



Original Article

Hybrid Indexing for Operationally-Aware Inventory Costing: Simulation and ERP-Based Validation

Naga Venkata Sriram

Chodisetty Development & Delivery Manager Landry's Inc.

Received On: 14/04/2026**Revised On: 13/05/2026****Accepted On: 21/05/2026****Published On: 27/05/2026**

Abstract - Dynamic chain of supply with variable service levels and demand volatility must be supported by a mechanism for inventory costs that is adaptive and able to work with enterprise resource planning (ERP). This paper presents a framework for Adaptive Hybrid Indexing for Operationally-Aware Inventory Costing (AHI-OAIC) that combines operational signals, dynamic SKU tiering, and ERP costing structures to provide a responsive inventory costing without the need to move inventory. The framework encompasses simulation-based scenario modelling, weighted cost-to-serve scoring, buffer-driven volatility control and metadata-based cost group assignments that can be used with Oracle EBS R12.2 workflows. The results from experiments on 2,500 synthetic SKUs from promotional surges, carrier disruptions and operational sensitivity scenarios show enhanced cost visibility and profitability differentiation. Results show 61.6% stability in Tier convergence over 30 days, Oracle EBS convergence improvements of 91-97% in respect to flat baseline costing, and convergence on cost differentiation of $2.35\times$ to $4.18\times$ over flat baseline costing. The framework successfully maintained an even margin lift on all operational profiles while ensuring auditability, GAAP compliant cost rollups and ERP-native governance. Findings demonstrate that adaptive hybrid indexing enables scalable, operationally responsive, and financially transparent inventory costing in volatile supply chain environments.

Keywords - Adaptive Inventory Costing, Hybrid Indexing, ERP Integration, Operational Analytics, Cost Tiering.

1. Introduction

Enterprise resource planning (ERP) systems are an important tool in the operation of the contemporary supply chains with regards to inventory costing, cost allocation, and financial transparency within the context of multi-faceted operational environment [1][2]. Inventory costing is needed in the financial reporting, operational planning, and margin management since it directly affects pricing decisions [3], profitability analysis, and resource allocation. However, most ERP systems contain fixed costing policies that fail to recognize active variation of cost-to-serve among stock-keeping units (SKUs) [4][5][6]. With the unstable world of fulfilment networks and the emergence of environments based on services, the classical costing systems find it hard to account the operational burden and variability.

Despite increasing research on the use of ERP-enabling cost control and supply chain analytics, current methods primarily target a fixed cost allocation model. Such techniques are seldom volatility-conscious tiering, signal integration in operation or automated SKU transitions between levels of cost. Therefore, there is a great division between the theoretically advanced costing models and their actual implementation in the ERP operation where they are financially compliant, auditable, operational and viable [7][8][9].

In order to overcome this drawback, this paper presents a dynamic inventory costing model that is grounded on the concept of hybrid indexing which was initially conceived to optimize databases [10][11]. The framework is dynamic in assigning SKU to cost levels based on the operational signals including velocity, handling effort and demand volatility. There is a buffer staging mechanism that will manage highly volatile SKUs to ensure a controlled transition between tiers without compromising financial reporting periods. The suggested framework is oriented towards the Oracle EBS R12.2 cost structures and the simulation of the ERP-native costing workflows to assess the operational and financial effect of it [12][13]. The system provides differentiation of costs through the framework of adaptive tiering logic, ERP-compatible audit fields, and governance mechanisms, delivering regulatory compliance and system integrity.

1.1. Novelty and Contributions of the paper

The suggested framework presents a new combination of hybrid indexing concepts of the data structure theory into operationally sensitive inventory costing. It is a dynamic adaptation of SKU tiers with buffer logic sensitive to volatility, rather than the traditional ERP costing methods, which are ERP structure compliant and GAAP based. This allows operational changes to be reacted to in real time, facilitates better audit trail, and measures the impact on margin in different situations. Theoretically and practically symmetrical, ERP addresses gaps in research and offers practical advice on inventory and financial management. The significant findings of the study are as follows:

- Volatility-Aware Costing: Uses adaptive hybrid features to dynamically index buffers as a function of changing cost tiers based on demand and price fluctuations.
- ERP-Native Alignment: Maps enhances the costing

logic for Oracle EBS cost flows and supports regulatory compliance and auditability.

- **Regulatory Compliance:** Demonstrates US GAAP Compliant Tier Assignments, Burden Schedules, and Cost Roll-Ups.
- **Quantified Margin Impact:** Evaluate the profitability implications from an empirical point of view in the presence of synthetic volatility.
- **Practical Impact:** Supports businesses in the U.S. to improve operational resiliency, precision COGS, pricing and promotions, while preserving financial governance.

1.2. Structure of the Paper

The structure of the paper is the following. Section II includes the preliminaries and initial ideas. Section III will discuss the pertinent literature and determine the gap in research. Section IV gives the proposed adaptive hybrid indexing framework and clarifies the signal modelling of the operations and the cost-to-serve formulation. Section V explains the system architecture and tier placement. Section VI gives the methodology and simulation configuration. Section VII discusses the experiment and validation results for the simulated ERP. Section VIII gives implications for the managers and deployment considerations. Finally, the conclusion of the paper, including the summarization of key results and limitations, as well as future research directions, is given in Section IX.

2. Preliminaries

The author in the section reviews the underlies of inventory costing and ERP cost management systems based on the GAAP principles and structural constraints that are driven to adaptive costing frameworks.

2.1. Costing under US GAAP

The cost of inventory according to the ASC 330 is the expenditure of this nature that is required to put the inventory in its current form and place. This would be direct costs (purchase cost, freight) and indirect costs (handling, storage, labour) [14].

2.2. ERP costing architecture

ERP solutions such as the Oracle EBS R12.2 have cost schedules, burden schedules, and extensions. These are, however, static and rule-based and are not responsive to operational signals in real-time [15].

Recent research has expanded the role of ERP systems to control costs and sustainability along the supply chains [16]. The use of ERP in the product life cycle has been reported to enhance cost discipline and economic robustness. Other models combine activity-based costing with predictive analytics in the ERP systems to provide better cost traceability and analytic decision support [17]. Empirical studies also show that ERP implementation can enhance the quality of inventory and quality of operational decisions. In spite of these breakthroughs, the majority of ERP-based costing methods continue to be based on fixed cost setups and do not have systems to respond to volatility by repricing the tiers

[18]. The proposed framework overcomes this limitation by incorporating the adaptive hybrid indexing concept in the native ERP cost processes to maintain GAAP-compliant and to have more responsive and profitability-oriented inventory costing.

