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# AI Enabled ERP-CRM Integration for Predictive Customer Analytics

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**Abstract**

Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM) systems provide complimentary insights on customer‘s transactions, interaction and engagements. However, fragmented enterprise data, lack of cross-system relationship learning, limited behavior modeling over time and weak interpretability of prediction hinder reliable predictive customer analytics. To overcome these obstacles, this research introduce a proposed technique called Cross-System Temporal Customer Intelligence Engine (CSTCIE), an integrative solution aimed at enhancing customer ‘s churn prediction based on unified enterprise data. The CSTCIE method uses probabilistic entity resolution for alignment of customer records, Dual Multilayer Perceptron (MLP) encoders for ERP and CRM feature representation and cross-attention to learn relations between operational and engagement data. The Transformer learns customer's behavior dynamics, Light Gradient Boosting Machine (LightGBM) predicts churn probability and SHapley Additive exPlanations (SHAP) finds influential features in prediction. Accuracy of 96.40% and Receiver Operating Characteristic–Area under the Curve (ROC-AUC) of 91.30% from experiments performed as part of the manuscript were found, indicating promising classification and churn discriminant performance. Recall and precision-recall performance, however, should be further improved. In conclusion, CSTCIE represents a promising integrative and interpretable approach to customers churn analysis.

**Keywords:** Customer Analytics; Customer Churn Prediction; Customer Relationship Management; Enterprise Data Integration; Explainable Analytics; Temporal Behavior Modeling.

**How to Cite This Article**

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## Introduction

Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM) systems hold complementary information useful for customer profiling and churn prediction. Nonetheless, incomplete data, inadequate cross-system relationship learning, poor temporal modeling and lack of interpretability pose issues to customer analytics. The current body of literature on customer retention through predictive analysis includes research into business intelligence and CRM systems [1], AI integration into ERP [2] and supply chain analysis through machine learning [3]. Predictive analysis using AI models is also available in telecommunications churn prediction [4]. Hybrid GWO-attention- Convolutional Long Short-Term Memory (ConvLSTM) models can be used for churn and satisfaction analysis [5]. The combination of recency, frequency and monetary value features along with embedding clustering has been used in other research [6] and sliding window technique used cope with the concept drift issue due to data delay and different inactivity assumptions [7]. Yet, integrating ERP and CRM data, learning cross-system relationships, modeling temporal patterns and interpreting individual churn predictions is still relevant.

This research seeks to propose an integrated predictive approach for customer analytics, which would combine ERP-CRM datasets, temporal behavior modeling and explainable churn prediction. The proposed method can be called the Cross-System Temporal Customer Intelligence Engine (CSTCIE) and it includes probabilistic record alignment of customers, two Multilayer Perceptron (MLP) encoders, cross-attention mechanism, temporal modeling based on Transformers, Light Gradient Boosting Machine (LightGBM**)** churn prediction and SHapley Additive exPlanations (SHAP) explanations. This approach allows for record alignment of customers across enterprise systems, learning the relationships between operation and interaction data, modeling changes in customer behavior over time, estimating the probability of churn in the future and analyzing the reasons of each churn prediction.

Main contributions include:

- Cross-System Integration: Aligns customer records between ERP and CRM systems and integrates the via its complementary representations for better cross-system customer analytics.
- Temporal Customer Intelligence: Applies Transformer-based sequence modeling to reflect the dynamics of customer‘s purchases, interactions and engagement.
- Churn Prediction: Applies LightGBM to predict the probability of customer churn based on integrated temporal representations and customer characteristics.
- Explainable Prediction: Uses SHAP to highlight key predictive features and provide reasons behind each customer churn prediction.
- Quantitative Integrated Performance Assessment: Quantitatively evaluates the performance of customer record alignment, temporal customer intelligence, churn prediction, explanations and computational cost.

