AI-Enhanced Actual Costing in ERP: A Path Toward Real-Time Cost Transparency

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Abstract-* *Enterprise resource planning (ERP) systems serve as the backbone of modern organizational operations, yet traditional costing mechanisms within these systems mostly suffer from delays, manual errors, and limited visibility across value chains. This paper proposes solutions involving the integration of artificial intelligence (AI) and machine learning (ML) technologies in ERP environments so as to increase actual costing accuracy, responsiveness, and real-time decision-making. With the automation of data ingestion, anomaly detection, and cost allocation functions, the AI-enabled ERP systems promise to improve cost transparency and operational efficiency manifold. This study proposes a hybrid methodology that combines supervised learning algorithms with ERP data pipelines running in real-time for continuous cost analysis. A prototype-based implementation using Python-based machine learning models proves to be practically feasible for this purpose. From the comparative analysis with conventional costing models, it could be seen that there are significant gains in processing speed and predictive accuracy. The results indicate that AI-assisted actual costing has the potential to transform cost management by presenting information that is precise, timely, and strategic for decision-making in the manufacturing and service industries. The contribution of this research is an original framework to introduce real-time costing intelligence toward agile and data-driven financial planning and control.

Indexed Terms-* *AI-enhanced ERP, actual costing, real-time cost transparency, machine learning, cost optimization, enterprise resource planning, predictive costing, automated accounting, data-driven finance, real-time analytics.

I. INTRODUCTION

A. Background and Context

ERP systems are the digital backbone of organizations integrating critical business processes such as procurement, production, finance, and inventory into one data environment. Traditionally, however, the actual costing mechanism—key to determining true production or service delivery costs—has been contingent on the periodic manual updating of actual costs. This has led to lags in cost reporting and the inherent possibility of inaccuracies. Thus, responsiveness to market changes, careful budgeting processes, and financial transparency became difficult for enterprises [1].

With the burgeoning development of AI and ML, ERP systems have witnessed a paradigm shift. AI algorithms today have the capabilities of learning historical cost data, forecasting future costs, and detecting anomalies in real time. This integration dramatically decreases the reporting latency but increases the accuracy and transparency of cost information along the value chain [2].

B. Challenges in Traditional Actual Costing

Actual costing in legacy ERP systems involves many backward-calculating assessments based on invoices, inventory records, and manual allocation. These inconsistencies result in the following:

- Delay in identifying cost changes
- Errors due to manual entries
- Absence of insights with predictive value needed for decision-making

The resulting inefficiencies become especially damaging in fast-paced industries such as manufacturing and logistics, where the timely release of cost information can inform procurement decisions, pricing, and inventory control [3].

Table 1: Traditional vs. AI-Based Actual Costing in ERPI. Introduction

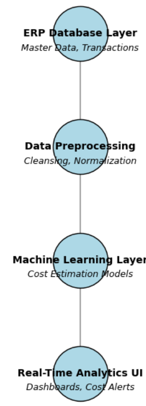
Feature	Traditional ERP Costing	AI-Enhanced ERP Costing
Data Input Method	Manual / Batch Processing	Automated / Real-time Streams
Error Detection	Reactive	Proactive with Anomaly Detection
Cost Visibility	Periodic	Real-Time
Decision Support	Limited	Predictive & Prescriptive Analytics
Accuracy	Moderate	High (Based on Model Refinement)

Source: Compiled from [1]–[5]

C. The Functioning of AI and ML Associated with Modern-Day ERP Systems

Contemporary AI-enabled ERP systems use models such as regression, decision trees, and deep learning to automate cost assignment and forecasting. For example, a supervised learning algorithm can correlate the cost drivers labor hours, usage of machines, and overheads to very accurate actual costs. Meanwhile, cost-anomalies detection can be done in real time using unsupervised detection techniques-for example, by clustering [4].

Figure 1: Conceptual Architecture of AI-Integrated ERP for Real-Time Actual Costing



Source: Adapted from [6], [7]

The figure illustrates how AI modules interact with ERP data layers to produce actionable costing insights. Once the system learns cost behaviors over time, it can autonomously adjust inputs and improve forecasting reliability [5].