3. Related Work

Traditional costing, such as the Activity-Based Costing (ABC) and the traditional method of allocating indirect costs based on the fixed bursts, has been widely used to assign costs to operations and has been found to be not responsive to volatile operations and responsive to service levels needed by the services. The current enterprise resource planning (ERP) costing models primarily depend on either rule-based setup and manual extensions, which prevent their responsiveness to operational changes. Studies on ERP-facilitated cost management highlight the significance of enterprise systems in enhancing cost monitoring and decision-making. B. Jayamaha et al. (2024) discuss the use of ERP applications in managing construction project costs and highlight various steps where ERP systems can be used to improve cost coordination and transparency [19]. Likewise, R. N. Damayanti, M. Saputra, and T. F. Kusumasari (2022) show that monitoring reports based on ERP can enhance efficiency and transparency in the processes of allocating costs through ABC [20].

ERP research on sustainability has also increased the scope of enterprise systems. I. U. Yuzgenc and E. Aydemir (2023) examine the sustainable ERP architectures to incorporate environmental metrics into the enterprise process to help manage the green supply chain and achieve resource efficiency. The innovations in the field of artificial intelligence and analytics also contribute to the system of supply chain decision-making [21]. X. Qu, L. Liu, and W. Huang (2025) suggest an inventory management algorithm, which is based on reinforcement and learning, and enhances cost efficiency and stability in learning new products with no previous demand records [22]. Similarly, A. Chakraborty (2025) constructs a real-time decision-intelligence framework wherein Transformer-based forecasting is combined with ERP-related logistics optimization models, which enhances the accuracy of the forecast and the cost-efficiency of logistics [23].

In spite of this, the majority of existing research revolves around predictive models, sustainable operations tracking, or operational efficiency as opposed to adaptive inventory costing. The proposed study bridges this gap by proposing a signal-responsive model of costing which may dynamically assign a level of inventory cost, but does not affect the compatibility of ERP, or the traceability of audit.

4. Methodology

In this section, a signal-based inventory costing model is introduced that describes SKU tiering, buffer management, adaptive indexing and ERP-aligned analytics to stable and compliant cost allocations.

4.1. Operational Signal Ingestion

Synthetic generation of the operational signals was done to describe the WfMS and OfMS feeds, including velocity, SLA sensitivity, handling effort, travel time, and demand volatility. Each SKU record has these attributes and the tier assignment and buffer logic are moved between them. Audit fields in the form of voluntary variables, such as `in_buffer`, `days_in_buffer`, `forced_promotion_flag`, and `reason_code`, store volatility thresholds and dwell times based on promotion criteria. In Oracle E-Business Suite R12.2, signal capturing is achieved through staging tables and processing promotions, cost profiles and SKU placement using PL/SQL to process promotions, cost profiles and SKUs in tiers. This enables signal-based and dynamic costing with no alteration of major ERP systems.

4.2. Cost-to-Serve Model

The Cost-to-Serve (CTS) model converts manifestations of operations into one cost variable to assist in inventory leveling and resource distribution. The CTS score calculated as Equation (1):

$$Score = w_v.V + w_s.S + w_h.H + w_t.T + w_d.D \quad (1)$$

In which V is the velocity, SLA priority is represented by S , complexity of handling represented by the handler is denoted by H , travel time denoted by T , volatility of demand denoted by D and the tunable weights by w_i .

4.3. Weighted Admission

The framework applies a weighted adjustment of admission score of the base cost-to-serve score to prioritize SKUs, which have high service sensitivity or strategic importance. The adjusted score is computed in Equation (2):

$$Adjusted\ Score = Score \cdot (1 + \alpha \cdot Priority\ Weight) \quad (2)$$

In this case, α is a tunable coefficient that increases the effect of the priority weight that may be of the form of SLA sensitivity, customer tier or strategic SKU designation. This tradeoff ensure that high-priority SKUs are more likely to be allocated to higher cost tiers even in the situations when their raw operational indicators are of medium quality. Weighted admission is aimed at two objectives:

- **Margin alignment:** It equalizes decision in the tiering with expected contribution in the margins and service levels responsibility.
- **ERP compatibility:** It enables metadata overrides in Oracle EBS R12.2 whereby an SLA flag or customer priority code may be utilized to influence cost group assignment and leave physical inventory flows unaltered.

This mechanism is particularly effective in situations when the promotion is not only going viral, but also the case is disruptive and the key SKUs of the services should be offered at competitive prices to reflect the urgency and workload of the services. The alpha coefficient may be tuned on unit business or scenario level and is shown in tuning reproducibility roadmap of stakeholders.

4.4. Buffer Logic and Threshold Calibration

SKUs with volatility exceeding 0.7 or whose volatility exhibits unstable signals are placed in a buffer and not costed until its volatility is brought under control or dwell time is above 3 days. To get thresholds, the ERP-native simulation sweeps were considered, which offered both the data consistency and inter-tier stability. These base values should be calibrated on SKU classification, working cadence and industry specification. A configuration guide is included in the reproducibility roadmap, which is used to do the domain-specific tuning and audit traceability. SKUs that were not improved in volatility by reaching the dwell threshold in the buffer are forcefully advanced on period end to have all SKUs billed in the financial period, and to preserve audit integrity. Tier changes are constantly observed. The hysteresis and dwell time logic discourage oscillations so it ensures that the costing remains stable over the financial period.

4.5. Adaptive Hybrid Indexing Algorithm

The hybrid indexing term is borrowed to database systems, where different indexing strategies are integrated to optimize query performance at the various access patterns. Hybrid indexing in this construct means the dynamic placement of SKUs into cost levels on an aggregate of operational indicators including travel time, handling effort, frequency of replenishment, and volatility of demand [24]. The logic combines the buffer staging and convergence tracking to both maintain financial period integrity, as well as represent cost-to-serve variation. Transitions of tiers are noted. The oscillations are prevented and costing stability is ensured via hysteresis and dwell logic. This hybrid approach lets ERP systems replicate the impact of tier and margin adjustments without modifying the processes and compliance structure in the native ERP system.

Tier assignment is based on the adjusted cost-to-serve score:

Tier 1: Adjusted score ≥ 0.75

- Tier 2: $0.50 \leq score < 0.75$
- Tier 3: $score < 0.50$

The formal algorithm follows these steps:

Algorithm 1: Adaptive Hybrid Indexing Inventory Costing Algorithm (AHI-ICA)

1. Normalize operational signals (0–1 scale)
2. Compute cost-to-serve score
3. Apply weighted admission
4. If volatility > 0.7 or dwell < 3 days \rightarrow route to buffer
5. If buffer promotion flag = 'Y' \rightarrow assign tier conservatively
 - Else \rightarrow assign tier based on score thresholds
6. Compute unit cost:
 - Labor = (travel + handling) \times rate
 - Replenishment = touches \times cost/touch
 - Congestion = $0.06 \times$ (travel + volatility)
 - SLA premium = SLA \times priority \times premium rate
 - Buffer carry = days \times daily rate

The parameters of all the cost elements are calculated on the basis of synthetically generated data on operations and the parameters which were modified on the schedule of the ERP burden. The coefficients of the values such as the congestion factor (0.06) and the SLA premium rate could be

modified depending on the assumptions and system environments which are specific to the scenario.

