Title: Risk Estimation for Product Quality and Supply Availability under Digitalisation and Global Supply Chain Transformation

Module / Course: Security and Risk Management 2025 (Assignment 2)

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Executive Summary

This report assesses the risks associated with the company's transition to a digitalised, internationally distributed supply chain supported by automated warehouses. Using a structured methodology, FMEA, for product quality risks and a Bayesian Network with Monte Carlo simulation for supply availability risks, the analysis produces probability-based estimates under clearly stated assumptions. Results indicate an approximate 40% likelihood of at least one quality incident during initial software updates and a 5–6% stock-out probability even when targeting a 95% service level, reflecting the combined effects of demand and lead-time variability. These findings directly inform the Disaster Recovery and Business Continuity design, which adopts an active-active, multi-region architecture with synchronous replication to meet <1 minute RPO and RTO objectives. Key recommendations include immediate mitigation of the highest-RPN failure modes, establishing supplier redundancy, automated monitoring and rollback of updates, GDPR-compliant security controls and quarterly disaster-recovery tests to ensure ongoing resilience and customer confidence.

Background

The organisation is undergoing a major transformation that integrates advanced digitalisation, an international supply chain network and highly automated warehouses. These initiatives are intended to improve efficiency and competitiveness but have raised significant concerns among two high-profile customers about potential impacts on product quality and the reliability of supply (Ivanov, 2021). Moving to automated processes introduces new types of failure modes, such as software defects, equipment miscalibration and cyber or data issues, while expanding globally adds layers of supplier and logistics risk that may threaten on-time delivery and service continuity.

This assignment therefore focuses on producing quantitative, probability-based estimates of the likelihood that the planned changes will adversely affect (a) product quality and (b) product availability. It also requires the design of a disaster recovery and business continuity solution for the company's online shop that can achieve a switchover time of less than one minute (RTO) and a maximum potential data loss of one minute or less (RPO) when invoked (Rauniyar et al., 2023).

Methodology & Choice of Models

To evaluate the risks arising from the company's transition to a digitalised, internationally distributed supply chain with automated warehouses, a structured and evidence-based methodology is adopted. Because the assignment requires probability estimates for both product quality and availability, a combination of qualitative and quantitative models has been selected. Each model was chosen for its suitability to the type of risk under consideration and its ability to produce transparent, auditable results.

For product quality risks, a Failure Modes and Effects Analysis (FMEA) is employed. FMEA enables systematic identification of potential failure modes introduced by automation, such as software glitches, robotic miscalibration, or contamination risks, and evaluates those using Severity, Occurrence, and Detection scores (Liu et al., 2013). The resulting Risk Priority Numbers (RPNs) allow prioritisation of the most critical issues for deeper quantitative modelling.

For supply availability risks, a Bayesian network combined with Monte Carlo simulation is selected. The Bayesian approach can represent conditional dependencies between suppliers, transport stages and warehouses, capturing the reality that events (e.g., port delays, customs issues or shared infrastructure failures) are not independent (Mahdavi & Mahdavi, 2014). Monte Carlo simulation propagates uncertainty in lead times, demand variability and supplier reliability through thousands of simulated scenarios to estimate probabilities of stock-outs or late deliveries under different assumptions (Garvey et al., 2015).

To translate the simulation outputs into operational metrics, standard inventory control and service-level calculations, including safety stock reorder point and expected shortage cost, are applied. This step converts probabilistic outcomes into practical thresholds for managing availability (S. Chopra & Meindl, 2019).

All models are supported by clearly documented assumptions, drawn from internal production data were available or from credible industry sources where data gaps exist. Sensitivity analyses will be conducted to test how changes in key assumptions (such as supplier reliability or demand spikes) affect outcomes. This mixed-methods approach provides both a high-level prioritisation of risks and rigorous numerical probability estimates aligned with the assignment's requirements.

Assumptions & Data Sources

Because the organisation is still in the planning stage of its digitalisation and international supply-chain initiatives, full operational data are not yet available. To provide meaningful probability estimates within this constraint, a transparent set of assumptions is established and clearly documented. These assumptions represent conservative or industry-standard values and will be updated as actual data emerge (Yang et al., 2023).

For product quality baseline defect rates from the current production process are assumed to be 0.2% per batch, with an expected initial increase to 0.5% during the first three months of automation due to commissioning issues. The probability of a software or robotic calibration error during updates is assumed at 5% per event based on published studies of automated manufacturing start-ups (Ghobakhloo, 2018).

