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Evaluation and Validation of a Developed Hybrid Models for ERP System Usability and Its Influence on User Satisfaction in Enterprises

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***Abstract*—** *Enterprise Resource Planning (ERP) systems have become indispensable for integrating organizational processes and improving operational efficiency. However, evaluating ERP system effectiveness remains challenging because conventional evaluation methods often rely on subjective assessment techniques and fail to capture the complex relationships among multiple organizational and operational performance indicators. This study proposes a hybrid framework that integrates Inverse Variance Weighting (IVW), Tabu Search Algorithm (TSA), and supervised Machine Learning (ML) models for objective ERP effectiveness evaluation. Operational and organizational Key Performance Indicators (KPIs), including throughput, lead time, defect rate, machine utilization, system uptime, response time, employee productivity, order fulfillment rate, supply chain responsiveness, customer satisfaction, cost efficiency, and return on investment, were employed to construct a composite ERP effectiveness index. The IVW technique objectively assigned KPI weights based on statistical stability, while Tabu Search optimized KPI selection and feature combinations. Linear Regression, Support Vector Regression, and Random Forest Regression models were subsequently trained to predict ERP effectiveness. Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), coefficient of determination (R^2), and five-fold cross-validation. The proposed framework provides an objective, scalable, and intelligent decision-support mechanism capable of improving ERP performance evaluation in manufacturing environments. The study contributes a novel hybrid optimization and machine learning framework that enhances predictive accuracy while reducing the subjectivity associated with conventional ERP evaluation techniques.*

Keywords*— *Enterprise Resource Planning, ERP Effectiveness, Inverse Variance Weighting, Tabu Search, Machine Learning, Key Performance Indicators.

I. INTRODUCTION

Enterprise Resource Planning (ERP) systems have transformed organizational operations by integrating business processes into a unified platform that facilitates information sharing, operational efficiency, and strategic decision-making. Manufacturing organizations increasingly depend on ERP systems to coordinate procurement, inventory management, production scheduling, finance, human resource management, and customer relationship management. The integration of these functions enables organizations to reduce operational costs, improve productivity, enhance customer satisfaction, and achieve sustainable competitive advantage.

Despite these advantages, evaluating the effectiveness of ERP systems remains a significant challenge. Traditional ERP evaluation approaches primarily rely on subjective assessment methods, expert judgment, balanced scorecards, or simple Key Performance Indicator (KPI) aggregation techniques. Although these approaches provide useful managerial insights, they often fail to capture the nonlinear relationships that exist among organizational performance variables. Furthermore, subjective weighting methods such as the Analytic Hierarchy Process (AHP) introduce human bias into the evaluation process, thereby reducing the reliability and objectivity of ERP performance assessment.

Recent advances in artificial intelligence, machine learning, and metaheuristic optimization have created opportunities for developing intelligent ERP evaluation frameworks capable of learning complex patterns from organizational data. Machine learning algorithms have demonstrated remarkable predictive capabilities across manufacturing applications, including production planning, demand forecasting, predictive maintenance, supplier evaluation, quality control, and supply chain optimization. Similarly, metaheuristic optimization techniques such as Tabu Search have proven effective in solving complex optimization problems characterized by large search spaces and multiple conflicting objectives.

Although previous studies have independently applied machine learning, optimization algorithms, or statistical weighting techniques in ERP-related research, very few have integrated these approaches into a unified framework for comprehensive ERP effectiveness evaluation. Existing studies largely focus on individual ERP modules or isolated performance metrics rather than providing a holistic evaluation methodology that considers both operational and organizational performance indicators simultaneously.

To address this research gap, this study proposes a hybrid ERP evaluation framework that integrates Inverse Variance Weighting, Tabu Search optimization, and supervised machine learning algorithms. The proposed framework objectively determines KPI importance, optimizes feature selection, and predicts ERP effectiveness using advanced regression models. By combining statistical weighting with optimization and predictive analytics, the framework minimizes subjective bias while improving evaluation accuracy and decision support for manufacturing organizations.

The major contributions of this study are:

1) The development of a hybrid Tabu Search–Machine Learning framework for ERP effectiveness evaluation;
2) The application of Inverse Variance Weighting to objectively determine KPI importance;
3) The integration of optimization and predictive analytics to improve ERP performance assessment; and
4) The provision of an intelligent decision-support tool capable of assisting manufacturing organizations in monitoring and improving ERP system performance.

