ECONOSCITECH INTEGRATION

ISSUE 5

INTERNATIONAL SCIENTIFIC ELECTRONIC JOURNAL

TASHKENT STATE UNIVERSITY OF ECONOMICS

American University of Technology
Powered by Arizona State University®

ISSN: 3060-5075

Acceptance of articles
PUBLISHED EVERY MONTHLY

ARTICLE CONTRIBUTORS
PROFESSORS-TEACHERS, SPECIALISTS AND SCIENTIFIC RESEARCHERS.

Google Scholar · Academic Resource Index ResearchBib · BASE · OpenAIRE · doi Digital Object Identifier · OPEN ACCESS

CONTACT: +998 94 3540880 https://econoscitech-integration-journal.uz 2026

THE SCIENTIFIC-POPULAR ELECTRONIC JOURNAL **"ECONOSCITECH-INTEGRATION"** HAS BEEN REGISTERED UNDER THE NUMBER C-5669651 BY THE AGENCY FOR INFORMATION AND MASS COMMUNICATIONS (AOKA) OF THE REPUBLIC OF UZBEKISTAN, EFFECTIVE FROM OCTOBER 9, 2024.

In accordance with Resolution No. 384/6 dated April 10, 2026, issued by the Presidium of the Supreme Attestation Commission under the Ministry of Higher Education, Science and Innovation of the Republic of Uzbekistan, this journal is included in the list of recommended international scientific publications for publishing the primary research findings of doctoral dissertations in the field of Economic Sciences.

Partners: Tashkent State University of Economics / American University of Technology in Tashkent (AUT)

Electronic publication, Issue 5. 374 pages.
Approved for publication on May, 2026.

Editorial Board Members:

CONTENTS

CONTENTS

CONTENTS

CONTENTS

CONTENTS

APPLICATION OF ARTIFICIAL NEURAL NETWORKS FOR PREDICTING CUSTOMER LOYALTY IN COMMERCIAL BANKS

Jumaniyozova Mukaddas
Associate Professor
Tashkent State University of Economics
E-mail: m.jumaniyozova@tsue.uz
Tel.: +998 97 760 26 84

Abstract. Bank customer behaviour has a pronounced temporal nature: the propensity to churn develops gradually and manifests itself in the dynamics of transactions, balances, and account activity. Static machine-learning models that operate on aggregated features ignore the sequence of events and lose significant predictive information. This paper proposes a customer loyalty prediction model based on a Gated Recurrent Unit (GRU) recurrent neural network capable of capturing temporal dependencies in customer behaviour. The model was trained on sequences of monthly behavioural profiles of 10,000 retail-bank customers over 12 months and compared with a static neural network (MLP), a vanilla RNN, an LSTM network, and logistic regression. The GRU model achieved ROC-AUC = 0.91 and an F1-score of 0.76, outperforming static approaches and matching LSTM performance with fewer parameters. The results confirm the effectiveness of accounting for the temporal dynamics of customer behaviour and the feasibility of applying GRU in customer-retention systems.

Keywords: recurrent neural networks, GRU, gating mechanism, customer loyalty, churn prediction, time series, banking, deep learning.

Аннотация. Поведение клиентов банков имеет ярко выраженный временной характер: склонность к оттоку развивается постепенно и проявляется в динамике транзакций, балансов и активности счетов. Статические модели машинного обучения, работающие с агрегированными признаками, игнорируют последовательность событий и теряют значительную прогностическую информацию. В данной статье предлагается модель прогнозирования лояльности клиентов, основанная на рекуррентной нейронной сети с управляемым рекуррентным блоком (GRU), способной выявлять временные зависимости в поведении клиентов. Модель была обучена на последовательностях ежемесячных поведенческих профилей 10 000 клиентов розничного банка за 12 месяцев и сравнена со статической нейронной сетью (MLP), обычной рекуррентной нейронной сетью (RNN), сетью LSTM и логистической регрессией. Модель GRU достигла значения ROC-AUC = 0,91 и F1-меры = 0,76, превзойдя статические подходы и показав сопоставимые с LSTM результаты при меньшем количестве параметров. Результаты подтверждают эффективность учёта временной динамики поведения клиентов и целесообразность применения GRU в системах удержания клиентов.

Ключевые слова: рекуррентные нейронные сети, GRU, механизм управления, лояльность клиентов, прогнозирование оттока клиентов, временные ряды, банковское дело, глубокое обучение.