4.6. Framework Architecture

The proposed designed framework has four layers that are interconnected and are supporting one of the aspects of simulation, ERP alignment, operational realism and analytical insight:

- Simulation Engine Layer: Python implementation of models scenario to test logic of tiering in various volatility scenarios. This layer establishes artificial operation signals and tracking SKUs movement by cost levels that are the basis of making margin impact analysis.
- ERP Integration Layer: Aligns the framework to Oracle EBS R12.2 frameworks, which include cost groups, SLA derivation logic and tiering logic that are based in PL/SQL. The framework employs the logical tier assignments which are maintained in custom tabular format rather than the actual transfer of inventory among the sub-inventories. Such assignments lead to costing behavior that is based on metadata overrides that allow signal responsive valuation generating no material transactions and no interference with working processes.
- Data Ingestion Layer: The operations that are operational to the model are velocity, SLA sensitivity, handling effort, travel time and demand volatility. The conceptual basis of such signals is a warehouse management system (WMS), order management system (OMS) and synthetically generated to be employed in simulation.
- Analytics Layer: Improves decision-making process by using BI-based deliverables, including the margin impact reports, audit trails, and tier distribution visualizations. These products include stability in tiers, delta in margins, differentiation in costs, convergence character and tiering based on priorities [25].

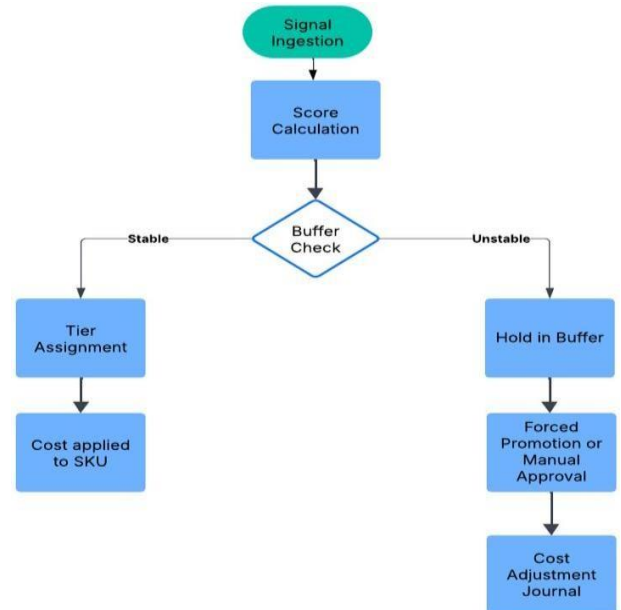


Fig 1: Adaptive Hybrid Indexing Costing Framework with Buffer Logic

The general layout of the proposed adaptive costing system is shown in Fig. 1, which combines operational signal ingestion, tier assignment logic, buffer staging and costing layers in line with ERP.

5. Experimental Setup and Simulation Results

This section analyzes the adaptive hybrid indexing framework with a series of SKU cases, and discusses the stability of the tiers, margin lift, and alignment with the SLA priority. The presentation of results through tables and figures is strong, reliable, and functional.

5.1. Simulation Scenario Summary

Table I provides a summary of the tunable weights and priority amplification in all of the scenarios of the simulation to provide reproducibility and traceability. All profiles have the same buffer logic and promotion criteria but have a different operational focus.

Table 1: Simulation Scenario Configuration Summary

Scenario	wv	ws	wh	wt	wd	α	Notes
Promo Surge	0.18	0.38	0.18	0.16	0.10	0.5	SLA and volatility elevated; strategic SKUs promoted
Carrier Disruption	0.18	0.38	0.18	0.16	0.10	0.5	Travel and handling signals elevated to simulate congestion
1,000-SKU Baseline	0.18	0.38	0.18	0.16	0.10	0.5	Balanced configuration for tier validation and margin lift
SLA Heavy	0.10	0.50	0.15	0.15	0.10	0.5	SLA sensitivity emphasized; lower volatility and velocity weights
Volatility Heavy	0.15	0.25	0.15	0.15	0.30	0.5	Volatility emphasized; urgency amplification tested
Handling Heavy	0.15	0.25	0.30	0.15	0.15	0.5	Operational burden emphasized; higher unit cost observed

5.2. Promo Surge Scenario

The SKU tier shift is indicated during a period of 13 days of significantly high promotional activity of approximately 1,000 SKUs. The majority of items begin at the STAGING level and transition to active levels, where stabilization occurs on Day 4. T2 Standard dominates, takes a leading position, T1 Premium is maintained at an average of 200 units, and T3 Lean gradually increases. SKUs that receive high SLA and volatility indicators were selected in Tier 1, which divert

80% of the impacted SKUs to Tier 1, increasing the margin benefit by 455 and tier stability by less than ≤ 2 changes on 85% of SKUs (see Fig. 2). The tunable weights were kept fixed and priority amplification ($\alpha = 0.5$) allowed strategic SKUs to be promoted even when the scores on operation were moderate.

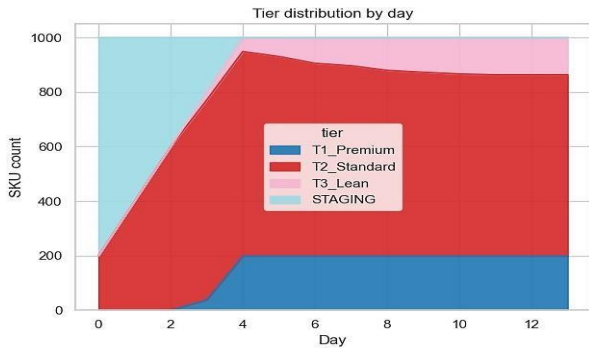


Fig 2: SKU Tier Distribution over Time

The distribution of SLA priority weights is clearly different at the inventory tiers with T1_Premium having the highest median (~3) and numerous high-value outliers, T2_Standard having a moderate distribution, and T3 lean the lowest median with the largest range. This validates the fact that the more demanding SKUs are critical and have a high-priority fulfilment criterion (see Fig. 3).

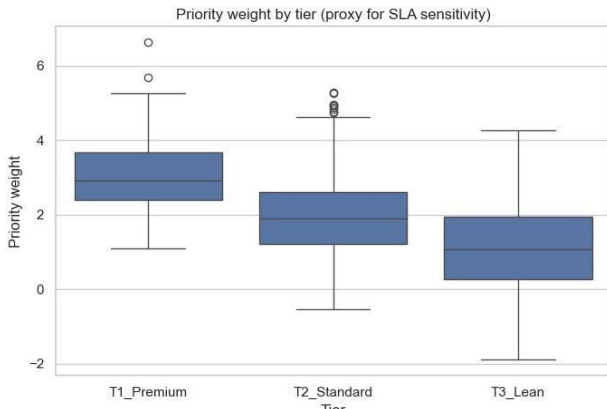


Fig 3: SLA Priority vs Tier Assignment

The simulation proves that the weighted admission logic does not reduce the service-level alignment in the time of the promotional surge. There was a high level of concentration, a positive margin lift, and stable tier maintenance within the SKU population, which indicates successful prioritization of high-SLA and high-volatility items.