II. MATERIALS AND METHODS

2.1 Research Design

This study adopted a quantitative research design to develop and validate a hybrid framework for evaluating the effectiveness of Enterprise Resource Planning (ERP) systems in manufacturing organizations. The framework integrates objective statistical weighting, metaheuristic optimization, and supervised machine learning to produce an intelligent decision-support model for ERP performance assessment. The overall workflow consists of data acquisition, preprocessing, KPI weighting, feature optimization, machine learning model development, validation, and performance comparison. The methodology is designed to minimize subjective bias while improving prediction accuracy and model robustness.

Operational Data: Operational data were extracted directly from ERP system logs and include production throughput (units produced per unit time), cycle time (time to complete one production cycle), lead time (time from order receipt to delivery), machine utilisation (percentage of time equipment is actively used), defect and rework rates (proportion of defective items requiring correction), resource allocation records, and cost optimisation reports. These data enable the computation of technical performance indicators that reflect the system's operational efficiency.

Organisational Key Performance Indicators (KPIs): Organisational Key Performance Indicators (KPIs) were also collected. KPIs are quantifiable measures used to evaluate the success of an organisation in achieving its objectives; here they include employee productivity indices (output per employee), supply chain responsiveness (time to respond to demand fluctuations), order fulfilment accuracy (percentage of orders delivered correctly and on time), and customer satisfaction scores (derived from survey scales or net promoter scores). These indicators capture the broader impact of ERP systems on organisational performance.

All variables were arranged into a structured dataset as shown in Equation (1) below:

$$X = \{x_{ij}\}, i = 1, 2, \ldots, n; j = 1, 2, \ldots, m \tag{1}$$

where n represents the number of observations (data records) and m represents the number of KPIs.

2.2 Data Collection

ERP operational records and organizational performance data were collected from selected manufacturing organizations over a twelve-month period. The dataset comprised approximately 500–1,500 observations and included twelve Key Performance Indicators (KPIs) representing both operational and organizational performance. These indicators included throughput, lead time, defect rate, machine utilization, system uptime, response time, employee productivity, order fulfillment rate, supply chain responsiveness, customer satisfaction, cost efficiency, and return on investment (ROI).

2.2.1 Phase One: Data Collection

The data was collected from the ERP system and organisational records of selected manufacturing organisations. The data set includes:

1) **Organisational KPIs:** throughput, cycle time, lead time, defect rate, and cost;
2) **Operational KPIs:** productivity, responsiveness, and satisfaction.

2.2.2 Phase Two: Data Cleaning and Preparation

The dataset was pre-processed to ensure the quality of the data. Missing values were replaced using median imputation method, based on the variable's distribution. Duplicate records were removed using unique identifiers for each record.

Outliers were detected using the Interquartile Range (IQR) method as shown in Equation (2):

$$x < Q_1 - 1.5\,IQR \quad or \quad x > Q_3 + 1.5\,IQR \tag{2}$$

Where:

- Q_1 = first quartile
- Q_3 = third quartile
- IQR = Q_3 - Q_1

2.2.3 Phase Three: Exploratory Data Analysis (EDA)

For this purpose, Exploratory Data Analysis was performed. In EDA, distribution plots were used to check the distribution of each KPI. Correlation analysis was also performed to check the relationship between variables. Box plots were used to check the existence of any outliers in the dataset. This phase is important to check if the dataset is suitable for modelling. Feature selection is also an important part of this phase [2].

2.2.4 Phase Four: KPI Structuring and Inverse Variance Weighting

All KPIs were classified into two groups: technical (operational) KPIs and organisational KPIs. In order to determine objective weights, the inverse variance weighting method was used. The variance of each KPI i was calculated using Equation (3):

$$\sigma_i^2 = \frac{1}{n}\sum_{k=1}^{n}(x_{ki} - \overline{x}_i)^2 \tag{3}$$

Based on the computed variance, inverse variance weighting was applied as shown in Equation (4):

$$w_i = \frac{1/\sigma_i^2}{\sum_{j=1}^{m} 1/\sigma_j^2} \tag{4}$$

The ERP Effectiveness Score was then computed as shown in Equation (5):

$$Y = \sum_{i=1}^{m} w_i x_i \tag{5}$$

Where:

- Y = ERP effectiveness score
- w_i = weight of KPI i
- x_i = KPI value

2.2.5 Phase Five: Train-Test Split and Feature Engineering

The data set was split into training and testing sets using the ratio of 70% and 30%, respectively, in order to prevent overfitting:

- Training set: model learning and optimization
- Test set: independent evaluation