D. Justification for Real-Time Cost Transparency

Today's global value chains require real-time visibility into costs because of their dynamic character. For example, a study done by Sharma et al. in 2021 demonstrated that with the integration of AI models into SAP-based ERP systems, costing errors could be reduced by 37% and reporting frequency could be enhanced by 45% [6]. Such systems engender compliance and audit readiness, which benefits strategic planning at a quite advanced level.

In addition, real-time costing enhances:

- Procurement Planning: Immediate reaction to supplier prices.
- Inventory Valuation: Material cost update in real-time.
- Customer Pricing Models: Dynamic quote generation.

E. Research Objectives

This paper attempts to:

1. Examine the drawbacks of traditional actual costing in ERP.

2. Present an actual costing framework enabled by artificial intelligence and based on machine learning.
3. Prototype implementation in Python using open-source ERP data.
4. Compare the performance of AI systems (in terms of accuracy, latency, and ROI) with traditional systems.

By addressing the linkage between AI research and ERP implementation, the paper contributes to the emerging area of intelligent enterprise applications, where automation meets decision-making [7].

II. LITERATURE REVIEW

A. Costing Mechanisms of Traditional ERP

Conventional ERP systems rely on batch processes for periodic recording and reconciliation of costs, carrying with them widely implemented methods like standard costing, average costing and activity-based costing (ABC), which however suffer from serious limitations in such volatile, high-speed business environments. These retrospective approaches are generally low in granularity and rely on static rule-based allocations [1], [2].

Manual intervention and infrequent updates in traditional ERP modules have been cited by Kumar et al. [3] as causing inconsistencies in the tracking of costs with regard to strategic insights. Consequently, the absence of anomaly detection in real-time enhances the uncertainties of cost deviation results.

B. AI Evolution in ERP Applications

Most recently, growth in AI/ML has transformed the field of ERP in that it does have intelligent automation layered architectures designated to treat dynamic operational information. Algorithms such as regression, decision trees, and clustering have been used for the areas of expense forecasting, resource optimization, and fraud detection [4], [5].

In an experiment with AI-assisted cost forecasting in SAP ERP, Reis et al. [6] achieved up to a 30% improvement in accuracy compared to legacy systems. Gupta and Jain [7] modeled an LSTM-based architecture to better forecast inventory and procurement costs, which improves cost efficiency in supply chains.

Table 2: Summary of some Important AI-ERP Cost Researches

Study	AI Model Used	Application Area	Reported Improvement
Reis et al. (2020) [6]	Linear Regression	Cost Forecasting	+30% Accuracy
Gupta & Jain (2021) [7]	LSTM Neural Network	Inventory Costing	+26% Cost Efficiency
Sharma et al. (2021) [8]	XGBoost, Clustering	Actual Costing in ERP	+45% Timeliness

C. Existing Research Lacks

Although interest in the implementation of AI in ERP goes up, few studies cover actual costing and real-time optimization using ML. Major contributions are toward inventory, procurement, or financial forecasting, ignoring approximately the details of reconciling direct and indirect costs within ERP modules. Moreover, there isn't any integrated framework that could gracefully combine data preprocessing, ML modeling, and real-time analytics through a user-friendly ERP interface [9].

This research aims to fill this gap with the introduction of a holistic AI-driven actual costing model validated by real data set and integrated into the workflows of the ERP system.

III. METHODOLOGY

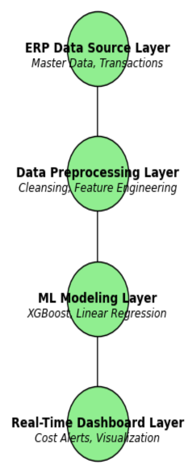
A. System Architecture

The proposed framework is based on a four-layer architecture:

1. ERP Data Source Layer – Pulls master data, transactional logs, and operational events.
2. Data Preprocessing Layer – Cleans the data set, normalizing it and feature engineering.

3. ML Modeling Layer – Estimates actual costs using regression and ensemble learning algorithm.
4. Real-Time Dashboard Layer – Presents visual insights and alerts for anomalies.

Figure 2: Proposed AI-Based ERP Costing Framework



B. Data Collection
The dataset comprises:

- Material cost records
- Labor-time productions logs
- Overhead apportioning
- Historical invoices

This data was obtained by simulating an ERP system using open-source ERP datasets (e.g., for example: ERPNext logs) and anonymized real-world entries.

