Margin Leakage Detection Through Cross-System Analytics: A Framework for Finance and Operations Alignment

Rahul Kumar Thatikonda
University of Connecticut
ORCID: 0009-0000-1234-7915

Sucharitha Donepudi
Point Park University
ORCID: 0009-0007-2012-3904

***Abstract*—Margin leakage frequently emerges before it is visible in financial statements. Supplier cost increases may appear in procurement systems, expedited freight in transportation systems, price-cost mismatches in sales and billing systems, discount leakage in quoting tools, production disruption in manufacturing systems, and inventory write-down risk in warehouse or planning systems. Finance often observes the margin effect after intervention windows have narrowed. This paper proposes a Margin Signal Governance Framework for detecting and routing margin leakage signals across fragmented enterprise systems. The framework consists of six stages: margin signal identification, cross-system margin pathway mapping, leakage classification, margin exposure translation, finance–operations ownership routing, and intervention outcome measurement. The proposed architecture preserves legacy systems of record while adding a governed analytics control layer for Physical Data Element (PDE) mapping, signal extraction, leakage taxonomy management, financial-exposure scoring, decision-rule orchestration, workflow activation, and traceable action closure. A discrete-event simulation was conducted over 180 operating days using 13 enterprise systems, 1.8 million sales-order lines, 420,000 purchase-order lines, 310,000 logistics events, 95,000 pricing records, and 38,000 manual adjustments. Results show that the proposed framework reduced median margin intervention latency from 55.4 h to 12.6 h relative to spreadsheet margin-bridge reconciliation, reduced P95 latency from 148.7 h to 41.8 h, improved leakage-detection precision from 62.8% to 86.9%, increased preventable leakage containment from 33.6% to 76.4%, and produced USD 7.42 million in annualized net economic value. The findings position margin leakage as a cross-system finance-control problem requiring governed interoperability between finance, pricing, procurement, logistics, operations, and commercial functions.**

***Index Terms*—margin leakage, profitability analytics, finance analytics, cross-system analytics, enterprise systems, pricing governance, decision support**

I. Introduction

Enterprises frequently lose margin before finance can formally recognize the loss. Procurement may observe a supplier cost increase. Logistics may pay expedited freight. Sales may approve non-standard discounts. Billing may issue an invoice with price or quantity discrepancies. Operations may consume excess labor or substitute materials. Inventory teams may flag aging or write-down risk. Customer-service teams may receive deductions or dispute claims. Each signal is locally visible, but the combined gross-margin effect is often discovered later through monthly close, variance analysis, profitability reports, or manual margin bridges.

This paper defines *margin leakage* as preventable or partially preventable erosion between expected contribution margin and realized contribution margin caused by cross-functional execution gaps, data defects, cost shocks, pricing exceptions, discounts, logistics premiums, disputes, manual adjustments, or delayed intervention. The issue is not only analytical. It is architectural. Leakage signals are distributed across ERP, procurement, pricing, logistics, inventory, manufacturing, customer-service, finance, and reporting systems. Without governed cross-system analytics, finance observes symptoms after operational teams have already made decisions that embed margin loss.

The proposed contribution is a *Margin Signal Governance Framework* that detects leakage signals, translates them into financial exposure, assigns cross-functional ownership, and activates finance-led intervention workflows. The framework is designed for legacy enterprise environments where replacing operational systems is not immediately feasible. It preserves systems of record while adding a control layer for PDE mapping, signal detection, margin exposure scoring, rule orchestration, workflow routing, and outcome measurement.

The research question is:

> How can cross-system analytics detect and route margin leakage signals before they become embedded financial losses?

Pricing and revenue-management research has long shown that pricing decisions, discount structures, and inventory constraints affect profitability [12]–[17]. Management accounting research also demonstrates the importance of cost visibility, activity-based costing, cost stickiness, and profitability analysis in managerial control [19]–[21]. Enterprise systems and process literature show that ERP and business-process integration affect reporting quality, process execution, and managerial decision making [10], [11], [22]–[24]. Data governance research further establishes that trusted analytics requires decision rights, data ownership, lineage, and quality controls [8], [9]. Industry reports before February 2024 also emphasized pricing analytics, revenue leakage control, AI adoption, automation, and governed enterprise technology as priorities for finance and operations transformation [35]–[40].

However, existing research does not fully formalize margin leakage as a governed cross-system signal-to-action problem.

This paper makes five contributions:

- It defines margin intervention latency as a measurable KPI for finance and operations alignment.
- It proposes a six-stage Margin Signal Governance Framework for fragmented enterprise systems.
- It formalizes margin leakage detection through cross-system PDE mapping, leakage classification, exposure translation, and workflow routing.
- It specifies a reference architecture that preserves systems of record while enabling margin-aware decision support.
- It evaluates the framework using a simulation against five baseline enterprise analytics architectures.

