The Paradox of Stability: Bayesian Network Analytics on IoT-Driven Supply Chain Risk Asymmetry in Startup Unmanned Retail

Yu Zhong[1], Sombat Teekasap[2]

[1] *Nanning Vocational and Technical University, Nanning 530008, Guangxi, China*
[2] *Bansomdejchaopraya Rajabhat University, Thon Buri 10600, Bangkok, Thailand, sombat.teekasap@gmail.com*

Abstract

This study addresses the critical challenge of supply chain risk management in startup unmanned retail enterprises, where conventional models struggle to capture dynamic risk transmissions under data scarcity. By innovatively integrating Bayesian network (BN) methodology with expert knowledge and fragmented operational data, we develop a tripartite risk framework encompassing technological, operational, and consumer behavior dimensions. Empirical validation through mixed-methods analysis of Chinese unmanned retail startups reveals three pivotal findings: First, procurement management (X3), network failures (X6), and sensor reliability (X7) emerge as core risk nodes, demonstrating heterogeneous effects across risk levels—network stability paradoxically serves both as a safety foundation ($P(T=0|X6=0)=26.82\%$) and crisis accelerator ($P(T=1|X6=1)=52.96\%$). Second, technology-operations coupling effects amplify risk propagation, where IoT component failures trigger cascading decision biases (e.g., 55.01% medium-risk probability from X3 disruptions). Third, posterior probability analysis identifies payment system stability (X8) as the global leverage point, with 40.42% influence on low-risk states. Theoretically, we extend complex adaptive systems theory by quantifying risk factor asymmetry and validating Haimes' risk coupling dynamics in digital retail contexts. Methodological limitations regarding static probability assumptions and startup sample bias are addressed through proposed dynamic Bayesian network extensions and AI ethics integration in future research.
Keywords: Bayesian network; Start-up unmanned retail enterprises; Supply chain; risk

1. Background and Statement of the Problem

The unmanned retail industry has experienced rapid growth in recent years, propelled by advancements in IoT, artificial intelligence, and big data technologies, establishing itself as a critical direction in the global retail sector's digital transformation. Positioned as a solution to the cost-intensive scaling challenges and thin profit margins inherent in conventional retail models (Denuwara et al., 2021), this emerging sector demonstrates substantial market potential. However, startup enterprises in unmanned retail confront distinctive supply chain management challenges characterized by three operational paradoxes: heightened technological dependence (particularly on IoT infrastructure and AI algorithms), dynamic inventory requirements (with high-frequency SKU rotations), and environmental volatility (including pandemic disruptions and regulatory uncertainties) (Denuwara et al., 2021; Liu et al., 2018, 2022). These interdependent factors collectively engender complex causal relationships and dynamic evolution patterns in supply chain risks. Empirical studies identify three critical risk clusters: inventory misallocation, procurement inefficiencies, and systemic technological failures(Rukundo et al., 2025). This risk profile reveals fundamental management dilemmas for startups in complex supply chain ecosystems. First-mover enterprises employing asset-light operational models exhibit excessive node dependency within supply networks and inadequate risk resilience, potentially eroding consumer confidence through suboptimal service experiences (Parasuraman, 2000); Second, the inherent unpredictability of market dynamics coupled with data scarcity undermines the effectiveness of conventional risk assessment methodologies in mapping risk transmission pathways.

While extant research has yielded substantial insights into supply chain risk management, three critical limitations persist. First, prevailing models predominantly target established corporations, inadequately addressing the operational realities of startups characterized by resource constraints and historical data paucity. Second, mainstream methodologies primarily employ static metrics — including Analytic Hierarchy Process (AHP), Fault Tree Analysis (FTA), and Failure Mode and Effects Analysis (FMEA) — that rely on stationary assumptions (Ayyildiz & Taskin Gumus, 2021; Kilic et al., 2023; Ramezanifar et al., 2023). These approaches prove inadequate for capturing latent risk transmission pathways under startups' data-scarce conditions and fail to quantify dynamic interaction effects among multiple risk factors. Third, scholarly attention in unmanned retail contexts remains disproportionately focused on consumer behavior and technology adoption (Adam & Dandutse, 2023; Szabó-Szentgróti et al., 2023; I.-C. Wang et al., 2021), with insufficient exploration into systematic supply chain risk modeling. These theoretical blind spots collectively result in the absence of risk-informed decision support tools specifically tailored for emerging unmanned retail ventures.

To address these research limitations, this study innovatively incorporates Bayesian network (BN) methodology. This approach offers three distinctive analytical advantages: Firstly, its probabilistic reasoning mechanism enables the integration of expert knowledge with fragmented datasets, effectively mitigating historical data deficiencies common in startup operations. Secondly, the directed acyclic graph structure provides visual representation of causal chains and cascade effects among risk determinants. Finally, dynamic updating capabilities facilitate real-time risk evaluation, aligning with the high-frequency operational requirements of unmanned retail supply chains (Hänninen et al., 2014; Hosseini & Ivanov, 2022; Marcot & Penman, 2019). Building upon these theoretical foundations, we develop a tripartite risk analysis framework encompassing technological, operational, and consumer behavior dimensions, with empirical validation using operational data from emerging unmanned retail ventures.

This study makes dual theoretical advancements. First, it extends Bayesian network applications to supply chain risk management in startup contexts, thereby advancing the implementation of complex adaptive systems theory within retail digital transformation. Second, it identifies emerging risk transmission mechanisms specific to unmanned retail supply chains, particularly the technology-operations coupled risks, addressing the underexplored realm of technology-embedded risks in extant literature.

For practical implications, the developed dynamic risk assessment tool provides actionable insights for startups to optimize supplier selection, inventory strategies, and contingency response protocols. Simultaneously, it offers policymakers quantitative references for formulating targeted industrial support measures.