INTRODUCTION

In recent years, Uzbekistan's banking sector has demonstrated an increasing commitment to the adoption of artificial intelligence technologies within the framework of ongoing digital transformation. In accordance with the Strategy for the Development of Artificial Intelligence Technologies until 2030, approved in 2024, particular emphasis is placed on the use of AI for fraud prevention, customer creditworthiness assessment, and market trend forecasting [1]. The global artificial intelligence market in the banking sector was estimated at USD 35.40 billion in 2025. According to projections, the market is expected to expand from USD 46.85 billion in 2026 to USD 440.60 billion by 2034, with a compound annual growth rate of 32.33% during the forecast period [2].

According to the Central Bank of the Republic of Uzbekistan, the penetration rate of digital solutions in the country's banking sector increased from 45% in 2018 to 78% in 2023, indicating a rapid pace of digitalization [3].

The use of artificial intelligence is becoming one of the key factors contributing to greater efficiency in Uzbekistan's banking sector. The implementation of AI improves customer service quality, reduces operational risks, increases the accuracy of decision-making processes, and strengthens banks' competitiveness in the

market. In the coming years, the application of artificial intelligence technologies in the country's banking system is expected to expand further in line with the national strategy for digital development.

Amid the accelerating digital transformation of Uzbekistan's banking sector, one of the most promising applications of artificial intelligence is the intelligent analysis of customer behaviour. In this context, the application of machine learning techniques and artificial neural networks has gained considerable scientific and practical significance for predicting customer churn, assessing customer loyalty, personalizing banking products and services, and developing individualized financial offerings. These AI-driven approaches enable commercial banks to improve customer relationship management, enhance decision-making processes, and strengthen long-term customer retention.

In the commercial banking sector of Uzbekistan, artificial intelligence remains at the stage of active implementation. The principal directions of AI adoption have already been established at the national policy level, while individual commercial banks are progressively introducing pilot initiatives and practical AI-based solutions. As digital transformation continues to advance, the integration of intelligent analytical systems is expected to become a fundamental component of customer-centric banking strategies and sustainable competitive development.

A natural approach to modelling the temporal structure of sequential data is the use of Recurrent Neural Networks (RNNs), which process sequential information while maintaining an internal hidden state that captures historical dependencies. However, conventional RNNs suffer from the vanishing gradient problem, which significantly limits their ability to learn and preserve long-term dependencies within sequences.

To address this limitation, gated recurrent architectures, including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, have been developed. The GRU architecture, introduced by Cho et al. in 2014, employs update and reset gates to regulate the flow of information through the network. This gating mechanism enables the model to effectively capture long-term temporal dependencies while requiring fewer trainable parameters and achieving faster convergence than LSTM networks. Owing to its computational efficiency and competitive predictive performance, the GRU architecture has become a widely adopted deep learning model for sequential data analysis in applications such as customer behaviour modelling, churn prediction, and customer loyalty forecasting.

LITERATURE REVIEW

Since 2020, a substantial body of research has been published on the application of machine learning techniques to customer loyalty prediction in the banking sector. Recent studies indicate a growing shift toward the use of Recurrent Neural Networks (RNNs), which are specifically designed to capture the temporal dynamics of customer behaviour. By maintaining an internal hidden state that preserves information from previous time steps, RNNs can effectively model sequential data, including transaction histories, customer interactions with banking services, and other time-dependent behavioural patterns.

Despite these advantages, conventional RNN architectures are constrained by the well-known vanishing and exploding gradient problems when processing long sequential data. These limitations hinder the network's ability to capture long-term dependencies, thereby reducing predictive performance in complex customer behaviour modelling tasks and motivating the development of more advanced gated recurrent architectures.

To overcome these limitations, Cho et al. (2014) proposed the Gated Recurrent Unit (GRU) architecture, which achieves predictive performance comparable to that of Long Short-Term Memory (LSTM) networks while using fewer trainable parameters and demonstrating faster training and convergence [4]. Building upon this advancement, Liu et al. (2024) introduced a hybrid deep learning model designed to enhance the accuracy of customer churn prediction by integrating complementary neural network architectures and optimizing feature extraction from sequential customer behaviour data [5]. Furthermore, the systematic review conducted by Imani and Arabnia (2025), based on an analysis of 240 peer-reviewed studies published between 2020 and 2024, demonstrates that LSTM, GRU, and hybrid recurrent architectures have emerged as some of the most promising approaches for developing intelligent prediction systems. Their superior capability to model complex sequential patterns and long-term temporal dependencies has contributed significantly to recent advances in customer behaviour analytics, churn prediction, and customer loyalty forecasting [6].