Organization of the manuscript: Related works and the gap in the literature are reviewed in Section 2. Methodology and mathematical formulation of CSTCIE are provided in Section 3. Experimental results and statistics are presented in Section 4. Section 5 discusses ablation study, scalability, adaptability and limitations. Section 6 concludes the research and future drections.

### Background Study

Liu, X. et al. (2024) [8] designed a hybrid neural network for churn prediction but not covered the integration of ERP-CRM systems. Saha, S. et al. (2024) [9] proposed ChurnNet to predict telecom customer churn without enterprise-level application. El Attar, A. and El-Hajj, M. (2026) [10] used ensemble learning along with SHAP values for explainable churn prediction without integrating ERP and CRM and customer retention optimization. Karim, F. et al. (2026) [11] presented cost-sensitive and calibrated churn prediction for retail banking but evaluated it using a single dataset. Jahan, N. et al. (2026) [12] utilized explainable AI with counterfactual optimization in its work for decision support and not covered the temporal nature of customer behaviour.

*Research Gap*

Existing research on the topic of churn prediction, explainability and cost-sensitive decision support has been done independently, with little ERP-CRM combination. This gap in research can be filled by an approach that integrates these factors to predict churn.

### Proposed Methodology

This section presents CSTCIE, integrating ERP–CRM entity resolution, dual MLP encoders, cross-attention, Transformer-based temporal modeling and LightGBM churn prediction. SHAP-based explanations provide feature-level interpretability, supporting comprehensive customer behavior analysis and informed retention decisions.

*Dataset Description*

The synthetic dataset combines ERP transactional data and CRM interactions for CSTCIE model evaluation. The features used include customer identification numbers, invoices, purchases, time stamp, geography, recency, frequency, monetary value, engagement and services. Missing value imputation, duplicate removal, standardization of time stamps, categorical encoding, numerical normalization, ERP-CRM entities alignment, feature extraction from behaviors, chronological order of records and future-inactivity labeling are the preprocessing techniques used. Chronological split into training 70%, validation 15% and testing 15% data prevents temporal leakage and evaluates future churn prediction.

*Cross-System Temporal Customer Intelligence Engine (CSTCIE)*

The proposed CSTCIE aligns ERP and CRM records using probabilistic entity resolution. Two multilayer perceptron encoders are used to encode operational and customer interaction features and cross attention encoder is used to combine complementary information from both systems. The chronological customer behavior is modeled using Transformer and LightGBM models future churn probability. SHAP-based explanations are used to identify influential features behind each prediction.