The article is organized as follows: Section 1 establishes the research context through a systematic introduction. Section 2 critically reviews theoretical and empirical developments in the field. Section 3 elaborates on methodological design and data acquisition protocols. Section 4 presents the BN model architecture and empirical findings from scenario analyses. Section 5 synthesizes theoretical and practical implications while discussing research limitations.

2. Literature Review

2.1 Key Technologies in Unmanned Retail

Traditional retail supply chains, extending from upstream manufacturers through multiple distributors and retailers before reaching consumers, inherently limit price competitiveness for end-users (Wu et al., 2014) However, unmanned retail enterprises require substantial R&D investments and equipment procurement costs, resulting in higher per-unit pricing (Kaur et al., 2011). Consequently, the advantages of machine-driven labor substitution through economies of scale become more pronounced in unmanned retail, generating diversified profit streams (Adapa et al., 2020).

Current mainstream unmanned retail technologies fall into three categories: RFID (Radio-Frequency Identification) (Denuwara et al., 2021), gravimetric sensing, and computer vision (Zhang et al., 2020; Liu et al., 2018; Zhang et al., 2019). RFID technology identifies targets and reads/writes data via radio signals without mechanical or optical contact. As an early-developed and relatively mature technology (Want, 2006; Kaur et al., 2011), RFID has been widely applied across scenarios including library systems, access control, food safety traceability, and IoT applications (Nambiar, 2009). Amazon's unmanned store AmazonGo exemplifies advanced implementations, integrating patented computer vision technologies for "detecting object interactions/movements" and "identifying item transfers from fixtures" (Zhang et al., 2020).

In summary, unmanned retail fundamentally relies on Internet of Things (IoT) and artificial intelligence (AI) technologies to deliver "low-contact services," primarily manifesting in two technological paradigms: AI-driven systems (e.g., Amazon Go) employing biometric recognition and visual sensors for automated checkout, and IoT-driven systems (e.g., Bingo Box) dependent on RFID tagging and barcode scanning for transaction processing (Rukundo et al., 2025; I.-C. Wang et al., 2021) . The evolutionary trajectory demonstrates technological convergence (e.g., AI+IoT integrated intelligent recognition systems) alongside legacy equipment modernization (e.g., vending machines with digital payment interfaces), with the overarching objective of establishing data-driven intelligent consumption ecosystems.

2.2 Supply Chain Risk Management Approaches

Supply Chain Risk Management (SCRM) research has established a theoretical framework centered on risk identification, assessment, and mitigation (Gurtu & Johny, 2021). Risk assessment methodologies predominantly bifurcate into two categories. The first involves quantitative static models, exemplified by integrated approaches combining the Analytic Hierarchy Process (AHP) with fuzzy comprehensive evaluation (Bozanic et al., 2023; Park & Kang, 2021). While dependent on expert-weighted parameters and linear assumptions, these methods struggle to capture dynamic nonlinear interdependencies among risk factors. The second category encompasses data-driven models, including machine learning techniques (e.g., random forests and neural networks) (Lin et al., 2022; Tirkolaee et al., 2021). Although capable of modeling complex nonlinear relationships, such approaches critically depend on extensive historical training data - a requirement conflicting with startups' operational immaturity and fragmented digital records, thereby creating a "small-sample paradox." While demonstrating robustness in traditional manufacturing and mature retail contexts, these methods exhibit significant limitations in addressing unmanned retail startups' unique technology-operations duality risks due to their static nature and data dependency.

Bayesian Networks (BNs) have been increasingly adopted in supply chain resilience studies due to their probabilistic reasoning capabilities and causal visualization advantages. Compared to Fault Tree Analysis (FTA), BNs excel in handling multifactorial dependencies and feedback loops (Zhang et al., 2014). Through conditional probability distributions, BNs quantify interdependencies among variables while explicitly modeling uncertainties (e.g., prior/posterior probabilities, sensitivity analyses). Their directed acyclic graphs (DAGs) visually formalize causal relationships, enabling bidirectional reasoning: forward prediction ("what outcomes may occur") and backward diagnosis ("what causes are probable") (Zhang et al., 2014). This dual functionality facilitates probabilistic forecasting of risk events and captures interactive effects among risk factors in complex systems. Crucially, under data-scarce conditions, domain experts can a priori define network structures and conditional probability tables (Marcot & Penman, 2019), making BNs particularly suitable for startup operational environments.

2.3 Risk of supply chain of start-ups

Failure to innovate beyond conventional retail supply chain models in unmanned retail often results in supply-demand misalignment (Yang, 2019). While technological advancements eliminate competitors lacking technical upgrades (Wang & Zheng, 2023), substantial pre-scale R&D investments coupled with supply chain inflexibility expose unmanned retail startups to heightened bankruptcy risks during their incubation phase (Zhang, 2019). Most startups disproportionately prioritize technological solutions while neglecting risk-aware operations management, thereby compromising consumer experience sustainability (Cao, 2017).

This study employs organizational life cycle theory and technology dependency theory to identify three distinctive supply chain risk characteristics in unmanned retail startups: one is resource constraints, capital limitations force reliance on single suppliers or lean inventory strategies, reducing supply chain node redundancy; the second is data scarcity, insufficient historical operational data impedes effective machine learning model training; third, risk neglect, early-stage supply chain vulnerabilities, if unaddressed, escalate into existential threats during scaling phases (Magliocca et al., 2023; Safari et al., 2024; Wagner, 2021).

Startups frequently adopt high inventory turnover strategies due to demand forecasting inadequacies and capital limitations, exponentially amplifying stockout/misallocation risks (Wagner, 2021). Weak bargaining power and overdependence on limited suppliers for cost reduction (Safari et al., 2024) render supplier delivery reliability a critical single-point failure risk. Unmanned stores' price-driven customer acquisition strategies may induce inventory distortions (Denuwara et al., 2021), creating a "suboptimal inputs → operational failures" vicious cycle.