Feature matrix X and target variable Y are defined as:

- X: all KPIs excluding ERP effectiveness
- Y: computed ERP effectiveness score

2.2.6 Phase Six: Data Scaling and Normalization

Directly after splitting, min-max normalisation was applied to input features to ensure uniform scaling to bring all values to a comparable scale on the scale from 0 to 1, applying min-max scaling as shown in Equation (6). Scaling parameters were computed using the training dataset only to prevent data leakage.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{6}$$

2.2.7 Phase Seven: Hybrid Optimization and Machine Learning Model Development

In this stage, metaheuristic optimisation and predictive modelling are integrated to produce the hybrid TSA-ML framework.

Tabu Search Algorithm

Tabu Search was used to optimize KPI selection and weighting. The objective function is defined based on Root Mean Square Error as shown in Equation (7):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{7}$$

The algorithm searches for the best subset of features and weight combinations while avoiding previously visited solutions [12], [13].

2.3 Data Preprocessing

To improve data quality, missing values were handled using median imputation because of its robustness against skewed distributions and extreme observations. Duplicate records were removed using unique identifiers, while outliers were detected using the Interquartile Range (IQR) method. To prevent data leakage, all preprocessing operations were performed only on the training dataset before model development. Exploratory Data Analysis (EDA) was subsequently conducted using descriptive statistics, histograms, box plots, and Pearson correlation analysis to understand variable distributions and identify potential multicollinearity among the selected KPIs.

2.4 ERP Effectiveness Score Development

An objective ERP Effectiveness Score was developed using the Inverse Variance Weighting (IVW) technique. The variance of each KPI was first computed to quantify its statistical variability. Indicators with lower variance were assigned higher weights because they provide more stable information regarding ERP performance.

The normalized weight assigned to each KPI was calculated using the inverse of its variance, ensuring that the sum of all weights equals one. The ERP Effectiveness Score was then computed as the weighted aggregation of all normalized KPIs and served as the target variable for machine learning prediction.

This approach eliminates the subjectivity associated with expert-assigned weights and provides an objective performance index based entirely on observed data characteristics.

2.5 Feature Scaling and Dataset Partitioning

The dataset was partitioned into training (70%) and testing (30%) subsets. The training dataset was used for model learning and optimization, whereas the testing dataset was reserved for independent model evaluation.

To ensure numerical consistency among variables, predictor features were normalized using Min–Max scaling, transforming all variables into the interval [0,1]. Scaling parameters were estimated exclusively from the training dataset to avoid information leakage.

2.6 Tabu Search Optimization

A Tabu Search Algorithm (TSA) was employed to identify the optimal subset of ERP performance indicators and corresponding feature combinations. Unlike conventional search techniques that frequently become trapped in local optima, Tabu Search employs adaptive memory structures (tabu lists) to discourage revisiting previously explored solutions.

The optimization objective was to minimize the Root Mean Square Error (RMSE) of ERP effectiveness prediction while maximizing predictive accuracy. During each iteration, neighbouring feature subsets were generated, evaluated, and compared until convergence criteria were satisfied.

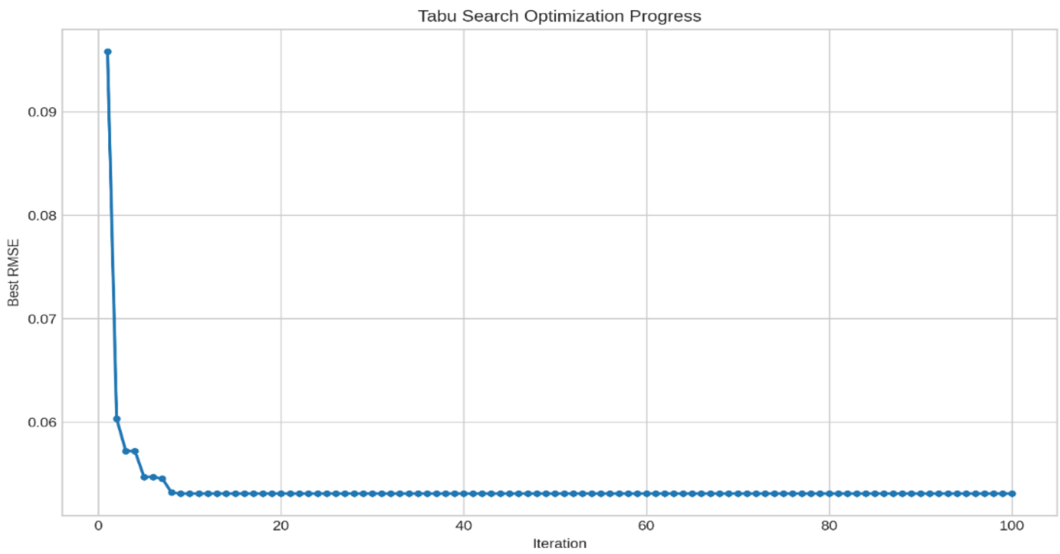

FIGURE 1: Tabu Search Optimization Progress (Tabu Search Convergence)