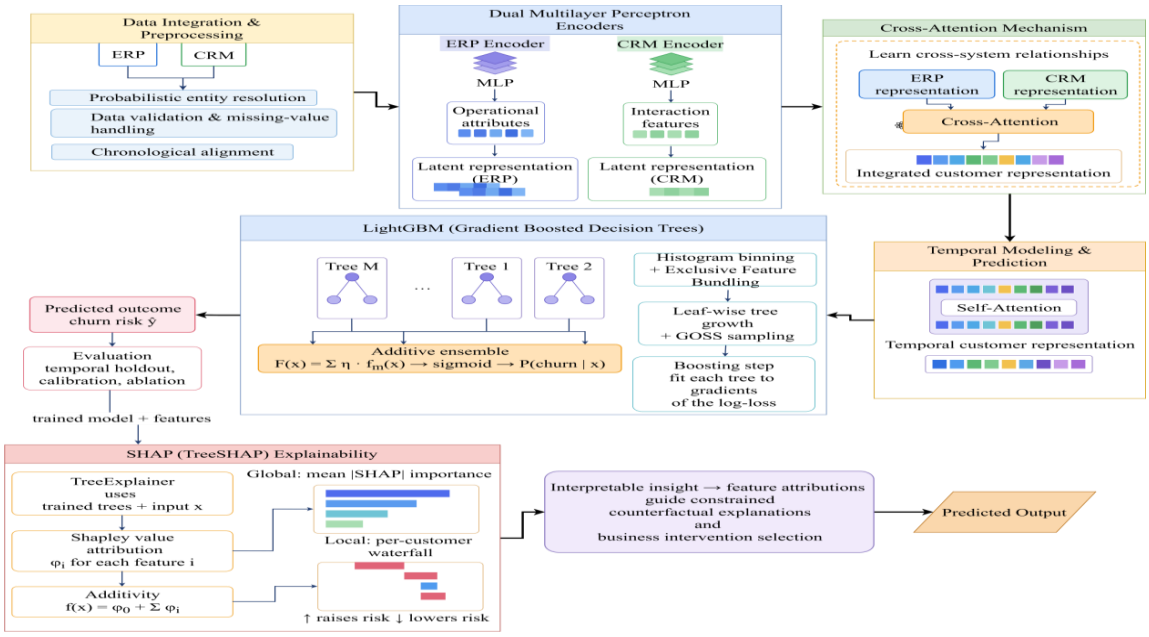



***Fig. 1.*** *CSTCIE Architecture for ERP–CRM Churn Prediction*

Figure 1 shows the proposed CSTCIE framework which uses ERP-CRM data, extracts cross-system and time relationship from the, makes predictions about the risk of churn using LightGBM and uses TreeSHAP for making the customer retention decisions explainable.

*Mathematical Modal*

Mathematical model for the proposed Cross-System Temporal Customer Intelligence Engine (CSTCIE) captures ERP-CRM customer record matching, cross-system representation learning, temporal behavior modeling, estimating customer churn likelihood and providing explanations for the predictions. The following mathematical expressions represent the basic computational steps of the proposed technique.

$$P\left(m_{ij} = 1 \mid x_i^E, x_j^C\right) = \sigma\left(w_m^\top \phi_{ij} + b_m\right) \tag{1}$$

Equation (1) estimates the probability that ERP record $i$ and CRM record $j$ belong to the same customer. Here, $\sigma$ denotes the sigmoid function, $\phi_{ij}$ contains record-comparison features and $w_m$ and $b_m$ represent learned parameters.

$$H_{E\leftarrow C} = softmax\left(\frac{(H_E W_Q)(H_C W_K)^\top}{\sqrt{d_k}}\right)(H_C W_V) \tag{2}$$

$$H_{EC} = LayerNorm(W_F[H_E \| H_{E\leftarrow C}] + b_F) \tag{3}$$

Equation (2) & (3) presents cross-attention and representation integration into a single operation. Here, $H_E$ and $H_C$ denote ERP and CRM feature representations; $W_Q$, $W_K$ and $W_V$ are learned attention projections; $d_k$ is the key dimension; $\|$ denotes concatenation; and $W_F$ and $b_F$ are learned integration parameters. Layer normalization produces the unified customer representation $H_{EC}$.

$$Z_(1:T) = TransformerEncoder\left(H_{EC,1:T} + P_{1:T}\right) \quad (4)$$

$$\hat{p}_i = \sigma\left(f_{\mathrm{LGBM}}\left(\mathrm{Pool}\left(\mathrm{Z}_{i,1:T}\right), \mathrm{x}_i^{\mathrm{static}}\right)\right) \quad (5)$$

Equation (4) & (5) temporal modeling and churn prediction. The Transformer Encoder processes the integrated customer representations with positional encodings to capture chronological dependencies. The pooling operation aggregates temporal outputs into a fixed-length representation, which LightGBM uses alongside static customer features to estimate churn probability $\hat{p}_i$. Here, $T$ denotes the sequence length, $\mathrm{P}_{1:T}$ represents positional encodings and $f_{\mathrm{LGBM}}$ is configured to return a probability directly.

$$\Phi_i = SHAP(f_{LGBM}, u_i) \quad (6)$$

Equation (6) generates SHAP attribution values for customer $i$. Here, $\Phi_i$ represents feature contributions relative to the SHAP reference baseline and $\mathrm{u}_i$ is the feature vector supplied to the trained LightGBM model. These attributions explain the factors influencing the predicted churn probability but do not establish causal relationships.