In unmanned retail contexts, shelf replenishment velocity directly impacts customer experience and inventory turnover rates (Shen, 2024). The operational continuity critically depends on seamless IoT device-algorithm-network integration (Wang & Zheng, 2023) , with intelligent checkout systems constituting the core experiential differentiator (Shen, 2024) - any malfunction incurs catastrophic losses. Furthermore, abrupt consumer behavior shifts (e.g., pandemic-induced contactless preferences) propagate demand-side shocks through inventory systems (Heins & Scheler, 2024; Hosseini & Ivanov, 2022).

3. Reacher Method

3.1 Research Design

This study employs a mixed-methods approach, integrating quantitative supply chain operational data with qualitative expert interviews to construct and validate a Bayesian network risk model. The sample comprises unmanned retail chain startups established within three years in Nanning, Guangxi, China, selected through three criteria: (1) technological dependency (mandatory use of IoT shelf monitoring, RFID, and video surveillance systems); (2) supply chain visibility (provision of ≥6-month procurement, inventory, and distribution logs with failure records); (3) risk event history (≥1 verified supply chain disruption within the past 12 months). Focusing exclusively on chain-operated unmanned convenience stores ensures methodological coherence.

3.2 Data Collection

Three data categories were acquired:Operational data: Historical ERP system records via API integration, encompassing 12 metrics including purchase order lead time, inventory turnover rate, and stockout frequency (June 2017 to June 2019).

Technical logs: IoT device-derived parameters (8 risk indicators: sensor false-alarm rate, network latency duration, etc.).

Expert assessments: Semi-structured interviews with three executives per firm (CEO, Supply Chain Director, CTO), employing Likert 7-point scales to quantify conditional probability relationships among risk factors.

To address data heterogeneity, Z-score normalization and K-nearest neighbors (KNN) imputation (K=5) preprocessed quantitative data. Expert judgments and historical data were fused via Dempster-Shafer theory to generate Bayesian network prior probability distributions, yielding 1,345 validated data instances.

3.3 Constructing Bayesian Networks for Supply Chain Risks in Startup Unmanned Retail Enterprises

Bayesian networks (BNs), also known as belief networks, are probabilistic networks based on Bayesian methods and probability theory for probabilistic reasoning (Liu et al., 2022). They are widely used to handle statistical uncertainties and are represented as directed acyclic graphs (Weber et al., 2012).

To address demand uncertainty in supply chains, Bayesian network models have been applied for prediction (Jäger et al., 2018; Cao, 2017; Wang & Liu, 2015; Wu et al., 2014; Zhang, 2017). The process involves two key steps: First, classifying the magnitude of nodes within the supply chain and defining their value ranges. Second, constructing a Bayesian network based on historical statistical data for each node to derive conditional probability distributions across the network (Stephenson, 2000; Weber et al., 2012) . This approach enables precise estimation of demand across nodes while accounting for their interdependencies, thereby assisting supply chain managers in mitigating demand fluctuations and uncertainties, ultimately enhancing operational efficiency and flexibility (Wu et al., 2014; Zhang, 2017).

3.3.1 Risk Node Identification

Through literature synthesis and expert interviews, we identified critical failure events including: procurement management predictability deficits, declining delivery punctuality rates, delayed shelf replenishment, operational disorganization, and customer transaction failures due to equipment malfunctions. Grounded in the literature and empirical insights, this study analyzes supply chain failure risks with enterprise, identifying four risk node clusters:

T: Supply Chain Risks

a. Operational layer: Inventory management (X1), supplier delivery punctuality rate (X2), procurement management (X3), shelf replenishment timeliness (X4)

b. Technological layer: Hardware/software failures (X5), network failures (X6), sensor reliability (X7), payment system stability (X8)

c. Consumer behavior layer: Customer behavior (X9)

Risk quantification requires computing specific probability values based on inter-variable dependencies. Event logic relationships within the supply chain were established through business process mapping and expert interview validation, yielding the Bayesian network topology presented in Figure 1.

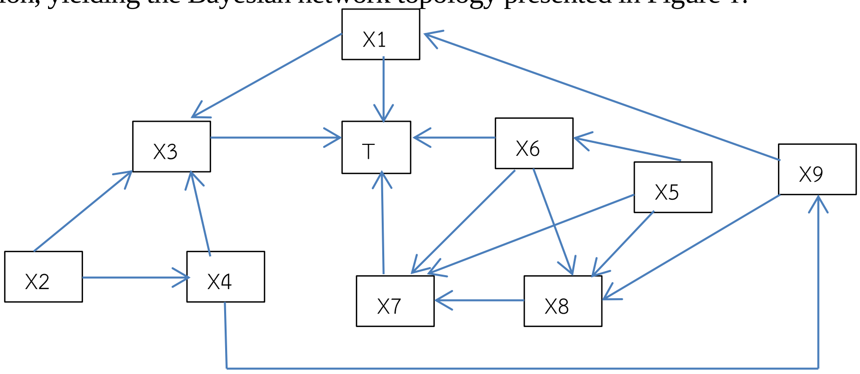

Figure 1 Bayesian Network Diagram of Supply Chain Risks in Startup Unmanned Retail Enterprises

4. Result

4.1 Tools

The modeling process utilized Python 3.6.7, with key third-party libraries including: pandas, numpy, and pgmpy.

4.2 Data and Variables

The variables encompass: supply chain risk (T), inventory management (X1), supplier delivery punctuality rate (X2), procurement management (X3), shelf replenishment timeliness (X4), hardware/software failures (X5), network failures (X6), sensor reliability (X7), payment system stability (X8), customer behavior (X9), loss (L), and total investment (I).

