PAMPERED PETS

PET FOOD SHOP

Executive Summary

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1. Introduction

Pampered Pets (PP) is undergoing a transition from a traditional brick-and-mortar retailer to an omni-channel enterprise with a global supply chain and digitalised platforms, as illustrated in Figure 1.

Figure 1. Visual overview of Pampered Pets' transition from local suppliers to a global supply chain, including the addition of an e-commerce platform to its brick-and-mortar operations, the implementation of an enterprise resource planning (ERP) system, and several automated warehouses.

These strategic initiatives are designed to drive business growth, reduce operational costs, and meet evolving customer demands. However, they concurrently introduce new risks to PP's renowned product quality and availability, as well as compliance with pet food regulations and the new GDPR. The following section enumerates the new risks that may arise as a result.

2. Potential risks

The PP Supply Chain (SC) operates within a four-echelon framework, wherein goods are produced, stored, and distributed to end customers via both the physical store and the e-commerce platform.

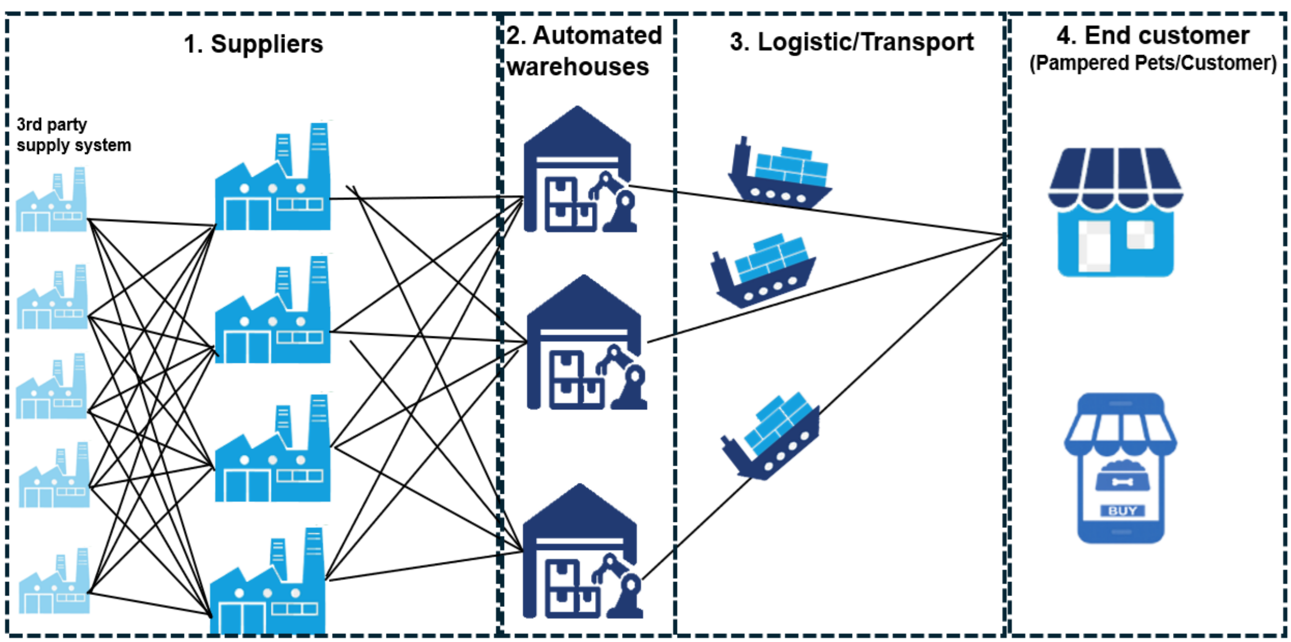

Figure 2. Visual overview of Pampered Pets' transition from local suppliers to a global supply chain, including the addition of an e-commerce platform to its brick-and-mortar operations, the implementation of an enterprise resource planning (ERP) system, and several automated warehouses.

Although globalisation and digitalisation significant efficiency gains offer, they have also introduced greater structural complexity, which has reduced visibility across the supply chain and heightened exposure to operational, quality, and compliance risks (Wu, David and Olson, 2008; Vilko and Hallikas, 2011; Li et al., 2023; Sharma, Tyagi, and Kazançoğlu, 2024). The increasing interdependencies between supply chain components elevate the probability of disruptions that could simultaneously affect both product quality and availability—two critical factors for maintaining PP's premium reputation.

The risks identified in this report align with the operational and information-flow categories proposed by Chopra and Sodhi (2004), who classify supply-chain risks into disruptions, delays, and systems failures as key drivers of performance loss. These categories are mapped across PP’s four echelons to identify the mechanisms that most directly impact product quality and availability.

1. **Supplier risks**
   - Contamination or mislabelling of ingredients may cause non-compliance and product recalls (DeBeer et al., 2024; Sharma, Tyagi and Kazançoğlu, 2024).
   - Regulatory variability across markets can delay certification and import approval (FEDIAF, 2020).
   - Limited supplier transparency and material shortages may cause production delays or disruptions in stock replenishment.
   - Geopolitical or environmental events can restrict access to raw materials or packaging, leading to delayed deliveries (Li et al., 2022; Sun et al., 2024).

2. **Automated-warehouse risks**
   - System or software failures (e.g. barcode or expiry tracking) may result in the release of non-compliant stock.
   - Cybersecurity breaches or power interruptions could disable temperature controls, leading to spoilage and halting order fulfilment.

3. **Transport risks**
   - Route disruption, customs delays, or strikes could result in shipping backlogs and temporary stockouts.
   - Delays, mishandling, or temperature fluctuations during transport could breach food-safety standards, compromise product quality and delaying delivery.

4. **E-commerce-platform risks**
   - Cyberattacks or data breaches could compromise payment and customer data, breaching GDPR or PCI DSS requirements, potentially resulting in fines (EU, 2016) and suspension from credit companies (VISA, 2025).
   - Platform outages or integration failures could disrupt online ordering and order tracking, impairing customer experience and operational efficiency.

To mitigate these risks and quantify their combined impact on product quality and availability, a quantitative risk-modelling approach is applied in the next section.

2.1 Quantitative risk modelling approach and justification

Monte Carlo Simulation (MCS) is employed to estimate the impact of digitalisation and globalisation on the reliability of PP’s supply chain. This approach particularly suitable as the company lacks historical disruption data and must account for multiple uncertain variables.