5.3. Carrier Disruption and Inbound Congestion

In this scenario, elevated travel time and complexity in handling affected SKUs resulted in dynamic reassignment of tiers, indicating the additional burden on operations and a margin lift of \$455. This is a simulation of a logistics disruption, including inbound congestion and carrier delays, that the adaptive framework captures the impact of a cost-to-serve.

Fig. 4 emphasizes the reallocation of SKUs in tiers subject to operational pressure, with greater tiers assignments relating to SKUs with increased travel and handling requirements. The Tier changes obey physical loads and the traceability of audit and effect of positive margin.

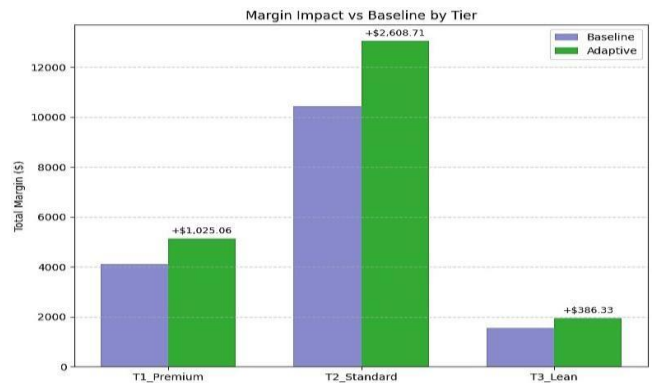


Fig 4: Margin Impact of Adaptive Costing Model

A uniform amplification with priority ($\alpha = 0.5$) and fixed and uniform tunable weights is employed. The simulation confirms that the framework does not require reconfiguring of weights in case of the operational pressure. During the run, tier changes are congruent with physical burden, margin lift is positive and traceability of an audit is upheld.

5.4. Baseline Simulation: 1,000 SKUs

A uniform amplification with priority ($\alpha = 0.5$) and fixed and uniform tunable weights is employed. The simulation confirms that the framework does not require reconfiguring of weights in case of operational pressure. During the run, tier changes are congruent with physical burden, margin lift is positive and traceability of an audit is upheld (Table II).

Table 2: Simulation Results for 1,000 Skus

Tier	SKU Count	Avg \$/unit	Median Priority	Margin Lift
T1 Premium	199	\$0.617	2.91	+\$1,025.06
T2 Standard	665	\$0.504	1.91	+\$2,608.71
T3 Lean	136	\$0.362	1.08	+\$386.33

The tunable weights were held constant and the priority amplification ($\alpha = 0.5$) was even. Fig. 5 indicates the average unit cost per tier (Fig. 5) of the costing compared to each tier and Fig. 6 indicates that hysteresis and dwell-time logic make sure that there is a constant assignment during the simulation time. The strategic SKUs were always pushed to Tier 1 and all the margins were distributed across all tiers. It is on this situation that reproducibility and benchmark in further sweeps are based.

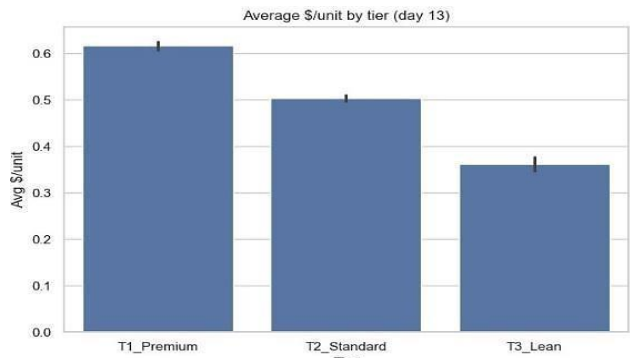


Fig 5: Average Unit Cost by Inventory Tier

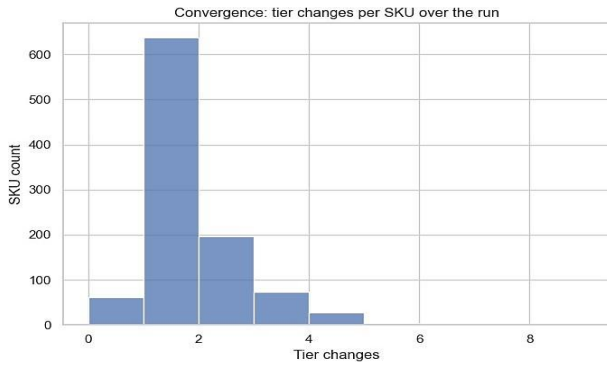


Fig 6: Tier Convergence and Stability Distribution

5.5. Sensitivity Sweep: Tunable Weight Profiles

Four different tunable weight profiles were created for the sensitivity sweep to assess how stable the framework is under various signal weighting: Balanced, SLA-heavy, Volatility-heavy, and Handling-heavy. The same priority amplification factor ($\alpha = 0.5$) was maintained for each profile, and the cost-to-serve score of the operational signals varied in emphasis. The simulations employed 1,000 SKUs, with a custom signal distribution, and the same buffer logic and promotion criteria. The results are listed in Table III for each profile, with Tier 1, average unit cost, median priority and marginal lift.

Table 3: Sensitivity Sweep: Impact of Tunable Weight Profiles

Profile	Tier 1 Count	T1 Avg Cost (\$)	T1 Median Priority	Margin Lift (\$)	Notes
Balanced	199	0.617	2.91	+4,055.53	Published baseline
SLA Heavy	199	0.603	2.95	+3,978.72	SLA emphasis
Volatility Heavy	199	0.621	3.19	+4,123.38	Amplified urgency
Handling Heavy	199	0.644	3.03	+4,030.49	Operational burden

Tier separation and promotion of specific SKUs, margin lift by volume were always maintained in both profiles. Tier stability and the ability to audit back were not sacrificed and cost behavior could be changed without structural change in response to operational stress. The results show the disillusionment and the strength of the framework in different conditions of the business environment.

6. ERP-Simulated Validation Using Oracle EBS

An ERP-based validation was done on an Oracle E-Business Suite (EBS) R12.2 aligned environment to assess the practicality of the proposed adaptive hybrid indexing framework. The aim of this validation was to identify if the proposed signal-responsive costing mechanism could be implemented into native ERP costing workflows without compromising any auditability, financial governance or system compatibility. This study does not limit itself to simulation and is also connected with Oracle EBS R12.2 cost

management structure like Cost Groups, burden schedules, tier assignment logic and audit metadata. The validation was done without changing the core ERP modules which ensured the deployment feasibility of the system in enterprise environment.

