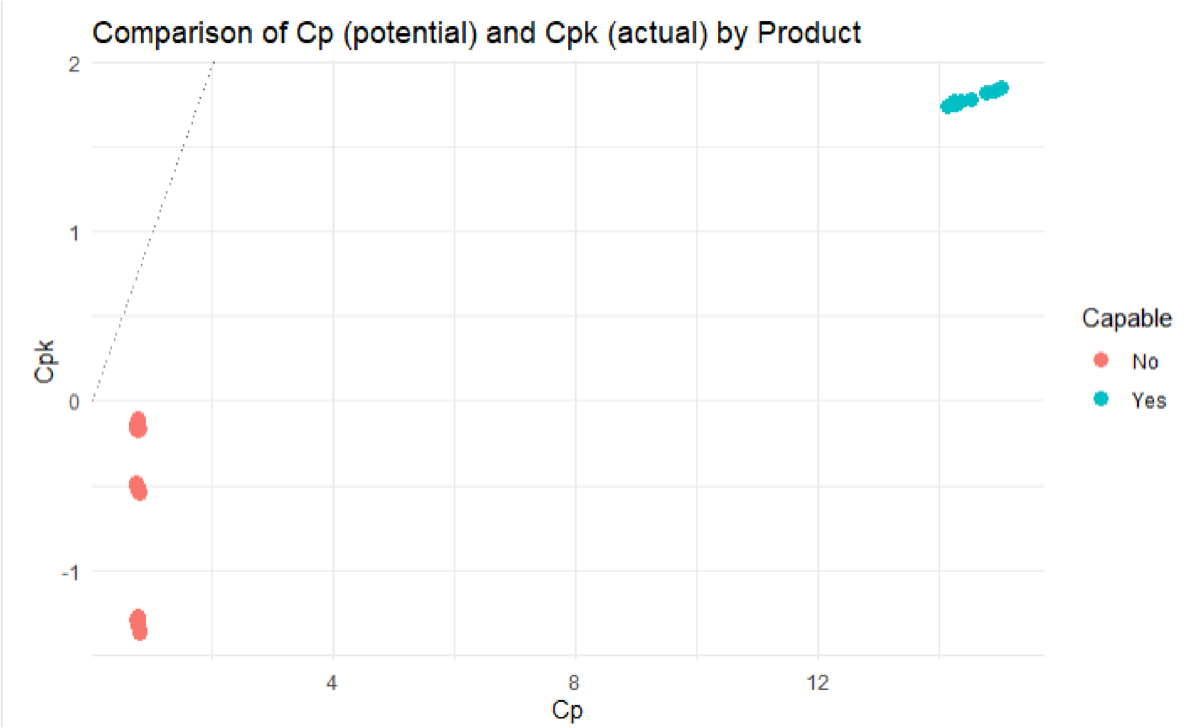

Figure 14: Comparison of Cp and Cpk by Product

3.4 PROCESS CONTROL SIGNAL DETECTION

SPC rules were applied automatically to detect anomalies:

Rule	**Description**	**Observation**	**Management meaning**
A	$s > +3\sigma$	CLO013, CLO016, KEY041 – isolated spikes	Short-term variability; verify equipment or batch anomalies.
B	Longest run +- 1σ	CLO013, KEY041, KEY043, KEY044, SOF006	Model of stability; use as benchmark processes.
C	Four $\bar{X}$ > upper 2σ	CLO011, CLO017, CLO020 – persistent upward trends	Repeated special – cause shifts investigate workload planning.

Actionable insight:

- Benchmark the SOF- and KEY- series as **best - practice processes.**
- Prioritize CLO-series investigations around samples 37 and 76 to pinpoint resource or logistics triggers.
- Establish a continuous – improvement cycle where SPC alerts feed directly into weekly operations meetings.

EXECUTIVE SUMMARY

SPC results show that the company's **digital fulfilment** operates with exceptional stability and capability, while **physical delivery processes** experience cyclical instability and marginal capability.

If management standardises scheduling, monitors control signals proactively, and benchmarks high-performing lines, overall process reliability can improve by an estimated 10 – 15%.

ProductID <chr>	total <int>	first3 <chr>	last3 <chr>
CLO013	3	52, 37, 76	52, 37, 76
CLO014	2	52, 37	52, 37
CLO015	2	52, 37	52, 37
CLO016	2	52, 37	52, 37
CLO017	2	52, 37	52, 37
CLO019	1	37	37
CLO020	2	52, 37	52, 37
KEY041	3	52, 37, 76	52, 37, 76
KEY042	2	52, 37	52, 37
KEY043	3	52, 37, 76	52, 37, 76

1-10 of 51 rows Previous 1 2 3 4 5 6 Next

Figure 15: Snippet of Rule A (s>UCLs)