MCS represents each uncertain factor as a probability distribution rather than a fixed value, facilitating scenario-based forecasting in the presence of incomplete or ambiguous information (Aven, 2015; D'Agostini and Petrillo, 2023). By generating thousands of random samples, MCS captures the nonlinear inter-dependencies between supply-chain stages, providing realistic probability ranges rather than deterministic point estimates.

In contrast, deterministic or regression-based models assume stable relationships between variables and require extensive historical data, which is unavailable in this case.

Therefore, MCS is the most transparent and flexible tool for assessing operational risk in a newly digitalised environment. Its inherent adaptability also allows the parameters to be updated as internal data become available, ensuring that the model remains a dynamic decision-support tool for management.

The MCS process used is outlined in Figure 3.

Figure 3. Steps of the Monte Carlo Simulation process (adapted from Mooney, 1997).

2.2 Explanation of calculations, assumptions, and data sources

The supply chain model in Figure 4 was simplified to capture the essential interactions between core echelons while excluding lower-impact processes. Additionally, the fourth echelon—the end customer—is excluded, as it represents an internal risk factor, which falls outside the scope of this analysis. This simplification ensures that the simulation remains focused on the dominant risk factors and is computationally tractable, without compromising the validity of the performance outcomes (Belvárdi et al., 2012; Dutta & Shrivastava, 2020; Kleinemolen, 2024).

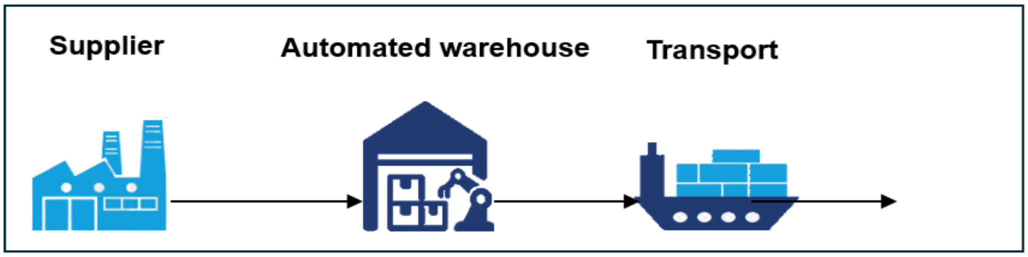

Figure 4. Simplified three-echelon supply chain model used in the Monte Carlo simulation, representing. the primary flow of materials from supplier to automated warehouse, and transport to the end customer. The structure focuses on the dominant external operational stages influencing product quality and availability for Pampered Pets.

The variables to be simulated are presented in Table1.

Table 1. Input variables, probability distributions, underlying assumptions, and data sources used in the Monte Carlo simulation of supply chain performance.

Variable	Assumptions		Associated risk	Justification
	Distribution	Probability		
Perfect Order Rate – Supplier (PORs)	Uniform distribution. All values in the range are assumed equally likely. This reflects uncertainty and avoids biasing the simulation	Between 82% - 95%, with a mean of 90% (APQC, 2016).	Risk of supplier performance variability leading to incomplete or delayed orders.	Benchmark reflects the average perfect order rate range for international suppliers
Perfect Order Rate – Automated Warehouse (PORw)		Between 92 % – 98 %, with a mean of 96 %, for automated organisations which is slightly higher than general POR (APQC, 2016; Brown, 2018).	Risk of warehouse system malfunction or order fulfilment errors.	Benchmark reflects typical performance levels in automated warehouse operations as reported in logistics industry studies
Transportation Delays (TD)		3%-7% port delays (Kuehne-Nagel, 2025) which is similar to global transport delays.	High variability in shipping times delaying deliveries.	45% of global pet food manufacturing capacity is located in China (Gitnux, 2025). Shipments usually take 30-40 days. Benchmark aligns with global port delay data.

Quality Degradation (QD)		5% to 10% degradation probability for perishable food (Mousavi, Bashiri and Nikzad, 2022). This is slightly lower than the 14% probability for all food waist (FAO, 2019).	Risk of product degradation during transport.	Benchmark derived from statistics on global food losses, adjusted downward to reflect one category of food.

The theoretical correctness of the input distributions was validated to confirm appropriateness of the methodology. A distribution validation (Appendix A) confirmed that all four input variables follow uniform probability distributions within their configured bounds. This was supported by consistent summary statistics and confirmed by Kolmogorov–Smirnov tests and visual diagnostics (histograms and Q–Q plots).

Based on this, the problem was defined as:

Supply Chain Element:

$$P(SCP) = \overbrace{POR_S}^{\textbf{Supplier}} * \overbrace{POR_W}^{\textbf{Automated Warehouse}} * \overbrace{(1 - QD) * (1 - TD)}^{\textbf{Transport}}$$

Indicator	**Description**
P(SCP)	Probability of Supply Chain Performance
POR_S	Perfect Order Rate – Supplier: The percentage of orders from the supplier meeting delivery performance expectations, including complete and accurate documentation and no delivery damage (SCOR (2025b)
POR_W	Perfect Order Rate – Automated Warehouse: The percentage of orders meeting delivery performance expectations, including complete and accurate documentation and no delivery damage (SCOR, 2025a)
QD	Quality Degradation during transport
(1-QD)	No quality degradation during transport
TD	Transport delay
(1-D)	No transport delay

This function assumes that the perfect order rates from suppliers and automated warehouses, quality degradation and transport delays are independent and contribute multiplicatively to the overall outcome. The multiplicative structure of the function is consistent with the independence principle (Ross, 2014; Aven, 2015), which assumes that each risk factor contributes independently to the overall probability of supply chain success or failure.

Each variable represents a critical dimension of performance across the supply chain. Perfect Order Rate (POR) is a widely accepted SCOR metric for reliability, capturing the probability of orders being delivered complete, on time, and undamaged (SCOR, 2025a; SCOR, 2025b). Its use in modelling supplier and warehouse performance is supported by studies that identify the POR as a primary indicator of supply chain reliability, directly influencing both product quality and availability (Mishra and Sharma, 2014; Nguyen, 2024).

Transport-related risks, specifically Quality Degradation and Transport Delay are critical and independent variables influence both product quality and availability in perishable supply chains (Manouchehri et al., 2020).

The model provides management with a clear, evidence-based understanding of how all supplier, warehouse, and transport performance jointly influence overall supply-chain reliability, enabling data-driven decisions.

