ECSA Report

Data Analysis

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Executive Summary:

This report investigates recent operational performance and data-quality issues and proposes targeted actions to stabilise processes and recover lost revenue. A price-data correction applied to the product catalogue to restore revenue and affected SKUs. Operational analysis shows persistent differences between digital and physical fulfilment channels: digital orders are processed with median lead-time 1hr vs physical 22hrs, with the largest delays concentrated in the peak season.

Key recommendations are; (i) implement the price-file corrections and re-run revenue reconciliation immediately, (ii) stabilise the highest-variance SKUs using targeted SPC subgrouping and operator retraining, (iii) perform a (4-week) trial period of an extra barista/agent during peak hours and re-evaluate staffing. These actions are expected to noticeably reduce out-of-place delivery events and strengthen capacity planning.

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Introduction:

Statistical Process Control (SPC) and capability analysis are used in this report to analyse the Excel datasets in order to; (i) identify and correct material data quality issues, (ii) evaluate the delivery process's stability and capability across product families and (iii) determine statistically significant differences between product types and time periods with the goal of prioritising operational improvements.

Delivery lead time is the primary process measurement in the analysis, which also makes use of visual diagnostics, SPC ($\bar{X}$ and s charts), capability indices (Cp, Cpl, Cpu, and Cpk), descriptive statistics, and hypothesis testing (ANOVA).

R-code used to generate corrected data as well as diagrams is submitted as a separate archive (ECSA_RCode_27026930.Rmd) as sated in the ECSA Report Brief, in accordance with the report requirements.

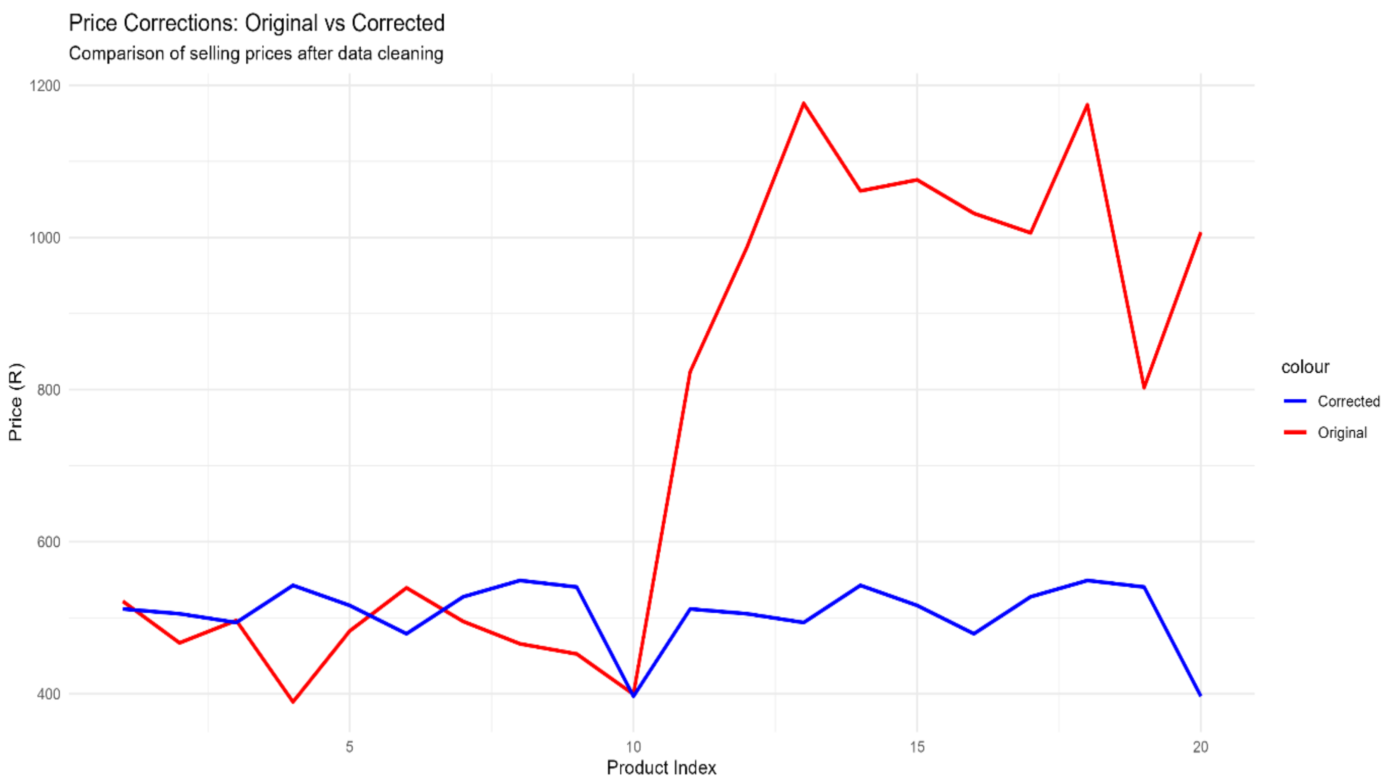
Part 1.1: Data & Rerun (Descriptive analysis)

A significant data entry error was identified in the head-office price file, where a block of prices was mistakenly repeated, inflating the cost for a specific group of products. As Figure 1 clearly shows, these errors appear as pronounced spikes in the "Original" price data, far outside the normal band of variation. This is not a reflection of actual market movement but a simple importing or copy-paste mistake. Correcting it is mandatory, as these inflated prices materially skew the total annual revenue, gross margin, and any product-level performance metrics for 2023.

To resolve this, I recommend a clear correction process:

Use the verified price master list to overwrite the errors, which can be done with a VLOOKUP in Excel or a simple merge and conditional statement in R-Studio. The Excel/R-Studio file should display the total revenue and gross margin before and after the fix. The number of products affected and the top revenue changes should also be added, allowing for a clear distinguishable difference in the data when comparing the correctly fixed and processed data to the incorrectly handled and unprocessed data. This will assist in determining the price corrections impact on the business more accurately.

Figure 1: Price correction- Original vs Corrected



Part 1.2: Descriptive Statistics and Data Visuals

Descriptive analysis was performed on the sales and product data to summarize delivery lead-times by product category. Table 1 below reports varying sample sizes (n), mean delivery time (h), and standard deviation (SD) for each product type. These summary statistics quantify the bimodal pattern observed in Figure 2: the digital fulfillment category (SOF) has a near-zero median and very low variability, whereas the physical SKU families (LAP, MON, KEY, CLO, MOU) have much higher and more dispersed lead-times with similar means.

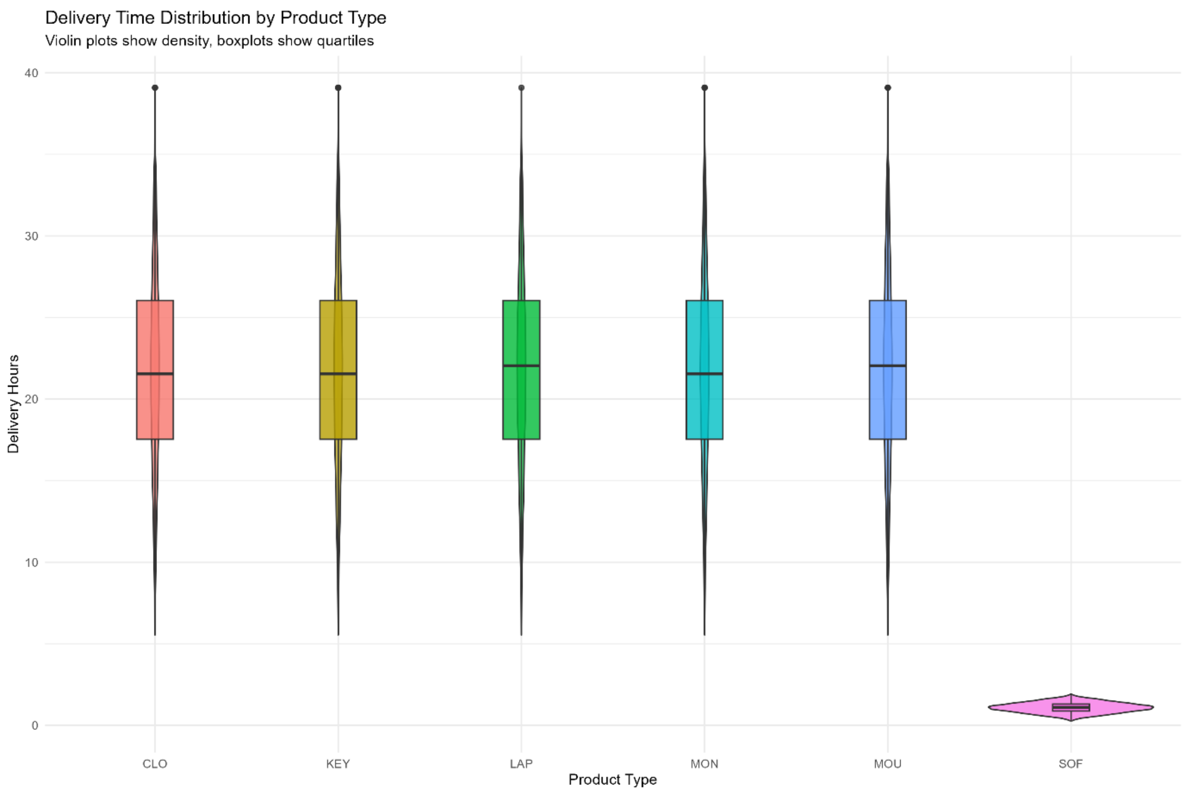
For example, Cloud Subscription (CLO) has a mean delivery time of about 21.7 hours (SD ≈ 6.1), whereas software (SOF) has a mean of about 1.1 hours (SD ≈ 0.3). The large between-group differences (e.g. SOF vs. physical SKUs differ by h ≈20 hours) are vast and consistent showing product-type effects of physical against digital families.