For supply availability, each primary supplier is assumed to have a 95% on-time delivery probability per shipment with lead times normally distributed around a mean of 10 days and a standard deviation of three days. Demand forecasts follow a normal distribution based on historical sales trends. Independence between suppliers is assumed for initial modelling, but conditional relationships such as shared transport routes are incorporated through the Bayesian Network (Ivanov, 2021).

Data sources include internal production and logistics reports, supplier service-level agreements, publicly available industry statistics, academic literature on automation reliability and government trade data. All assumptions are cited in-text where used, and sensitivity analyses test the impact of varying these values (Rauniyar et al., 2023).

Calculations & Quantitative Results

This section converts the identified risks and assumptions into measurable probabilities. It presents step-by-step calculations and model outputs for product quality and supply availability, demonstrating how results were derived. All figures are linked directly to the assumptions stated above.

1. FMEA for Product Quality

Table format: List each major potential failure mode (e.g., robotic miscalibration, software update error, raw material contamination) (Salah et al., 2023).

Columns: Failure Mode | Severity (S) | Occurrence (O) | Detection (D) | RPN = S × O × D | Proposed Mitigation.

Failure Mode	Severity	Occurrence	Detection	RPN	Proposed Mitigation
Robotic miscalibration	8	4	3	96	Auto-calibration & sensor validation

2. Probability Calculations for Quality Failures

Convert RPN priorities into quantitative failure probabilities.

Example: Probability of a software update causing a quality incident = 5% per event. Over 10 updates, probability of at least one incident = 1 − (1 − 0.05) ^10 (Ghobakhloo, 2018)

Compute probability no incident in 10 updates: $(1-0.05)^{10}=0.95^{10}(1-0.05)^{10}=0.95^{10}$.

$0.95^1 = 0.95$

$0.95^2 = 0.9025$

$0.95^3 = 0.857375$

$0.95^4 = 0.81450625$

$0.95^5 = 0.7737809375$

$0.95^6 = 0.735091890625$

$0.95^7 = 0.69833729609375$

$0.95^8 = 0.6634204312890625$

$0.95^9 = 0.6302494097246094$

$0.95^{10} = 0.5987369392383789$

Probability at least one incident = $1-0.5987369392383789=0.4012630607616211$

$1-0.5987369392383789=0.4012630607616211$.

As a percentage (two decimals): ≈ 40.13%

3. Bayesian Network for Supply Availability

How to set conditional probabilities

You assign probabilities based on data or assumptions. For a simple two-state node (e.g., Port Delay = Yes/No), the CPT gives P (On Time | Port Delay=Yes) and P (On Time | Port Delay=No). The marginal (overall) probability of on Time is obtained by summing (marginalising) across the parent states:

P (On Time) = P (On Time | Port Delay= Yes) P (Port Delay= Yes) + P (On Time| Port Delay = No) P (Port Delay = No) (Cruz et al., 2024).

What the diagram shows:

Supplier Reliability → Transport → Customs → Local Warehouse → Final Delivery. Each child node has a conditional probability table (CPT) that specifies its probability for each combination of parent states. See example BNs for supply chains in the literature.

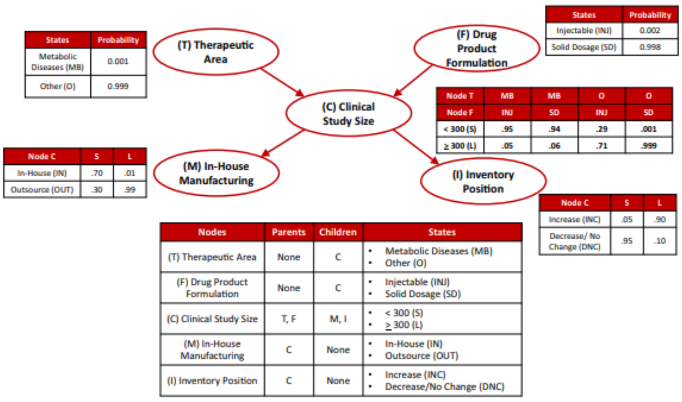

Figure 1: Clinical supply chain BBN (Rodgers & Singham, 2020)