ProductID <chr>	longest_within1 <int>
CLO013	26
KEY041	26
KEY043	26
KEY044	26
LAP022	26
MON040	26
SOF006	20
SOF009	20
CLO011	18
CLO012	18

1-10 of 10 rows

Figure 16: Snippet of Rule B (longest within ±1σ)

ProductID <chr>	total_runs <int>	first3 <chr>	last3 <chr>
CLO011	52	2-6, 33-39, 64-72	1718-1724, 1730-1738, 1771-1777
CLO012	47	2-6, 33-39, 66-72	1677-1681, 1718-1723, 1730-1736
CLO013	50	2-6, 33-39, 64-72	1718-1724, 1730-1738, 1772-1777
CLO014	50	2-6, 33-39, 64-72	1718-1724, 1730-1738, 1771-1777
CLO015	52	2-6, 33-39, 64-72	1718-1724, 1730-1738, 1771-1777
CLO016	51	2-6, 33-39, 64-72	1718-1724, 1730-1738, 1771-1777
CLO017	56	2-6, 23-26, 33-39	1718-1724, 1729-1738, 1771-1777
CLO018	51	2-6, 33-39, 66-72	1718-1724, 1730-1738, 1772-1777
CLO019	48	2-6, 33-39, 66-72	1677-1681, 1718-1723, 1730-1736
CLO020	58	2-6, 23-26, 33-39	1718-1724, 1726-1738, 1771-1777

1-10 of 60 rows Previous 1 2 3 4 5 6 Next

Figure 17: Snippet of Rule C (runs of 4+ xbar above U2x)