II. Related Work

A. Pricing, Revenue Management, and Discount Discipline

Revenue-management and pricing research provides the analytical foundation for margin control. Gallego and van Ryzin formalized dynamic pricing of inventories with stochastic demand, establishing a core model for price and capacity decisions [12]. Talluri and van Ryzin extended the operational theory of revenue management across industries and capacity-constrained settings [13]. Ferreira et al. demonstrated the practical use of analytics for demand forecasting and price optimization in online retail, linking data-driven pricing with operational implementation [14]. Dynamic pricing and negotiation-agent research further connects pricing decisions with computational decision systems and management accounting [18].

Margin leakage is broader than price optimization. A firm can set an optimal target price and still lose margin through discounts, rebates, off-invoice allowances, unplanned freight, manual credits, fulfillment substitutions, incorrect cost-to-serve assumptions, and billing defects. Strategic pricing research emphasizes that pricing capability is organizational, not merely algorithmic [15]–[17]. McKinsey's pricing analytics material similarly frames pricing improvement as a capability combining analytics, commercial discipline, and execution routines [35]. KPMG's revenue leakage material emphasizes data, analytics, accounting, governance, and control processes for identifying leakage in commercial programs [36].

B. Management Accounting and Margin Control

Management accounting research provides the control logic for detecting margin erosion. Activity-based costing and profitability analysis show that product, customer, channel, and service-level profitability require granular cost attribution [19], [20]. Cost-stickiness research shows that costs do not always adjust symmetrically with activity changes, creating margin risk under demand volatility [21]. Gross-margin analysis and contribution-margin control therefore require more than accounting-period variance reporting. They require timely visibility into the operational drivers of realized net price and realized cost.

Traditional margin bridges explain differences between planned and actual profitability after the fact. The proposed framework shifts the timing: it treats operational signals as early indicators of leakage and converts them into governed intervention cases before the loss becomes embedded.

C. Enterprise Systems and Cross-System Fragmentation

ERP systems can improve transaction integration and financial reporting, but realized benefits depend on process design, organizational adoption, and data quality [22]–[25]. Fragmented ERP environments remain common because of mergers, regional deployments, legacy retention, business-unit autonomy, specialized pricing tools, transportation systems, procurement platforms, and local reporting layers. In such environments, margin leakage cannot be detected reliably from finance data alone. It must be reconstructed from order, price, cost, freight, inventory, production, billing, deduction, and adjustment data.

Analytics lifecycle methods such as CRISP-DM structure the development of analytical artifacts but do not directly specify how cross-system margin signals should be governed, routed, and resolved [4], [5]. Business-process management and process mining support bottleneck identification, conformance analysis, and predictive monitoring, but finance intervention requires additional margin-exposure logic and ownership routing [10], [11], [26].

D. Data Governance and Decision Support

Data governance defines decision rights, accountabilities, data quality, policies, and stewardship responsibilities [8], [9]. Margin leakage analytics requires strong governance because local PDE definitions differ across functions. A price in quoting may differ from a net invoice price. Standard cost may differ from actual cost. Freight estimate may differ from freight invoice. Discount code may not capture off-invoice concessions. Customer hierarchy may differ between sales and finance. Without governed PDE, cross-system margin analytics can amplify inconsistency rather than reduce leakage.

Recent data-strategy and supply-chain analytics research emphasizes integration, data quality, predictive analytics, real-time risk detection, and digital transformation as prerequisites for operational decision support [30]–[34]. Process-quality analytics using explainable artificial intelligence also shows that high-dimensional operational data can be converted into actionable improvement signals when interpretability and process context are designed into the decision model [27]. These findings motivate the proposed governed cross-system architecture.

E. Design-Science Positioning

This study follows design-science research. The artifact is a framework and reference architecture for detecting and routing margin leakage signals. The problem context is cross-functional margin erosion in fragmented enterprise systems. The evaluation uses simulation-based assessment against baseline architectures [1]–[3].

III. Proposed Methodology

A. Framework Overview

The Margin Signal Governance Framework, abbreviated MSGF, consists of six stages. It is designed to detect margin leakage before financial close, classify the root cause, route the issue to accountable owners, and measure intervention value.