4.3 Risk Level Classification

For supply chain risk (T), multiple quantification methods exist across risk typologies. Building upon prior research, we define supply chain risk loss T as the ratio of loss to total investment following any risk event (Wu et al., 2014):

$$Ti=L/I$$

where I denotes total investment, and L represents loss caused by a risk event.
The distribution of T is as follows:

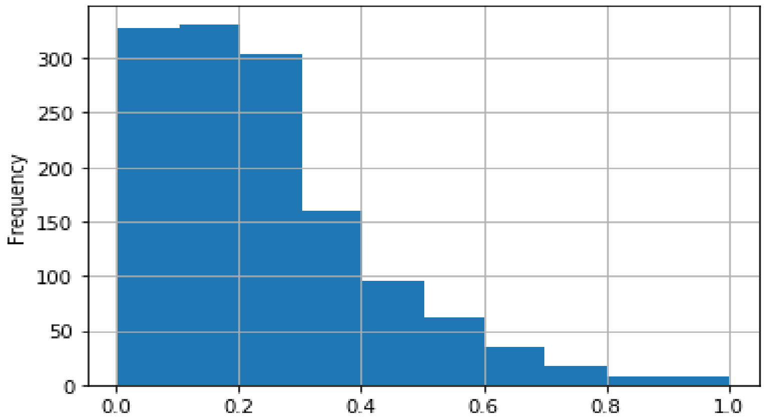

Figure 2 Data T Distribution Diagram

Table 1 Data T Distribution Table

	count	mean	std	min	25%	50%	75%	max
T	1345.0	0.240376	0.180938	0.003698	0.106225	0.207358	0.328126	1.0

The "count" in the above table denotes sample size, "mean" indicates the average loss rate, "std" represents standard deviation, "min" signifies the minimum value, "25%-75%" corresponds to the lower quartile, median, and upper quartile, while "max" refers to the maximum value.

The distribution reveals that 75% of observations exhibit loss rates below 32.8%. Accordingly, we discretize risk into three categories based on empirical quantiles:

Category 0 (Low supply chain risk): Loss rate < 10.6%, labeled as risk level T0
Category 1 (Medium supply chain risk): 10.6% ≤ Loss rate ≤ 32.8%, labeled as risk level T1
Category 2 (High supply chain risk): Loss rate > 32.8%, labeled as risk level T2

4.4 Bayesian Network Parameter Learning

4.4.1 Bayesian Network for Supply Chain Risks

Parameter estimation methods primarily include two conventional approaches: Maximum Likelihood Estimation (MLE) and Bayesian estimation. While both methods have respective advantages and limitations, this study employs MLE for structured datasets due to its lower computational complexity. However, its parameter estimation accuracy on limited datasets depends on whether the sample data distribution aligns with the underlying true data distribution.

The required probabilities for constructing the Bayesian network are obtained through parameter learning.

Table 2 T Bayesian Network Probability

X_i				T		
X6	X7	X3	X1	0	1	2
0	0	0	0	0.260989	0.491758	0.247253
			1	0.336449	0.373832	0.28972
		1	0	0.246753	0.480519	0.272727
			1	0.242424	0.515152	0.242424
	1	0	0	0.32	0.493333	0.186667
			1	0.257576	0.5	0.242424
		1	0	0.211538	0.557692	0.230769
			1	0.21875	0.46875	0.3125
1	0	0	0	0.198198	0.459459	0.342342
			1	0.211765	0.505882	0.282353
		1	0	0.150943	0.54717	0.301887
			1	0.212766	0.638298	0.148936
	1	0	0	0.3125	0.40625	0.28125
			1	0.265625	0.59375	0.140625
		1	0	0.229167	0.583333	0.1875
			1	0.176471	0.676471	0.147059

The prior probability tables of variables and conditional probability tables between independent-target variables are shown in Table 2. Table 2 reveals the parameters (i.e., probabilities) of node T in the network structure. Node T is connected to four variables (X1, X3, X6, X7), with probabilities ≥0.5 predominantly occurring in the T=1 column, indicating higher likelihoods of high-risk states (T2).

Observational analysis demonstrates limited impacts of single risk events on T. When T=0 (low-risk), the highest probabilities occur under:

P(T=0|X6=0,X7=0,X3=0,X1=1)=33.64%
P(T=0|X6=0,X7=1,X3=0,X1=0)=32.00%

These results suggest low-risk states are predominantly associated with inventory management (X1) or product identification (X7).

For T=1 (medium-risk), probabilities ≥0.5 emerge when any of the following conditions are met:
①X6=0,X7=0,X3=1,X1=1 ; ②X6=0,X7=1,X3=0,X1=1 ; ③X6=0,X7=1,X3=1,X1=0 ;
④X6=1,X7=0,X3=0,X1=1 ; ⑤X6=1,X7=0,X3=1,X1=0 ; ⑥X6=1,X7=0,X3=1,X1=1 ;
⑦X6=1,X7=1,X3=0,X1=1 ; ⑧X6=1,X7=1,X3=1,X1=0 ; ⑨X6=1,X7=1,X3=1,X1=1

For T=2 (high-risk), probabilities exceed 30% under:
①X6=0,X7=1,X3=1,X1=1 ;
②X6=1,X7=0,X3=0,X1=0 ;
③X6=1,X7=1,X3=1,X1=0

This highlights unmanned retail's critical dependency on network stability (X6), where network failures invariably elevate supply chain risks. Procurement management (X3) and sensor reliability (X7) also exert significant influences.

Prioritization analysis based on prior probabilities identifies X3 (procurement management) as the primary mitigation priority due to its inherent risk severity, followed by X6 (network failures), X7 (sensor reliability), and X1 (inventory management).

4.4.2 Conditional Probability Results

The above analysis confirms the direct impacts of X1 (inventory management), X3 (procurement management), X6 (network failures), and X7 (sensor reliability) on T. The conditional probability distributions for Xj (j=1,2,3,…,9) are detailed in the subsequent Table 3.