2.3 Results of the quantitative model

A distribution validation confirmed that all four input variables followed the intended uniform distributions within their configured bounds (Appendix A). Additional checks verified that the simulator generated inputs within the correct ranges and consistent with the assumed probability parameters (Appendix B), thereby validating the input assumptions used in the MCS.

The MCS with 10,000 iterations estimated:

- Probability of PP's supply chain success (P(SCP)): 74%
- 90% confidence interval: 68% - 80%
- Probability of Supply Chain failure: 26%

Sensitivity analysis and correlation results indicate that the Perfect Order Rate – Supplier exerts the strongest positive effect on performance outcomes (r = 0.84), followed by the Perfect Order Rate – Automated Warehouse (r = 0.36). Conversely, Quality Degradation (r = –0.31) and Transport Delay (r = –0.26) show negative sensitivities, indicating that increases in these risk factors reduce overall supply chain performance and could lower product quality and availability.

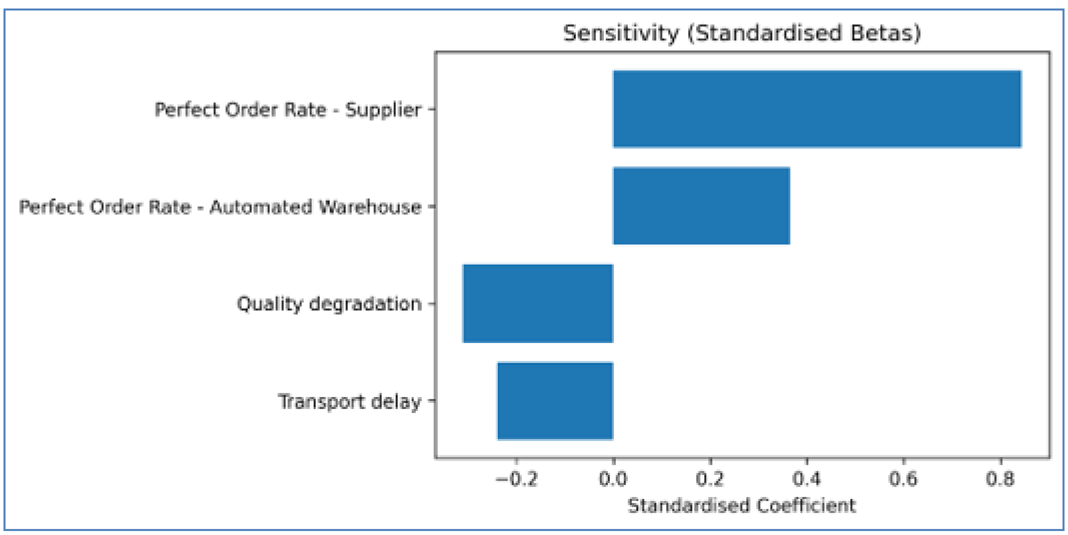

Figure 4. Sensitivity analysis of standardised beta coefficients illustrating the relative influence of each input variable on the simulated outcome.

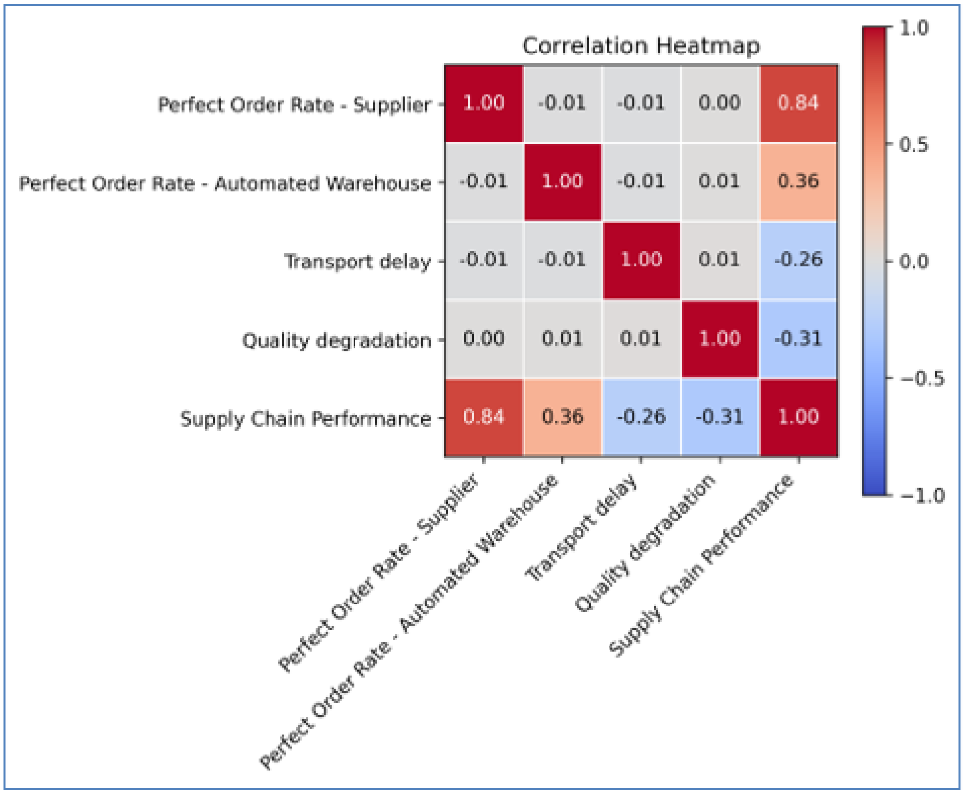

Figure 5. Correlation heatmap illustrating the strength and direction of linear relationships between key supply chain input variables and overall supply chain performance. The heatmap highlights that supplier and warehouse order rates are positively correlated with performance, while transport delay and quality degradation show negative correlations, further reinforcing the findings from the sensitivity analysis.

These results provide management with quantitative evidence to prioritise supplier-performance improvements and stricter warehouse-quality controls as the most effective actions for maintaining product quality and availability.

3. Summary of results

3.1 Summary of risk probabilities

Based on the quantitative modelling above, the MCS (10,000 iterations) was interpreted using Aven's (2015) probability-theory framework for system reliability. In a series structure, the overall success event is expressed as:

$$C = S \cap W \cap \bar{D} \cap \bar{Q} \qquad \text{and} \qquad P(\bar{C}) = 1 - P(C),$$

(S)=supplier success, (W)=warehouse success, $\bar{D}$=no transport delay, and $\bar{Q}$= no quality degradation.