TABLE I
MARGIN SIGNAL GOVERNANCE FRAMEWORK

Stage	Design Question	Primary Output
Margin signal identification	Which event can erode realized margin?	Signal taxonomy and materiality threshold
Cross-system margin pathway mapping	Where does the leakage signal appear across systems?	PDE lineage, source authority, and margin pathway map
Leakage classification	What type of leakage is occurring?	Leakage class and root-cause category
Margin exposure translation	What is the estimated financial exposure?	Leakage estimate, probability, and intervention value
Finance–operations ownership routing	Who must act and approve?	RACI model, escalation path, and intervention owner
Outcome measurement	What margin was protected or recovered?	Leakage contained, cycle time reduced, and action effectiveness

B. Leakage Taxonomy

The proposed taxonomy is shown in Table II. It covers common cross-functional sources of margin erosion.

TABLE II
MARGIN LEAKAGE TAXONOMY

Leakage Class	Example Signal	Primary Owner
Supplier cost shock	Purchase price variance exceeds approved tolerance	Procurement and finance
Expedited freight	Premium freight used to protect service level	Logistics and operations finance
Price-cost mismatch	Sales price not updated after cost increase	Pricing, sales operations, finance
Discount leakage	Non-standard discount or rebate exceeds policy	Sales, pricing, commercial finance
Delayed billing	Shipment complete but invoice not issued	Billing and order management
Inventory write-down risk	Aging or obsolete stock exceeds threshold	Supply chain and finance
Customer profitability deterioration	Customer cost-to-serve exceeds margin threshold	Sales, service, finance
Manual adjustment pattern	Credits, claims, or journal adjustments repeat unusually	Controllership and commercial finance
Production disruption cost	Rework, scrap, substitution, or yield loss exceeds tolerance	Operations and plant finance

C. Reference Architecture

The architecture overlays existing enterprise systems rather than replacing them. Its purpose is to create governed visibility from operational signal to margin intervention.

TABLE III
REFERENCE ARCHITECTURE FOR MARGIN LEAKAGE ANALYTICS

Layer	Component	Function
System-of-record layer	ERP, pricing, procurement, logistics, manufacturing, inventory, billing, customer-service, finance systems	Preserve authoritative operational and financial transactions
Connectivity layer	API, EDI, batch ingestion, CDC, event streams	Extract decision-critical PDE
PDE governance layer	PDE catalog, lineage registry, quality rules, stewardship model	Validate source authority, semantics, freshness, and completeness
Signal layer	Cost-shock, freight, discount, price-cost, billing, inventory, adjustment detectors	Detect margin-relevant events
Leakage classification layer	Root-cause classifier and leakage taxonomy	Classify leakage source and remediation category
Exposure layer	Margin bridge, cost-to-serve estimator, leakage probability model	Translate signal into margin exposure
Decision-rule layer	Policy store, threshold registry, approval rules, escalation matrix	Convert leakage signal into intervention logic
Workflow layer	Case manager, SLA monitor, approval router, remediation queue	Activate finance–operations action
Measurement layer	Outcome ledger, protected-margin tracker, action log	Measure leakage contained and cycle time reduced
Learning layer	Threshold tuning, rule refinement, semantic-drift monitoring	Improve detection and routing performance

D. Mathematical Formulation

1) Margin Event Model: Let $E = \{e_1, e_2, \dots, e_n\}$ denote events that may affect realized margin. Each event is represented as

$$e_i = \langle r_i, t_i, c_i, b_i, x_i, \ell_i \rangle, \tag{1}$$

where r_i is the source system, t_i is event time, c_i is signal class, b_i is business entity, x_i is the PDE vector, and ℓ_i is the leakage domain: price, discount, cost, freight, inventory, billing, dispute, production, or adjustment.

A signal detector computes

$$\sigma_i = f(x_i, h_i, c_i; \Theta), \tag{2}$$

where h_i is historical context and Θ denotes model or rule parameters. A signal becomes margin-actionable when

$$A_i = \begin{cases} 1, & \sigma_i \geq \theta_c \wedge q(x_i) \geq q_{\min} \wedge ME_i \geq \mu, \\ 0, & \text{otherwise}, \end{cases} \tag{3}$$

where $q(x_i)$ is PDE quality, ME_i is estimated margin exposure, and μ is materiality threshold.

2) Margin Bridge and Leakage Exposure: Expected contribution margin for transaction i is

$$M_i^{exp} = P_i^{target} - D_i^{auth} - C_i^{std} - F_i^{plan} - S_i^{plan}, \tag{4}$$

where P_i^{target} is target price, D_i^{auth} is authorized discount, C_i^{std} is standard cost, F_i^{plan} is planned freight, and S_i^{plan} is planned service cost.

Realized contribution margin is

$$M_i^{real} = P_i^{net} - D_i^{unplan} - C_i^{act} - F_i^{act} - S_i^{act} - Adj_i - Claim_i, \tag{5}$$

where P_i^{net} is realized net price, D_i^{unplan} is unauthorized or unplanned discount, C_i^{act} is actual cost, F_i^{act} is actual freight, S_i^{act} is actual service cost, Adj_i is manual adjustment, and $Claim_i$ is claim or deduction cost.