An analysis of recent international research demonstrates that the application of recurrent neural network architectures, including RNN, LSTM, and GRU, has substantially enhanced the capabilities of customer loyalty prediction in the banking sector. By effectively capturing temporal dependencies and complex sequential patterns in customer behaviour, these deep learning models provide superior predictive performance compared with conventional machine learning approaches. Consequently, recurrent neural architectures have become a fundamental component of modern intelligent decision-support systems for customer loyalty assessment, churn prediction, and personalized banking services.

RESEARCH METHODOLOGY

To forecast customer loyalty in commercial banks, this study employs a dataset comprising monthly behavioural profiles of 10,000 anonymised retail banking customers observed over a 12-month period. Each customer is represented as a sequence of 12 time steps, where each time step contains a vector of behavioural features, as presented in Table 1.

Table 1
Features Observed at Each Time Step[1]

Feature	Description
Account Balance	The remaining account balance at the end of each month.
Transaction Count	Total number of transactions performed by the customer during the month.
Transaction Volume	Total transaction amount during the month.
Customer Activity Indicator	Binary indicator specifying whether the customer was active during the month (1 = active, 0 = inactive).
Number of Banking Products	Total number of banking products used by the customer.
Support Contacts	Number of customer contacts with the support service during the month.
Payment Delinquency Indicator	Binary indicator of overdue payment status (1 = overdue payment, 0 = no overdue payment).

The target variable is defined as the occurrence of customer churn within the subsequent three months following the end of the observation period. Time-invariant characteristics, including age, country of residence, gender, and credit score, are incorporated into the model as static contextual variables.

The proportion of customers who churned was approximately 20%, indicating the presence of class imbalance in the dataset. This imbalance should be taken into account during model training and evaluation to ensure reliable predictive performance.

ANALYSIS AND RESULTS

A GRU cell updates its hidden state through two gating mechanisms: the update gate and the reset gate. These gates regulate the flow of information within the network by determining how much information from the previous hidden state should be retained and how much should be replaced with newly acquired information. This mechanism enables the GRU architecture to effectively capture both short-term and long-term temporal dependencies while mitigating the vanishing gradient problem commonly encountered in conventional recurrent neural networks (Figure 1).

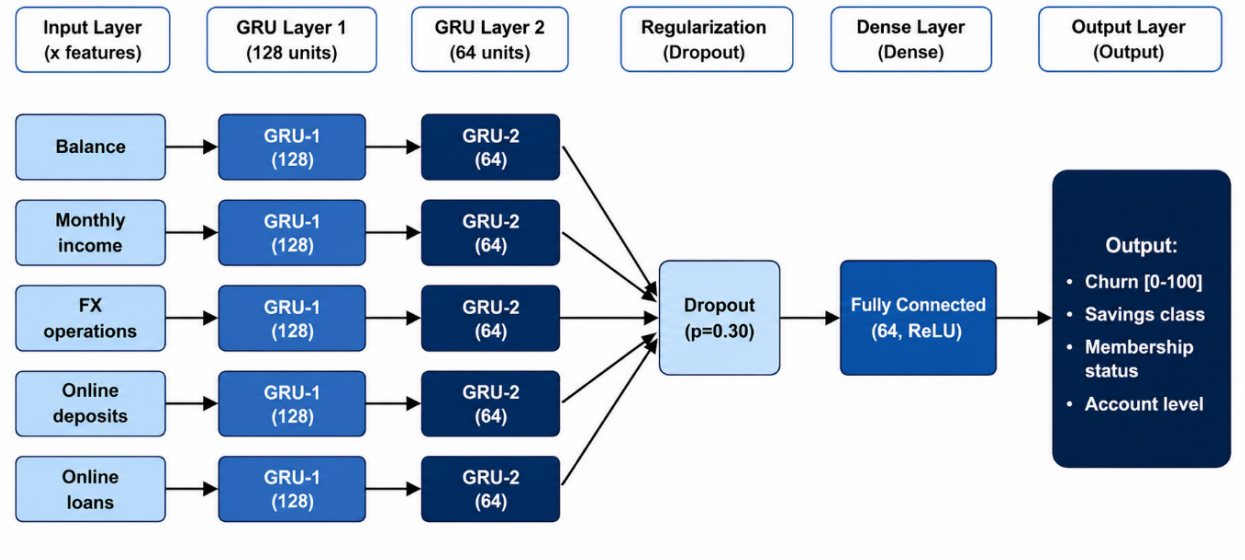

Figure 1. GRU Model Architecture for Predicting Customer Loyalty in Commercial Banks[2]