Following Aven (2015), each probability (P(X)) represents the long-run relative frequency of that event's occurrence in the simulation:

$$\hat{P}(X) = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}_X^{(i)}.$$

Table 2. Probability of supply chain issues and associated impacts

Risk Event	Probability of Issue (%)	Impact description
Supplier performance failure - $P(\bar{S})$	11.6	Affects: Product quality and availability. Contamination, mislabelling, or delayed deliveries caused by supplier non-compliance, regulatory variability, or geopolitical disruption can lead to stock shortages and non-compliance with pet food safety regulations (FEDIAF, 2020; FDA, 2022).
Automated-warehouse failure - $P(\bar{W})$	5.0	Affects: Product quality and availability. Downtime or data-exchange errors may cause traceability errors, leading to delayed order fulfilment, increasing the risk of non-compliant stock release or late dispatch.
Transport delay or mishandling -P(D)	5.0	Affects: Product quality and availability. Route disruptions, customs delays, can result in stockouts, late deliveries. Mishandling or temperature deviations could breach food safety regulations (FEDIAF, 2020; FDA, 2022).
Quality degradation during transport - - P(Q)	7.5	Affects: Product quality and availability Temperature or humidity fluctuations lead to quality degradation, breaching food safety regulations (FEDIAF, 2020; FDA, 2022), resulting in stockouts or unsellable goods
Overall supply-chain disruption - P($\bar{C}$)	26.0	Probability that at least one echelon—supplier, warehouse, or transport—experiences a quality non-compliance or availability failure in a given operational cycle.

3.2 Recommended mitigation strategies

The recommendations to mitigate risks are prioritised according to their expected reduction of total supply-chain failure probability.

Table 3. Prioritised recommendations and mitigation strategies

Priority	Business Need / Risk Driver	Recommended mitigation
1	Supplier reliability (11.6 %)	• Establish multiple, geographically diversified sources of supply, including backup suppliers in alternative regions, to reduce exposure to single-source disruptions (Chopra and Sodhi, 2004; Yang et al., 2009; McDougall and Davis, 2024). • Develop strong digital collaboration mechanisms and formal contracts with suppliers to ensure transparent information sharing and clearly defined performance and compliance obligations (Li et al., 2022). • Establish supplier quality rating criteria
2	Quality degradation (7.5 %)	• Establish digital collaboration mechanisms and formal contracts with transport services to ensure transparent information sharing and clearly defined performance and compliance obligations (Li et al., 2022). For

Priority	Business Need / Risk Driver	Recommended mitigation
		example, include temperature-control, traceability, and data-sharing clauses in third-party logistics (3PL) contracts (Li et al., 2022) or require the integration of IoT temperature and humidity sensors in vehicles, with live data feeds shared for real-time monitoring (Yang et al., 2020). • Perform regular quality audits of delivered goods
3	Transport delay or mishandling (5 %)	• Implement redundant carrier networks, dynamic route optimisation, and predictive transport analytics to manage delay and spoilage risk (Chopra and Sodhi, 2004; Yang et al., 2020).
4	Automated-warehouse reliability (5 %)	• Strengthen third-party Service Level Agreements (SLAs) with uptime, data integrity, and traceability clauses; ensure compliance with ISO 9001 and ISO 27001 for process and information security (Li et al., 2022). • Establish multiple geographically dispersed warehouses to minimise exposure to disruptions.

4. Business Continuity and Disaster Recovery (BC/DR) strategy

To ensure uninterrupted e-commerce operations, a cloud-based Disaster Recovery (DR) solution is proposed. Given that international order processing is mission-critical for PP, continuous service availability is essential to maintain operations and safeguard revenue.

The company requires a Recovery Time Objective (RTO) and Recovery Point Objective (RPO), both set to less than 1 minute. This classifies the system as 'highly critical', necessitating an Active-Active (Hot Standby) configuration, as outlined in Appendix C. This design ensures 24/7/365 availability and mitigates the risk of data loss or downtime, which could negatively affect both revenue and reputation.

4.1 Recommended architecture

The Active–Active architecture operates two live environments (production and disaster recovery (DR)) that replicate data in real time. In the event of a failure in one region, the other continues operations immediately, ensuring the objectives. A DNS-based load-balancer distributes traffic between identical regional stacks of web servers and synchronised databases, ensuring continuous redundancy and compliance with GDPR and ISO 27001 (Sutton, 2021).