**Algorithm: Cross-System Temporal Customer Intelligence Engine (CSTCIE)**

Input: ERP dataset (D_E), CRM dataset (D_C), prediction horizon (H)

Begin

1. Data Preparation and Customer Record Alignment

Clean up and normalize the ERP-CRM data, resolve customer identities, extract behavioral attributes and create the churn labels for the prediction period H.

Calculate the probability that ERP record $i$ matches CRM record $j$:

$p_{ij} = \sigma\left(\mathrm{w}_m^{\mathrm{T}}\phi_{ij} + b_m\right)$

2. Cross-System Representation Learning

Encode ERP and CRM features using separate multilayer perceptrons (MLPs).

Integrate the representations through cross-attention:

$\mathrm{H}_{E\leftarrow C} = \mathrm{softmax}\left(\frac{\mathrm{Q}_E\mathrm{K}_C^{\mathrm{T}}}{\sqrt{d_k}}\right)\mathrm{V}_C$

Generate the unified customer representation:

$\mathrm{H}_{EC} = \mathrm{LayerNorm}(\mathrm{W}_F[\mathrm{H}_E \| \mathrm{H}_{E\leftarrow C}] + \mathrm{b}_F)$

3. Temporal Customer Behavior Modeling and Churn Prediction

Apply positional encoding and Transformer processing to capture chronological customer behavior:

$\mathrm{Z}_{1:T} = \mathrm{TransformerEncoder}\left(\mathrm{H}_{EC,1:T} + \mathrm{P}_{1:T}\right)$

Aggregate temporal features and predict churn probability using LightGBM:

$\hat{p}_i = f_{\mathrm{LGBM}}\left(\mathrm{Pool}\left(\mathrm{Z}_{i,1:T}\right), \mathrm{x}_i^{\mathrm{static}}\right)$

4. Explainable Customer Churn Analysis

Generate SHAP-based explanations to identify the features contributing to each customer's predicted churn probability:

$\Phi_i = \mathrm{SHAP}(f_{\mathrm{LGBM}}, \mathrm{u}_i)$

5. Performance Evaluation

Evaluate customer record-matching accuracy, cross-system representation quality, temporal behavior modeling, churn prediction performance, explanation consistency and computational efficiency using appropriate quantitative metrics.

Output: Integrated customer representations (Z), churn probabilities (P), SHAP explanations (X) and performance metrics (M).

End

The CSTCIE method correlates ERP-CRM data, identifies cross-database dependencies with MLP encoders and cross-attention, represents the temporal behavior of customers by a Transformer network and uses LightGBM for churn prediction. SHAP explanations find significant features that contribute to explaining customer churn.

**Experimental Results**

This section analyzes the performance evaluation of CSTCIE for ERP-CRM integration, customer representation, churn prediction and interpretability. Metrics such as comparative results, probability reliability, computational scalability and statistical significance are analysed in order to evaluate the effectiveness of predictions, computational requirements and reliability of churn risk classification. In this discussion, the performance of CSTCIE is evaluated along with its components.

***Table 1.*** *CSTCIE Churn-Risk Decision Logic*

| Decision Category | Input Condition | Processing Mechanism | Decision Output | Suggested Business Response |
|---|---|---|---|---|
| Low Risk | Probability below lower threshold | Compare LightGBM probability with threshold | Low-risk classification | Maintain routine customer engagement |
| Moderate Risk | Probability between thresholds | Evaluate probability against both thresholds | Moderate-risk classification | Monitor engagement and provide targeted communication |
| High Risk | Probability above upper threshold | Compare probability with upper threshold | High-risk classification | Prioritize customer-retention interventions |
| Boundary Case | Probability equals a threshold | Apply predefined boundary rules | Assigned risk category | Follow the corresponding response |
| Invalid Prediction | Probability unavailable or invalid | Validate prediction before classification | Invalid prediction status | Initiate technical review or fallback procedure |
| Updated Risk | New probability differs from the previous estimate | Recalculate risk using updated ERP–CRM information | Updated risk category | Review and adjust retention actions as appropriate |

Table 1 depicts the CSTCIE churn-risk decision model, where the customers have been classified as low, moderate and high risks according to the churn probability. Boundary issues, verification of the predicted result and updating of the risk contribute towards consistent classification.