1 developed by the author
2 developed by the author

The proposed model architecture consists of an input layer that receives sequences of behavioural features, followed by two recurrent GRU layers with 64 and 32 hidden units, respectively. To reduce the risk of overfitting and improve the generalization capacity of the model, dropout layers with a rate of 0.3 are incorporated into the architecture.

The output of the recurrent component is subsequently concatenated with the customer's static attributes, enabling the model to jointly exploit both temporal behavioural patterns and time-invariant contextual information. The resulting representation is passed to a fully connected layer with a ReLU activation function, followed by a single output neuron with sigmoid activation, which produces the estimated probability of customer churn.

Model training was performed using backpropagation through time (BPTT). Weighted binary cross-entropy was employed as the loss function to account for class imbalance, while the Adam optimizer was used with a learning rate of 0.001. The model was trained with a mini-batch size of 64 for up to 100 epochs, with early stopping applied based on validation set performance [7].

For comparative evaluation, the proposed GRU model was benchmarked against four widely used baseline models: Logistic Regression, Multilayer Perceptron (MLP), a conventional Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM). The hyperparameters of all models were optimized using the validation dataset to ensure a fair and unbiased comparison.

Model performance was assessed using Precision, Recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (ROC–AUC), which provide a comprehensive evaluation of classification performance, particularly in the presence of class imbalance. A comparative analysis of the predictive performance of the evaluated models on the independent test dataset is presented in Table 2.

Table 2
Comparison of Predictive Model Performance[3]

Модель	Model	Accuracy	Precision	Recall	F1-мера	ROC-AUC
Logistic Regression	Static	0,81	0,58	0,53	0,55	0,82
MLP	Static	0,85	0,68	0,65	0,66	0,87
RNN	Dynamic	0,86	0,69	0,70	0,69	0,88
LSTM	Dynamic	0,88	0,73	0,77	0,75	0,91
GRU	Dynamic	0,88	0,74	0,78	0,76	0,91

The results of the comparative analysis presented in Table 2 indicate that deep learning models capable of capturing the sequential structure of customer behaviour outperform static methods across all evaluated metrics. Among the models considered, the GRU-based architecture demonstrated the best overall predictive performance, achieving the highest F1-score of 0.76 and recall of 0.78, with a ROC–AUC value of 0.91. These results confirm the effectiveness of gated recurrent architectures in modelling temporal patterns in customer behaviour and improving the accuracy of customer loyalty and churn prediction.

The GRU model achieved predictive performance comparable to that of LSTM while requiring approximately 25% fewer trainable parameters and demonstrating faster training. This makes it more suitable for computationally constrained environments. The training and validation loss curves converged after approximately 30–40 epochs without noticeable overfitting due to the application of dropout and early stopping. Compared with the static MLP model, the GRU improved ROC–AUC by 0.04 and the F1-score by 0.10. Furthermore, the model assigned higher churn probabilities to customers exhibiting sustained declines in activity and account balance during the final three to four months of observation, indicating that temporal behavioural trajectories provide more informative predictive signals than aggregated customer characteristics.

The obtained results confirm that incorporating the temporal dynamics of customer behaviour substantially improves the accuracy of customer loyalty prediction. The superior performance of recurrent models over static approaches is attributable to their ability to capture temporal patterns preceding churn, including declining customer activity, decreasing account balances, and increasing customer support interactions, which are typically lost when behavioural data are aggregated.

The comparable performance of GRU and LSTM, combined with the lower computational complexity of GRU, is consistent with established empirical observations. In tasks of moderate complexity and with limited data availability, the simpler gated architecture of GRU often achieves performance comparable to LSTM while training faster and being less prone to overfitting. These characteristics make GRU a practically attractive choice for industrial customer-retention systems.

3 developed by the author

The practical significance of the proposed approach lies in the integration of the GRU model into a bank's CRM system. Through regular recalculation, the model can generate a ranked list of customers with an increasing risk of churn and support the timely initiation of proactive retention measures, such as personalized offers, targeted communication, and tariff adjustments. Such interventions are particularly valuable at an early stage, when the probability of retaining the customer remains relatively high.