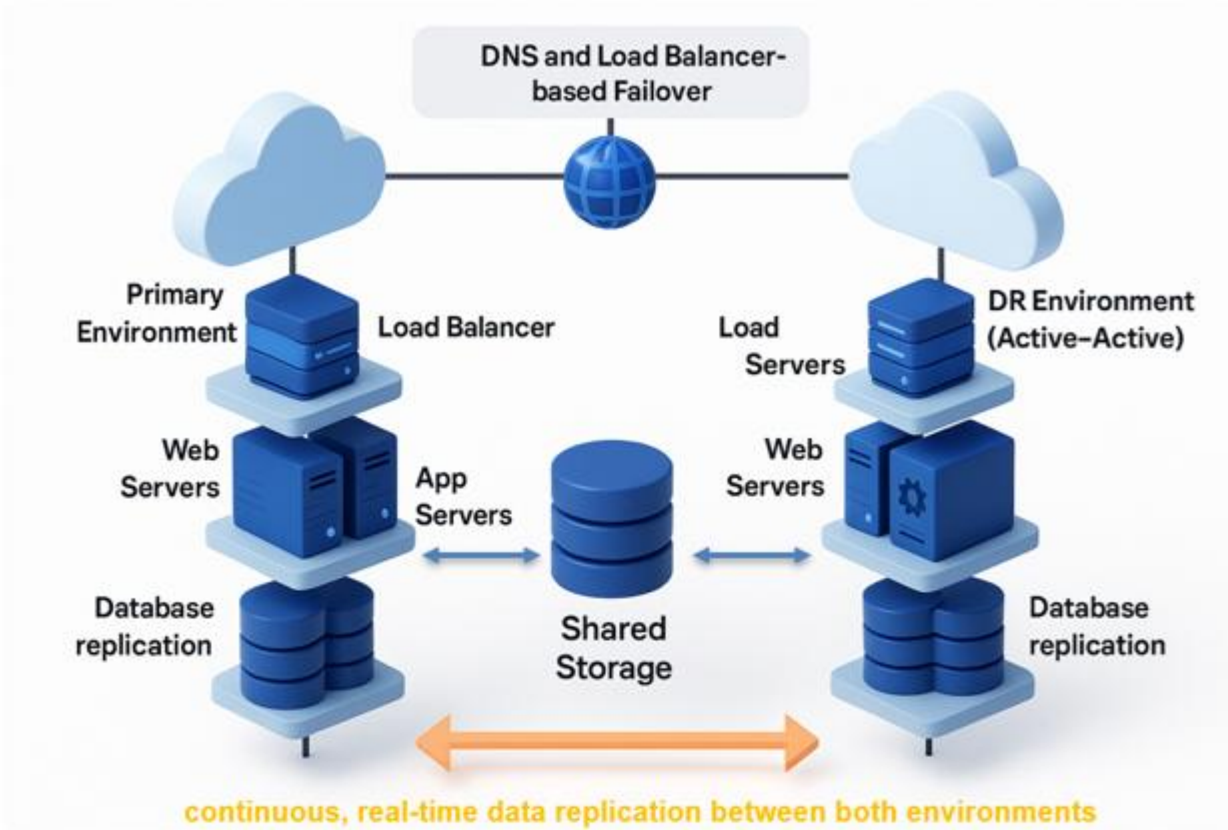

Figure 6. Proposed Active–Active cloud-based disaster recovery architecture (adapted from University of Essex Online, 2025)

Table 4: Key components and rationale of the proposed DR architecture.

Component	Description	Rationale
Primary cloud environment (Active–Active)	Operates the live e-commerce platform.	Ensures global redundancy, high availability, and ISO 27001 compliance (Sutton, 2021).
DR Environment (Hot Standby)	Real-time mirrored system in a secondary region.	Achieves RTO/RPO < 1 min via synchronous replication and automated orchestration.
Database replication	Continuous near-synchronous replication between primary and DR environments.	Minimises data loss, consistent with ALARP principles for critical data (Popov, Lyon and Hollcroft, 2022).
Failover automation	DNS and load balancer-based detection and redirection.	Enables seamless user transition, ensuring minimal downtime (Sutton, 2021).
DevOps pipelines	Quarterly failover tests and annual audits.	Confirms operational readiness and alignment with ISO 22301 (Popov, Lyon and Hollcroft, 2022).

4.2 Platform recommendation

A multi-region Microsoft Azure deployment is recommended due to its integrated high-availability, security, and compliance tools, which align with existing Microsoft 365 and ERP environments. Azure's geo-redundant architecture supports live failover, continuous monitoring, and automated replication, achieving sub-minute RTO/RPO (Microsoft (2024). Comparable functionality is available through AWS or Google Cloud, but Azure's built-in integration and compliance tooling provide a cost-effective fit for SMEs.

4.3 Challenges and mitigations

Table 5. DR implementation challenges and recommended mitigations

Challenge	Business impact	Recommended mitigation
High cost of deployment and maintenance	Running two live, synchronised environments increases operational expenditure and cloud service fees (Sutton, 2021).	Conduct a Business Impact Analysis (BIA) to confirm the cost is proportionate to system criticality (Popov, Lyon and Hollcroft, 2022). Use auto-scaling and pay-as-you-go models to optimise resources.
Vendor lock-in risk	Dependence on one cloud provider's proprietary tools may limit flexibility and future cost control.	Adopt open standards, containerisation (Docker/Kubernetes), and explore a hybrid or multi-cloud model to enable portability across providers (Ayepola & Abos, 2024; Adelia et al., 2024). Additionally, where feasible, store critical data backups in a secondary provider's object storage (e.g., AWS S3 or Google Cloud Storage) to ensure independence from a single cloud vendor.
Provider-level outage	Outage at the provider level may affect both primary and DR sites.	Deploy a hybrid or multi-cloud model for geographic and provider redundancy (Sutton, 2021).
Network security	Two always-active environments create more network endpoints and data flows increases exposure to data breaches or misconfigurations, potentially breaching GDPR and/or PCI DSS requirements.	Apply encryption in transit and at rest, secure VPN/private links, and conduct regular penetration testing (Popov, Lyon and Hollcroft, 2022).

The design delivers exceptional resilience and global reach but requires disciplined cost control and governance. Recovery capabilities should remain ALARP—as low as reasonably practicable—balancing resilience with business value (Popov, Lyon and Hollcroft, 2022). Effective BC/DR should form part of broader information risk management (Sutton, 2021), ensuring continuous monitoring, validation, and board-level oversight.

5. Conclusion

In this study, the Monte Carlo Simulation (MCS) was used to estimate the probability that changes in operations and the supply chain could affect product quality and availability. The simulation results indicate a 74% probability of supply chain success, suggesting that product quality and availability are likely to remain unaffected by these changes. The 90% confidence interval of 68% to 80% further reinforces the reliability of these estimates. However, the 26% probability of failure highlights potential risks to these critical factors and, consequently, to compliance with stringent pet food regulations. Additionally, the introduction of digitalised infrastructure, which requires 24/7/365 availability with sub-minute recovery objectives, introduces risks to both product availability and adherence to the new GDPR and PCI DSS requirements.

Maintaining Pampered Pets' renowned high standards of pet food quality and ensuring compliance with regulatory requirements are critical business priorities. Mitigating the risks identified through this analysis is a top priority, with measures to ensure that mitigation efforts and recovery capabilities are balanced with business value, adhering to the ALARP (As Low As Reasonably Practicable) principle (Popov, Lyon & Hollcroft, 2022).

The proposed mitigations, informed by the results of the MCS and the Disaster Recovery (DR) strategy, ensure that Pampered Pets continues to meet the highest operational and security standards. The BC/DR strategy address both operational and security requirements by implementing appropriate measures and incorporating GDPR and other regulatory standards.
Compliance with pet food regulations is assured through stringent quality controls and well-defined contracts with third-party partners. This strategy is critical to supporting the company's ongoing globalisation and digital transformation, enabling the business to meet the evolving expectations of customers and regulators.

Future work will involve expanding the model to include additional suppliers, warehouses, and transport services as real-time data becomes available. This will enhance the model's predictive accuracy, improve decision-making capabilities, and ensure continued resilience as Pampered Pets scales its operations.