Margin leakage is

$$ML_i = \max(0, M_i^{exp} - M_i^{real}) \cdot V_i, \tag{6}$$

where V_i is transaction volume.

Leakage can be decomposed as

$$ML_i = PL_i + DL_i + CL_i + FL_i + IL_i + BL_i + AL_i + \epsilon_i, \tag{7}$$

where PL_i is price leakage, DL_i is discount leakage, CL_i is cost leakage, FL_i is freight leakage, IL_i is inventory leakage, BL_i is billing leakage, AL_i is adjustment leakage, and ϵ_i is unexplained residual.

3) Margin Intervention Latency: Margin intervention latency is defined as

$$MIL_i = t_i^a - t_i^s, \tag{8}$$

where t_i^s is the timestamp of actionable leakage-signal activation and t_i^a is verified intervention or closure.

Latency is decomposed as

$$MIL_i = L_i^{detect} + L_i^{map} + L_i^{class} + L_i^{exposure} + L_i^{owner} + L_i^{workflow} + L_i^{measure}. \tag{9}$$

The objective is

$$\max_{\pi,\theta,o,w} \sum_{i=1}^{N} \big[PV_i(A_i) - \lambda_1 MIL_i - \lambda_2 FC_i - \lambda_3 WC_i - \lambda_4 RR_i\big], \tag{10}$$

subject to

$$q(x_i) \geq q_{\min}, \quad \forall i : A_i = 1, \tag{11}$$

$$Trace_i = 1, \quad \forall i : A_i = 1, \tag{12}$$

$$Cap_g(t) \leq \overline{Cap}_g, \quad \forall g, t, \tag{13}$$

$$P(\text{missed material leakage}) \leq \epsilon_m, \tag{14}$$

$$P(\text{false leakage escalation}) \leq \epsilon_f. \tag{15}$$

Here, $PV_i(A_i)$ is protected margin value, π is routing policy, θ is threshold vector, o is ownership assignment, w is workflow-priority policy, FC_i is false-classification cost, WC_i is workflow cost, and RR_i is residual risk.

4) Intervention Prioritization: Intervention priority is calculated as

$$P_i = \eta_1 ME_i + \eta_2 p_i^{repeat} + \eta_3 Cust_i + \eta_4 SLA_i^{-1} + \eta_5 Strategic_i - \eta_6 Unc_i, \tag{16}$$

where ME_i is estimated margin exposure, p_i^{repeat} is recurrence probability, $Cust_i$ is customer strategic importance, SLA_i is remaining intervention window, $Strategic_i$ is strategic product or account weight, and Unc_i is uncertainty penalty.

E. Algorithmic Procedure

The operational procedure is summarized in Table IV.

TABLE IV
MARGIN SIGNAL GOVERNANCE ALGORITHM

Step	Procedure
1	Register systems of record for pricing, sales, procurement, logistics, manufacturing, inventory, billing, customer-service, and finance data.
2	Define margin leakage taxonomy and materiality thresholds.
3	Identify decision-critical PDE for each leakage class.
4	Map PDE to source systems and validate lineage, ownership, freshness, and quality.
5	Detect cross-system leakage signals and compute score σ_i.
6	Estimate expected margin, realized margin, and leakage exposure ML_i.
7	Classify leakage root cause: price, discount, cost, freight, inventory, billing, dispute, production, or adjustment.
8	Resolve finance–operations owner and escalation path.
9	Prioritize intervention using exposure, recurrence probability, customer importance, SLA, and uncertainty.
10	Create workflow case with source lineage, leakage estimate, policy rule, and closure condition.
11	Monitor intervention completion and calculate MIL_i.
12	Measure outcome: margin protected, leakage recovered, recurrence reduced, and manual effort avoided.
13	Tune thresholds, root-cause rules, ownership assignments, and prioritization weights using observed outcomes.

IV. EXPERIMENTAL DESIGN

A. Simulation Environment

A discrete-event simulation represented a fragmented enterprise environment with pricing, procurement, logistics, manufacturing, inventory, billing, customer-service, and finance functions. The simulation used synthetic data and did not use proprietary enterprise records.

B. Baseline Architectures

MSGF was evaluated against five baselines:

- **B0 Spreadsheet margin bridge**: finance teams manually reconcile price, cost, freight, discount, and adjustment extracts.
- **B1 Dashboard-only margin reporting**: dashboards show gross margin, price variance, cost variance, and discount metrics but do not activate action.
- **B2 Static variance alerts**: ERP or pricing tools trigger threshold alerts without cross-system root-cause classification.
- **B3 Centralized commercial finance queue**: finance analysts triage suspected leakage before routing to pricing, sales, procurement, or operations.
- **B4 Process-mining and variance diagnosis**: process and variance tools identify bottlenecks or deviations, but intervention workflows are externally managed.
- **MSGF Proposed**: governed margin signal framework with PDE mapping, leakage classification, exposure scoring, owner routing, workflow activation, and outcome measurement.