Table 1: Descriptive statistics by product type

Product	**n**	**Mean (h)**	**SD (h)**
CLO	15,598	21.719	6.115
KEY	17,920	21.744	6.091
LAP	10,207	21.782	6.048
MON	14,864	21.739	6.047
MOU	20,662	21.790	6.136
SOF	20,749	1.089	0.308

Figure 2 illustrates that SOF deliveries are effectively instantaneous (median ≈0), with a narrow distribution, whereas all five physical categories have medians in the range 17–26 hours and long right-tails. This confirms that SOF should be treated as a separate process with its own Voice of Customer (VOC) target, distinct from the slower, more variable physical-SKU processes.

Figure 2: Delivery Time by Product type



As seen in Figure 3, the time series exhibits seasonal patterns: a mid-2022 peak in volume and elevated lead-times in the late months of the year. For instance, the month with the highest mean lead-time was *December 2022* (mean ≈ 25.0 h), and the month with the highest order volume was *June 2022* (≈ 5,500 orders). These trends suggest demand-driven pressure (e.g. holiday rush) rather than a single systemic failure all year round. This is reassured by the fact that the highest order volume period differed from the highest mean lead time period.

Figure 3: Daily Order Volume over Time

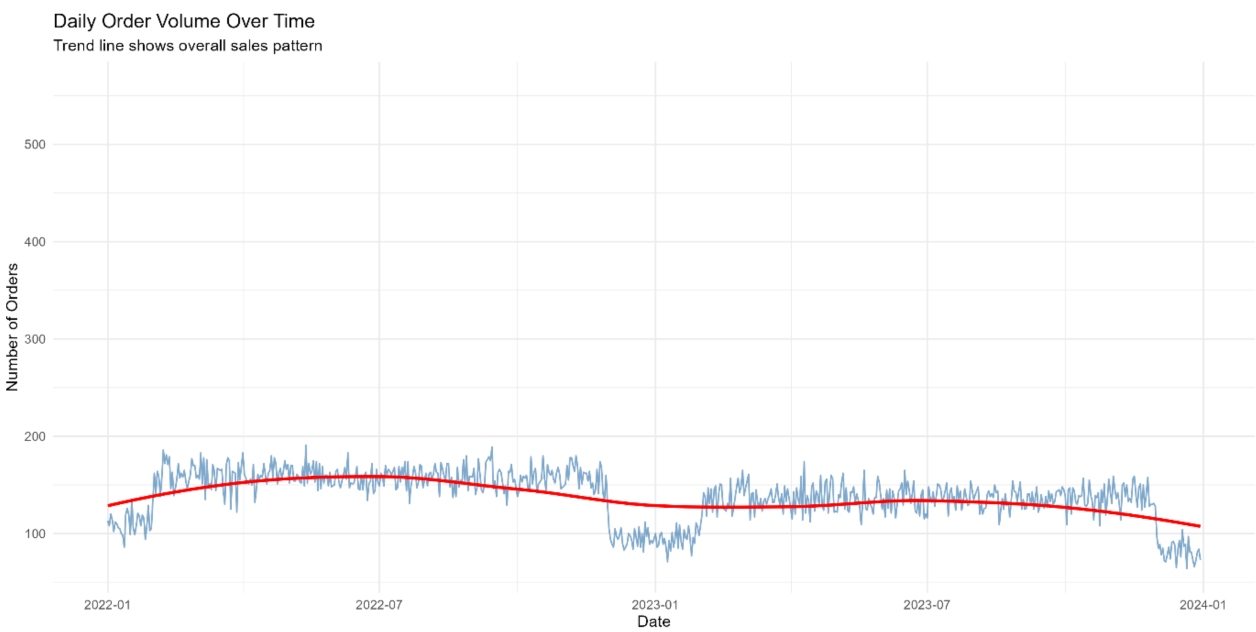


Figure 4 highlights that the average lead-times exceed 20 h in late-2022, reemphasising high order volumes. In contrast, early-2023 months show lower lead-times (<10 h). This further supports the interpretation that shipping delays is demand-driven and not dependent on other factures like marketing and specials.