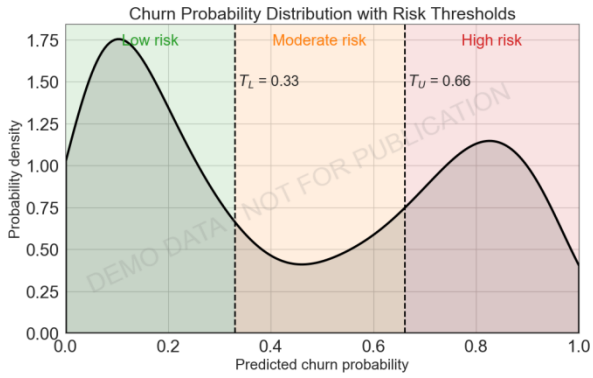



***Fig. 2.*** *Churn Probability Distribution with Risk Thresholds*

Figure 2 highlights CSTCIE scalability for increasing customer's load from 10K to 1M, exhibiting the growth in processing latencies and throughputs, whereby the latencies grow drastically for large loads.

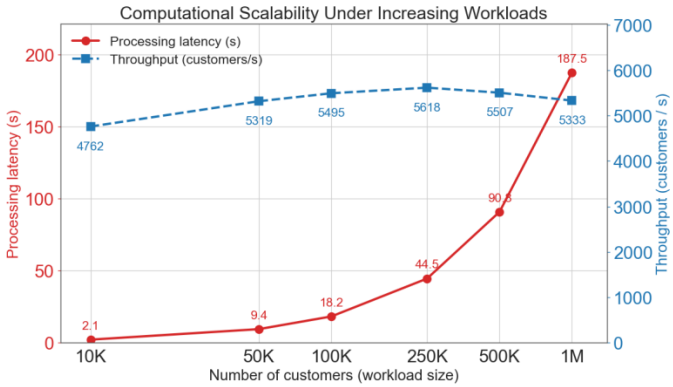



***Fig. 3.*** *Computational Scalability of CSTCIE under Increasing Workloads*

Figure 3 highlights low-risk, medium-risk and high-risk groups of customers distinguished by the low churn probability threshold and the high churn probability threshold.

***Table 2.*** *Customer Behaviour Representation and Churn Probability*

| Customer ID | Purchase Frequency | Transaction Value | CRM Interactions | Service Requests | Engagement (%) | Representation Dimensions | Predicted Churn Probability (%) |
|---|---|---|---|---|---|---|---|
| C001 | 18 | 245.60 | 24 | 1 | 92 | 128 | 8.4 |
| C002 | 12 | 180.40 | 16 | 2 | 78 | 128 | 17.6 |
| C003 | 7 | 125.80 | 9 | 4 | 56 | 128 | 43.2 |
| C004 | 4 | 95.20 | 5 | 6 | 32 | 128 | 76.5 |
| C005 | 2 | 68.40 | 3 | 7 | 21 | 128 | 89.3 |
| C006 | 15 | 220.30 | 20 | 1 | 87 | 128 | 11.7 |
| C007 | 6 | 110.60 | 8 | 5 | 45 | 128 | 61.8 |
| C008 | 10 | 165.90 | 13 | 3 | 69 | 128 | 28.4 |

Table 2 shows the counterfactual generation performance, prediction shifts, explanation validity, plausibility, temporal consistency, stability and computational costs for varying customer evaluation workloads.