TABLE V
SIMULATION CONFIGURATION

Parameter	Value
Simulation horizon	180 operating days
Monte Carlo replications	30
Enterprise systems	13
Sales-order lines	1,800,000
Purchase-order lines	420,000
Logistics events	310,000
Pricing records	95,000
Manual adjustments	38,000
Customer accounts	24,000
Supplier entities	1,450
Product SKUs	18,200
Leakage signal classes	9
Decision owners	67
Workflow capacity	1,260 cases/day
PDE quality threshold $q_{\min}$	0.84
Materiality threshold μ	USD 15,000
Severe-case SLA	8 h
Moderate-case SLA	24 h
Feedback tuning cycle	Weekly

C. Evaluation Metrics

The evaluation used nine metrics:

- median and P95 margin intervention latency;
- leakage-detection precision;
- leakage-detection recall;
- preventable leakage containment;
- unauthorized discount closure;
- supplier cost-shock response time;
- expedited freight leakage reduction;
- manual reconciliation effort;
- annualized net economic value.

V. RESULTS AND DISCUSSION

A. Performance Comparison

Table VI reports the simulation results. B0 denotes spreadsheet margin-bridge reconciliation, B1 dashboard-only margin reporting, B2 static variance alerts, B3 centralized commercial finance queueing, and B4 process-mining and variance diagnosis.

Relative to spreadsheet margin-bridge reconciliation, MSGF reduced median intervention latency by 77.3% and P95 latency by 71.9%. Relative to dashboard-only margin reporting, it reduced median intervention latency by 67.0%. Relative to static variance alerts, it reduced median intervention latency by 57.3%. The improvement came from cross-system signal integration and workflow activation rather than faster financial reporting alone.

Leakage-detection precision increased from 62.8% to 86.9%, and recall increased from 49.7% to 88.1%. Static variance alerts improved recall but generated weaker precision because local thresholds lacked cross-system context. For example, a procurement price variance may not be margin-relevant if the sales price was updated, and a discount exception may be commercially valid if offset by lower cost-to-serve. MSGF improved precision by combining source lineage, leakage taxonomy, margin exposure, and rule-based materiality gates.

B. Leakage-Class Results

Table VII reports MSGF outcomes by leakage class.

Discount leakage and price-cost mismatch achieved the fastest intervention because rule ownership and approval policies were relatively deterministic. Customer profitability deterioration and production disruption costs required longer intervention because they involved commercial negotiation, operational diagnosis, or capacity trade-offs. Supplier cost shocks were containable when detected early enough to trigger price updates, sourcing alternatives, or finance-approved margin exceptions.

C. Latency Decomposition

Table VIII decomposes median latency.

The largest reductions occurred in PDE mapping, margin exposure translation, and ownership resolution. These are the areas most affected by fragmented enterprise systems. Finance teams can identify actual margin erosion after close, but intervention requires earlier knowledge of source events, accountable functions, and viable corrective actions.

D. Economic Interpretation

Annualized net economic value was calculated as

$$NEV = B_{protected}+B_{recovered}+B_{capacity}+B_{risk}-C_{integration}-C_{gover} \tag{17}$$

ROI was calculated as

$$ROI = \frac{NEV}{C_{integration}+C_{governance}+C_{operation}}. \tag{18}$$

MSGF generated USD 7.42 million in annualized net economic value with a simulated ROI of 2.63. Benefits came from unauthorized discount containment, faster response to supplier cost shocks, reduced expedited freight leakage, lower manual reconciliation effort, improved billing accuracy, and earlier customer profitability intervention. Costs were concentrated in source integration, PDE governance, leakage taxonomy design, margin bridge calibration, workflow configuration, and change management.

The economic result supports a finance-transformation principle: margin improvement is not only a pricing initiative or an FP&A reporting initiative. It is a cross-system control problem. Pricing, procurement, logistics, operations, billing, and finance must operate against a shared view of expected margin, realized margin, and leakage exposure.

E. Stress Testing

Stress testing increased cost volatility, discount activity, freight disruption, production variance, and source-system delay. Table IX reports P95 intervention latency.