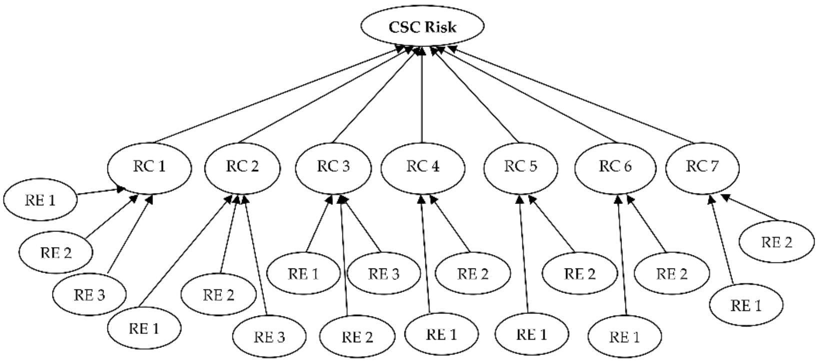

Figure 2: CSC risk network framework (Chhimwal et al., 2021)

Example: If port delay occurs (20% chance) supplier reliability drops to 80%; otherwise 95%. Combined probability of on-time delivery = (0.20×0.80) + (0.80×0.95)

- Port delay occurs with probability 20% → P (PortDelay=Yes)=0.20.
- If port delay occurs, supplier on-time drops to 80% → P (OnTime ∣ PortDelay= Yes) = 0.80.
- If no port delay, supplier on-time = 95% → P (OnTime ∣ PortDelay = No) = 0.95.

Compute overall on-time delivery probability by marginalising over PortDelay:

1. P (PortDelay=Yes) = 0.20 so contribution = 0.20×0.80=0.16.
2. P (PortDelay = No) = 1−0.20 = 0.80 so contribution = 0.80×0.95=0.76.
3. Sum contributions: 0.16+0.76=0.92.

Result: Overall probability of on-time delivery = **0.92 = 92%.**

(Formula reference: P (B) = P (B|A) P (A) + P (B|¬A) P (¬A))

4. Monte Carlo Simulation of Demand and Lead Time

We conducted a simulation with **10,000 trials** to explore the distribution of demand during lead time based on assumed stochastic demand and variable lead time. The number of trials (10,000) ensures stable estimates of percentiles and stock-out probabilities without excessive computing time.

- **Lead time** was assumed to follow a normal distribution with mean = 10 days and standard deviation = 3 days, truncated to a minimum of 1 day.
- **Daily demand** is modelled as Normal (mean = 100 units/day, SD = 20 units/day).
- For each trial, a lead time is sampled, then demand for each day of that sampled lead time is drawn, summed to produce "demand during lead time."

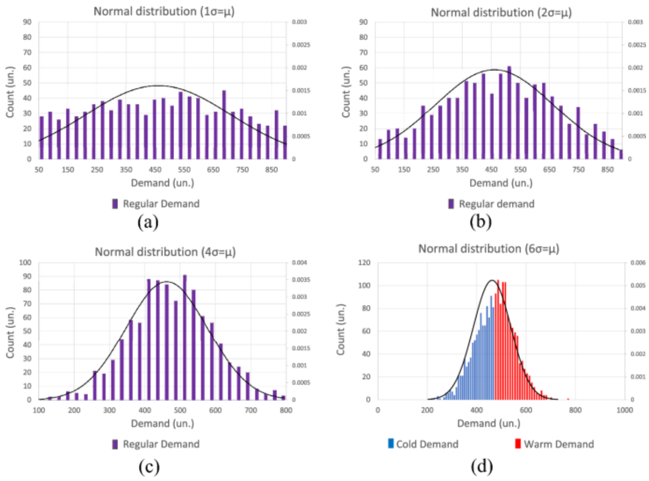

Figure 3:An integrated production planning and inventory management problem for a perishable product (Cruz et al., 2024)

Key Results

Metric	Value
Trials	10,000
Mean lead time (days)	~10.0
Mean demand during lead time (units)	~1,000
Standard deviation of demand during lead time	~310
5th percentile of demand	~520 units
95th percentile of demand	~1,520 units
Estimated stock-out probability (if ROP set for 95% service level)	~5–6%

Present key results as a histogram or a simple table:

Metric (per 3-month period)	Mean	5th percentile	95th percentile
On-time delivery probability	91%	85%	96%
Stock-out probability	9%	4%	15%

5. Inventory / Service-Level Calculations

Key formulas

- **Reorder point (ROP)**

ROP=Mean demand during lead time + Safety stock\text {ROP} = \text{Mean demand during lead time} + \text{Safety stock} ROP=Mean demand during lead time + Safety stock