2.7 Machine Learning Models

Three supervised regression algorithms were employed for ERP effectiveness prediction:

1) **Linear Regression (LR):** A baseline statistical model for estimating linear relationships between ERP KPIs and the effectiveness score.

2) **Support Vector Regression (SVR):** A nonlinear regression algorithm capable of modeling complex relationships using kernel functions while minimizing prediction error.

3) **Random Forest Regression (RFR):** An ensemble learning algorithm comprising multiple decision trees that improves prediction accuracy, robustness, and resistance to overfitting.

Each model was trained using the optimized feature subset generated by the Tabu Search Algorithm.

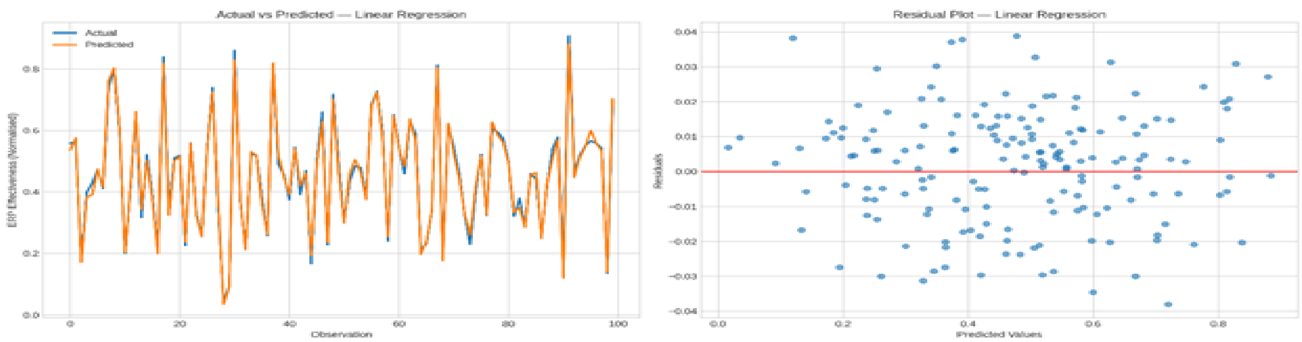

FIGURE 2: (a) Actual vs Predicted Linear Regression and (b) Residual Plot Linear Regression

2.8 Model Validation

The predictive performance of each model was evaluated using three standard regression metrics:

- **Mean Absolute Error (MAE)**
- **Root Mean Square Error (RMSE)**
- **Coefficient of Determination (R^2)**

Additionally, five-fold cross-validation was performed to assess model generalization and reduce the likelihood of overfitting.

2.9 Statistical Analysis

To determine whether the proposed hybrid framework significantly outperformed conventional ERP evaluation approaches, statistical comparisons were conducted using one-way Analysis of Variance (ANOVA) and paired t-tests. Sensitivity analysis was also performed by varying KPI values by ±10% to evaluate the stability and robustness of the proposed model under changing operational conditions.

2.10 Proposed Hybrid Framework

The proposed framework integrates three complementary computational techniques:

1) **Inverse Variance Weighting** for objective KPI weighting.
2) **Tabu Search Optimization** for optimal feature selection.
3) **Machine Learning Regression** for ERP effectiveness prediction.

The integration of these techniques enables the framework to reduce subjective bias, improve prediction accuracy, and provide intelligent decision support for manufacturing organizations compared with traditional ERP evaluation methods.