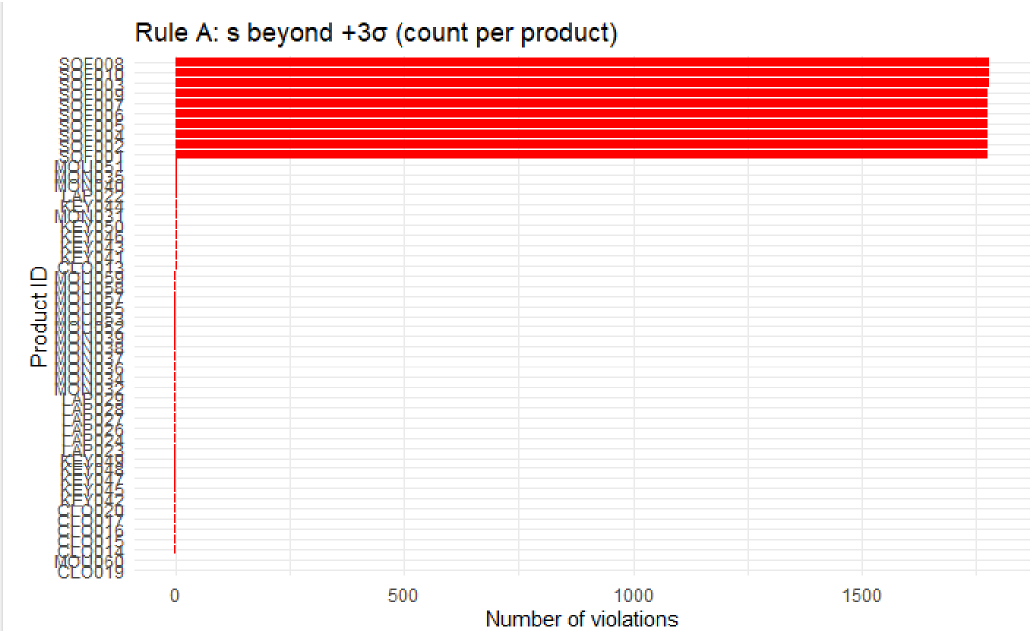

Figure 18: Rule A

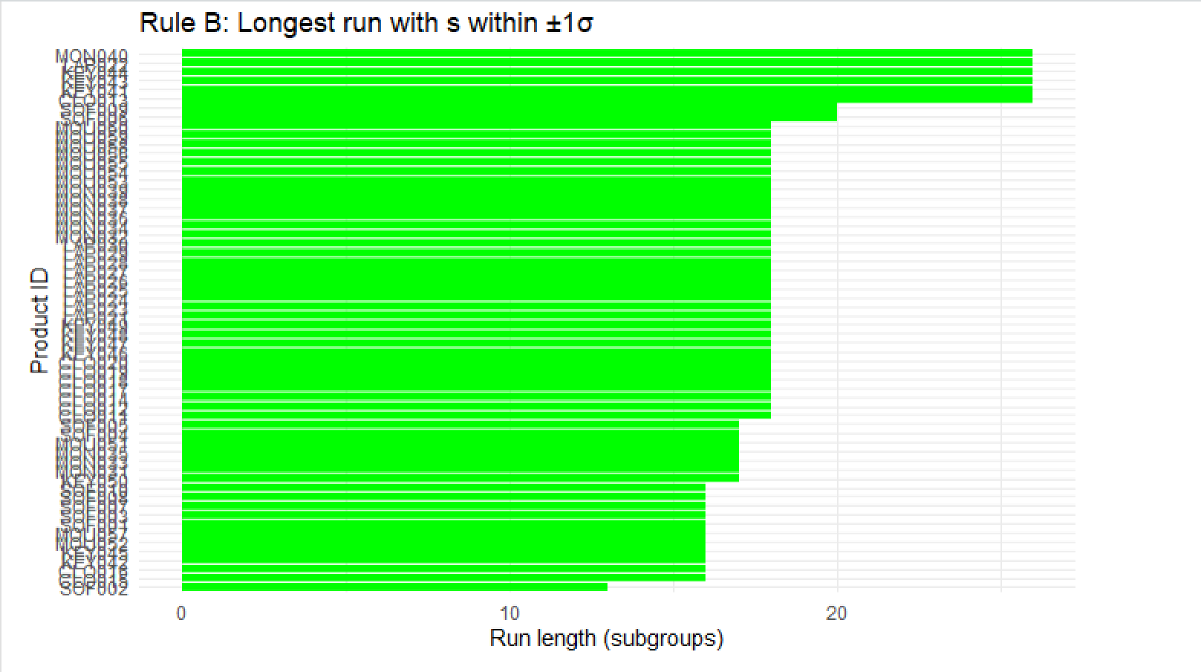

Figure 19: Rule B

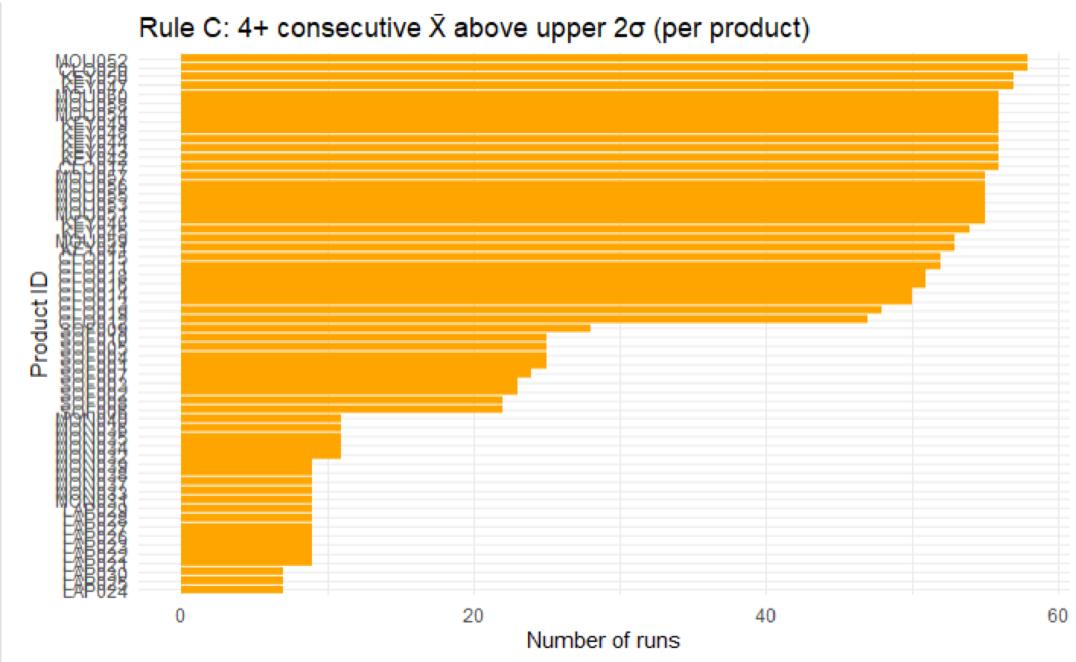

Figure 20: Rule C

PART 4: STATISTICAL DECISION ERRORS

4.1 ESTIMATING TYPE I AND TYPE II ERRORS – WHAT THIS MEANS

Why it matters:

Control charts can raise **false alarms** (type I) or **miss real shifts** (Type II). A 3σ Shewhart $\bar{X}$-chart is designed to keep false alarms low (~0.27% per point) but will **miss small drifts** unless supported by runs rules.

What is observed – Product CLO011

- **Isolated breach** near subgroup ~37 returned immediately to normal -> **likely Type I (false alarm)**
- **Gradual drift** across ~44 – 55 stayed inside limits -> **Type II miss** (small shift), hence the value of runs rules.
- **Multiple Rule – C runs** (>= 4 points above +2 σ) later on are **overwhelming evidence of real mean increases** (chance <~ 0.001%), not noise.