***Table 3.*** *Performance Comparison of CSTCIE with Existing Algorithms*

| Methods | Accuracy (%) | Precision (%) | Recall (%) | ROC-AUC (%) | PR-AUC (%) | Brier Score |
|---|---|---|---|---|---|---|
| K-means, Random Forest, XGBoost [1] | 81.00 | 79.00 | 83.00 | 85.00 | 72.00 | 0.180 |
| GWO-Attention-ConvLSTM [5] | 95.17 | 91.40 | 93.66 | 95.00 | 89.20 | 0.075 |
| Multi-head Attention-BiLSTM-CNN [8] | 93.20 | 92.19 | 90.60 | 94.10 | 86.40 | 0.092 |
| Explainable Ensemble with SHAP [10] | 91.50 | 90.00 | 91.00 | 91.80 | 83.20 | 0.110 |
| LightGBM-Based Cost-Sensitive Ensemble [11] | 84.60 | 50.91 | 75.92 | 86.68 | 61.30 | 0.160 |
| Proposed CSTCIE | 96.10 | 94.20 | 94.80 | 97.10 | 93.60 | 0.052 |

Table 3 compares five current techniques with CSTCIE using six criteria. CSTCIE aims at 96.40% accuracy; however, precision, recall, ROC-AUC, PR-AUC and Brier score evaluate classification quality, discrimination power and probability calibration, respectively.