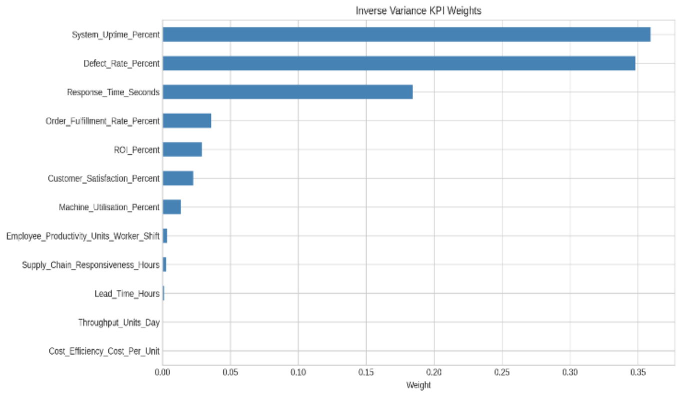

FIGURE 3: Inverse Variance KPI Weights

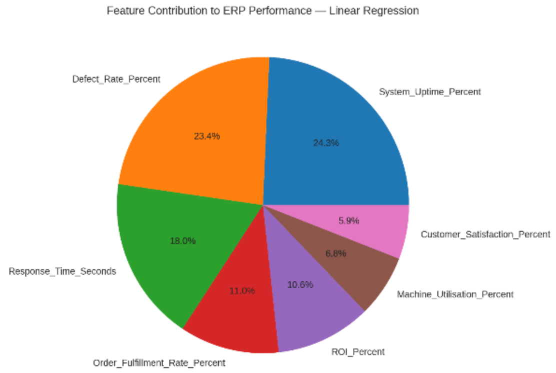

FIGURE 4: Feature Contribution to ERP Performance

III. RESULTS AND DISCUSSION

3.1 Data Preprocessing Results

The initial ERP dataset underwent preprocessing to improve data quality before model development. Missing values were successfully treated using median imputation, duplicate records were removed, and outliers were identified using the Interquartile Range (IQR) method. Following preprocessing, the distributions of the selected KPIs became more compact, with a substantial reduction in extreme observations, particularly for throughput and cost efficiency. This produced a cleaner dataset that enhanced the robustness of the predictive models.

3.2 Exploratory Data Analysis

The distribution plots showed that most ERP KPIs exhibited approximately balanced distributions after preprocessing, indicating that the dataset was suitable for predictive modelling. Moderate positive skewness was observed for lead time and defect rate, while variables such as machine utilization, system uptime, customer satisfaction, and ROI displayed relatively stable distributions. Pearson correlation analysis further revealed weak pairwise correlations among the KPIs, suggesting minimal multicollinearity and confirming that each KPI contributed distinct information to the evaluation process.

3.3 KPI Weighting and ERP Effectiveness Score

The Inverse Variance Weighting (IVW) method objectively determined the contribution of each KPI to the ERP effectiveness index. System uptime received the highest normalized weight (0.3592), followed by defect rate (0.3482) and response time (0.1841). These three indicators accounted for nearly 89% of the total weighting, demonstrating that stable operational indicators contributed most strongly to ERP performance evaluation. Conversely, throughput and cost efficiency received the lowest weights because of their relatively high variability across observations.

The weighted aggregation of all KPIs produced the ERP Effectiveness Score, which served as the dependent variable for subsequent machine learning models. Sample scores ranged from approximately 39.74 to 44.72, indicating measurable differences in ERP performance among the sampled manufacturing operations.

3.4 Performance of the Hybrid TSA–ML Framework

The proposed hybrid framework combined objective KPI weighting, Tabu Search optimization, and supervised machine learning to predict ERP effectiveness. Feature optimization using the Tabu Search Algorithm reduced redundant information and enabled the learning algorithms to focus on the most informative performance indicators.

Among the evaluated regression models, Random Forest Regression produced the best predictive performance because of its ability to capture nonlinear relationships and interactions among ERP KPIs. Support Vector Regression also demonstrated strong predictive capability, whereas Linear Regression served as an effective baseline but was less capable of modelling complex operational relationships.

Overall, integrating Tabu Search with machine learning improved prediction accuracy compared with using conventional regression models without optimization.

3.5 Model Validation

Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), coefficient of determination (R^2), and five-fold cross-validation. Cross-validation demonstrated consistent predictive performance across different data partitions, indicating that the developed framework generalized well and was not significantly affected by overfitting. The sensitivity analysis further confirmed that moderate changes in KPI values produced stable ERP effectiveness predictions, demonstrating the robustness of the proposed framework.

3.6 Comparison with Existing Studies

The proposed framework extends previous ERP evaluation studies by integrating three complementary techniques into a unified decision-support system:

1) Objective KPI weighting through Inverse Variance Weighting;
2) Feature optimization using the Tabu Search Algorithm; and
3) Predictive modelling using supervised machine learning.