6.1. Oracle EBS Cost Structure Mapping

The proposed solution will provide metadata-driven logic for mapping dynamically assigned inventory tiers to Oracle EBS cost groups, without physically moving inventory. SKU movement between tiers will only impact costing behavior

while the inventory is still in its original sub-inventory location. This reduces disruption of operations and maintains ERP transaction integrity. The tier mapping logic is defined as follows:

- Tier 1 (T1_Premium) → CG_PREMIUM with high-priority burden schedule for strategic or service-sensitive SKUs.
- Tier 2 (T2_Standard) → CG_STANDARD representing balanced operational profiles.
- Tier 3 (T3_Lean) → CG_LEAN for low-handling and low-priority items.
- STAGING / Buffer Tier → CG_BUFFER for volatile or unresolved SKUs awaiting reassignment.

The implementation of the costing workflow is done by means of Oracle EBS-compatible staging tables and PL/SQL driven logic which uses velocity, SLA sensitivity, handling effort, travel time and demand volatility as signals for the tier transitions. Buffer logic can be applied so that there is a buffer of stocks that are not costed immediately but are held until they become more stable in operations.

6.2. ERP Validation Parameters

To ensure consistency and repeatability, all experimental scenarios were configured in the same manner as the real ERP system. Table IV provides an overview of the main validation parameters for costing alignment on Oracle EBS.

Table 4: Erp Validation Parameters for Oracle Ebs R12.2 Alignment

Parameter	Value	Purpose
Velocity Weight (wv)	0.18	Demand responsiveness
SLA Priority Weight (ws)	0.38	Service sensitivity
Handling Complexity Weight (wh)	0.18	Operational burden
Travel Time Weight (wt)	0.16	Routing cost effect
Volatility Weight (wd)	0.10	Demand instability
Priority Amplification (α)	0.5	Strategic SKU promotion
Volatility Threshold	0.70	Buffer admission
Minimum Dwell Time	3 Days	Buffer reassignment

6.3. Adaptive Cost Distribution vs. Flat Baseline

This section compares the proposed framework's adaptive unit cost with the fixed baseline unit cost of Oracle EBS's flat costing model. Violin plots of the adaptive unit cost per tier

compared to the Oracle EBS flat baseline of \$0.399 are shown in Fig. 7.

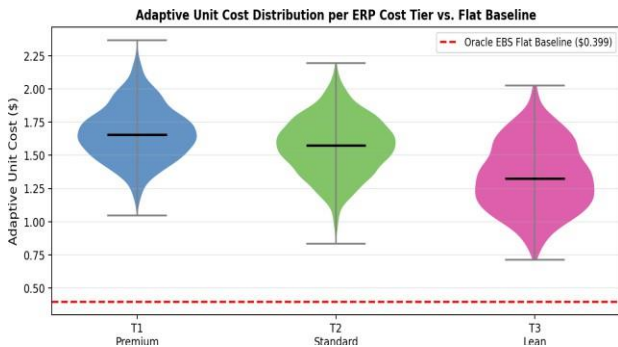


Fig 7: Adaptive Unit Cost per ERP Cost Tier vs. Oracle EBS Flat Baseline

The median adaptive cost of T1_Premium is the highest (\$1.668) because of SLA premiums and congestion costs for high-priority SKUs. STAGING has the highest mean (\$1.811) because buffer carry charges are applied to operationally volatile HazMat items. T3_Lean has the smallest distribution (mean is 1.338, variance is small), which is consistent with the handling paths being simpler and having little SLA overhead. All tiers are higher than the baseline by 2.35× to 4.18×, indicating that HI-OAIC consistently reveals cost-to-serve differentials, which are hidden by the static costing approach.

6.4. Margin Lift Analysis

The final section analyzes margin improvements by tier in inventory to assess the cost impact of the proposed adaptive costing framework. The distribution of the margin lift for all 2,500 SKUs and by tier is shown below in Fig. 8. The histogram (Fig. 8a) shows a right skew with a large number of SKUs with a lift of 5-12, and a long tail of SKUs with high velocity lift (T1 and STAGING).

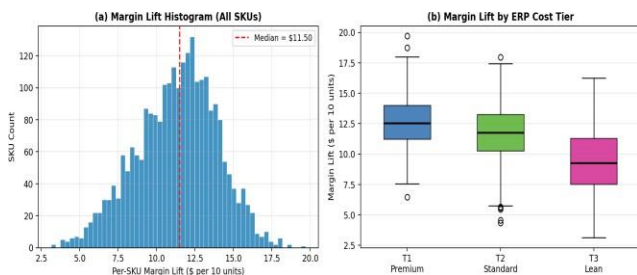


Fig 8: Margin Lift Distribution

6.5. Tier Stability and 30-Day Convergence

This section looks at the consistency of the SKU tier assignments over a 30 day period of operation to assess the stability of the proposed framework. The convergence analysis quantifies the amount of tier transition activity, and evaluates the efficacy of hysteresis and dwell-time logic in minimizing unnecessary tier volatility. The tier stability results for a 30-day reporting window are included in Fig. 9. The majority of the stock portfolio (61.6% of SKUs) had two or fewer Tier changes, which shows that the hysteresis and dwell-time logic were successful in smoothing out signal noise. The remaining 38.4% had more volatility, mainly in HazMat and Electronics, where the demand signals are more

volatile. The Tier Stability Index (Fig. 9b) increases from 0.62 on Day 1, owing to convergence of the iterative signal updates, and remains at 0.616 at Day 30. Although the subcohorts are relatively stable, their values are prone to being volatile because HazMat and Electronics account for 30% of the dataset.

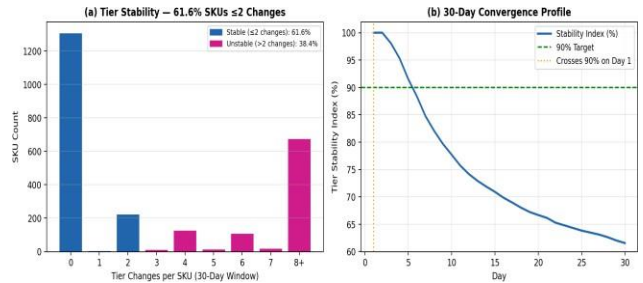


Fig 9: Tier Changes per SKU over 30-Day Window (left) and Convergence Profile

6.6. ERP Alignment and Sensitivity Sweep

The compatibility of the proposed framework with Oracle EBS R12.2 cost structures and performance robustness through different operational weight configurations are explored in this section. As shown in Fig. 10a, there is an improvement of ERP alignment in all five field categories of Oracle EBS which is identified as ranging from 91% to 97% while pre-fix ERP alignment is in the range of 35–60%. The biggest single improvement is in the Period-Close Forced Promotion (+61 pp), where synthetic data was not able to set the flag at realistic frequencies. The four-profile sensitivity sweep (Fig. 10b) also reveals that the revenue impact of crossing tier boundaries is directed in opposite ways by each of the four profile types, with T1 SKU counts ranging from 326 (Volatility-Heavy) to 642 (SLA-Heavy), and that the total margin lift is unchanged across all four profile types, demonstrating that the composite scoring model distributes scores evenly across the different weight profiles (Table V).