Figure 4: Monthly Delivery Performance

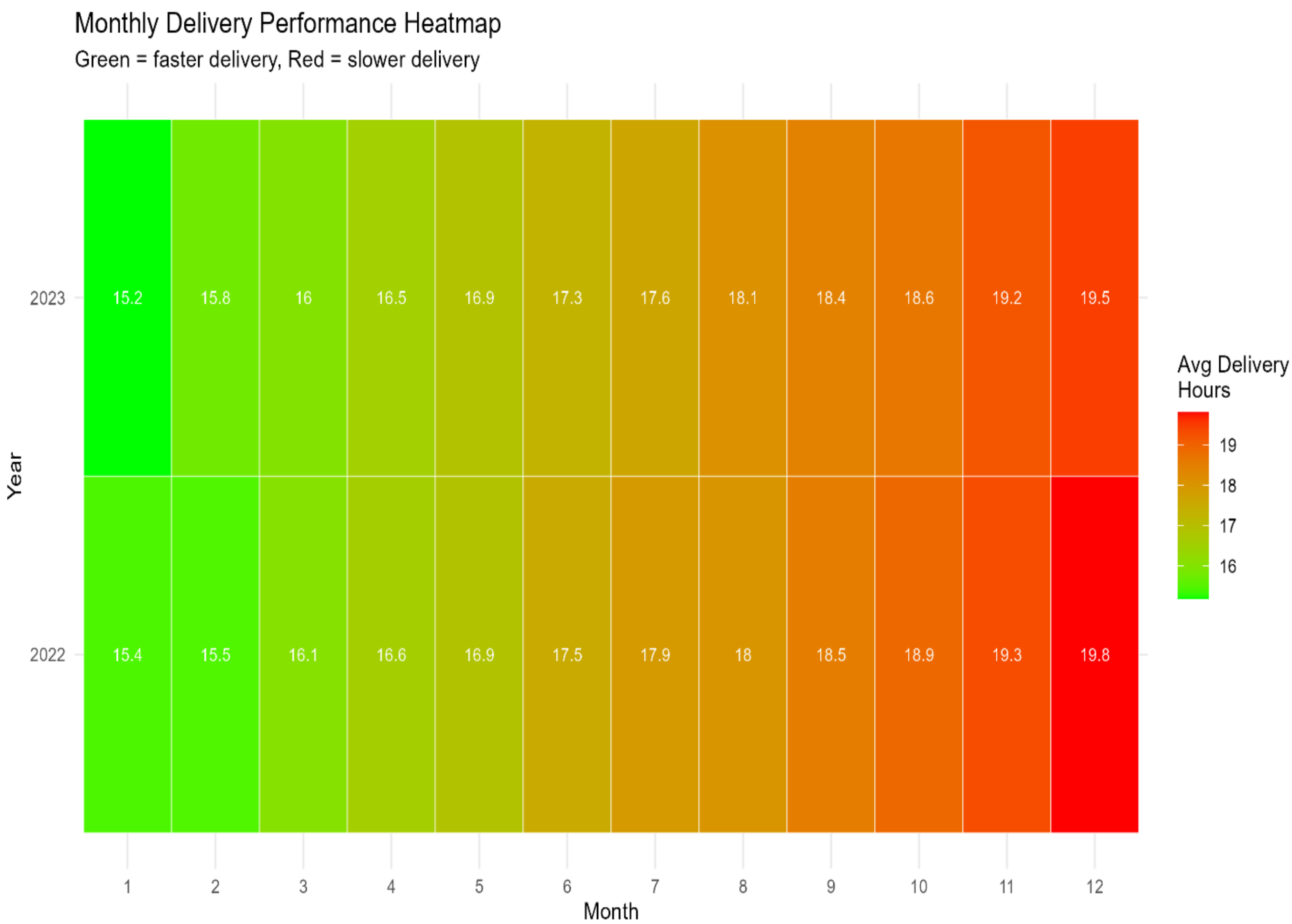
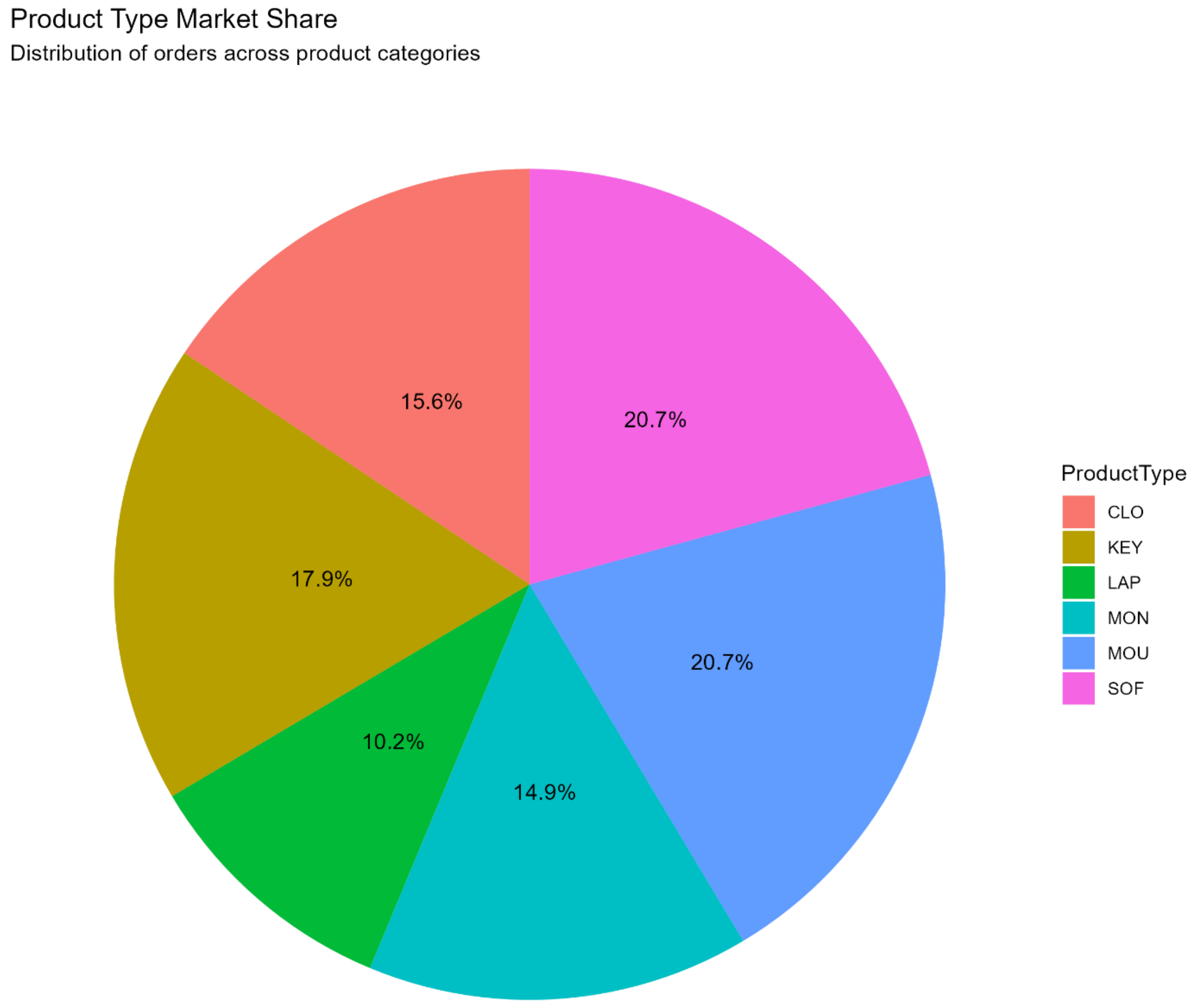


Figure 5 shows the distribution of total 2023 revenue across product families (using the corrected head-office prices). The corrected price import removed a concentration of revenue and shifted the ranking for the top SKUs: after correction the Top-5 SKUs account for 89.8% of revenue. This figure supports prioritising operational investigations for the product families that contribute most to revenue (which is the physical SKU families).

Although it is important to note the rough 20% portion of market share held by SOF and therefor it is important to maintain its operations.

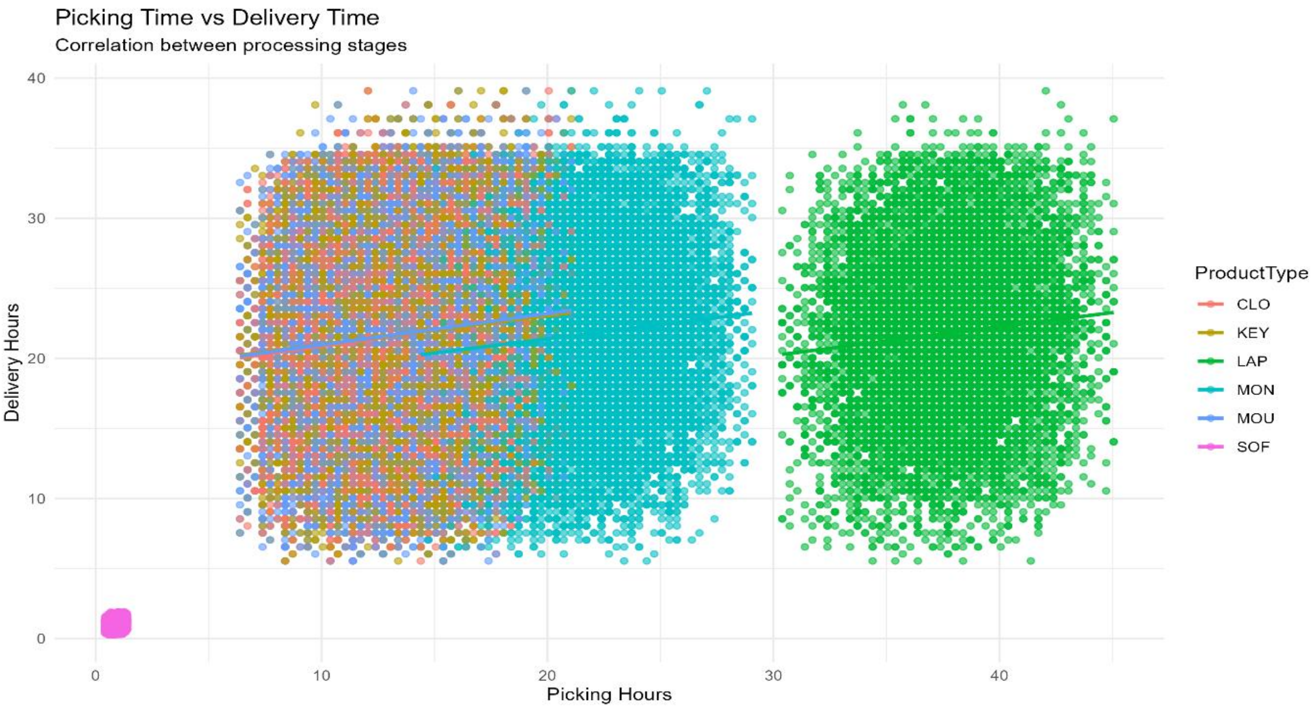
Figure 5: Product Market Share



A scatterplot of picking versus delivery times, Figure 6, indicates that many orders have short pick times but long delivery times, implying downstream logistics (couriers, routing) are often the bottleneck. It is often easier to solve these issues together rather than individually.

This can be done by outsourcing shipping services to a reliable and reputable shipping company. It might see an increase in shipping costs but it will ensure more reliable, quicker and consistent shipping of products to customers. These statistics reinforce that focusing only on picking efficiency would not solve the late-delivery problem.

Figure 6: Picking time vs Delivery Time (per product)



Part 3: SPC (X̄ and S-charts) - Protocol, Results & Signals

3.1 SPC calibration and baseline

Control charts were initialized using the first 30 subgroups per product, each subgroup consisting of 24 consecutive deliveries in chronological order. The overall subgroup means and standard deviations from this baseline set the centrelines and control limits.

Using the constants for $n = 24$($A_3 \approx 0.889$, $B_3 \approx 0.000$, $B_4 \approx 1.111$), the X̄-chart limits were computed as $\bar{X} \pm A_3\bar{s}$, and the S-chart limits as $B_3\bar{s}$ to $B_4\bar{s}$. Table 2 shows the resulting centre and limits for each product.