Table 3 P(T=Ti|X=Xj)(i=0,1,2; J=1,2,3,…,9) Probability Distribution

Conditional Probability	Is there a risk (0= no risk; 1= have risk)	T		
		0	1	2
P(T=Ti|X=X1)	0	0.2488	0.4929	0.2583
	1	0.2535	0.5110	0.2355
P(T=Ti|X=X2)	0	0.2485	0.4896	0.2619
	1	0.2538	0.5153	0.2309
P(T=Ti|X=X3)	0	0.2660	0.4776	0.2564
	1	0.2152	0.5501	0.2347
P(T=Ti|X=X4)	0	0.2500	0.4976	0.2524
	1	0.2514	0.5029	0.2457
P(T=Ti|X=X5)	0	0.2640	0.4871	0.2488
	1	0.2270	0.5215	0.2515
P(T=Ti|X=X6)	0	0.2682	0.4815	0.2503
	1	0.2213	0.5296	0.2490
P(T=Ti|X=X7)	0	0.2462	0.4868	0.2670
	1	0.2598	0.5264	0.2138
P(T=Ti|X=X8)	0	0.2599	0.4950	0.2450
	1	0.2365	0.5065	0.2570
P(T=Ti|X=X9)	0	0.2533	0.4898	0.2569
	1	0.2461	0.5156	0.2383

The following histogram can be obtained.

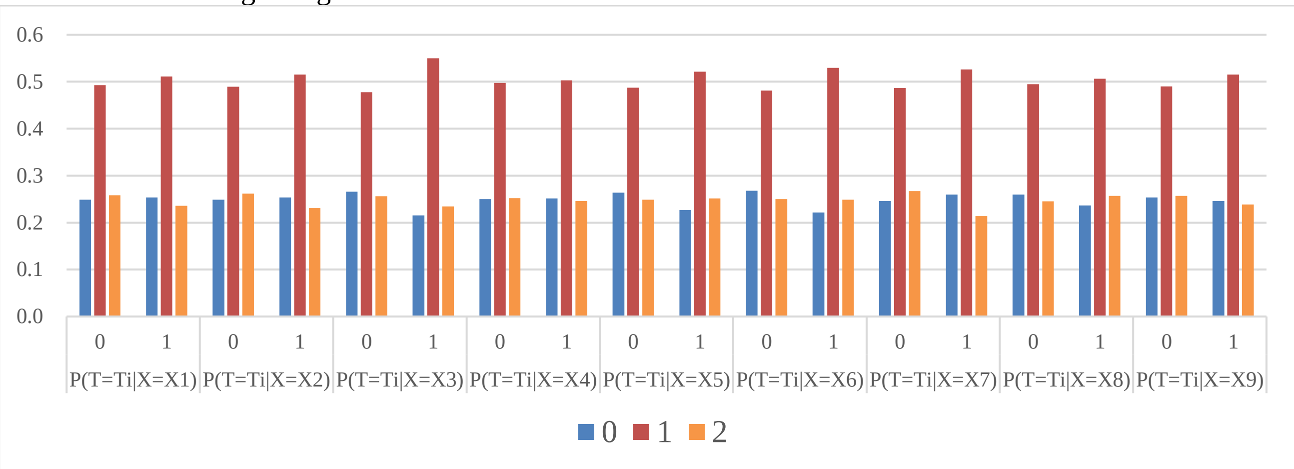

Figure 3 P(T=Ti|X=Xj) Probability Distribution

As indicated in the preceding figure and table, the top three events associated with low-risk supply chain (T=0) are:

P(T=0 | X6=0) = 0.2682, indicating a 26.82% probability of low-risk occurrence when network failures (X6) are absent.

P(T=0 | X3=0) = 0.2660, reflecting a 26.60% probability of low-risk status when procurement management (X3) remains stable.

P(T=0 | X5=0) = 0.2640, demonstrating a 26.40% probability of low-risk conditions without hardware/software failures (X5).

For high-risk supply chain (T=2), the predominant contributors are:

P(T=2 | X7=0) = 0.2670, showing a 26.70% high-risk likelihood when sensor reliability (X7) is compromised.

P(T=2 | X2=0) = 0.2619, revealing a 26.19% high-risk probability under supplier delivery delays (X2).

P(T=2 | X1=0) = 0.2583, suggesting a 25.83% high-risk chance with inventory management (X1) inefficiencies.

Regarding medium-risk supply chain (T=1), the critical factors include:

P(T=1 | X3=1) = 0.5501, denoting a 55.01% medium-risk probability when procurement management (X3) is suboptimal.

P(T=1 | X6=1) = 0.5296, corresponding to a 52.96% medium-risk likelihood during network failures (X6).

P(T=1 | X7=1) = 0.5264, indicating a 52.64% medium-risk occurrence when sensor reliability (X7) deteriorates.

Conditional probability analysis reveals the key driving mechanisms and dynamic transmission pathways of risk hierarchies in startup unmanned retail supply chains. The results indicate that X3 (procurement management), X6 (network failures), and X7 (sensor reliability) are core variables influencing supply chain risk (T), with effect magnitudes exhibiting significant heterogeneity across risk levels.

In low-risk scenarios (T=0), mitigating X6 (network failures) emerges as the highest priority (P(T=0 | X6=0) = 26.82%), followed by X3 (procurement management) and X5 (hardware/software failures). This suggests that technical infrastructure stability (e.g., network reliability) constitutes the foundational safeguard for maintaining low-risk operations under normal conditions.

For medium/high-risk scenarios (T=1/T=2), the risk-triggering effects of X3, X6, and X7 intensify substantially:

X3 (procurement management) failure elevates medium-risk probability to 55.01% (P(T=1 | X3=1) = 55.01%)

X7 (sensor reliability) degradation drives high-risk probability to 26.70% (P(T=2 | X7=0) = 26.70%), highlighting the catastrophic amplification effects of technical component failures.

The dual-threat nature of X6 (network failures) is particularly notable. It functions both as:

A critical defensive node for low-risk maintenance (P(T=0 | X6=0) = 26.82%)

A core risk accelerator for medium/high-risk escalation (P(T=1 | X6=1) = 52.96%)

This duality positions network stability as both a safety foundation and a risk lever.

X3 (procurement management) demonstrates a butterfly effect through its upstream dominance over medium-risk propagation. Suboptimal supplier selection or contractual vulnerabilities progressively amplify downstream technical risks (e.g., sensor data inaccuracies) and operational risks (e.g., inventory mismatches).