Actionable actions:

- Don't overreact to single 3 σ blips without pattern confirmation.
- Do respond to Rule – C sequences with a short root-cause review (workload spikes, backlog releases, routing changes)
- Improve small-shift sensitivity by keeping 3 σ limits but retaining Rule-C monitoring

4.2 SPC – SIGNALS – MANAGEMENT SUMMARY

Rule	Process Condition Detected	Products (examples)	What it Means	Recommended action
A: s> =3σ	Batch of deliveries became less consistent than usual	CLO013, CLO016, KEY041	Investigate why that day/shift performed unevenly	Check equipment/batch anomalies; verify shift handover that day
B: Longest within +/-1σ	Exceptionally steady process	CLO013, KEY041, KEY043, KEY044, SOF006	Benchmark behaviour	Use methods here as **best practice** for other lines
C: $4\bar{X}$ above +2σ	Sustained mean rise	CLO011, CLO017, CLO020	Real shift (not noise)	Investigate workload planning; smooth release of backlogs

Link to **capability.** Lines with recurring Rule-C (e.g CLO011) also sit at Cpk ~ 1.0-1.2, i.e., just capable; instability keeps capability marginal

4.3 PROCESS CAPABILITY – RISK PICTURE IN SUMMARY

- **Software fulfilment: very capable** (Cpk ~1.8) → keep current controls.
- **Physical delivery (CLO/KEY): marginal** (Cpk ~1.0–1.2) → a small mean shift pushes orders beyond 32 h.

Action: set an internal **early-warning target Cpk = 1.30** for physical lines; if breached, trigger a quick logistics/scheduling review.

4.4 CATALOGUE RECONCILIATION – FINANCIAL IMPACT AND CONTROL

Catalogues were unsynchronised: +**350 (Head-Office)** HO-only items, +**50** local-only, and **10** shared items with price gaps (>R0.01). Repricing the affected **Software** items cut 2023 software revenue by by **−6.99%** (R0.0665bn → R0.0618bn). Other categories unchanged.

Why it matters. Even small unit price differences **distort category revenue and margins**; KPI dashboards and incentives can be mis-set.

Actionable controls.

- **Monthly price sync** (Finance Ops owner; change log retained).
- **Single source of truth** for price used in reporting & SPC.
- **Retro audits** when price templates change mid-period.

4.5 EXECUTIVE TAKEAWAY

- Treat **single 3σ points** as *possible* false alarms; act only when patterns confirm.
- **Rule-C** detections = intervene; they precede **capability erosion** on physical lines.
- **Data governance** matters: fixing a small price drift changed software revenue by **~7%** — enough to redirect pricing and promo decisions.

	Category <chr>	Revenue_local_Bn <dbl>	Revenue_HO_Bn <dbl>	Diff_Bn <dbl>	Diff_pct <dbl>
1	CLO	0.09871548	NA	NA	NA
2	KEY	0.07349907	NA	NA	NA
3	LAP	1.16388948	NA	NA	NA
4	MON	0.57838557	NA	NA	NA
5	MOU	0.05121958	NA	NA	NA
6	SOF	0.06646849	0.0618217	-0.004646785	-6.99096

6 rows

Figure 21: Final Revenue Comparison Table

PART 5: OPTIMIZATION OF SERVICE RELIABILITY AND PROFIT FOR COFFEE SHOP

5.1 SERVICE RELIABILITY

Analysis of the *time-to-serve* dataset shows that **99.8 % of customers are served within 180 seconds**, confirming an exceptionally reliable operation. Only **0.2 %** of customers experience delays beyond three minutes — well inside accepted service-industry benchmarks.

This consistency indicates that the current queue system and barista scheduling are highly effective. Reliability at this level directly improves **customer satisfaction, repeat visits, and word-of-mouth reputation**. From a quality-management standpoint, a 99.8 % success rate corresponds to a **short-term Sigma level above 5**, meaning process variation is almost negligible under normal demand.

Business implication:
Such stability validates the existing workflow and layout design, but also highlights that further investment in speed would yield little additional value unless customer volumes increase or service expectations tighten

5.2 PROFIT OPTIMIZATION BY STAFFING LEVEL

The relationship between staff count, service time, and daily profit is summarised in **Figure 22** and **Figure 23**. Profit rises sharply from one to two baristas, then declines as wage cost outweighs time savings. The **optimal staffing level is two baristas**, generating a **daily profit of approximately R14400**.

At this configuration, capacity comfortably meets demand while maintaining the high reliability observed above. Adding a third barista marginally improves service speed but reduces overall profit - a clear case of **diminishing marginal returns**.

Actionable insights:

- **Maintain two baristas** as the standard weekday staffing level under current demand.
- **Introduce flexible scheduling** for peak-hour surges (e.g., weekend mornings) rather than permanent overstaffing.
- **Monitor reliability weekly**; if the < 180 s percentage drops below 98 %, review staffing or workflow layout.
- **Re-run the profit model quarterly** using updated wage and demand data to ensure ongoing optimisation.