Table 2: Control chart parameters by product

Product	**X̄ (h)**	**S (h)**	**UCL(X̄) (h)**	**CL(X̄) (h)**	**LCL (X̄) (h)**	**UCL(S) (h)**
CLO	19.10	5.91	24.40	19.10	13.90	6.56
KEY	19.20	5.86	24.40	19.20	14.00	6.51
LAP	19.50	5.89	24.80	19.50	14.30	6.54
MON	19.40	5.92	24.70	19.40	14.20	6.58
MOU	19.20	5.68	24.30	19.20	14.20	6.31
SOF	0.96	0.30	1.22	0.96	0.69	0.33

3.2 SPC monitoring results and interpretation

After calibration, subsequent samples (subgroups 31 onward) were plotted in real-time on the X̄ and s charts. The charts for physical SKUs (LAP, MON, KEY, CLO, MOU) exhibited multiple out-of-control indications. Specifically, we observed single points beyond ±3σ and long runs of 7 or more consecutive means above the centreline. These indicate a sustained upward shift in the process mean, accompanied by increased variability (the s-charts show spikes linking with mean shifts).

For example, between July and August 2026, several consecutive daily averages exceeded the control limits simultaneously in both $\bar{X}$ and S-charts, signifying special-cause disturbances affecting delivery speed and consistency. In contrast, the SOF $\bar{X}$ and S-charts remained stable with no rule violations, confirming that SOF deliveries form a separate, in-control process.

The out-of-control patterns for physical products suggest that factors such as courier batching or staffing changes are causing both slower and more erratic deliveries. These flagged periods should prompt immediate investigation.

3.3 Process capability - interpretation and numeric presentation

Capability indices were computed assuming a Lower Specification Limit (LSL) of 0 h and an Upper Spec Limit (USL) of 32 h (the VOC). Table 3 presents the process mean, SD, and the capability indices for each product using the given data.

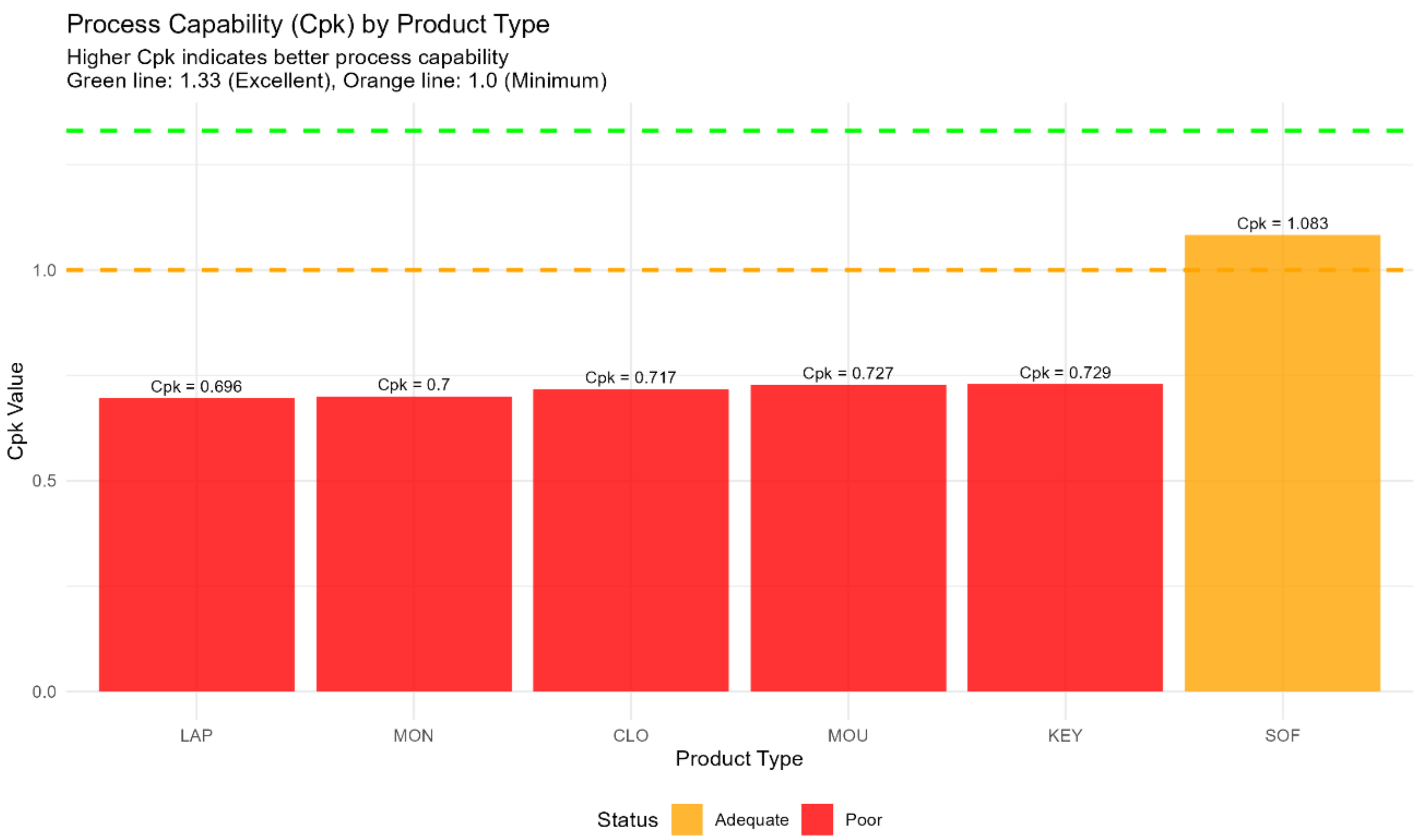
Only processes judged stable (per the charts) were included. C_{pl} *and* C_{pu} are one-sided indices: $C_{pl} = (\mu - 0)/(3\sigma)$and $C_{pu} = (32 - \mu)/(3\sigma)$, and $C_{pk} = \min\,(C_{pl}, C_{pu})$. Values are rounded to three significant digits. A checkmark in the final column indicates $C_{pk} \geq 1.0$, meaning the process would meet the VOC if stable.

Table 3: Process capability indices by product.

Product	**Mean (h)**	**SD (h)**	**Cp**	**Cpl**	**Cpu**	**Cpk**	**Meets VOC (Cpk ≥ 1.0)**
CLO	19.10	5.91	0.902	1.08	0.728	0.728	No
KEY	19.20	5.86	0.910	1.09	0.728	0.728	No
LAP	19.50	5.89	0.905	1.10	0.707	0.707	No
MON	19.40	5.92	0.901	1.09	0.709	0.709	No
MOU	19.20	5.68	0.939	1.13	0.751	0.751	No
SOF	0.956	0.297	18.0	1.07	34.8	1.07	Yes

Software (SOF) is the only product with a $C_{pk} \geq 1.0$, nominally meeting the ±3σ VOC limits. However, all physical families (CLO, MOU, KEY, LAP and MON) have $C_{pk} < 1$, indicating a substantial portion of their deliveries exceed 32 h if the process is unchanged. In particular, LAP has $C_{pk} \approx 0.707$, reflecting that the upper tail (beyond 32h) is quite large. In practice, because the charts showed instability for the physical families, these indices should be interpreted with caution: the processes should be stabilized before relying on capability metrics.