Although X7 (sensor reliability) exhibits limited direct impacts on low-risk states, its latent single-point failure potential demands heightened vigilance. Sensor failures trigger abrupt high-risk transitions (P(T=2 | X7=0) = 26.70%) and synergize with X6 (network failures) to exacerbate systemic collapse risks (e.g., data synchronization failures during network outages).

4.4.3 Posterior Probability Results and Analysis

After completing parameter learning in the Bayesian network, posterior probabilities can be computed. This study primarily investigates influencing factors of supply chain risks. By conditioning on variable T (with three discrete states), we calculate posterior probabilities under different risk levels as follows:

Table 4 P(X|T=0) Posterior Probability

	X1	X2	X3	X4	X5	X6	X7	X8	X9
0	0.61745	0.615349	0.728272	0.614157	0.643502	0.66807	0.654712	0.59578	0.618637
1	0.38255	0.384651	0.271728	0.385843	0.356498	0.33193	0.345288	0.40422	0.381363

As evidenced by the Table 4, when low-risk supply chain states (T=0) occur, the highest posterior probability is associated with X8 (P(X8=1 | T=0) = 40.42%), followed by X4 (P(X4=1 | T=0) = 35.58%), and subsequently X2 (P(X2=1 | T=0) = 38.47%).

Table 5 P(X|T=1) Posterior Probability

	X1	X2	X3	X4	X5	X6	X7	X8	X9
0	0.623867	0.607291	0.651551	0.607007	0.630774	0.605075	0.659178	0.582296	0.618135
1	0.376133	0.392709	0.348449	0.392993	0.369226	0.394925	0.340822	0.417704	0.381865

As evidenced by Table 5, when medium-risk supply chain states (T=1) occur, the node with the highest posterior probability is X8 (P(X8=1 | T=1) = 41.77%), followed by X6 (P(X6=1 | T=1) = 39.49%), and thirdly X4 (P(X4=1 | T=1) = 39.30%).

Table 6 P(X|T=2) Posterior Probability

	X1	X2	X3	X4	X5	X6	X7	X8	X9
0	0.644572	0.611456	0.699205	0.610279	0.640226	0.615451	0.719306	0.593215	0.622324
1	0.355428	0.388544	0.300795	0.389721	0.359774	0.384549	0.280694	0.406785	0.377676

As shown in Table 6, when high-risk supply chain states (T=2) occur, the node with the highest posterior probability is X8 (P(X8=1 | T=2) = 40.68%), followed by X4 (P(X4=1 | T=2) = 38.97%), and thirdly X2 (P(X2=1 | T=2) = 38.85%).

Integrated analysis of the Bayesian network structure and the aforementioned tables reveals that X8 (payment system stability) exerts the most substantial influence on T (supply chain risk), consistently exhibiting the highest probabilities across all risk levels. The network topology indicates that X8 is directly influenced by X6 (network failures), X5 (hardware/software failures), and X9 (customer behavior), with X6 further dependent on X5, and X9 affected both directly and indirectly by X4 (shelf replenishment timeliness) and X2 (supplier delivery punctuality). Consequently, the posterior probability distribution of X8 is quantified as follows:

Table 7 P(X|X8=1) Posterior Probability

	X2	X4	X5	X6	X9
0	0.609497	0.605402	0.534551	0.490872	0.544846
1	0.390503	0.394598	0.465449	0.509128	0.455154

As shown in Table 7, X6 (network failures) demonstrates the strongest causal impact on X8 occurrence, followed by X5 and X9. Notably, beyond X8:

Under T=0 (low-risk), X1 (inventory management), X2, X4, and X9 exhibit relatively higher influence magnitudes (≥50%)

For T=1 (medium-risk) and T=2 (high-risk), X2, X4, X6, and X9 dominate the risk propagation (≥50%)

Posterior probability analysis underscores that X8 constitutes the most critical leverage point for unmanned retail supply chain risk mitigation, demonstrating globally superior influence across risk transmission pathways. Secondary yet non-negligible nodes include X4, X2, and X9, which require integration into systemic risk governance frameworks. Importantly, in medium/high-risk scenarios, X6 (network failures) surpasses X9 in impact intensity and serves as a key risk amplifier by directly interacting with X8.

6. Conclusion and Discussion

6.1 Conclusion

First, the strategic leverage effect of procurement management (X3). As the origin point of supply chain operations, procurement management optimization directly governs raw material cost control, supplier relationship stability, and delivery punctuality. Its risk exposure triggers cascading failures in downstream operational processes (e.g., shelf replenishment timeliness, inventory turnover). For instance, the absence of elasticity clauses in procurement agreements may amplify the disruptive impacts of demand volatility, validating the primacy of "source governance" in startup risk management.

Second, vulnerability transmission in technology-operations coupled systems. The elevated risk weights of X6 (network failures) and X7 (sensor reliability) underscore unmanned retail's inherent vulnerability to IoT infrastructure dependencies—network outages paralyze payment systems and inventory synchronization, while sensor data inaccuracies propagate demand forecasting errors and replenishment decision failures. This reveals that technological robustness functions not merely as an isolated risk factor but as a latent catalyst amplifying operational risks. Practically, sample Enterprise S incurred catastrophic losses during its inaugural month due to a week-long network outage, prompting the adoption of dual-network redundancy with independent carriers—a case empirically validating our findings.

Third, posterior probability insights uncover two latent mechanisms:

Nonlinear transmission of technology-dependent risks: Vulnerabilities in foundational infrastructure (e.g., network stability) propagate through core operational nodes (e.g., payment systems), inducing cascading failures.

Dynamic risk prioritization: Risk mitigation priorities shift with event severity—routine management should prioritize payment system optimization and supplier collaboration, whereas crisis scenarios necessitate enhanced network redundancy and failure response protocols.