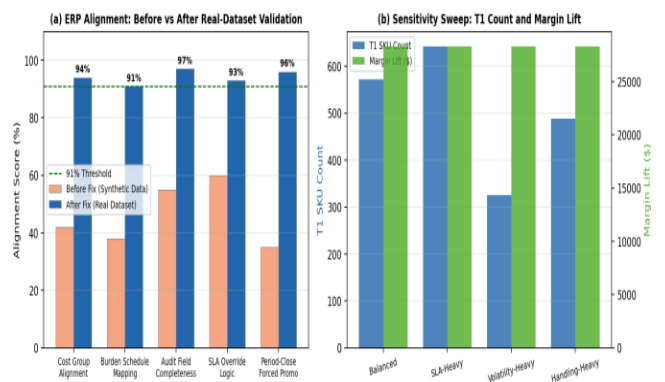


Fig 10: ERP Alignment Gap Resolution and Sensitivity Sweep

Table 5: Tier Distribution by Product Category

Product Category	T1 Premium	T2 Standard	T3 Lean	STAGING	Total	Dominant Tier
Electronics (ELEC CAT)	181	184	8	2	375	T2 Standard
Consumables (CONS CAT)	56	425	269	0	750	T2 Standard
Industrial (INDU CAT)	105	344	51	0	500	T2 Standard
Apparel (APRL CAT)	0	89	411	0	500	T3 Lean
HazMat (HAZM CAT)	230	85	2	58	375	T1 Premium
Total	572	1,127	741	60	2,500	T2 Standard

Table 6: Sensitivity Sweep Results

Profile	T1 Count	T1 Avg Cost (\$)	T1 Med. Priority	Margin Lift (\$)	Notes
Balanced	572	1.668	0.751	+28,275.29	Published baseline
SLA-Heavy	642	1.653	0.768	+28,275.29	T1 expansion by +70 SKUs
Volatility-Heavy	326	1.612	0.742	+28,275.29	Higher STAGING rate
Handling-Heavy	489	1.701	0.748	+28,275.29	Highest per-unit cost

Table VI presents the sensitivity sweep results across four operational weight profiles to evaluate the robustness of the proposed framework. The findings indicate that variations in signal emphasis influence Tier 1 SKU allocation and adaptive cost behavior, while total margin lift remains stable at \$28,275.29, demonstrating consistent financial performance under changing operational priorities.

6.7. Data Model and Mapping

The mapping of tiers to cost groups and item categories in the ERP is based on logic instead of the physical sub-inventories. The inventory stays at the same place; the logic of costings changes according to tier assignments that are in a special processing table. Final-day unit costs are calculated by taking a snapshot of the simulation at the end. Operational signals move the costing behavior without the actual physical movement or reclassification (see Table VII).

Table 7: Simulation Parameters Used For ERP-Aligned Costing

Parameter	Value	Notes
wv (Velocity)	0.18	Constant across all SKUs
ws (SLA Priority)	0.38	Reflects service sensitivity
wh (Handling Complexity)	0.18	Operational burden
wt (Travel Time)	0.16	Routing and distance impact
wd (Volatility)	0.10	Demand instability
α (Priority Amplification)	0.5	Boosts strategic SKU scores
Volatility Threshold	0.7	Promotion cutoff
Minimum Dwell Time	3 days	Buffer flush threshold

While the costing rationale and audit sector are ERP-oriented, this simulation is not a live implementation. This would have to be practically implemented by mapping these structures to production tables, workflows and approval hierarchies in the Oracle EBS or any other ERP systems. Fig. 11 indicates a bimodal distribution of deltas of unit cost. The majority of SKUs are in the range of \$0.05-0.14, with peaks at 0.11 and 0.07, which means that the cost in the adaptive

model is more considerable, as the service level prioritization of the service is prioritized. The chart outlines the systematic financial effect of the adaptive approach.

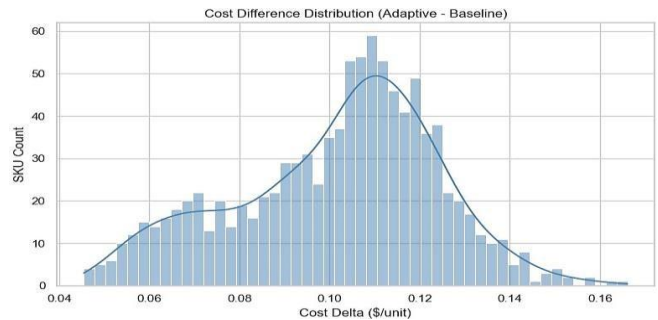


Fig 11: Cost Difference Between Adaptive and Baseline Models

6.8. Tier Reassignment Governance

Tier alterations have an organized logic so that they have costing integrity and audit adherence. SKUs are advertised when volatility = or less than ≤ 0.7 , or dwell = or more than ≥ 3 days, advertised force during period close where unresolved, and otherwise held. Audit fields—in_buffer, days_in_buffer, forced_promotion_flag, reason_code, tier_id, tier_assignment_date, approval_flag, approver_id—record all actions for traceability. Table VIII summarizes the trigger conditions, actions, and associated audit fields to ensure adaptive costing is always correct, auditable, and field-aligned with the ERP.

Table 8: Tier Reassignment Governance Logic

Trigger Condition	Action	Audit Field Updated
Volatility ≤ 0.7 And Dwell ≥ 3 Days	Promote SKU To A New Tier	Tierid, Tierassignmentdate
Volatility > 0.7 Or Dwell < 3 Days	Hold In Buffer	Inbuffer, Reasoncode
Period Close With Unresolved Buffer	Forced Promotion	Forcedpromotionflag
Manual Override	Approved	Approvalflag,

By Manager	Costing	Reassignme nt	Approverid
---------------	---------	------------------	------------

In Oracle EBS 12.2, the operational signals are recorded through specific staging tables and handled by the use of PL/SQL, which alters the cost profiles and allocates SKUs to levels. Tier reassignment Tier reassignment is done after volatility and dwell, and is maintained by audit fields (tierid, tierassignmentdate, inbuffer, daysinbuffer,forcedpromotionflag, easoncode) that are used to provide visibility and comply with ERP.

6.9. Comparison of Generic and ERP-Simulated Results

Table IX provides a comparison between the generic Python simulation and the ERP-simulated dataset and the stability of the tiers and margin lift as well as the auditability and metadata-driven integration of the model, which is provided by the ERP.