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APPENDIX A – DISTRIBUTION VALIDATION

The probability distributions of the four input variables—Perfect Order Rate (POR Supplier), Perfect Order Rate (POR Automated Warehouse), Transport delay (TD), and Quality degradation (QD)—were validated prior to the Monte Carlo Simulation by generating 10,000 random samples for each variable. Each variable was parameterised according to its configured probability bounds to reflect the expected range of uncertainty within the supply chain model.

The summary statistics (mean, standard deviation, and range [min–max]) confirm that all samples fall within the expected bounds and are centred approximately at each interval's midpoint, consistent with the properties of a uniform distribution.

Input Distribution Summary

	Mean	StdDev	Min	Median	P01	P99	Max
Perfect Order Rate - Supplier	0.8848	0.0374	0.82	0.8844	0.8213	0.9488	0.95
Perfect Order Rate - Automated Warehouse	0.9497	0.0173	0.92	0.9496	0.9208	0.9794	0.98
Transport delay	0.0498	0.0115	0.03	0.0498	0.0304	0.0695	0.07
Quality degradation	0.0749	0.0144	0.05	0.0748	0.0505	0.0995	0.1

Figure A1. Summary statistics of generated samples.

The Kolmogorov–Smirnov (KS) test compared each empirical sample distribution (the 10,000 simulated values) with its corresponding theoretical uniform distribution defined by the variable's lower and upper bounds. The goodness-of-fit results show that all p-values were greater than the chosen significance level ($\alpha = 0.05$). This means that there is no statistical evidence to reject the null hypothesis that the samples follow a uniform distribution. Consequently, the uniform assumption is considered appropriate for all four variables.

KS Goodness-of-Fit Results

	Dist	KS_stat	p_value	alpha	Decision
Perfect Order Rate - Supplier	Uniform	0.006	0.8641	0.05	ACCEPT
Perfect Order Rate - Automated Warehouse	Uniform	0.011	0.1746	0.05	ACCEPT
Transport delay	Uniform	0.0091	0.3781	0.05	ACCEPT
Quality degradation	Uniform	0.0063	0.822	0.05	ACCEPT

Figure A2. Kolmogorov–Smirnov goodness-of-fit test results.

The Q–Q (quantile–quantile) plots complement the statistical test by providing a visual diagnostic that highlights any potential discrepancies in the tails or central region of the data. The plotted points align closely with the 45-degree reference line, confirming that the empirical quantiles match the theoretical ones, verifying uniformity across the entire range.

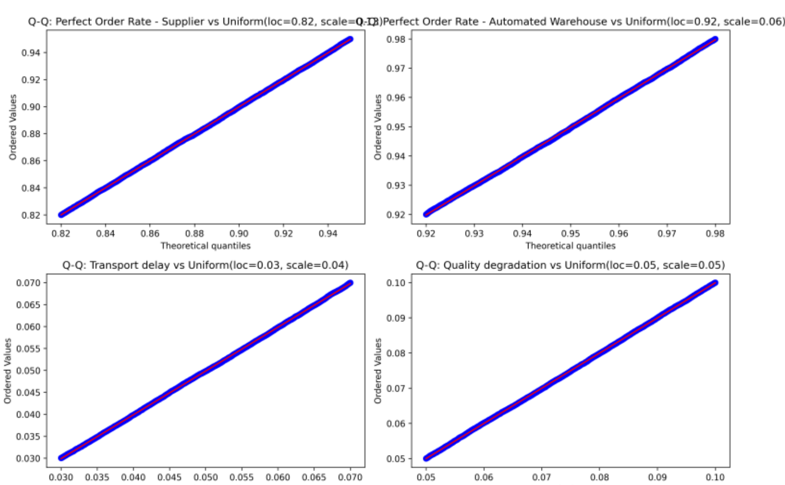

Figure A3. Q–Q plots comparing empirical and theoretical uniform distributions.

The histograms show flat, rectangular shapes across the configured bounds, confirming that the simulated data are evenly distributed within their respective ranges and that no systematic bias or skewness is present in any of the variables.

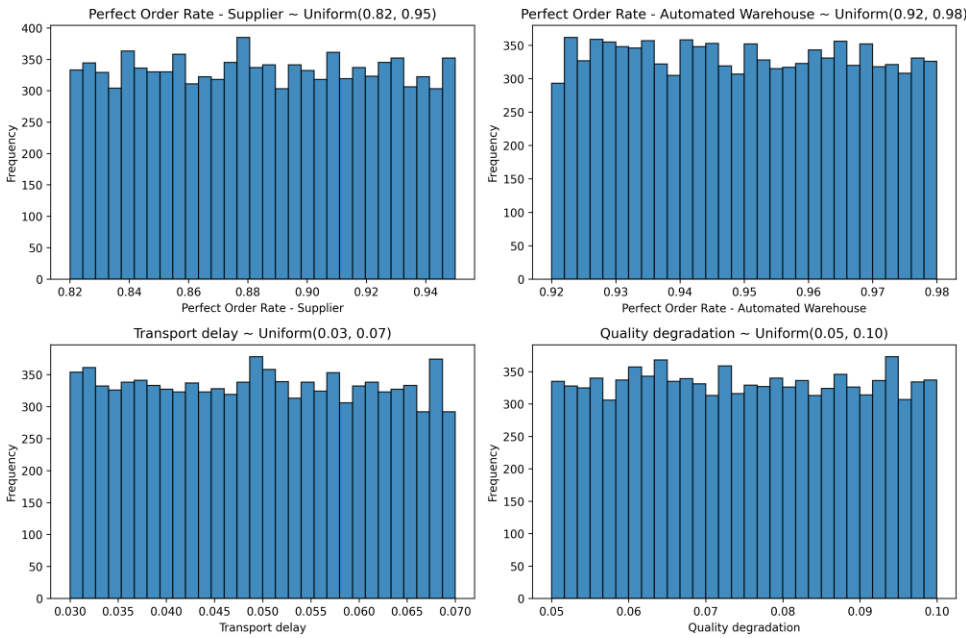

Figure A4. Histograms of input variable samples.

Conclusion: The results from both the statistical tests and the visual diagnostics confirm that the chosen uniform distributions are suitable representations of uncertainty for all four input variables used in the Monte Carlo Simulation model.