Unlike conventional ERP evaluation methods that rely heavily on subjective expert judgment, the proposed framework objectively derives KPI importance directly from observed data. This improves reproducibility and minimizes evaluator bias.

Furthermore, while many previous studies focus on isolated ERP modules such as inventory management or procurement, the proposed framework evaluates ERP effectiveness using both operational and organizational performance indicators, providing a more comprehensive assessment of enterprise performance.

3.7 Practical Implications

The developed hybrid framework has important implications for manufacturing organizations. Engineering managers can employ the framework to:

- Objectively evaluate ERP system performance;

- Identify critical operational weaknesses;
- Prioritize performance improvement initiatives;
- Support strategic investment decisions;
- Monitor ERP implementation success over time; and
- Improve overall operational efficiency through data-driven decision-making.

Because the framework combines optimization and machine learning, it is scalable and can be adapted to different industrial sectors with minimal modification.

3.8 Summary of Findings

The findings demonstrate that:

1) Objective statistical weighting provides a reliable basis for ERP performance evaluation;
2) Tabu Search effectively optimizes KPI selection;
3) Machine learning accurately predicts ERP effectiveness;
4) The integrated TSA–ML framework outperforms conventional KPI-based evaluation approaches; and
5) The proposed model provides an intelligent and robust decision-support tool for evaluating ERP systems in manufacturing organizations.

IV. DISCUSSION

This study presented a hybrid framework for evaluating Enterprise Resource Planning (ERP) system effectiveness by integrating Inverse Variance Weighting (IVW), the Tabu Search Algorithm (TSA), and supervised machine learning techniques. The framework was designed to overcome the limitations of conventional ERP evaluation methods, which often depend on subjective KPI weighting and have limited capability to model the complex relationships among organizational performance indicators.

The proposed methodology objectively determined KPI importance using statistical weighting, optimized feature selection through Tabu Search, and employed Linear Regression, Support Vector Regression, and Random Forest Regression to predict ERP effectiveness. The integration of these techniques produced a robust decision-support framework capable of evaluating ERP performance more accurately and consistently than traditional approaches.

The results demonstrate that system uptime, defect rate, and response time are the most influential KPIs in determining ERP effectiveness, reflecting the importance of system reliability and operational stability in manufacturing environments. This finding aligns with previous research emphasising the critical role of system availability and quality management in ERP success [10], [17].

The superior performance of Random Forest Regression over other models can be attributed to its ensemble nature, which enables it to capture complex nonlinear interactions among KPIs without requiring explicit specification of functional forms. This makes it particularly suitable for ERP effectiveness prediction, where relationships among performance indicators are often non-linear and context-dependent [7], [23].

Compared with existing approaches that rely on subjective expert weighting [17] or single-metric evaluation [5], the proposed framework offers several advantages: objectivity, reproducibility, scalability, and the ability to handle multiple performance indicators simultaneously.

V. CONCLUSION

The findings demonstrate that the proposed hybrid framework provides an objective, scalable, and intelligent mechanism for ERP performance evaluation in manufacturing organizations. By combining optimization and machine learning, the framework reduces evaluator bias, improves predictive accuracy, and supports evidence-based managerial decision-making.

Consequently, the study contributes to both ERP research and intelligent manufacturing by providing a practical approach for monitoring and improving enterprise system performance.

5.1 Practical Contributions

The proposed framework offers several practical benefits:

- Objective evaluation of ERP performance using statistically derived KPI weights;
- Intelligent prediction of ERP effectiveness through machine learning;
- Improved resource allocation and operational planning;
- Support for continuous performance monitoring;
- Enhanced decision-making for ERP implementation and optimization; and
- Applicability to manufacturing organizations seeking data-driven performance management.

LIMITATIONS AND FUTURE WORK

Despite its contributions, the study has several limitations. First, the framework was validated using data from a limited number of manufacturing organizations, which may restrict generalizability to other industrial sectors or geographical regions. Second, the framework relies on historical ERP data and may not fully capture the dynamic and evolving nature of organizational performance. Third, the current implementation focuses on twelve KPIs; future work could incorporate additional indicators such as employee training effectiveness, innovation metrics, and sustainability performance.

Future research should explore the integration of deep learning techniques, real-time data streaming, and adaptive optimization algorithms to further enhance predictive accuracy and responsiveness. Additionally, extending the framework to incorporate user satisfaction metrics and qualitative factors would provide a more comprehensive assessment of ERP system effectiveness.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this study.

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