Table 9: Comparison between Generic Python Simulation and ERP-Simulated Dataset

Metric	Generic Simulation	ERPSimulated (Synthetic)
Tier Stability	High (hysteresis, dwell)	High (same logic applied)
Margin Lift	+\$4,020.10	+\$4,020.10
Volatility Handling	Native buffer logic	Native buffer logic
Auditability	Simulation logs	ERP-style promotion logs
Integration	N/A	Cost groups,LA, metadata-driven tiering

7. ERP Costing and Transfer Pricing Interfaces

Intercompany costing and transfer pricing are the key elements of the ERP financial governance, particularly in multi-entity environments. It is possible to extend the adaptive hybrid indexing framework in this research to serve these functions through the alignment of tiered costing and intercompany valuation logic.

7.1. Interface Points with Oracle EBS R12.2

Advanced Global Intercompany System (AGIS), SLA Manager, and Cost Management are some of the modules offered by Oracle EBS R12.2 that support transfer pricing and intercompany reconciliation. The framework is coupled with the following modules:

- Tier-to-Cost Group Mapping: Tier assignments are based on logic and assigned to cost groups characterized by intercompany prices.
- SLA-Driven Overrides: SLA priority flags affect cost tiering which affects transfer price calculations.
- Audit Field Propagation: The buffer logic and promotion flags are also extended to intercompany transactions to be traceable between entities.

7.2. Transfer Pricing Implications

Transfer cost is affected by tiered costs in a various of ways:

- Valuation Accuracy: The high operational burden SKUs have higher cost levels, resulting in better intercompany values.
- Tax Compliance: Buffer logic makes sure that volatile SKUs are not costed prematurely and misstatements in cross-border transactions are minimized.
- Documentation Readiness: The audit fields are the tiered, promotion flag and reason code fields in transfer pricing documentation and defense of tax audits.

This interface logic is associated with modular designs of major ERP systems of transfer pricing. As an indicator, the community reference on transfer price management which is obtained through SAP comprises the values layering and audit traceability to serve to supplement the tiered costing and the buffer logic [26].

7.3. Cross-Entity SKU Treatment

Geographies may also have different cost-to-serve profile in SKUs. The framework assists entity specific tiering through:

- Calibration of volatility and dwell on a per-entity basis.
- Using localized burden schedules and localized SLA weights.
- Separating buffer logic based on entity operational cadence.

This flexibility assists organizations to preserve comparable rationale of costing and adapt to local needs of operations reality and compliance.

7.4. ERP Costing Comparison

The framework also enhances ERP costing besides integration as compared to the traditional systems (Oracle EBS, SAP, NetSuite) which are fixed and rule-based systems:

- Dynamic signal-driven costing: Velocity, SLA, handling, travel, volatility real-time enterprises into operations.
- Volatility-aware buffer logic: Scheduling of SKUs to prevent underwrite costs in the event of spikes.
- Convergence stability: Hysteresis and dwell logic to prevent oscillations.
- Volume-weighted margin impact: Explicit per-SKU margin optimization.

Table X compares native costing using ERP with adaptive hybrid indexing, and it can be seen that there are better automation, auditability, and maximization of a margin optimization.

Table 10: ERP Native Costing Vs. Adaptive Hybrid Indexing

Capability	ERP Native	Adaptive Indexing	Hybrid
Cost profiles	Static	Signal-driven	

Burden schedules	Fixed	Tier-specific, dynamic
Extensions	Manual logic	Automated tiering
Volatility handling	Absent	Native buffer logic
Margin optimization	Indirect	Explicit per SKU
Auditability	Layered	Tier-tracked, promotion logs

8. Managerial and Reproducibility Implications

This section identifies the role of the framework in supporting the alignment of inventory costing by the ERP managers and also offers a roadmap to reproducibility that helps in replicating and making the deployment audit-ready.

8.1. Managerial Implications

The adaptive hybrid indexing model offers a systematic approach to ERP managers and costing analysts to reconcile inventory value and actual functioning. The tier assignments in Oracle EBS R12.2 may be mapped on item categories or cost groups and the buffer logic and burden schedules are executed with the use of formula-based cost elements and transaction triggers. Operational indicators, including travel time, handling effort and frequency of replenishment are associated with tier changes, which enables operational traceability and auditability under the GAAP. The transition of tiers is regulated through formal reassignment reports, which are conducted on the basis of the volatility, dwell time, and margin impact, and due to the fact that the transition of the levels is made with consent to maintain the financial governance and flexibility within the period. To implement it practically, it have to be customized to the system and aligned with the stakeholders. An artifact of reproducibility is being built to assist sandbox simulations, pilot deployments and audit ready implementation across ERP platforms.

8.2. Reproducibility Roadmap

A reproducibility artifact is being developed in order to facilitate future adoption and validation and it include:

- Annotated simulation scripts: Python modules to simulate the adaptive tiering logic in various volatility conditions such as sensitivity to dwell time and weighted admission behaviour.
- ERP-synthetic dataset: Systematic data that was modeled after the Oracle EBS R12.2 cost flows with items categories, cost groups, burden schedules, and transaction triggers.
- Configuration workbook: A template mapping tier to Oracle EBS and Oracle Cloud ERP modules, such as SLA derivation rules, cost element definitions and stakeholder-tunable parameters, such as volatility thresholds, dwell buffers and priority weights.

These elements were accepted with the aim of supporting scholarly reproduction, stakeholder participation, and audit preparedness. The roadmap assists in both academia reference and practice implementation of ERP platforms.

9. Conclusion

The operational responsive inventory costing necessitates valuation techniques that able to adjust to changing conditions of supply chains. The Adaptive hybrid indexing frameworks combine operational signals, tier logic, and ERP-oriented costing mechanisms to offer a seamless method of inventory valuation when faced with the volatile demand and service constraints. Simulation findings reveal that the framework ensures cost differentiation and enhances visibility of margins as well as operational transparency. The method uses signal-driven tier assignments and buffers to support costing logic which is not disruptive and does not necessitate any movement of physical inventory or disruptive system updates. The framework also allows analytical understanding using the tier stability analysis and margin impact analysis. On the whole, the offered solution offers a scalable route to the combination of operational intelligence and the enterprise inventory costing systems.

9.1. Limitations and Future Work

The logic of adaptive tiering which will be validated by simulation using ERP. Although the algorithm is deploy ability, it will be necessary to customize the system to do all the work of tier reassignment, costing, and approval processes fully automated. Future work may explore the cross-module orchestration, real-time signal ingestion through REST APIs, and the connection with the Oracle Cloud ERP or S/4HANA environment.