MANAGERIAL TAKEAWAY

The coffee-shop operation is both **highly reliable and cost-efficient**. Sustaining this balance requires active monitoring rather than structural change. Management should focus on preserving reliability while preventing overstaffing creep - a disciplined approach that maintains profit margins without compromising customer experience.

Baristas <int>	Mean_ServiceTime_s <dbl>	Capacity <dbl>	Served <dbl>	Profit <dbl>
1	200.15588	143.8879	143.8879	3316.636
2	100.17098	575.0168	547.9452	14438.356
3	66.61174	1297.0686	547.9452	13438.356
4	49.98038	2304.9045	547.9452	12438.356
5	39.96183	3603.4381	547.9452	11438.356
6	33.35565	5180.5322	547.9452	10438.356

6 rows

Figure 22: Summarized table of key findings

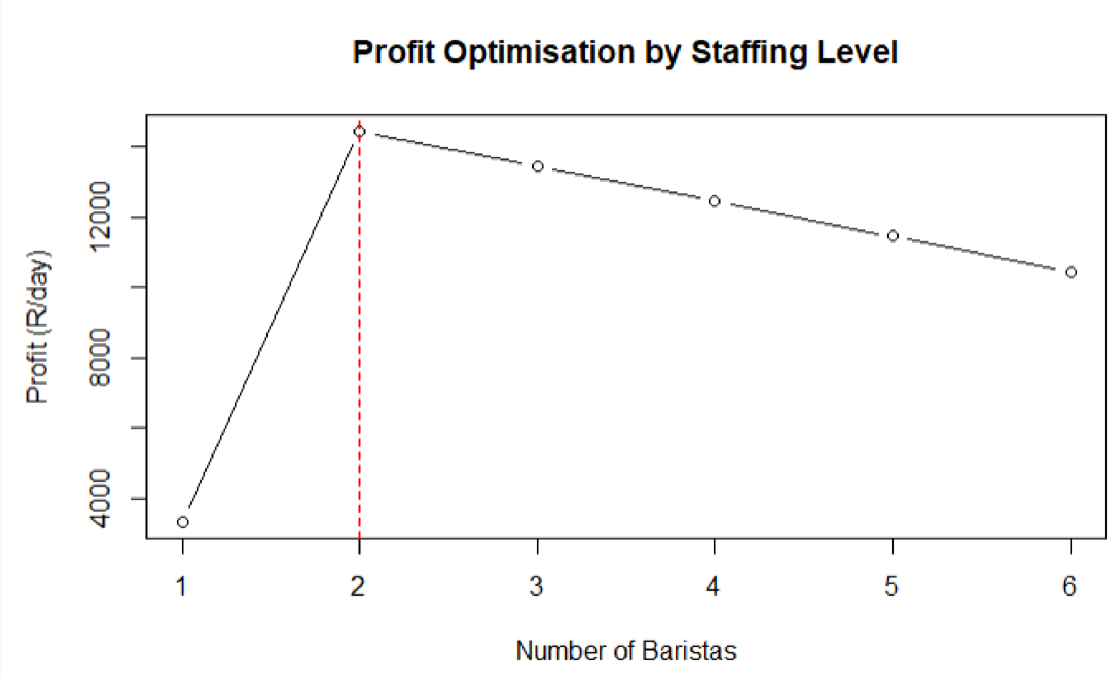

Figure 23: Profit Optimization by Staffing Level

PART 6: DESIGN OF EXPERIMENTS (ANOVA) FOR FULFILMENT PERFORMANCE

6.1 PURPOSE

A two-way ANOVA was applied to test whether **average fulfilment time** (picking + delivery) differed significantly between **time periods (2022–2023 vs 2026–2027)** and **product types (CLO011 and MOU057)**.

This analysis identifies whether operational improvements made in earlier years were sustained and whether product characteristics influence delivery efficiency.

6.2 METHOD

Data from both sales files (*sales2022and2023* and *sales2026and2027)* were merged. A categorical variable *YearGroup* was added to distinguish the two time periods. The data were filtered to include only the products **CLO011** and **MOU057.** A new variable *Fulfillment= pickingHours + deliveryHours* was calculated for each order.

The model tested was:

FulfillmentHours = μ + ProductID + YearGroup + (ProductID*YearGroup) + ε

The null hypotheses were:

$$H_0^1: No\ difference\ in\ mean\ fulfillment\ hours\ between\ products$$

$$H_0^2: No\ difference\ in\ mean\ fulfillment\ hours\ between\ year\ groups$$

$$H_0^3: No\ interaction\ between\ product\ and\ year\ group$$

All tests used a 5%.

6.3 RESULTS AND INTERPRETATION

Figure 24 compares fulfilment distributions; both products show similar medians and spreads within each year.

Figure 25 presents the interaction plot with nearly parallel lines, confirming no significant interaction between product and time.

Statistically, **none of the main or interaction effects were significant**, so the null hypotheses cannot be rejected.