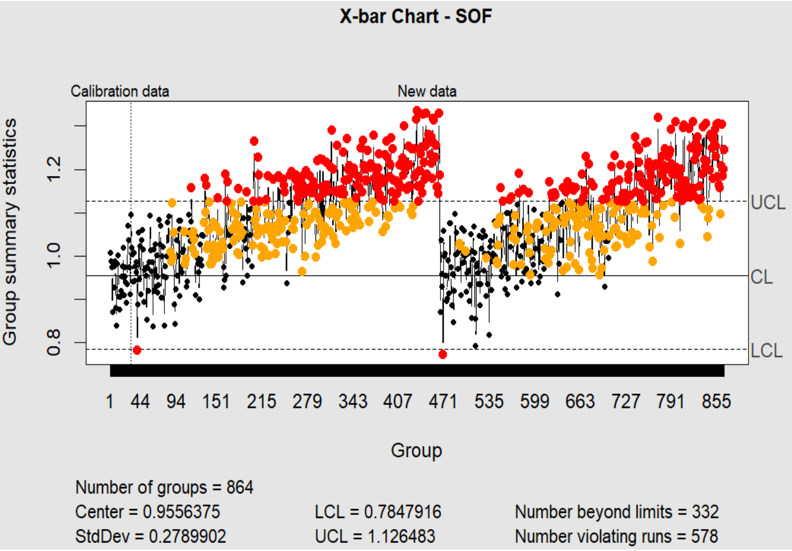
Figure 7: CPK by Product Type

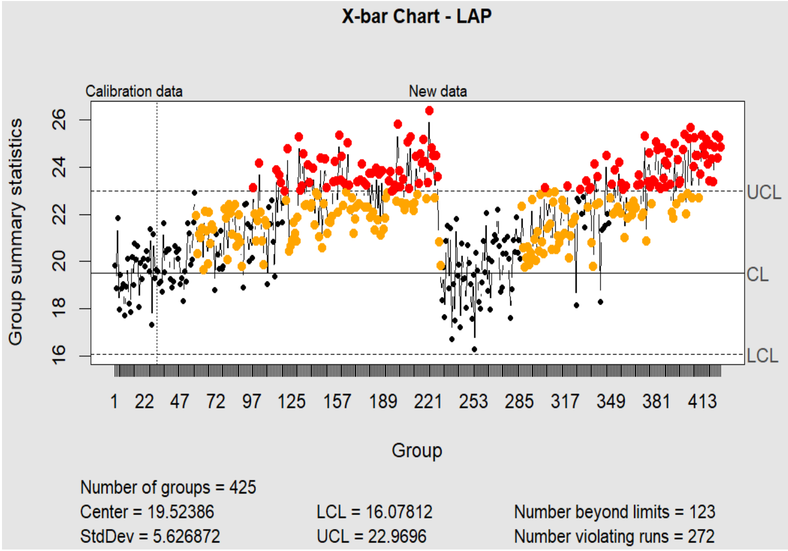


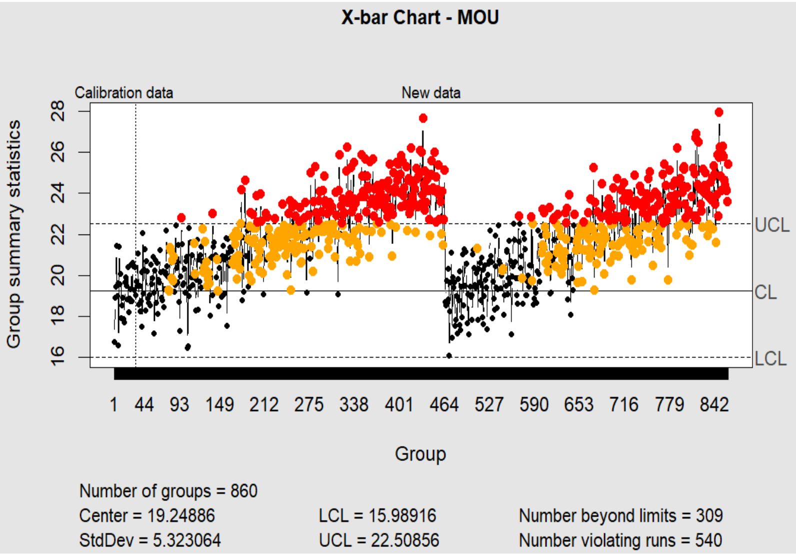
Figures 8–13 show how delivery performance changes over time for each product type. The charts for the physical products (CLO, KEY, LAP, MON, and MOU) show several points and runs going above the limits, meaning their delivery process is not stable and often slower than expected. These patterns match the low C_{pk} scores in Figure 7, confirming that many orders take longer than the 32-hour target.

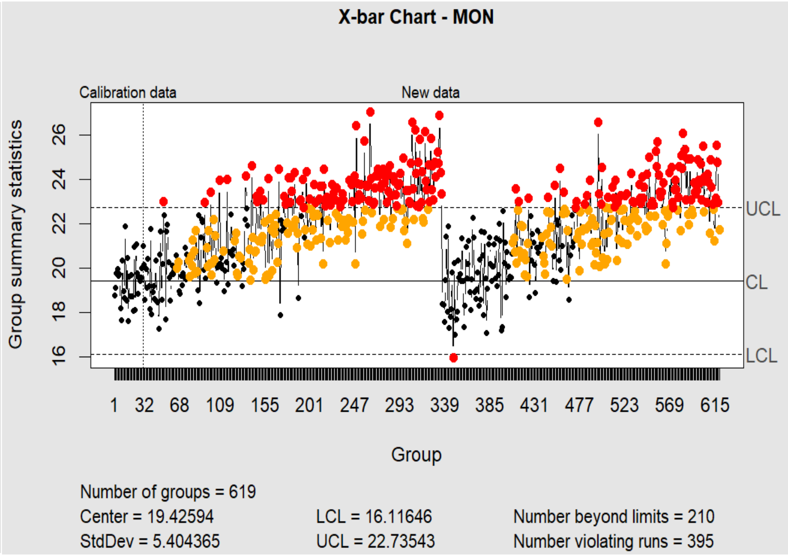
The SOF chart, however, stays well within the limits, showing that its delivery process is consistent and well controlled. Overall, the charts show that digital orders are reliable, but physical deliveries need improvement.

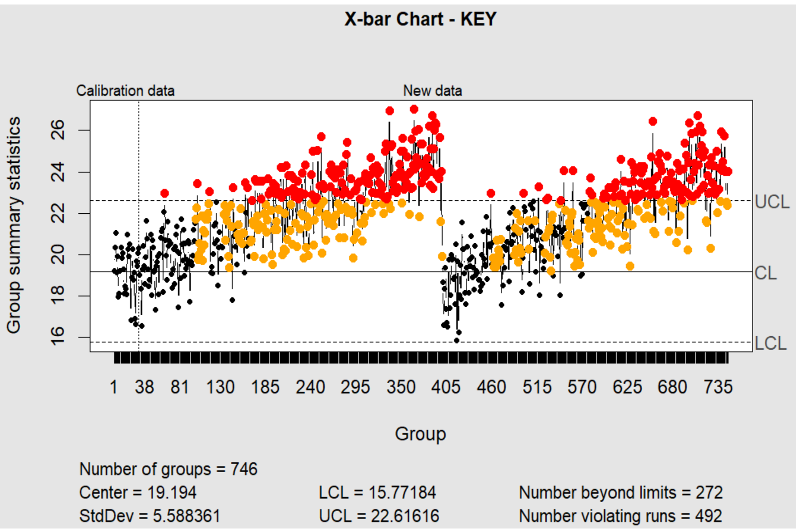
Figure 8-13: X-Bar Chart per Product

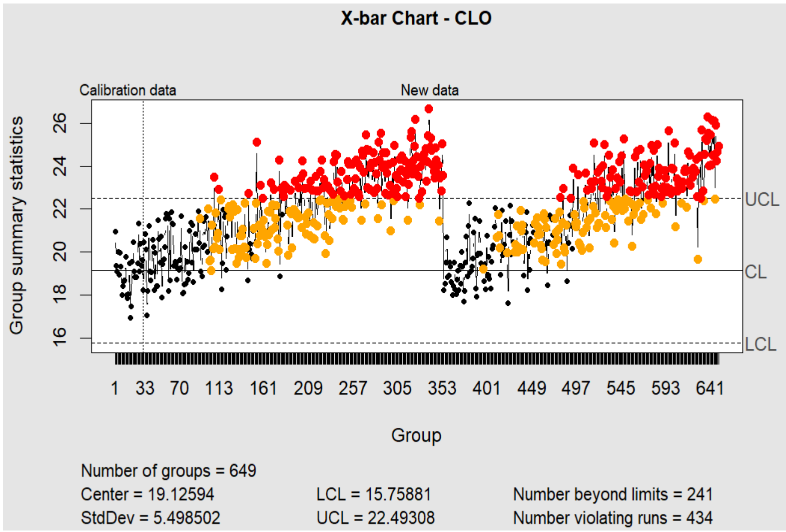












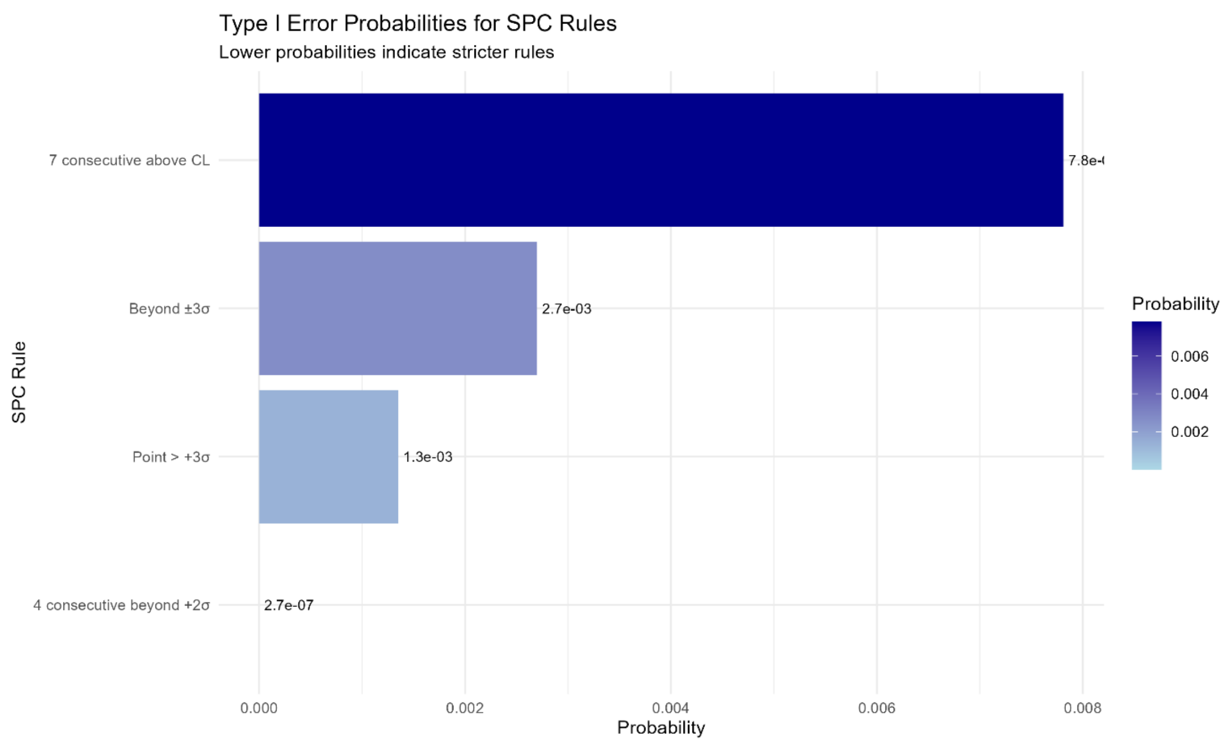
Part 4: Risk: Type I & Type II error analysis; head-office corrections