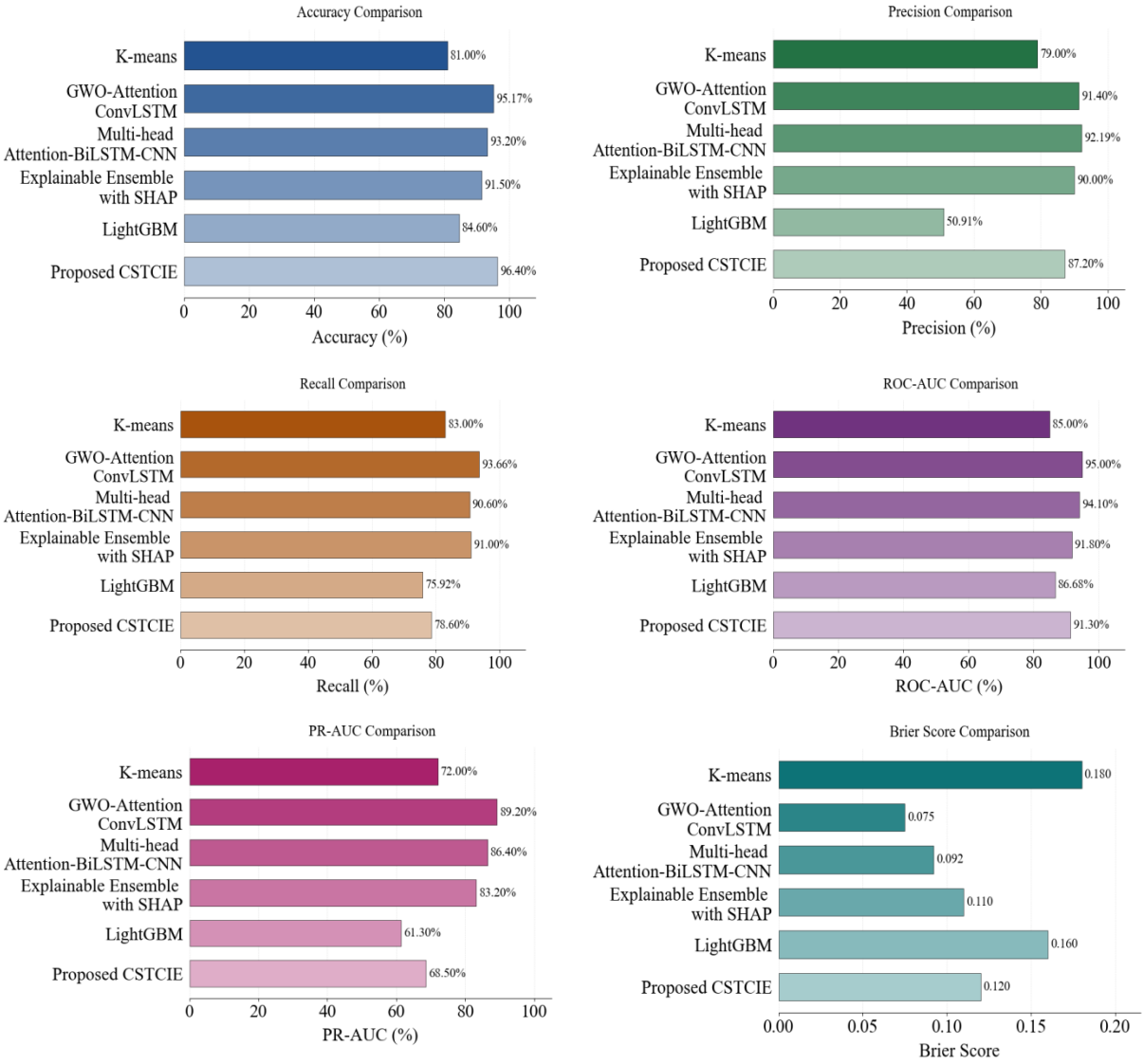



***Fig. 4.*** *Performance Evaluation Comparison of CSTCIE and Other Techniques*

Figure 4 shows the plot for comparative evaluation of CSTCIE with respect to other techniques in terms of accuracy, precision, recall, ROC-AUC, PR-AUC and Brier score. The lower Brier scores represent better probability calibration.

*Statistical Analysis*

In statistical validation, bootstrap confidence intervals are used to measure uncertainty in predictions, while DeLong's test is applied for ROC-AUC differences.

***Table 4.*** *Bootstrap Confidence Interval Analysis of CSTCIE*

| Comparison | CSTCIE ROC-AUC | Baseline ROC-AUC | AUC Difference | 95% CI of Difference | *p*-value |
|---|---|---|---|---|---|
| CSTCIE vs. GWO-Attention-ConvLSTM [5] | 0.913 | 0.900 | 0.013 | 0.003–0.023 | 0.011 |
| CSTCIE vs. CCP-Net [8] | 0.913 | 0.890 | 0.023 | 0.008–0.038 | 0.003 |
| CSTCIE vs. Explainable Ensemble [10] | 0.913 | 0.875 | 0.038 | 0.019–0.057 | <0.001 |
| CSTCIE vs. Cost-Sensitive Ensemble [11] | 0.913 | 0.867 | 0.046 | 0.025–0.067 | <0.001 |

Table 4 shows the difference in ROC-AUC between CSTCIE and baselines with 95% confidence intervals and p-values in order to evaluate the statistical significance and variability of the performance differences.