Under disruption load, dashboards accumulated unresolved variance explanations, and static alerts generated excessive

TABLE VI
PERFORMANCE COMPARISON ACROSS MARGIN ANALYTICS ARCHITECTURES

KPI	B0	B1	B2	B3	B4	MSGF
Median margin intervention latency, h	55.4	38.2	29.5	22.8	19.6	**12.6**
P95 margin intervention latency, h	148.7	109.4	87.6	72.8	61.5	**41.8**
Leakage-detection precision, %	62.8	68.5	71.9	77.4	79.8	**86.9**
Leakage-detection recall, %	49.7	58.6	66.1	72.8	76.3	**88.1**
Preventable leakage containment, %	33.6	44.8	54.2	61.7	65.4	**76.4**
Unauthorized discount closure, %	41.5	52.7	63.8	70.4	72.1	**84.6**
Supplier cost-shock response time, h	64.2	48.5	37.9	31.4	28.8	**17.9**
Expedited freight leakage reduction, %	8.4	16.8	24.1	31.6	34.2	**48.9**
Manual reconciliation effort, h/week	610	472	356	284	251	**136**
Annualized net economic value, USD million	0.00	1.92	3.14	4.56	5.08	**7.42**

TABLE VII
LEAKAGE-CLASS RESULTS UNDER MSGF

Leakage Class	Share %	Containment %	Median Intervention h
Supplier cost shock	16.8	78.4	17.9
Expedited freight	13.1	71.2	18.6
Price-cost mismatch	14.7	82.5	11.8
Discount leakage	17.4	84.6	9.7
Delayed billing	8.9	76.1	13.5
Inventory write-down risk	10.6	69.8	22.4
Customer profitability deterioration	7.8	64.9	27.6
Manual adjustment pattern	6.2	72.7	16.3
Production disruption cost	4.5	67.5	24.8

TABLE VIII
MARGIN INTERVENTION LATENCY DECOMPOSITION

Latency Component	B0, h	MSGF, h
Signal detection	8.8	1.9
PDE mapping and validation	10.4	2.1
Leakage classification	8.2	1.8
Margin exposure translation	9.5	2.2
Ownership resolution	8.7	1.7
Workflow activation	7.1	2.1
Outcome measurement	2.7	0.8
Total median latency	55.4	12.6

TABLE IX
STRESS-TEST RESULTS

Load Condition	B1 P95 h	B2 P95 h	B4 P95 h	MSGF P95 h
1.0× normal load	109.4	87.6	61.5	**41.8**
2.0× volatility load	176.2	138.7	96.4	**59.5**
4.0× disruption load	292.8	231.4	164.1	**97.6**

unprioritized notifications. Process diagnosis retained value but did not consistently activate intervention ownership. MSGF degraded more slowly because materiality gates, PDE quality controls, root-cause classification, and finance–operations routing constrained the action queue.

The margin-control load condition can be expressed as

$$\rho_m = \frac{\lambda_m}{\mu_m}, \tag{19}$$

where λ_m is arrival rate of actionable leakage signals and μ_m is effective intervention capacity. When $\rho_m > 1$, leakage cases accumulate as unresolved cost variance, discount exceptions, premium freight, billing errors, and customer profitability erosion. MSGF reduces λ_m through quality and materiality gating while increasing μ_m through structured ownership, prioritization, and workflow routing.

F. *Managerial and Architectural Implications*

The results support four implications.

First, margin leakage should be measured as an intervention-latency problem, not only a period-end variance problem. Finance should measure time from leakage signal to action, not only margin variance after close.

Second, margin governance requires cross-functional PDE control. Target price, authorized discount, realized net price, standard cost, actual cost, freight cost, service cost, claims, deductions, customer hierarchy, and product hierarchy must be governed as decision-critical PDE.

Third, finance and operations alignment requires shared exception taxonomies. A margin decline should be classified by actionable root cause: supplier cost shock, freight premium, price-cost mismatch, discount leakage, billing delay, inventory write-down risk, customer profitability deterioration, manual adjustment pattern, or production disruption.

Fourth, ERP replacement is not the only path to margin improvement. A governed analytics overlay can preserve legacy systems of record while improving margin visibility and intervention speed.

VI. CONCLUSION

This paper proposed a Margin Signal Governance Framework for detecting and routing margin leakage signals across fragmented enterprise systems. The framework connects finance, pricing, procurement, logistics, operations, billing, and commercial teams through margin signal identification, cross-system margin pathway mapping, leakage classification, margin exposure translation, ownership routing, and outcome measurement.

Simulation results showed that MSGF reduced median margin intervention latency from 55.4 h to 12.6 h, reduced P95 latency from 148.7 h to 41.8 h, improved detection precision from 62.8% to 86.9%, increased leakage recall from 49.7% to 88.1%, improved preventable leakage containment from 33.6% to 76.4%, and generated USD 7.42 million in annualized net economic value.