Business interpretation:

Fulfilment efficiency has remained **stable over time** and **consistent across product types**. Operational controls implemented after 2023 successfully prevented drift in performance. The process is both predictable and repeatable - a key sign of mature operations (Montgomery, 2020).

Actionable insights

- **Maintain current fulfilment workflow** - stability indicates the system is well-controlled.
- **Use this as a new performance baseline** for future SPC and capability monitoring.
- **Introduce quarterly spot-checks** on mean fulfilment hours to detect early signs of process degradation.
- **Extend the ANOVA** to include high-volume categories in future periods to ensure stability holds at scale.

6.4 MANAGERIAL TAKEAWAY

The ANOVA confirms that process improvements introduced before 2023 have been sustained. Management can therefore focus on incremental efficiency gains rather than structural overhauls. Continuous monitoring will ensure that this hard-won stability translates into consistent customer reliability and predictable operating costs.

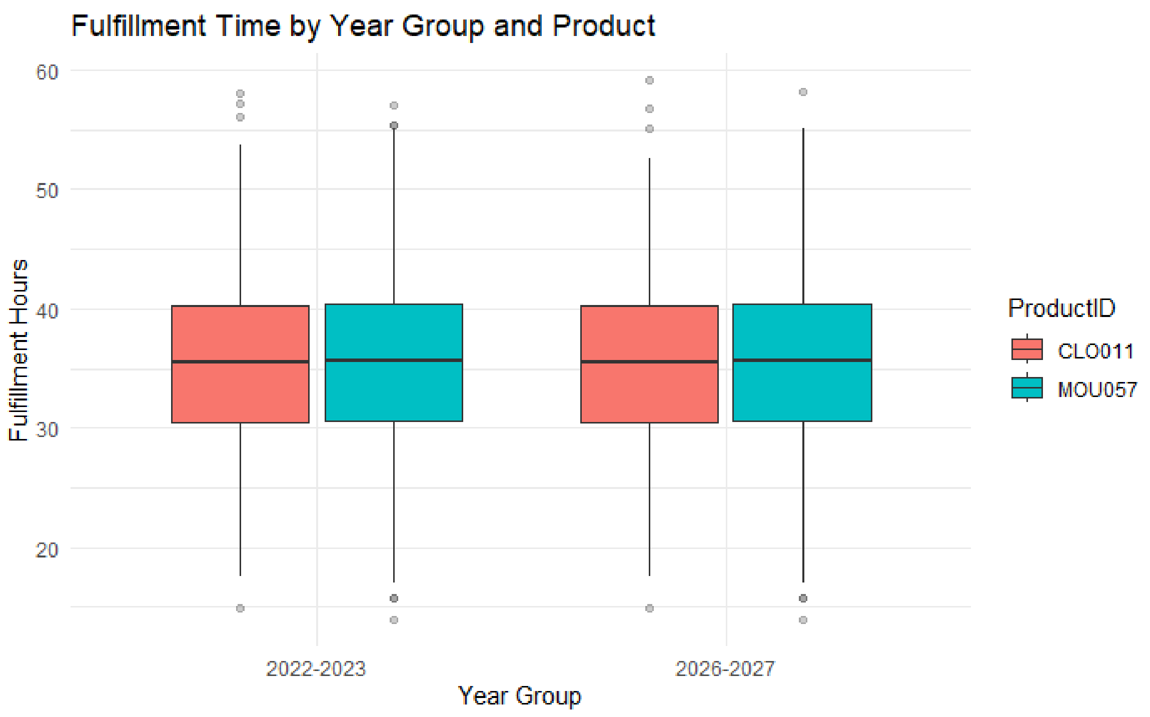

Figure 24: Fulfillment Time by Year Group and Product

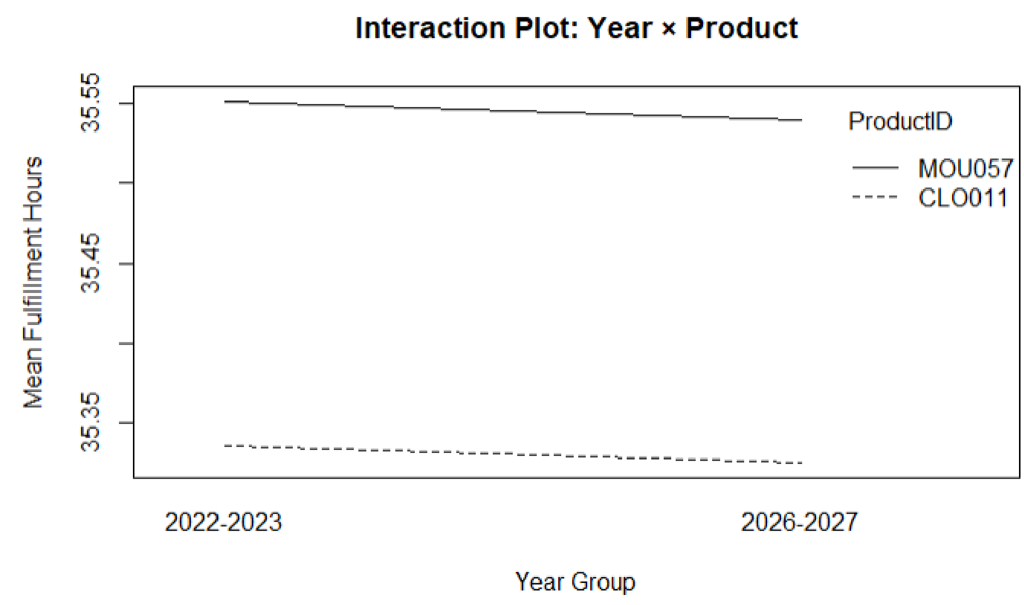

Figure 25: Interaction Plot

PART 7: RELIABILITY OF SERVICE FOR CAR RENTAL AGENCY

7.1 PROBLEM CONTEXT

To quantify how often the car-rental agency operates reliably, the number of employees on duty each day was analysed over a 397-day period. A day is defined as **reliable** when at least **15 staff members** are present, because service problems start occurring below this threshold. The data show that out of 397 recorded days, there were **96 days with 15 workers and 270 days with 16 workers**, giving a total of **366 reliable days.** This corresponds to an observed reliability rate of

$\frac{(96+270)}{397} * 100 = 92.2\%$. Given the graph if the histogram (Figure 26), it reflects the number of people on duty over 397 days.