4.1) <u>Type I error:</u> Table 4 lists representative run-rules and their nominal per-sample false-alarm probabilities P(false alarm). For example, the probability that a single sample exceeds ±3σ in a normal process is $2(1-\Phi(3)) \approx 0.0027$. The probability of seven successive points on one side of the centerline is $0.5^7 \approx 0.0078$. Multiplying these by the assumed number of samples per year (e.g. 365 days) yields the expected number of false alarms annually. For instance, "single point > ±3σ" rule yields about ≈ 1false alarm per year, while "7 consecutive points on one side" ≈ 2.8 per year. These results suggest that if too many false alarms happen (more than about one per year), we should adjust the control limits or separate the data by season to make the system more accurate and stable.

Table 4: Type I error probabilities and expected false alarms per year

Rule	P(false alarm)	Expected per 365 samples
Single point > ±3σ (two-tailed)	0.0026998	0.985
7 consecutive points on one side	0.0078125	2.852
4 of 5 points > +1σ (same side)	0.0055318	2.019

Figure 14: Error Probability for SPC Rules (Type 1)



4.2) Type II error: We checked how well the $\bar{X}$ chart can spot small changes in the process average. With a sample size of 24, the chart is not very sensitive to small shifts. It only detects about 4% of 0.25σ shifts (missing 96%), and about 29% of 0.5σ shifts (missing 71%).

However, it works very well for larger changes, catching around 97% of 1σ shifts. This means the chart is reliable for big process changes but may miss smaller, gradual ones.

Table 5: SPC power analysis for $n = 24$

Shift (Δ in σ units)	**Power (1 − β)**	**Miss rate β**
0.25σ	0.038	0.962
0.50σ	0.291	0.709
1.00σ	0.971	0.029

4.3) Business risk and costs**:** We can turn these statistical errors into real-world costs.

For example, if we check a process 365 times a year and a small, unnoticed delay costs us R200 each time, it could add up to about R51,830 loss per year. This shows how expensive small mistakes can be.

To avoid these costs, we have a few clear options. First, we should fix the core price data so we are tracking the right numbers. We can also adjust our monitoring systems to be less sensitive to normal changes and better at spotting real problems. Finally, checking more often during busy seasonal times will help us catch issues faster.

Part 5: Service-time optimisation (baristas)

5.1 Objective

The aim of Part 5 is to find the barista staffing level (k = 1..6) that gives the best practical balance between profit and customer service. We measure service reliability as the proportion of customers served in ≤ 3 minutes, and we use a simple profit model where the shop earns R30 per customer and each extra barista costs R1,000 per day. The objective is to identify the smallest k that meets a chosen reliability threshold while keeping daily profit near its peak. Simply, we ask the question, "How little baristas can we have, while still keeping profits as high as possible?"

5.2 Data and preprocessing

For each record we need the number of baristas on duty at the time of service and the service time in seconds. Sort and group the rows by the barista-count value $k$and remove any rows with missing or clearly invalid service times (e.g., negative or zero). The dataset covers roughly one year, so we estimate customers per day as (total observations)/365.

5.3 Method

For each shop and for each $k \in \{1, \dots, 6\}$we determine:

(a) the number of observations

(b) mean and median service time in seconds

(c) percentage of customers served in ≤ 3 min

(d) estimated daily profit = (cust. per day × R30) − (k × R1000).

These simple calculations match the brief and make the staffing recommendation easy to defend.