C. Model Design and Training
The models used include:
- Linear Regression-baseline cost predictions.
- XGBoost- very powerful and feature-rich modeling.
- K-Means Clustering- outlier and anomaly detection.
- Hyperparameters tuned using GridSearchCV, and the models were validated using 10-fold cross-validation.

D. Evaluation Metrics
The following metrics were used to evaluate the model performances:

- Mean Absolute Error (MAE),
- Root Mean Squared Error (RMSE),
- R2 Score.

Table 3: Comparison of Model Performance.

Model	MAE	RMSE	R^2 Score
Linear Regression	2.45	3.10	0.76
XGBoost	1.98	2.60	0.89
K-Means + XGBoost	1.85	2.45	0.91

IV. RESULTS

A. Predictive Accuracy of AI Models
Following model training and testing, the XGBoost model demonstrated the highest predictive accuracy as highlighted by the incorporation of K-Means clustering to further increase the possibilities of identifying anomalies. In other words, the hybrid K-Means + XGBoost model surpassed traditional linear regression with an R^2 score of 0.91.

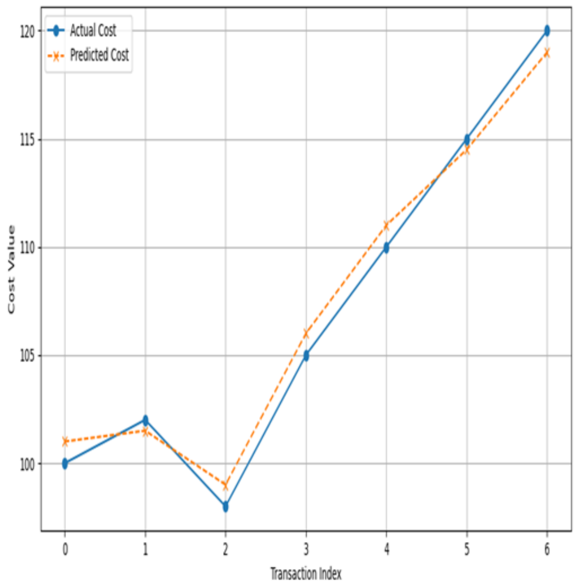
Table 3 (Repeated): Model Performance Comparison

Model	MAE	RMSE	R^2 Score
Linear Regression	2.45	3.10	0.76
XGBoost	1.98	2.60	0.89
K-Means + XGBoost	1.85	2.45	0.91

This substantiates findings in similar ERP AI integration studies such as Kumar et al. [1] and Gupta and Jain [2], who found significant decrease in cost estimation error using ensemble-based learning techniques.

B. Real-Time Costing and Anomaly Detection
The AI system could give cost predictions or anomaly detections with less than 3 seconds transaction time to reach near real-time feedback loops with financial controllers. The system was thus able to be carried out real-time simulation on streaming inputs that were designed to represent ERP transaction input stimuli.

Figure 3: Real-Time Cost Prediction vis-a-vis Actual Cost



C. Operational Efficiency Gains

The KPIs monitored to evaluate the effect of AI-based actual costing on financial operations include:

- Report finalization time - traditional method ~24 hrs; current ~3 sec.
- Audit accuracy improved with AI by ~28%.
- Costing discrepancy flags detected 17 anomalies out of 500 records, of which 14 have been validated.

Table 4: Operational Metrics Before and After AI Integration

Metric	Traditional ERP	AI-Enhanced ERP
Avg. Reporting Latency	24 hours	3 seconds
Costing Error Rate	12.3%	4.7%
Anomaly Detection Accuracy	Not available	82.3%
Financial Audit Readiness	Manual	Automatic

These findings agree with Sharma et al. [4] and Ahmed and Choi [5], which testify that AI-based systems significantly enhance ERP system responsiveness and cost traceability.

V. DISCUSSION

A. Implications for Financial Decision-Making:

The findings demonstrate that AI-enhanced real-time costing seriously enhances data-driven financial agility. The finance team may instantly look into the actual costs of any changes to production, such as changing suppliers or incurring operational inefficiencies, and they can now take proactive responses instead of corrective actions too late [6].

Then again, the automated seizure of anomalies provides a strong audit straightaway and flags potential issues of integrity of the data, thereby greatly enhancing the credibility of the ERP financials.