6.2 Discussion

6.2.1Theoretical Discussion

This study, through Bayesian network modeling, yields two pivotal theoretical insights:

First, it demonstrates the asymmetry of risk factors. A single variable (e.g., X6) may simultaneously function as a defensive target and a crisis accelerator across risk levels, challenging the assumption of fixed risk weights in static models. This finding aligns with Risk Coupling Theory (Haimes, 1998) and empirically validates inventory tracking and consumer behavior as critical challenges in autonomous retail systems (Rukundo et al., 2025).

Second, it reveals technology-operation interaction effects. Failures in IoT components (X6, X7) indirectly induce operational decision biases (e.g., inventory mismatches) via dataflow disruptions, confirming that unmanned retail's core competency lies in seamless IoT-algorithm integration (e.g., RFID, computer vision) (Wang & Zheng, 2023). This provides novel evidence for technology-embedded risks(Markus & Tanis, 2000)。

6.2.2 Practical Implications

First, startups should establish graded risk response mechanisms, prioritizing payment system stability (X8) and supplier delivery efficiency (X2) during routine operations. Concurrently, digital twin technology can simulate the interactive effects of network failures (X6) and consumer behavior shifts (X9), enabling dynamic inventory adjustments and emergency resource allocation.

Second, the core distinction of startup supply chain risks lies in the tripartite coupling of resource constraints, technological dependencies, and environmental uncertainties. Risk mitigation should prioritize event nodes with the highest causal weights, implementing targeted interventions to systematically reduce cross-process risks and enhance resolution efficiency.

Third, policymakers must accelerate inclusive infrastructure development (e.g., 5G networks, edge computing nodes) to mitigate asymmetric risks borne by startups due to technology spillover effects.

6.2.3 Limitations and Future Directions

Model limitations: The current Bayesian network relies on static conditional probabilities, failing to capture the long-term impacts of technological iterations (e.g., hardware upgrades in X7) on risk hierarchies. Future research should integrate dynamic Bayesian networks (DBN) with real-time data streams for minute-level risk prediction.

Sample coverage bias: The exclusive focus on startups limits insights into maturity-stage risk evolution patterns. Subsequent studies should incorporate mature enterprise data to explore risk dynamics and investigate emerging challenges like AI ethics (e.g., algorithmic biases) in technology-driven supply chains, thereby enriching theoretical toolkits.

References:

Adam, M. S., & Dandutse, T. (2023). Improving supply chain performance of a start-up company: A case study of avakino limited. *International Journal of Supply Chain Management, 12*(3), 45–60.

Adapa, S., Fazal-e-Hasan, S. M., Makam, S. B., Azeem, M. M., & Mortimer, G. (2020). Examining the antecedents and consequences of perceived shopping value through smart retail technology. *Journal of Retailing and Consumer Services, 52*, 101901. http://doi.org/10.1016/j.jretconser.2019.101901

Ayyildiz, E., & Taskin Gumus, A. (2021). Pythagorean fuzzy AHP based risk assessment methodology for hazardous material transportation: An application in Istanbul. *Environmental Science and Pollution Research, 28*(27), 35798–35810. https://doi.org/10.1007/s11356-021-13223-y

Bozanic, D., Tešić, D., Komazec, N., Marinković, D., & Puška, A. (2023). Interval fuzzy AHP method in risk assessment. *Reports in Mechanical Engineering, 4*(1), 131–140.

Cao, J. R. (2017). Research on food supply chain risk based on Bayesian network. *Modern Food, 18*, 52–55. https://doi.org/10.16736/j.cnki.cn41-1434/ts.2017.18.016

Denuwara, N., Maijala, J., & Hakovirta, M. (2021). The impact of unmanned stores' business models on sustainability. *SN Business & Economics, 1*(10), 143. https://doi.org/10.1007/s43546-021-00136-8

Gurtu, A., & Johny, J. (2021). Supply chain risk management: Literature review. *Risks, 9*(1), 16.

Haimes, Y. Y. (1998). *Risk Modeling, Assessment, And Management*. Wiley.

Hänninen, M., Valdez Banda, O. A., & Kujala, P. (2014). Bayesian network model of maritime safety management. *Expert Systems with Applications, 41*(17), 7837–7846. https://doi.org/10.1016/j.eswa.2014.06.029

Heins, C., & Scheler, S. (2024). Customer acceptance of unmanned stores with a focus on grocery retail. International *Journal of Services Technology and Management, 29*(1), 18–38.

Hosseini, S., & Ivanov, D. (2022). A multi-layer Bayesian network method for supply chain disruption modelling in the wake of the COVID-19 pandemic. *International Journal of Production Research, 60*(17), 5258–5276. https://doi.org/10.1080/00207543.2021.1953180

Jäger, W. S., Christie, E. K., Hanea, A. M., den Heijer, C., & Spencer, T. (2018). A Bayesian network approach for coastal risk analysis and decision making. *Coastal Engineering, 134*, 48-61.

Kaur, M., Sandhu, M., Mohan, N., & Sandhu, P. S. (2011). RFID technology principles, advantages, limitations & its applications. *International Journal of Computer and Electrical Engineering, 3*(1), 151.

Kilic, H. S., Canbakis, S. K., Karabas, M., Koseoglu, S., Unal, E., & Kalender, Z. T. (2023). Integrated Supply Chain Risk Assessment Methodology Based on Modified FMEA. *Journal of Risk Analysis and Crisis Response, 13*(2). https://www.jracr.com/index.php/jracr/article/view/359

Liu, L., Cui, J., Huan, Y., Zou, Z., Hu, X., & Zheng, L. (2022). A Design of Smart Unmanned Vending Machine for New Retail Based on Binocular Camera and Machine Vision. *IEEE Consumer Electronics Magazine*, *11*(4), 21–31.