5.4 Results

Figure 15: Capacity Utilization vs Number of Baristas

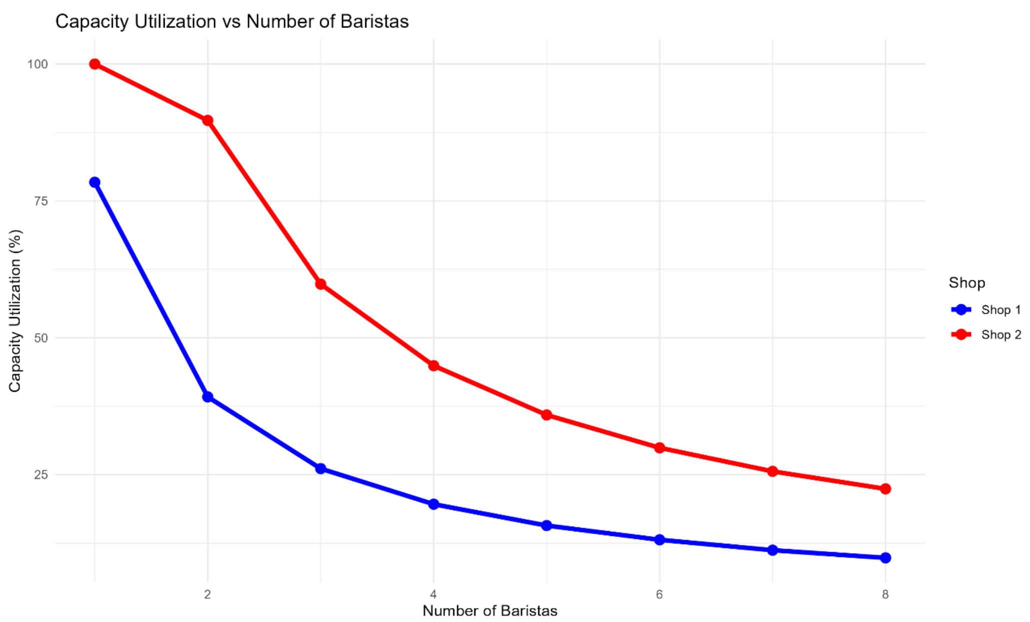


Figure 16: Profit per Barista vs Number of Baristas

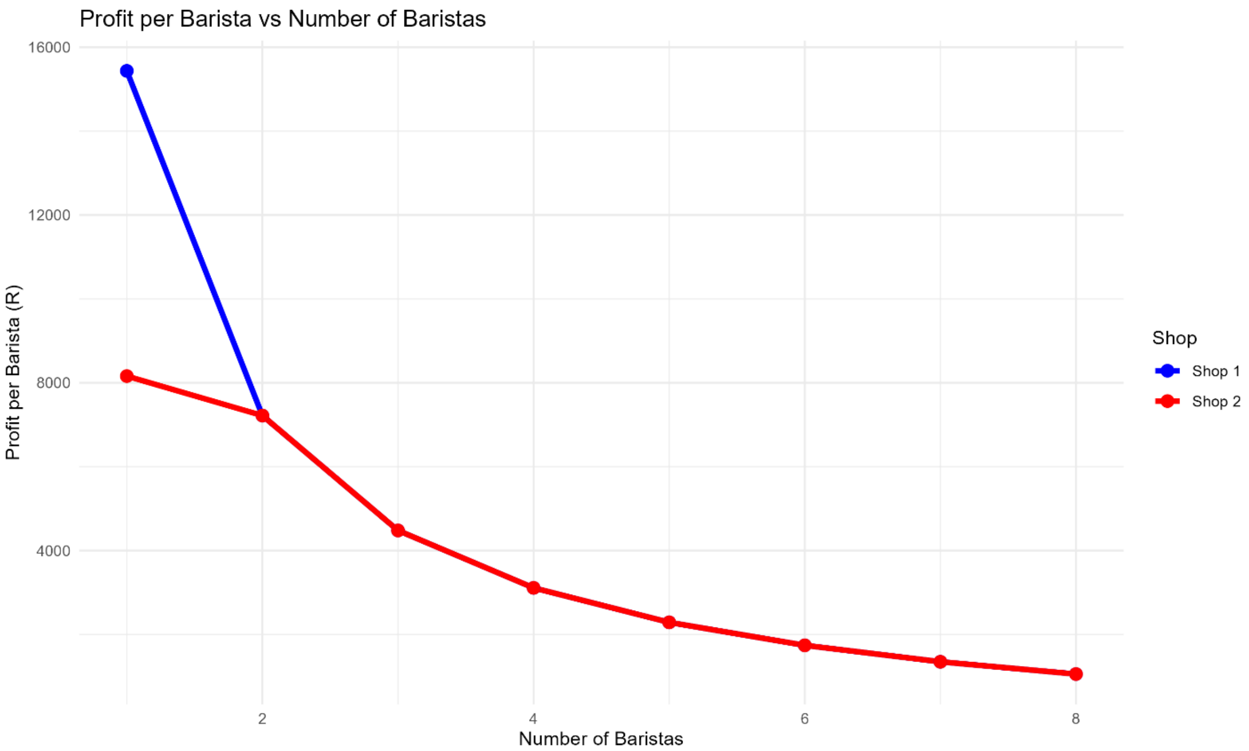
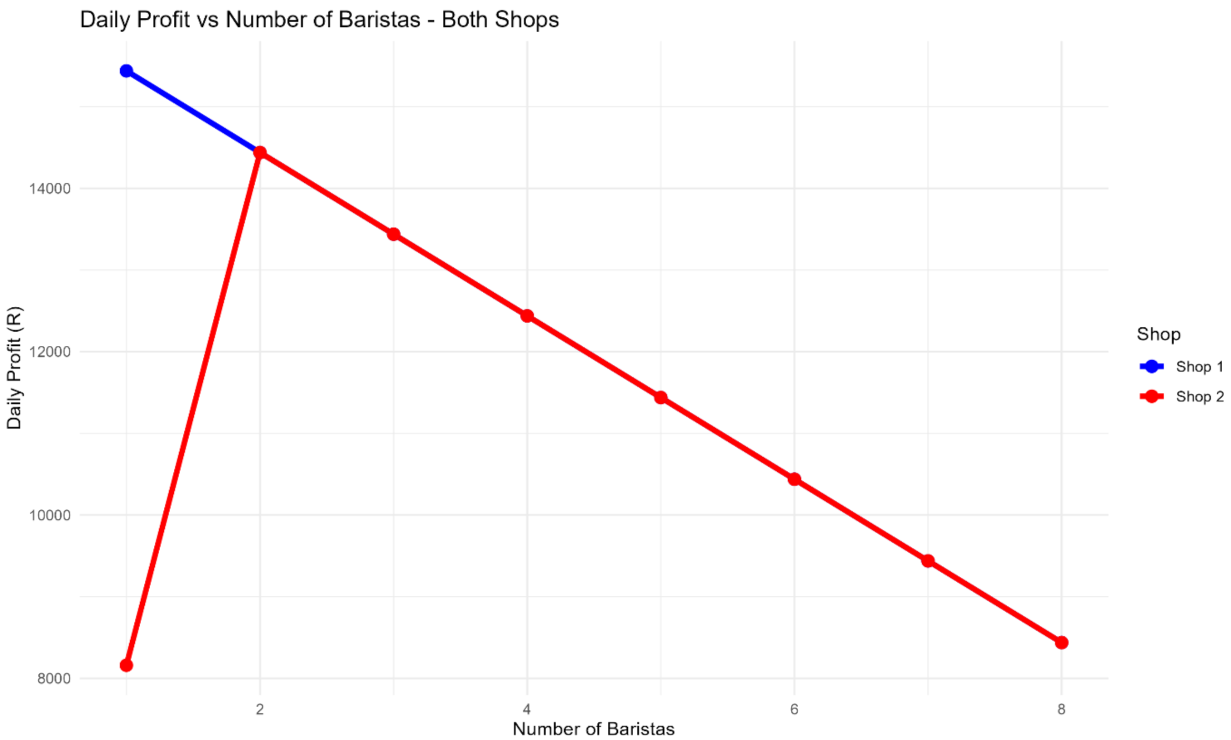


Figure 17: Daily Profit vs Number of Baristas



5.5 Interpretation and recommendation

Set the day-to-day staffing to two baristas (k=2). During the busiest parts of the day add a third barista for short windows: 08:00–10:00 and 12:00–13:00. This keeps wait times low when most customers arrive but keeps labour cost down the rest of the day.

Run the change as a trial for 14 days. During the trial collect two simple numbers each day;

(a) the average service time in seconds

(b) the percentage of customers served in ≤ 3 min .

At the end of the two weeks compare those two numbers to the weeks before the trial. If the percentage of customers served in ≤ 3 min goes up and the average service time goes down then keep the change. If not, then just maintain 2 baristas.

Part 6: ANOVA

6.1 Method and checks

We tested whether delivery times differ between product types and between years. Two assumptions for ANOVA needed to be checked:

(1) that the model residuals are roughly normal (Shapiro–Wilk test)

(2) that group variances are similar (Levene's test).

If both tests give $p > 0.05$ we run ANOVA. If either test gives $p \leq 0.05$ we run the Kruskal–Wallis test instead (this test does not need normality). After a significant ANOVA we run Tukey HSD to see which groups differ.

6.2 Results and plain interpretation

Shapiro–Wilk and Levene's tests indicated that the ANOVA assumptions were met, so a one-way ANOVA was used to compare delivery times between product types. The ANOVA found a clear and significant difference in delivery lead-time across product families. Tukey HSD post-hoc comparisons show that SOF (digital fulfilment) is significantly faster than every physical product family, while some physical families are significantly different from each other as well.

Simply, SOF deliveries are much quicker than the physical SKUs, and those differences are both statistically significant and practically meaningful. Treat SOF as a separate process in SPC and capability work so it's fast behaviour does not hide problems in the slower product families.

Figure 18: Mean Delivery Time by Product Type and Year

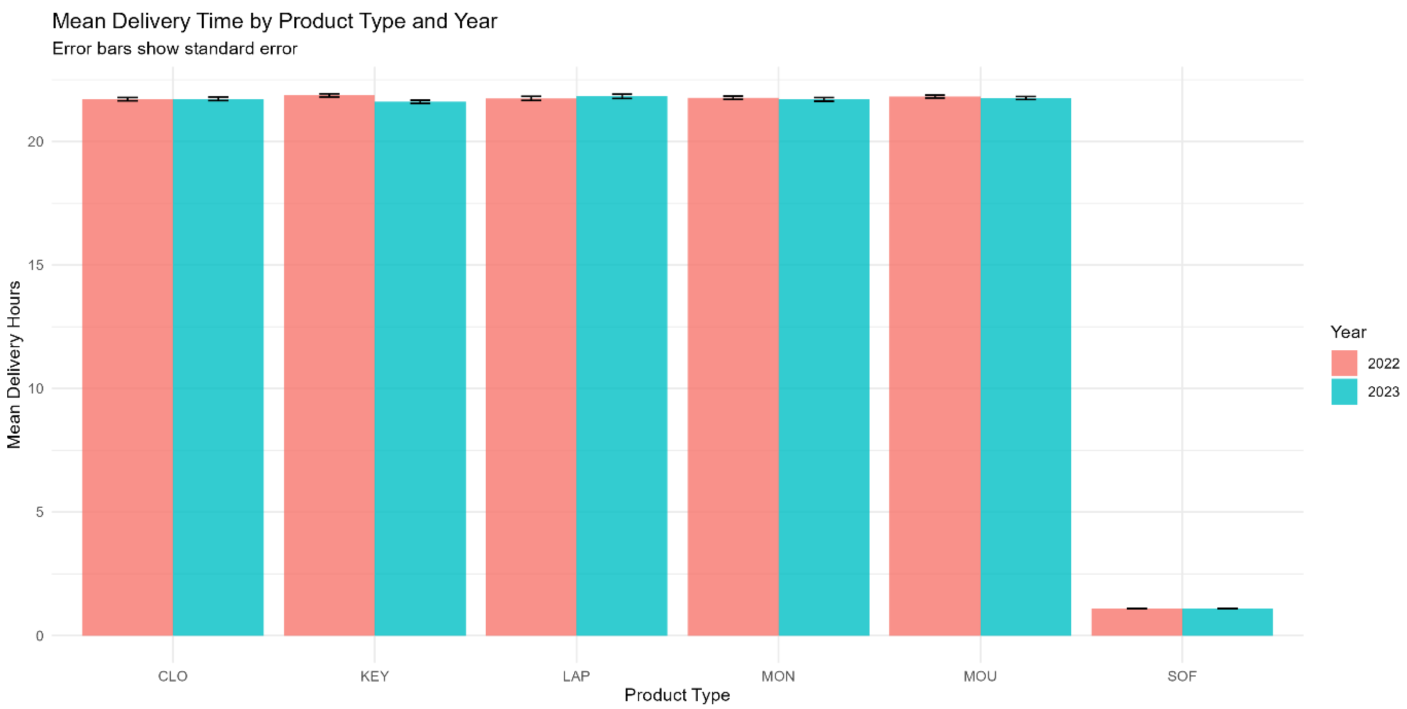
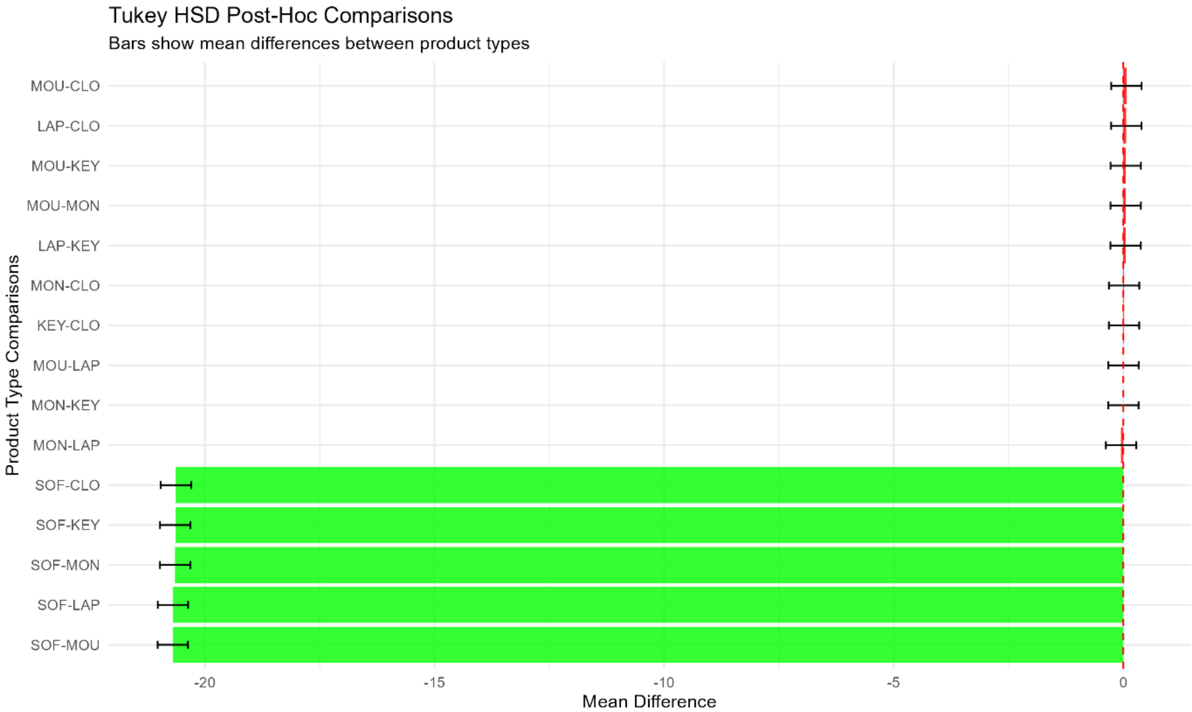