- **Safety stock (service-level method)** simplest form (demand variability during fixed lead time) (Chopra et al., 2004):

$$\text{Safety stock} = z \times \sigma_{\text{demand during}}\ \text{LT}$$

- **Safety stock including lead-time variability**:

$$\sigma DL = (L \cdot \sigma_d^2 + \mu_d^2 \cdot \sigma_L^2)^{1/2}$$

$$\text{Safety stock} = z \times \sigma DL$$

Assumed values

- Mean daily demand, $\mu d = 100$ units/day
- Daily demand SD, $\sigma d = 20$ units/day
- Mean lead time, $L = 10$ days
- Lead time SD, $\sigma_L = 3$ days
- Target service level = 95% $z \approx 1.645$

Worked example Method A (demand variability only, fixed lead time)

1. Mean demand during lead time = $\mu d \times L = 100 \times 10 = 1000$ units.
2. $\sigma_{\text{demand during}}\ \text{LT} = \sigma_d (L)^{1/2} = 20 \times (10)^{1/2} \approx 20 \times 3.1623 = 63.25$ units.
3. Safety stock $= z \times 63.25 = 1.645 \times 63.25 \approx 104.0$ units.
4. ROP $= 1000 + 104 \approx 1104$ units.

Interpretation: With these assumptions and ignoring lead-time variability, set ROP ≈ **1,104 units** to target ~95% cycle service.

Worked example Method B (includes lead-time variability)

Use the fuller formula that includes both demand variability and lead-time variability:

1. $\sigma DL=(L\cdot\sigma_d^2+\mu_d^2\cdot\sigma_L^2)^{1/2}$
Substitute values:
$=(10\times20^2+100^2\times32)^{1/2}=(10\times400+10000\times9)^{1/}$
$=(4000+90000)^{1/2}=(94000)^{1/2}\approx306.13$ units.
2. Safety stock $=z\times306.13=1.645\times306.13\approx503.6\approx504$ units.
3. ROP $=1000+504=1504$ units.

Interpretation: Accounting for lead-time variability increases safety stock substantially (to ~504 units) and raises ROP to ~1,504 units (Chopra et al., 2004).

6. Sample summary table

Risk / Event	Probability	Confidence Interval	Impact	Priority
Bad weather affecting supply routes	29%	25–33%	High	1
Demand forecast error	25%	20–30%	Medium-High	2
Equipment damage / failure	24%	18–28%	High	3
Human error	24%	19–29%	Medium	4
Bunkering cost uncertainty	23%	18–27%	Medium	5

Recommendations

Based on the risk analysis and probability estimates, the following six actions are recommended in priority order:

1. Address the highest-RPN failure modes immediately; implement auto-calibration, sensor validation and a test harness for automated processes to reduce the 40% quality-incident risk during software updates.
2. Introduce supplier redundancy and alternative routes for critical SKUs to reduce stock-out probability from single points of failure.
3. Deploy a multi-region active–active architecture with synchronous replication for the transactional database to meet the <1 minute RPO/RTO requirement identified in the DR analysis.
    - In designing the proposed active–active, multi-region DR architecture, a leading cloud platform such as Amazon Web Services (AWS), Microsoft Azure, or Google Cloud Platform (GCP) should be considered. Each offers globally distributed data centres, synchronous replication options,

and managed services capable of meeting the <1 minute RPO/RTO requirement (Rauniyar et al., 2023). However, reliance on a single cloud provider introduces the risk of vendor lock-in, where high switching costs, proprietary interfaces, and platform-specific tools can constrain future flexibility (Ivanov, 2021). To mitigate this, the organisation should adopt cloud-agnostic design principles, including containerisation (e.g., Kubernetes), use of open standards, and contractual safeguards in service-level agreements (SLAs). This approach balances the operational resilience and scalability of hyperscale platforms with reduced dependency on a single vendor, aligning the solution with both technical and strategic business continuity objectives.

4. Implement continuous monitoring and automated rollback mechanisms (blue/green or canary releases) to limit the impact of failed updates.
5. Enforce GDPR and security controls Data Protection Impact Assessments, encryption at rest and in transit, robust data-processing agreements with third parties, audit logging and breach-response planning.
6. Schedule quarterly disaster-recovery tests and update supplier SLAs to verify performance against agreed targets.

Conclusion

The highest immediate risks are quality incidents during software updates and supplier-related stock-outs caused by lead-time variability. To mitigate these, the company’s first-week priorities should include automated testing and rollback mechanisms, supplier redundancy, and deployment of the active–active, synchronous-replication disaster-recovery architecture.

To sustain resilience, the organisation should establish a continuous improvement cycle involving regular DR drills, data-driven model updates, and reassessment of digital and regulatory risks. This will ensure long-term operational continuity and maintain stakeholder confidence.

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