APPENDIX B – RESULTS OF MONTE CARLO SIMULATION SCENARIO

1) Configure and sample the inputs

The simulation was configured to generate 10,000 random samples for each of four independent input variables, all following uniform probability distributions within their defined bounds (refer to Appendix A):

Variable	Indicator	Lower bound	Upper bound
Perfect Order Rate – Supplier	PORS	0.82	0.95
Perfect Order Rate – Automated Warehouse	PORW	0.92	0.98
Transport delay probability	TD	0.03	0.07
Quality degradation probability	QD	0.05	0.10

2) Input validation

2.1) Sanity Check

This step acts as a sanity check to confirm that all randomly generated input samples remain within their configured probability bounds for each variable, verifying that the Monte Carlo simulation used the intended parameter ranges during execution.
For this, each variable's minimum and maximum sampled values were compared with its configured low and high limits. A "PASS" outcome confirms that the sampling procedure respected the correct bounds.

Input Bound Check

	Configured_Low	Configured_High	Sample_Min	Sample_Max	Within_Bounds
Perfect Order Rate - Supplier	0.82	0.95	0.82	0.95	PASS
Perfect Order Rate - Automated Warehouse	0.92	0.98	0.92	0.98	PASS
Transport delay	0.03	0.07	0.03	0.07	PASS
Quality degradation	0.05	0.1	0.05	0.1	PASS

Figure B1: Input bound sanity check verifying that sampled values remain within the configured probability limits (01_bound_check.png).

The results show that all four variables perfectly matched their configured bounds (min = low, max = high) and returned PASS, confirming that the sampling implementation adhered exactly to the specified ranges.

2.2) Z-score

We tested whether the sample mean matches the theoretical mean $(a + b) / 2$ using a two-sided z-test. If $|z| \leq 1.96$ ($\alpha = 0.05$), we do not reject that the mean is correct.

Spread check
We also compared the sample standard deviation to the theoretical $SD = (b - a) / \sqrt{12}$ (large-sample variance check).

Input Validation: Benchmark vs Simulated

	Alias	Low	High	Theoretical	Theoretical	Simulated	Simulated	Mean_Che	SD_Check	Overall
Perfect Order Rate - Supplier	PORS	0.82	0.95	0.885	0.0375	0.8849	0.0375	MATCH	MATCH	MATCH
Perfect Order Rate - Automated Warehouse	PORW	0.92	0.98	0.95	0.0173	0.9502	0.0173	MATCH	MATCH	MATCH
Transport delay	TD	0.03	0.07	0.05	0.0115	0.0499	0.0115	MATCH	MATCH	MATCH
Quality degradation	QD	0.05	0.1	0.075	0.0144	0.075	0.0145	MATCH	MATCH	MATCH

Figure B1b: Input validation: benchmark vs simulated (theoretical vs simulated mean and standard deviation) (01b_input_validation_moments.png)

Result: all inputs matched the benchmark Uniform(a, b) specifications for both center and spread.

Input validation check conclusion:
Both checks confirm that the MCS simulator generates inputs with the correct center (mean) and spread (standard deviation) implied by the benchmark Uniform(a, b) bounds.

3) Compute Supply Chain Performance

The simulated Supply Chain Performance (SCP) was computed using the multiplicative success model:

$$P(SCP) = POR_S * POR_W * (1 - QD) * (1 - TD)$$

Each factor represents a success probability; multiplying them yields the overall success rate within [0, 1].

Performance Summary

	Mean	StdDev	Min	P05	P10	P50	P90	P95	Max
Supply Chain Performance	0.7391	0.037	0.6427	0.6803	0.6904	0.7381	0.7883	0.8004	0.8471

Figure B2: Performance summary and 90 % confidence interval (**02_performance_summary.png**).

On average, the supply chain performs at ~74%, with typical variation of about ±4 percentage points. In most scenarios (90% of cases), performance falls between 68% and 80%, indicating moderate volatility driven by uncertainty in four key inputs.”

4) Target mean check

The observed mean performance was compared against the target mean = 0.82 (82%).

Target Mean Check

	Target_Mean	Observed_Mean	Delta	Delta_%_of_Target	Meets_or_Exceeds_Target
Mean Performance Check	0.82	0.7391	-0.0809	-9.8659	NO

Figure B3: Target mean check comparing simulated and target performance (03_target_mean_check.png).

The results show that the current supply chain underperforms relative to the 82%target. Improvements in key variables, particularly supplier reliability and warehouse accuracy, are required to achieve the desired service level.

5) Sensitivity Analysis

Sensitivity analysis was performed to quantify the relative influence of each input variable on the overall Supply Chain Performance and to prioritise potential improvement actions. Standardised regression coefficients (betas) were computed to indicate each variable's impact while controlling for scale.

Sensitivity (Standardised Betas)

	Standardised_Beta
Perfect Order Rate - Supplier	0.8437
Perfect Order Rate - Automated Warehouse	0.3651
Transport delay	-0.2408
Quality degradation	-0.3112

Figure B4: Sensitivity coefficients (04_sensitivity_betas_table.png).