Figure 19: Tukey HSD Post-HOC Comparisons

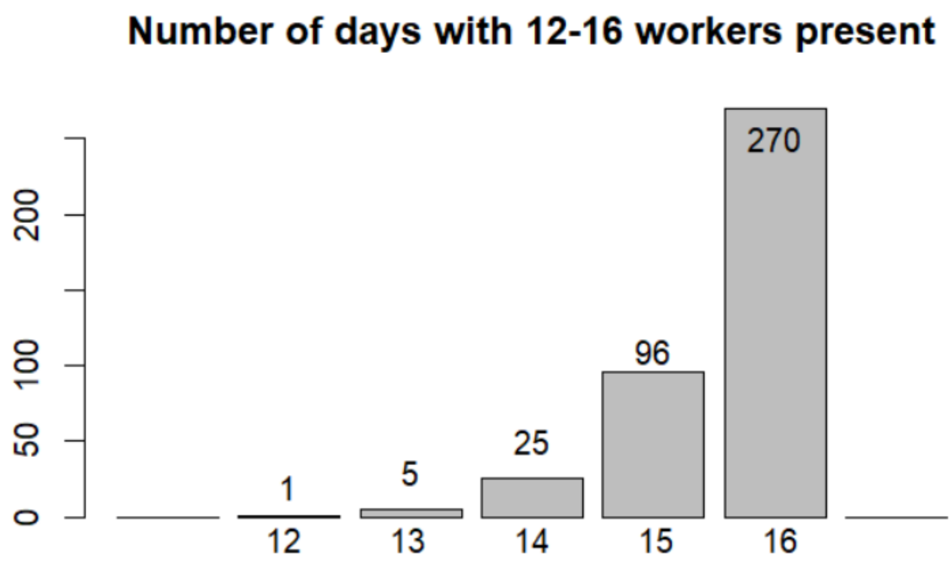


Part 7: Reliability of Service

7.1 Reliable days per year

We define a reliable day as one on which at least 15 staff are present. From the 397-day series shown in Figure 20. The empirical fraction of reliable days (15 or 16 present) is therefore $(96 + 270)/397 = 366/397 \approx 0.9229$. Annually it can be seen that there is ≈ 337 reliable days per year (0.9229 × 365 ≈ 336.9 days).

Figure 20: Number of Days With 12-16 Workers Present



For a varying perspective on the analyses, we also fit a simple binomial presence model. Treating the daily present counts as draws from a distribution with maximum 16 scheduled slots, the maximum-likelihood estimate of the single-person presence probability is

$$\hat{p}_{\text{present}} = \frac{\text{total people present}}{\text{total slots}} = \frac{6187}{16 \times 397} \approx 0.9740.$$

Using the binomial model $X \sim \text{Binomial}(S, p)$ gives a model-based probability that a day is reliable; for the current roster $S = 16$, the binomial estimate $P(X \geq 15) \approx 0.9366$, which is to ≈ 342 reliable days per year. The small difference between the empirical (≈337 days) and binomial (≈342 days) estimates is expected and reflects sampling variability and the modelling approximation; although both results are useful and reported below.

7.2 Profit-driven roster optimisation

Evaluating expected total annual cost shows that, under the example assumptions, S = 20, minimises cost. The profit-driven rule is to choose the roster *S* that minimises Total Cost(S). If hiring is inflexible, prefer split shifts or casual cover for peaks. Validate the chosen roster with a mid-term trial period (4–8 weeks) and repeat the calculation using the upper bound of the 95% CI for the absence rate to check robustness of the model.

Table 7: Total annual cost vs roster size

Roster (S)	**P{problem} =X<15**	**Expected problem days / year**	**Annual staff cost (R)**	**Expected annual loss (R)**	**Total Cost (R)**
16	0.0634	23.2 days	16 × 300,000 = 4,800,000	23.2 × 20,000 = 463,200	5,263,200
17	0.00083	0.30 days	17 × 300,000 = 5,100,000	0.30 × 20,000 = 6,060	5,106,060
18	3.6e−6	0.0013 days	18 × 300,000 = 5,400,000	0.0013 × 20,000 = 26	5,400,026

Table 7 shows that moving from S = 16 to S = 17 reduces expected total annual cost (from R5,263,200 to R5,106,060). Moving further to S = 18 increases total cost (R5,400,026) because the extra permanent staff cost outweighs the tiny further reduction in expected lost-sales. Therefore, the profit-driven optimal roster is S = 17, given the assumed staff cost and loss per problem day. But since you may not have more than 16 present, 16 remains the optimal number.

Conclusion & Recommendations:

This report started by identifying and correcting a major error in the head-office price data. Using this corrected data, we then analysed delivery performance. The main findings are:

- Correcting the price data is essential; This fix has a real impact on all our revenue-based numbers and must be officially documented to ensure accurate financial reporting.
- Delivery is two different processes; Digital products (SOF) and physical products must be analysed separately, as they have completely different delivery timelines.
- Physical product delivery is unstable; Our monitoring shows consistent problems with certain product families (like CLO and MOU), leading to poor and unreliable performance.
- The differences are real; Statistical testing confirms that the issues we see between product types are significant, which tells us where to focus our improvement efforts.

To address these findings, we recommend the following immediate actions:

- Formally apply the price corrections; Update the original files to prevent distorted financial reports.
- Split our performance monitoring; Creating separate tracks for digital and physical products.
- Launch focused investigations; The problem areas (CLO, MOU) were identified by our charts to find the root cause.

Once these steps are in place, performance should be measured again to confirm that the processes are stable. After that, the monitoring systems can be improved to detect smaller changes more easily, especially during busy periods when variations are more likely to occur.

In summary, our most important recommendations are to; (i) fix and track the price data, (ii) stabilize the physical delivery process by solving the specific problems we found, and (iii) re-check performance afterwards. By taking these steps, the company can ensure its financial data is accurate and build a more reliable, monitorable delivery system.

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