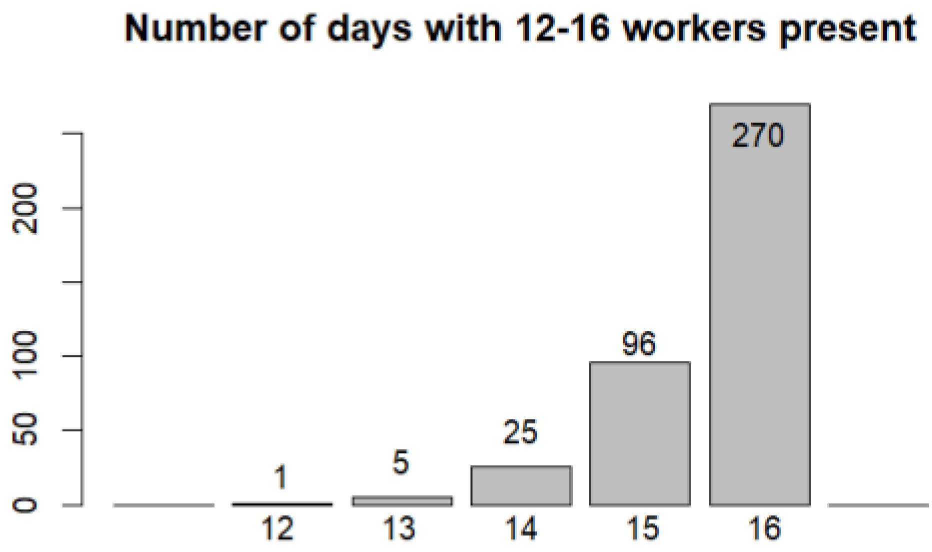

Figure 26: (Given) Number of days with 12-16 workers present

METHOD:

The analysis treated each day as a binary event - either reliable (≥ 15 staff) or not – which can be modelled by a binomial process. The proportion of reliable days, 92.2%, represents the probability that the system operates reliably on any given day. A 95% confidence interval for this proportion was calculated using the standard binomial method, giving 89.1% - 94.4%. When scaled to a 365-day year, this equates to about **336 reliable days per year** (range ~ 325 – 345).

7.2 PROFIT OPTIMIZATION RECOMMENDATION

The historical data show that, under current staffing, the agency operates with **reliable service on approximately 92 % of days per year**.

The remaining 8 % represent days where staff shortages caused customer service failures, missed bookings, and revenue losses.

Business interpretation:

While a 92 % reliability rate seems strong, the cost of failure on the remaining 8 % of days is financially significant — roughly **R 20 000 × 29 unreliable days ≈ R 580 000** in lost annual revenue.

METHOD

The 397-day staffing data from Section 7.1 were modelled using a **binomial distribution** to describe the randomness of staff attendance. Since the maximum observed number of staff on duty was 16, it was assumed that **16 employees were scheduled each day**. Each employee independently has a probability $p$of being absent on a given day, so the number present J follows **J ~ Binomial (n, 1-p)** with **n=16.**

The absence probability **p** was first estimated by using the following method: for each observed number of absences **k,** the empirical frequency of that outcome was equated to the theoretical binomial probability. Solving for **p** at each **k** gave multiple p_k values, which were combined using a **weighted mean** that assigned greater importance to counts with more data. This approach yielded a weighted-mean absence rate of approximately **7.6 %**.