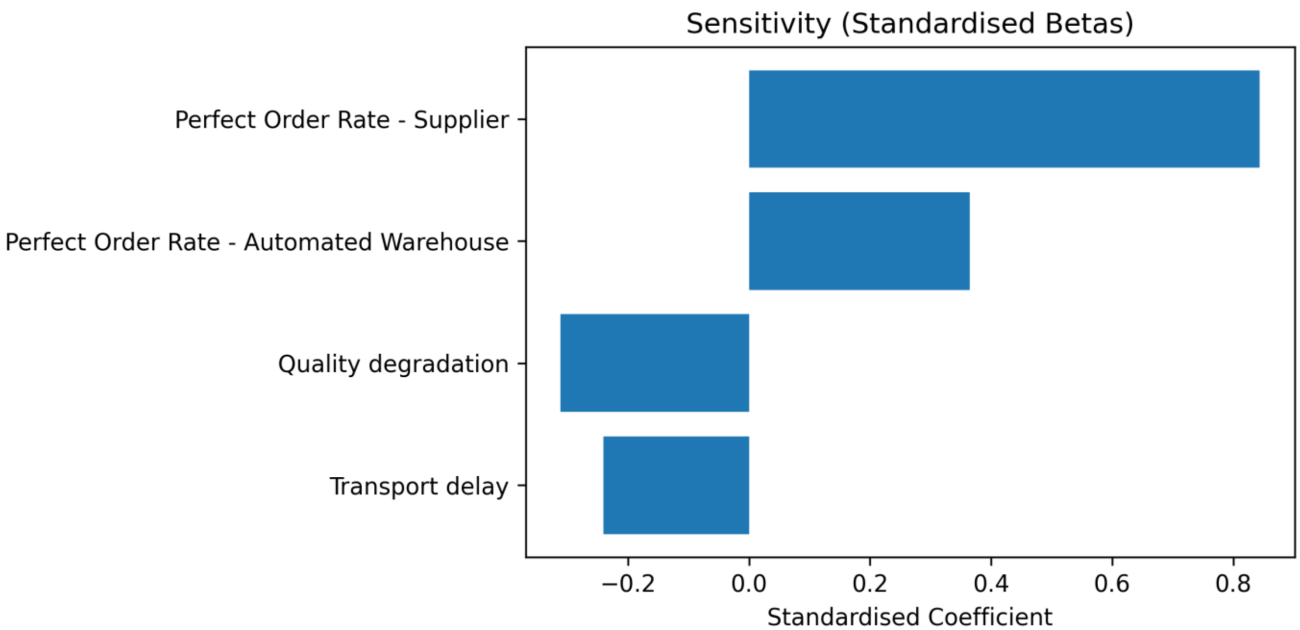

Figure B5: Sensitivity bar chart (05_sensitivity_betas_bar.png).

The results show:

Input variable	Standardised regression coefficients (β)	Effect
Perfect Order Rate – Supplier	β = 0.845	Strongest positive effect on performance
Perfect Order Rate – Automated Warehouse	β = 0.363	Moderate positive effect
Quality degradation	β = −0.310	Moderate negative effect
Transport delay	β = −0.242	Weak-to-moderate negative effect

Supplier reliability is the most influential driver of overall supply chain success, followed by warehouse accuracy; reducing quality degradation and transport delays also yields measurable improvement.

6) Correlation with performance (Pearson)

Pearson correlation coefficients were calculated between each input variable and the simulated Supply Chain Performance to assess the direction and strength of linear relationships.

Pearson Correlations with Performance

	Pearson_Corr_with_Performance
Perfect Order Rate - Supplier	0.8424
Perfect Order Rate - Automated Warehouse	0.3595
Transport delay	-0.2553
Quality degradation	-0.3083

Figure B6: Pearson correlation table with performance (**06_corr_with_y_table.png**).

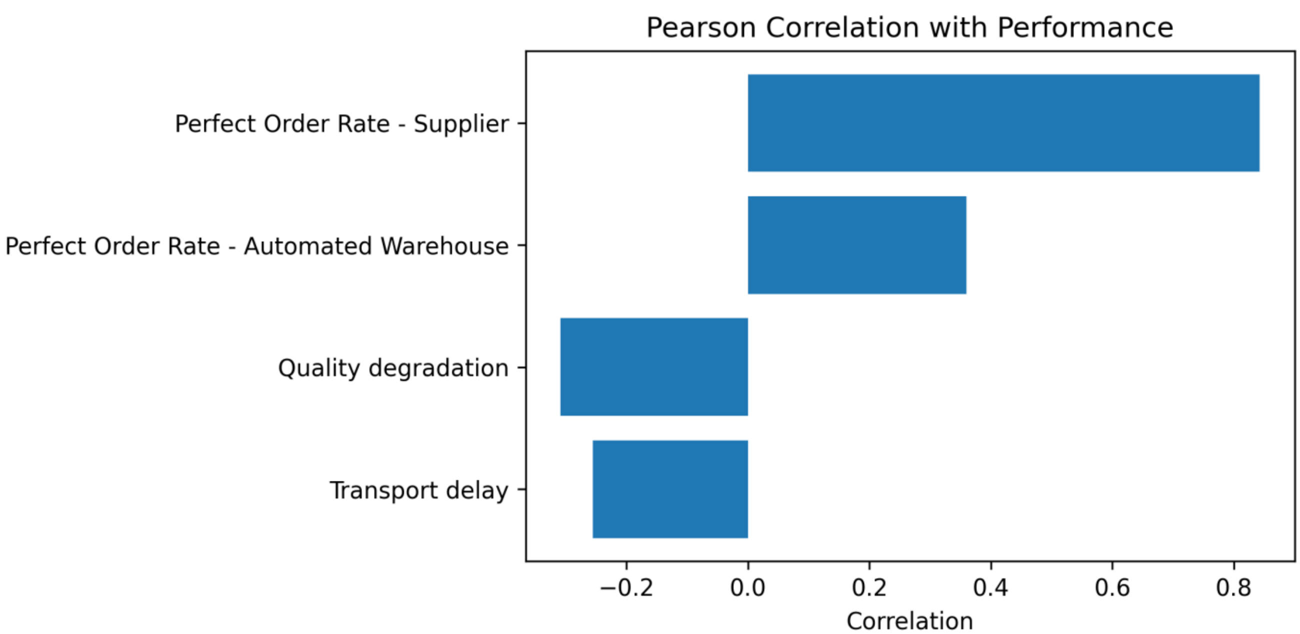

Figure B7: Pearson correlation bar chart (**07_corr_with_y_bar.png**).

The results show:

- PORS ↔ SCP = +0.846 (very strong positive)
- PORW ↔ SCP = +0.372 (moderate positive)
- QD ↔ SCP = −0.310 (moderate negative)
- TD ↔ SCP = −0.223 (weak-to-moderate negative)

Positive correlations indicate that improving supplier or warehouse performance increases total supply chain reliability, while higher transport delays or quality degradation reduce it.

Final confidence statement:

With 90 % confidence, the Supply Chain Performance lies between 0.6791 and 0.7992.

Performance Summary

	Mean	StdDev	Min	P05	P10	P50	P90	P95	Max
Supply Chain Performance	0.7391	0.037	0.6427	0.6803	0.6904	0.7381	0.7883	0.8004	0.8471

APPENDIX C – SYSTEM CRITICALITY AND DISASTER RECOVERY OBJECTIVES

Table C1. Classification of system criticality levels and corresponding disaster recovery configurations, showing the typical standby approach and target recovery objectives (RTO/RPO) for each category (University of Essex Online, 2025).

System Criticality	Typical DR system	Target RTO	Target RPO
Non-critical system	Cold Standby	> 48 hr	> 24 hr
Medium criticality	Warm Standby	> 6 hr	> 15 min
High criticality	Active–Passive (Warm Standby)	> 12 hr	> 1 hr
Highly critical system	Active–Active (Hot Standby)	< 1 hr	< 1 min