Liu, L., Zhou, B., Zou, Z., Yeh, S.-C., & Zheng, L. (2018). A smart unstaffed retail shop based on artificial intelligence and IoT. 2018 *IEEE 23rd International Workshop on Computer Aided Modeling and Design of Communication Links and Networks* (CAMAD), 1–4. https://ieeexplore.ieee.org/abstract/document/8514988/

Magliocca, P., Herold, D. M. M., Canestrino, R., Temperini, V., & Albino, V. (2023). The role of start-ups as knowledge brokers: A supply chain ecosystem perspective. *Journal of Knowledge Management*, *27*(10), 2625–2641.

Marcot, B. G., & Penman, T. D. (2019). Advances in Bayesian network modelling: Integration of modelling technologies. *Environmental Modelling & Software*, *111*, 386–393. https://doi.org/10.1016/j.envsoft.2018.09.016

Markus, M. L., & Tanis, C. (2000). *The Enterprise System Experience: From Adoption to Success*. Pinnaflex Educational Resources, Inc.

Nambiar, A. N. (2009, 2009-1-1). RFID technology: A review of its applications. Paper presented at the.

Parasuraman, A. (2000). Technology Readiness Index (Tri): A Multiple-Item Scale to Measure Readiness to Embrace New Technologies, 2(3), 307-320.

Park, J., & Kang, W. (2021). A Study on the Transition Strategy of Military Service in Korea Using PEST-SWOT-FUZZY-AHP. *신산업경영저널*, *39*(1), 3–30.

Ramezanifar, E., Gholamizadeh, K., Mohammadfam, I., & Mirzaei Aliabadi, M. (2023). Risk assessment of methanol storage tank fire accident using hybrid FTA-SPA. *PLoS One*, *18*(3), e0282657.

Rukundo, S., Wang, D., Wongnonthawitthaya, F., Sidibé, Y., Kim, M., Su, E., & Zhang, J. (2025). *A Survey of Challenges and Sensing Technologies in Autonomous Retail Systems* (No. arXiv:2503.07997). arXiv.

Safari, A., Balicevac Al Ismail, V., Parast, M., Gölgeci, I., & Pokharel, S. (2024). Supply chain risk and resilience in startups, SMEs, and large enterprises: A systematic review and directions for research. *The International Journal of Logistics Management*, *35*(2), 680–709. https://doi.org/10.1108/IJLM-10-2022-0422

Shen, K. (2024). *The Impact of Intelligent Unmanned Stores in the Context of New Retail: A Case Study of JD Intelligent Unmanned Store* [Master's Thesis, ISCTE-Instituto Universitario de Lisboa (Portugal)]. https://search.proquest.

Stephenson, T. A. (2000). *An introduction to Bayesian network theory and usage*. Idiap.

Szabó-Szentgróti, E., Konczos-Szombathelyi, M., Rámháp, S., & Kézai, P. K. (2023). How Consumers Accept Unmanned Smart Stores?–Introducing a Proposed Technology Acceptance Model. *Chemical Engineering Transactions*, *107*, 373–378.

Tirkolaee, E. B., Sadeghi, S., Mooseloo, F. M., Vandchali, H. R., & Aeini, S. (2021). Application of Machine Learning in Supply Chain Management: A Comprehensive Overview of the Main Areas. *Mathematical Problems in Engineering*, *2021*, 1–14. https://doi.org/10.1155/2021/1476043

Wagner, S. M. (2021). Startups in the supply chain ecosystem: An organizing framework and research opportunities. *International Journal of Physical Distribution & Logistics Management*, *51*(10), 1130–1157. https://doi.org/10.1108/IJPDLM-02-2021-0055

Wang, I.-C., Liao, C.-W., Lin, K.-P., Wang, C.-H., & Tsai, C.-L. (2021). Evaluate the Consumer Acceptance of AIoT-Based Unmanned Convenience Stores Based on Perceived Risks and Technological Acceptance Models. *Mathematical Problems in Engineering*, *2021*, 1–12.

Wang, Q., & Zheng, N. (2023). Research on Artificial Intelligence Technology Empowering New Retail: A Case Study of Unmanned Retail. *Proceedings of the 2nd International Academic Conference on Blockchain, Information Technology and Smart Finance* (ICBIS 2023), 1135–1145. https://www.atlantis-press.com/ proceedings/icbis-23/125989707

Want, R. (2006). An introduction to RFID technology. *IEEE Pervasive Computing*, *5*(1), 25-33.

Weber, P., Medina-Oliva, G., Simon, C., & Iung, B. (2012). Overview on Bayesian networks applications for dependability, risk analysis and maintenance areas. *Engineering Applications of Artificial Intelligence*, *25*(4), 671-682.

Wang, W. J., & Liu, Y. H. (2015). Study on retail supply chain coordination with Bayesian combination forecasting modeling. *Journal of Donghua University* (Natural Science Edition), *41*(1), 109–112.

Wu, T. K., Wang, B., Gu, J. F., & Zhou, X. H.. (2014). Fuzzy comprehensive evaluation of supply chain risks based on Bayesian networks. *Economic Mathematics*, *2*, 69–75. https://doi.org/10.3969/j.issn.1007-1660.2014.02.014

Yang, J. J. (2019). Analysis on the development trend of unmanned supermarkets in the new retail era. *Modern Marketing* (Fortune Information Edition), *6*, 60.

Zhang, B. (2019). Research on the supply chain management model of unmanned retail convenience stores: A case study of "Bianlifeng". *Hebei Enterprise*, *5*, 29–30.

Zhang, H., Li, D., Ji, Y., Zhou, H., Wu, W., & Liu, K. (2019). Toward new retail: A benchmark dataset for smart unmanned vending machines. *IEEE Transactions on Industrial Informatics*, *16*(12), 7722–7731.

Zhang, L., Wu, X., Skibniewski, M. J., Zhong, J., & Lu, Y. (2014). Bayesian-network-based safety risk analysis in construction projects. *Reliability Engineering & System Safety*, *131*, 29–39.

Zhang, X. Z. (2017). Research on demand forecasting in supply chain uncertainty: A model based on Bayesian network. *Science and Technology Innovation and Productivity*, *2*, 50–52.