The deployment strategy should begin with leakage domains where finance can quantify exposure and operations can intervene: supplier cost increases, expedited freight, price-cost mismatches, discount leakage, delayed billing, inventory write-down risk, customer profitability deterioration, manual adjustment patterns, and production disruption costs. Implementation should register systems of record, define margin-critical PDE, establish leakage taxonomy, calibrate margin exposure, assign owners, activate workflows, and measure protected margin.

Future research should validate the framework in longitudinal enterprise field studies, extend the exposure model with causal inference for margin attribution, compare leakage taxonomies across industries, and examine how AI-enabled agents can be deployed safely after PDE governance, rule controls, and finance–operations accountability are established.

REFERENCES

[1] S. T. March and G. F. Smith, "Design and natural science research on information technology," *Decision Support Systems*, vol. 15, no. 4, pp. 251–266, 1995, doi: 10.1016/0167-9236(94)00041-2.

[2] A. R. Hevner, S. T. March, J. Park, and S. Ram, "Design science in information systems research," *MIS Quarterly*, vol. 28, no. 1, pp. 75–105, 2004.

[3] K. Peffers, T. Tuunanen, M. A. Rothenberger, and S. Chatterjee, "A design science research methodology for information systems research," *Journal of Management Information Systems*, vol. 24, no. 3, pp. 45–77, 2007, doi: 10.2753/MIS0742-1222240302.

[4] P. Chapman, J. Clinton, R. Kerber, T. Khabaza, T. Reinartz, C. Shearer, and R. Wirth, *CRISP-DM 1.0: Step-by-Step Data Mining Guide*. SPSS Inc., 2000.

[5] R. Wirth and J. Hipp, "CRISP-DM: Towards a standard process model for data mining," in *Proc. 4th Int. Conf. Practical Applications of Knowledge Discovery and Data Mining*, Manchester, U.K., 2000, pp. 29–39.

[6] T. H. Davenport and J. G. Harris, *Competing on Analytics: The New Science of Winning*. Boston, MA, USA: Harvard Business School Press, 2007.

[7] F. Provost and T. Fawcett, "Data science and its relationship to big data and data-driven decision making," *Big Data*, vol. 1, no. 1, pp. 51–59, 2013, doi: 10.1089/big.2013.1508.

[8] V. Khatri and C. V. Brown, "Designing data governance," *Communications of the ACM*, vol. 53, no. 1, pp. 148–152, 2010, doi: 10.1145/1629175.1629210.

[9] K. Weber, B. Otto, and H. Österle, "One size does not fit all—A contingency approach to data governance," *ACM Journal of Data and Information Quality*, vol. 1, no. 1, pp. 1–27, 2009, doi: 10.1145/1515693.1515696.

[10] W. M. P. van der Aalst, *Process Mining: Data Science in Action*, 2nd ed. Berlin, Germany: Springer, 2016.

[11] M. Dumas, M. La Rosa, J. Mendling, and H. A. Reijers, *Fundamentals of Business Process Management*, 2nd ed. Berlin, Germany: Springer, 2018.

[12] G. Gallego and G. van Ryzin, "Optimal dynamic pricing of inventories with stochastic demand over finite horizons," *Management Science*, vol. 40, no. 8, pp. 999–1020, 1994, doi: 10.1287/mnsc.40.8.999.

[13] K. T. Talluri and G. J. van Ryzin, *The Theory and Practice of Revenue Management*. Boston, MA, USA: Springer, 2004.

[14] K. J. Ferreira, B. H. A. Lee, and D. Simchi-Levi, "Analytics for an online retailer: Demand forecasting and price optimization," *Manufacturing & Service Operations Management*, vol. 18, no. 1, pp. 69–88, 2016, doi: 10.1287/msom.2015.0561.

[15] S. Dutta, M. J. Zbaracki, and M. Bergen, "Pricing process as a capability: A resource-based perspective," *Strategic Management Journal*, vol. 24, no. 7, pp. 615–630, 2003, doi: 10.1002/smj.323.

[16] A. Hinterhuber, "Customer value-based pricing strategies: Why companies resist," *Journal of Business Strategy*, vol. 29, no. 4, pp. 41–50, 2008, doi: 10.1108/02756660810887079.

[17] T. T. Nagle, G. Müller, and E. Hogan, *The Strategy and Tactics of Pricing: A Guide to Growing More Profitably*, 6th ed. New York, NY, USA: Routledge, 2018.

[18] D. Davcev and K. Koceski, "Dynamic pricing models and negotiating agents: Developments in management accounting and decision systems," *Administrative Sciences*, vol. 13, no. 2, Art. no. 57, 2023, doi: 10.3390/admsci13020057.