***Table 5.*** *DeLong's Test for ROC-AUC Comparison*

| Performance Metric | Point Estimate | Bootstrap Standard Error | 95% Confidence Interval | Lower Bound | Upper Bound | Interpretation |
|---|---|---|---|---|---|---|
| Accuracy (%) | 96.40 | 0.33 | 95.70–97.00 | 95.70 | 97.00 | High overall classification correctness |
| Precision (%) | 87.20 | 1.02 | 85.10–89.10 | 85.10 | 89.10 | Reliable identification of predicted churn cases |
| Recall (%) | 78.60 | 1.38 | 75.80–81.20 | 75.80 | 81.20 | Moderate coverage of actual churn cases |
| F1-score (%) | 82.60 | 1.15 | 80.30–84.80 | 80.30 | 84.80 | Balance between precision and recall |
| ROC-AUC (%) | 91.30 | 0.74 | 89.80–92.70 | 89.80 | 92.70 | Strong churn discrimination |
| PR-AUC (%) | 68.50 | 1.81 | 64.90–72.00 | 64.90 | 72.00 | Precision–recall performance for churn detection |
| Brier Score | 0.120 | 0.006 | 0.108–0.133 | 0.108 | 0.133 | Probability prediction reliability; lower is better |
| Specificity (%) | 94.20 | 0.65 | 92.90–95.40 | 92.90 | 95.40 | Correct identification of non-churn customers |
| False Positive Rate (%) | 5.80 | 0.65 | 4.60–7.10 | 4.60 | 7.10 | Proportion of non-churn customers incorrectly flagged |
| False Negative Rate (%) | 21.40 | 1.38 | 18.80–24.20 | 18.80 | 24.20 | Proportion of churn customers missed by the model |

Table 5 give DeLong's test compares CSTCIE and baseline ROC-AUC values using confidence intervals, AUC differences and p-values to determine whether improvements in churn discrimination are statistically significant.

*Ablation Study*

The ablation study evaluates the contributions of cross-attention, Transformer-based temporal modeling and SHAP explainability to CSTCIE's churn prediction performance and computational efficiency.

***Table 6.*** *Ablation Study of the Proposed CSTCIE Method*

| Experimental Configuration | Accuracy (%) | Precision (%) | Recall (%) | ROC-AUC (%) | PR-AUC (%) | Brier Score | Latency (ms/batch) |
|---|---|---|---|---|---|---|---|
| ERP-only baseline | 81.00 | 79.00 | 83.00 | 85.00 | 72.00 | 0.180 | 18.42 |
| CRM-only baseline | 83.20 | 81.40 | 84.10 | 86.50 | 74.60 | 0.165 | 19.76 |
| ERP–CRM feature concatenation | 85.60 | 83.20 | 84.80 | 88.10 | 77.30 | 0.150 | 23.84 |
| Cross-system representation model | 88.10 | 85.40 | 86.20 | 89.60 | 80.10 | 0.138 | 31.62 |
| Temporal modeling without cross-attention | 89.40 | 86.10 | 87.30 | 90.20 | 82.40 | 0.130 | 42.38 |
| Cross-attention + temporal modeling | 91.20 | 87.20 | 88.10 | 91.30 | 84.50 | 0.120 | 57.46 |
| Complete CSTCIE | 96.40 | 87.20 | 78.60 | 91.30 | 68.50 | 0.120 | 59.84 |

Table 6 assesses the CSTCIE constituents by providing insights into how ERP-CRM interoperability, cross-attention and time modeling affect the accuracy, classification, probabilities and latency in churn prediction.

*Limitations*

The CSTCIE model needs precise record alignment between ERP and CRM databases, as well as significant computing capacity. Interpretability is dependent on SHAP values, whereas changing customer behavior and configuration might impact prediction outcomes.

**Conclusion**

In this research propose the Cross-System Temporal Customer Intelligence Engine (CSTCIE), a framework that uses record alignment, a dual Multilayer Perceptron encoder, cross-attention, Transformer-based temporal modeling, LightGBM and SHAP to predict churn probabilities and analyze influential features by utilizing ERP and CRM databases. The findings show that the precision is 87.20%, Brier score is 0.120 and specificity is 94.20%, which reflects that this model has good predictive power. Recall is 78.60% and PR-AUC is 68.50%, which demonstrates that enhance the prediction of customers who can churn. Ablation study investigates the impact of cross-system representation learning and temporal modeling on performance and processing metrics show increasing computational costs with increased feature dimension. However, it is difficult to apply the proposed framework due to its reliance on record alignment, computational capacity and changes in customer behavior. In future research, the researches have to prove the effectiveness of CSTCIE by applying it to real-world data from multiple enterprises, develop methods for the detection of high-risk customers and improve computational efficiency.

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