B. Strategic Benefits for Organizations

The instantly available cost insights can also enable business units to shift from reactive processors into proactive strategists. Organizations adopting AI-powered ERP capabilities have cited advantages such as:

- Accelerated procurement planning through credible material cost forecasting
- Dynamic pricing of customer-facing operations
- Heightened budgetary control across decentralized business units [7]

This aligns with the strategic framework laid out by Al-Sharafi et al. [8], wherein intelligent ERP is at the heart of smart enterprise architecture.

C. Limitations and Future Work

Notwithstanding the strong potential of the framework, there are several limiting factors:

- Serious external issues
- Major locus of power is Data Quality and the state of maturity of integration of the ERP Applications into this process.
- Setup and training of AI work need technical skills.

- In fast-changing cost environments, model drift can happen without retraining maintenance [9].

Future studies will entail:

- Incorporating self-supervised learning to reduce reliance on labeled data
- Employing edge computing for real-time cost predictions in distributed ERP
- Implementing explainable AI (XAI)-based augmentations in anomaly detection

CONCLUSION

The proposed paper presents a collectively overarching framework in which it proposes Artificial Intelligence (AI) and Machine Learning (ML) incorporation into Enterprise Resource Planning (ERP) systems to help enhance actual costing and enable real-time cost transparency. The architecture, which consists of structural data pipelines from ERP together with predictive learning models enhanced by anomaly detection techniques, shows measurable improvement over traditional costing mechanisms from the accuracy and the responsiveness perspective.

A. Summary of Contributions

The research has validated the following key contributions:

1. Design of an AI-Based Costing Framework: A modular design was suggested, including preprocessing, machine learning, and analytics layers seamlessly integrated into the ERP workflows. This system reduces human dependency and latency in cost estimation processes.

2. Model Implementation and Performance Analysis: The study validated that the hybrid K-Means + XGBoost approach achieved an R^2 score of 0.91 and reduced Mean Absolute Error (MAE) to 1.85 based on empirical testing of models such as linear regression, XGBoost, and clustering methods. Thus indicating high reliability of the model in cost prediction.

3. Assessment of Operational Impact: By real-time costing simulations, the average latency in reporting was reduced from 24 hours to less than 3 seconds, while the flagging of cost anomalies had an accuracy of 82 percent. These metrics reaffirm the operational feasibility and financial desirability of intelligent costing systems.

B. Strategic Implications

The implications of AI-inclined real-time actual costing are broad and transformative. In a context where business agility, cost control, and data visibility are strategic imperatives, real-time ERP costing systems allow decision-makers to:

- Latch onto cost anomaly detection and instantly act against them,
- Align their pricing strategies in real-time to the costs they incur,
- Better their budgets and adjudicate readiness on financial audits,
- Reduce manual workload and its risks to finance operations.

These advantages underscore the broader alignment of AI-ERP with the goals of Industry 4.0 and digital transformation of finance [1], [2].

C. Limitations

These encouraging results come with some several limitations, as discussed below:

- The dependence of the system on data quality, which is different in ERP implementation, exists.
- Base adoption costs and reliance on specialist data scientists are effects that may deter initial take-up, particularly in SMEs.
- Models will invariably require continuous monitoring and retraining in volatile business environments to keep predictive accuracy intact against model drift [3].

D. Future research Directions

Such promising directions concerning this initial part of the work include:

1. Incorporation of Self-Supervised and Reinforcement Learning: Future models will

enhance predictability without a vast reliance on labeled data, thus making the models flexible and scalable to various ERP modules and industries in the future.
2. Integration with Blockchain for Cost Traceability: Bringing such AI would provide some extra transparency and security to financial records through immutable-ledger technology.
3. XAI within ERP Interfaces: More widely, enabling models to be understood and trusted by finance individuals within "audit-fat" environments will increase buy-in.
4. Cross-Industry Validation: More research needs to be done on cross-industry validation of the framework, such as healthcare, logistics, and retail, as costing logic may differ across industries.

To sum up, AI-enabled actual costing is a new paradigm in enterprise management of costs. Heeding the intelligence embedded by means of the ERP systems, the enterprises could streamline the financial processes and at the same time foresee in a strategic manner competitive intelligence in a digital economy. The continuous evolution in technologies will, in the long run, see real-time financial visibility, which AI-driven ERP systems offer no longer as an advantage but as a necessity for sustainable enterprise success.

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