[19] R. Cooper and R. S. Kaplan, "Profit priorities from activity-based costing," *Harvard Business Review*, vol. 69, no. 3, pp. 130–135, 1991.

[20] R. S. Kaplan and R. Cooper, *Cost and Effect: Using Integrated Cost Systems to Drive Profitability and Performance*. Boston, MA, USA: Harvard Business School Press, 1998.

[21] M. C. Anderson, R. D. Banker, and S. N. Janakiraman, "Are selling, general, and administrative costs sticky?" *Journal of Accounting Research*, vol. 41, no. 1, pp. 47–63, 2003, doi: 10.1111/1475-679X.00095.

[22] J. E. Hunton, B. Lippincott, and J. L. Reck, "Enterprise resource planning systems: Comparing firm performance of adopters and non-adopters," *International Journal of Accounting Information Systems*, vol. 4, no. 3, pp. 165–184, 2003, doi: 10.1016/S1467-0895(03)00008-3.

[23] B. Wieder, P. Booth, Z. P. Matolcsy, and M.-L. Ossimitz, "The impact of ERP systems on firm and business process performance," *Journal of Enterprise Information Management*, vol. 19, no. 1, pp. 13–29, 2006, doi: 10.1108/17410390610636850.

[24] A. Kanellou and C. Spathis, "Accounting benefits and satisfaction in an ERP environment," *International Journal of Accounting Information Systems*, vol. 14, no. 3, pp. 209–234, 2013, doi: 10.1016/j.accinf.2012.12.002.

[25] M. Granlund and T. Malmi, "Moderate impact of ERPS on management accounting: A lag or permanent outcome?" *Management Accounting Research*, vol. 13, no. 3, pp. 299–321, 2002, doi: 10.1006/mare.2002.0189.

[26] G. Park and M. Song, "Optimizing resource allocation based on predictive process monitoring," *IEEE Access*, vol. 11, pp. 38309–38323, 2023, doi: 10.1109/ACCESS.2023.3267538.

[27] J. Senoner, T. H. Netland, and S. Feuerriegel, "Using explainable artificial intelligence to improve process quality: Evidence from semiconductor manufacturing," *Management Science*, vol. 68, no. 8, pp. 5704–5723, 2022, doi: 10.1287/mnsc.2021.4190.

[28] C. Cimini, R. Pinto, S. Cavalieri, and S. Pirola, "Eligibility of BPMN models for business process redesign," *Information*, vol. 10, no. 7, Art. no. 225, 2019, doi: 10.3390/info10070225.

[29] R. Pereira, J. Brás, and S. Moro, "Intelligent process automation and business continuity: Areas for future research," *Information*, vol. 14, no. 2, Art. no. 122, 2023, doi: 10.3390/info14020122.

[30] A. Aldoseri, K. N. Al-Khalifa, and A. M. Hamouda, "Re-thinking data strategy and integration for artificial intelligence: Concepts, opportunities, and challenges," *Applied Sciences*, vol. 13, no. 12, Art. no. 7082, 2023, doi: 10.3390/app13127082.

[31] A. Aljohani, "Predictive analytics and machine learning for real-time supply chain risk mitigation and agility," *Sustainability*, vol. 15, no. 20, Art. no. 15088, 2023, doi: 10.3390/su152015088.

[32] L. Ning and D. Yao, "The impact of digital transformation on supply chain capabilities and supply chain competitive performance," *Sustainability*, vol. 15, no. 13, Art. no. 10107, 2023, doi: 10.3390/su151310107.

[33] C. Marinagi, P. Reklitis, P. Trivellas, and D. Sakas, "The impact of Industry 4.0 technologies on key performance indicators for a resilient

Supply Chain 4.0," *Sustainability*, vol. 15, no. 6, Art. no. 5185, 2023, doi: 10.3390/su15065185.
[34] A. A. Tubis, K. Grzybowska, and B. Krol, "Supply chain in the digital age: A scientometric–thematic literature review," *Sustainability*, vol. 15, no. 14, Art. no. 11391, 2023, doi: 10.3390/su151411391.
[35] N. Magnette, R. Verity, and W. Baker, "Playing every hand better in the pricing game," McKinsey & Company, Jan. 2017.
[36] KPMG LLP, "Revenue leakage," KPMG Healthcare and Life Sciences Advisory, 2023.
[37] McKinsey & Company, "The state of AI in 2023: Generative AI's breakout year," Aug. 2023.
[38] Deloitte AI Institute, "The State of AI in the Enterprise, 5th edition," Deloitte, 2022.
[39] Gartner, "Gartner identifies the top 10 strategic technology trends for 2024," Gartner Newsroom, Oct. 2023.
[40] Forrester Research, "Forrester's Predictions 2024," Forrester Research, 2023.