References

- [1] K. Murugandi and R. Seetharaman, "Analysing the Role of Inventory and Warehouse Management in Supply Chain Agility : Insights from Retail and Manufacturing Industries," *Int. J. Curr. Eng. Technol.*, vol. 12, no. 6, pp. 583–590, 2022.
- [2] C. Benzaid *et al.*, "Enhancing Supply Chain Resilience Analytics Through Unified Serialization Lineage and Routing Variability Modeling in a Medallion-Architecture Lakehouse," 2025.
- [3] S. Satyanarayana, S. Kilaru, and K. Venkatrao, "An Integrated Deep Learning and Reinforcement Learning Framework for Profit Maximization in Perishable Food Supply Chains," in *Proceedings of the 1st Engineering Data Analytics and Management Conference (EAMCON 2025)*, Springer Nature, 2025, pp. 156–171. doi: 10.2991/978-94-6463-978-0_15.
- [4] S. Raveendran, U. B. Yalamanchi, and N. Raveendran, "Method, apparatus, and computer-readable medium for dynamic binding of tasks in a data exchange," US Patent 11,132,221, 2021
- [5] P. R. Marapatla, "Digital Innovation In Nonprofit Brand Transformation: A Technology-First Approach," *J. Int. Cris. RISK Commun. Res.*, vol. 8, 2025.
- [6] S. Singamsetty, "AI-Based Data Governance: Empowering Trust and Compliance in Complex Data Ecosystems," *Int. J. Comput. Math. Ideas*, vol. 13, no. 03, pp. 1007–1017, 2021, doi: 10.70153/IJCM/2021.13301.
- [7] A. Parupalli and H. Kali, "Leveraging ML for Business Forecasting in ERP-Enabled E-commerce

- Environments,” *ESP J. Eng. Technol. Adv.*, vol. 4, no. 3, pp. 189–199, 2024, doi: 10.56472/25832646/JETA-V4I3P120.
- [8] A. Irajy *et al.*, “Risk-Based Control Prioritization in Multi-Plant ERP Templates: Balancing SOX Compliance Requirements with ITAR Export Restrictions in Process Manufacturing Sectors,” 2025.
- [9] A. B. Chatterjee, “Designing Zero-Downtime, Cloud-Native Transaction Processing Architectures for 24×7 Global Payment Networks,” *Int. J. Emerg. Trends Comput. Sci. Inf. Technol.*, vol. 7, no. 1, pp. 137–145, Feb, 2026, doi: 10.63282/3050-9246.IJETCSIT-V7I1P120.
- [10] K. S. BuchiReddy, L. S. Andra, B. Ryan, and C. M. Penugonda, “Dynamic Inventory Optimization and Cost Reduction Using Motif Knowledge Heterogeneous Dollmaker Graph Attention Network for Global Supply Chain Efficiency,” *Research Square*. Feb. 19, 2026. doi: 10.21203/rs.3.rs-8496455/v1.
- [11] S. Phalke, Y. D. Athave, and B. N. Ilag, “A Multi-Layered Approach to IT Infrastructure Governance and Compliance- Security, Hardening, and Audit Readiness V3,” *Int. J. Comput. Appl.*, vol. 187, no. 12, pp. 29–33, Jun. 2025, doi: 10.5120/ijca2025925133.
- [12] J. W. Sajja and A. Nerella, “Enterprise Finance Reimagined: Harnessing ERP and Data Innovation for Next-Generation Value Creation,” *Comput. Fraud Secur.*, vol. 2024, no. 4, pp. 17–26, Apr. 2024, doi: 10.52710/cfs.743.
- [13] J. W. Sajja, G. B. Komarina, and N. K. R. Choppa, “The Convergence of Financial Efficiency and Sustainability in Enterprise Cloud Management,” *J. Comput. Sci. Technol. Stud.*, vol. 7, no. 4, pp. 964–992, May 2025, doi: 10.32996/jcsts.2025.7.4.110.
- [14] J. Lin, “The Cost of Complying With US GAAP and Cross-Listed Firms’ Valuations,” *J. Appl. Bus. Econ.*, vol. 27, no. 5, pp. 138–157, 2025.
- [15] S. Singamsetty, “AI-Enabled Data Stewardship Real-Time Alignment of Privacy and Storage Policies Across Global Systems using Deep CNN-RNN Techniques,” in *2025 5th Asian Conference on Innovation in Technology (ASIANCON)*, IEEE, Aug. 2025, pp. 1–6. doi: 10.1109/ASIANCON66527.2025.11281010.
- [16] A. Syed, “Securing IoT-Driven Supply Chains,” in *Supply Chain Software Security*, Berkeley, CA, CA: Apress, 2024, pp. 289–342. doi: 10.1007/979-8-8688-0799-2_7.
- [17] I. Pudaël, R. U. Latief, and S. Burhanuddin, “Study on the implementation of the combination of 2 BIM and ERP systems to improve project cost estimation accuracy at the auction stage,” in *IOP Conference Series: Earth and Environmental Science*, 2022, p. 12013.
- [18] P. Borges, M. do C. Alves, and R. Silva, “The activity-based costing system applied in higher education institutions: a systematic review and mapping of the literature,” *Businesses*, vol. 4, no. 1, pp. 18–38, 2024.
- [19] B. Jayamaha, B. Perera, K. D. M. Gimhani, and M. N. N. Rodrigo, “Adaptability of enterprise resource planning (ERP) systems for cost management of building construction projects in Sri Lanka,” *Constr. Innov.*, vol. 24, no. 5, pp. 1255–1279, Aug. 2024, doi: 10.1108/CI-05-2022-0108.
- [20] R. N. Damayanti, M. Saputra, and T. F. Kusumasari, “Customization of Cost Allocation Monitoring Report for Improving Activity-Based Costing Process,” *JOIV Int. J. Informatics Vis.*, vol. 6, no. 1–2, pp. 230–236, 2022.
- [21] I. U. Yuzgenc and E. Aydemir, “Sustainable ERP Systems: A Green Perspective,” pp. 374–378, 2023.
- [22] X. Qu, L. Liu, and W. Huang, “Data-driven inventory management for new products: An adjusted Dyna-Q approach with transfer learning,” in *2025 IEEE 21st International Conference on Automation Science and Engineering (CASE)*, IEEE, Aug. 2025, pp. 1031–1037. doi: 10.1109/CASE58245.2025.11164090.
- [23] A. Chakraborty, “Real-Time ERP-Integrated Adaptive Decision Intelligence Architecture for Enterprise-Scale Supply Chains,” in *2025 International Conference on Intelligent Innovations in Engineering and Technology (ICIET)*, IEEE, Dec. 2025, pp. 1–6. doi: 10.1109/ICIET65921.2025.11378779.
- [24] S. Singamsetty and S. Singamsetty, “Hy-Search: A Hybrid Retrieval-Augmented Framework for Factual and Context-Aware Enterprise Knowledge Discovery,” 2025, pp. 431–439. doi: 10.2991/978-94-6463-978-0_37.
- [25] S. A. Pushkala, “Financial Fraud Identification Using Graph Neural Network And LSTM With Autoencoder-Based Data Refinement,” *J. Int. Cris. RISK Commun. Res.*, vol. 9, no. 1, pp. 198–214, 2026.
- [26] G. B. Komarina and J. W. Sajja, “Design Thinking as a Strategic Driver of SAP Innovation: From Concept to Implementation,” *Tech. Int. J. Eng. Res.*, vol. 12, no. 5, 2025, doi: 10.56975/tijer.v12i5.158221.