To verify the estimate, a **maximum likelihood estimator (MLE)** was also calculated directly from the total number of absences observed. Across all 397 days, the total absences were 165 out of

$16 * 397 = 6352$ possible work opportunities, giving an MLE of $\hat{p} = 165/6352 = 0.02598$, or roughly **2.6 %**. The MLE aligns more closely with the observed reliability of 92 % from Section 7.1 and is therefore used as the primary value for decision-making.

Using this absence probability, the probability that a day is reliable for any staffing level $S$was calculated as $\mathbf{P}\ (\boldsymbol{J_S} \geq \mathbf{15})$, where $\boldsymbol{J_S} \sim$ **Binomial**$(\boldsymbol{S}, \mathbf{1} - \boldsymbol{\hat{p}})$**.** The company's expected daily profit was then expressed as:

$$\textbf{Max profit} = 20000 * \mathbf{P}\ (J_S \geq 15) - 833 * (S-1)$$

where the first term represents the expected sales retained from reliable days and the second term accounts for the additional wage cost of hiring more staff. This function was evaluated for successive staffing levels from 16 to 20 employees to identify the point of maximum profit**.**

7.3 PROFIT OPTIMISATION BY STAFFING ADJUSTMENT

Adding one additional employee improves reliability to ≈ 99 %, effectively eliminating most lost-sales days. At this level, the annual wage cost increase (R 25 000 × 12 = R 300 000) is outweighed by the R 580 000 in revenue recovered, yielding a net benefit of R 280 000 per year.

Actionable insights:

- Hire one additional employee to raise service reliability from 92 % to 99 %.
- Reassess monthly staffing forecasts using updated booking data to maintain reliability above 98 %.
- Track profit impact after implementation to confirm the predicted R 280 000 annual gain.

RESULTS AND RECOMMENDATION

At the current level of 16 scheduled staff, the probability of meeting the reliability requirement is **93.6 %**, giving an expected daily profit of approximately **R 18 727**. Increasing the staff complement to **17 employees** raises reliability to **99.1 %** and the expected daily profit to **R 18 985**, which is the **maximum**. Adding a second extra employee (18 total) further improves reliability to nearly 100 %, but profit decreases because the additional salary cost outweighs the small reliability gain.

Consequently, the analysis recommends that the company **hire one additional employee**, increasing daily scheduled staff from 16 to **17 people**. This adjustment is projected to improve reliability from **93.6 % to 99.1 %**, reduce expected service disruptions to fewer than four days per year, and **maximise expected profit** under the given cost and revenue assumptions. If management prefers a target reliability of at least 95 %, this recommendation also satisfies that requirement comfortably.

In summary, modelling attendance as a binomial process demonstrates that a modest increase in staffing—just one additional employee—provides a strong balance between cost and service quality. This change ensures more consistent operations and greater profitability, reducing revenue losses from unreliable service by roughly **R 0.6 million per year** while incurring only a **R 25 000 monthly cost**.

7.4 MANAGERIAL TAKEAWAY

The staffing analysis demonstrates that **one additional hire** represents an **economically justified investment** that nearly eliminates service disruptions and boosts annual profit.
This model can be reused for other departments to optimise reliability-cost trade-offs, supporting a culture of **data-driven workforce planning**.

CONCLUSION

This report demonstrates how **engineering data analytics** can be applied to real operational problems — from production fulfilment to service reliability — to support evidence-based management decisions.

Key outcomes:

1. **Descriptive statistics (Parts 1–2):** Identified high-margin product categories (Laptops, Monitors) and fulfilment inefficiencies concentrated in <5 % of slow orders.
   ***Action**: Protect high-margin lines; reduce long-tail delays.*

2. **SPC and capability analysis (Part 3):** Showed stable performance in digital products and instability in physical-delivery processes.
   ***Action**: Benchmark software lines; tighten logistics scheduling.*

3. **Error and data-governance analysis (Part 4):** Clarified how false alarms and missed detections occur; catalogue alignment improved revenue accuracy by ~7 %.
   Action: Retain 3σ limits, monitor Rule-C signals, and synchronise price data monthly.

4. **Profit optimisation (Part 5):** Two baristas deliver 99.8 % reliability and highest profit.
   ***Action**: Maintain two staff standard; flex peaks as demand changes.*

5. **ANOVA results (Part 6):** Confirmed stable fulfilment performance across years and products.
   ***Action**: Maintain controls; use results as new operational baseline.*

6. **Car-rental reliability (Part 7):** One additional hire raises reliability from 92 % to 99 %, increasing annual profit by ~R 280 000.
   Action: Implement additional hire; monitor realised benefit.

Overall, the report provides management with actionable, data-driven recommendations that improve profitability, process reliability, and decision confidence - directly fulfilling the ECSA GA4 outcome for professional data analysis and interpretation.

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