Promising directions for further research include extending the GRU model with an attention mechanism to enhance interpretability, applying explainable AI methods such as SHAP and integrated gradients to temporal banking data, employing bidirectional GRU architectures, and developing hybrid models that combine recurrent processing of customer behaviour with static tabular features and external macroeconomic factors.

The GRU model identifies customers at high risk of churn by jointly analysing temporal behavioural and financial indicators, including declining account balances, reduced transaction frequency, decreased mobile banking activity, discontinued use of deposit and lending products, and an overall reduction in customer engagement with banking services. By capturing the temporal evolution of these indicators, the model enables the early detection of customers exhibiting behavioural patterns associated with an elevated probability of churn (Figure 2).

GRU Predicted Score	Churn Risk Level	Customer Segmentation
0.00 – 0.30	**Low Risk** The client maintains stable activity and demonstrates signs of loyalty.	The client maintains stable activity and demonstrates signs of loyalty.
0.30 – 0.60	**Medium Risk** Partial decrease in activity and interest in banking products is observed.	Partial decrease in activity and interest in banking products is observed.
0.60 – 0.80	**High Risk** A noticeable reduction in transactions and interaction with the bank is recorded.	A noticeable reduction in transactions and interaction with the bank is recorded.
0.81 – 1.00	**Critical Risk** The client is highly likely to discontinue banking services within 1–3 months.	The client is highly likely to discontinue banking services within 1–3 months.

Figure 2. Segmentation of Commercial Bank Customers by Churn Risk Levels Based on the GRU Predictive Model[4]

As shown in Figure 2, the most critical segment is the 0.81–1.00 category, which corresponds to a critical level of churn risk. Customers in this group have the highest probability of discontinuing banking services within the next one to three months. Therefore, this segment requires priority retention measures, including individualized service conditions, personalized financial offers, and active customer engagement.

The proposed risk scale provides a practical interpretation of the GRU model's predictions and enables banks to move beyond simple churn probability estimation toward risk-oriented customer segmentation. This approach facilitates more efficient allocation of retention resources, supports the timely implementation of targeted customer retention strategies, and ultimately contributes to improving customer loyalty in commercial banks.

CONCLUSION AND RECOMMENDATIONS

This article proposes and empirically validates a customer loyalty prediction model for banking clients based on a GRU recurrent neural network that accounts for the temporal dynamics of customer behaviour. The model achieved a ROC–AUC value of 0.91 and an F1-score of 0.76, outperforming static approaches, including Logistic Regression and MLP, while demonstrating performance comparable to LSTM with lower computational complexity.

4 developed by the author

The results indicate that customers' behavioural trajectories, rather than aggregated indicators alone, contain the key predictive information. These findings substantiate the feasibility of integrating GRU-based models into banking decision-support systems for the early identification of customers prone to churn and for improving the effectiveness of customer-retention programmes.

REFERENCES

President of the Republic of Uzbekistan. (2024). *Resolution No. PP-358 of the President of the Republic of Uzbekistan dated October 14, 2024, "On the Approval of the Strategy for the Development of Artificial Intelligence Technologies until 2030"*. Tashkent, Uzbekistan. https://lex.uz/ru/docs/7158606

Fortune Business Insights. (2025). *Analysis of the Use of Artificial Intelligence in the Global Banking System*. FBI Working Paper, December 2025.

Central Bank of the Republic of Uzbekistan. (2025). *Bulletin of the Central Bank of the Republic of Uzbekistan*. https://www.cbu.uz

Cho, K., van Merriënboer, B., Bahdanau, D., & Bengio, Y. (2014). *Learning Phrase Representations Using RNN Encoder–Decoder for Statistical Machine Translation*. arXiv:1406.1078.

Liu, X., Xia, G., Zhang, X., et al. (2024). Customer churn prediction model based on hybrid neural networks. *Scientific Reports, 14*, Article 30707.

Imani, M., & Arabnia, H. (2025). Customer churn prediction: A systematic review of machine learning and deep learning approaches (2020–2024). *AI, 7*(3), 105.

Rahman, M., & Kumar, V. (2020). Machine learning-based customer churn prediction in banking. In *Proceedings of the Fourth International Conference on Electronics, Communication and Aerospace Technology (ICECA-2020)*. IEEE Xplore. ISBN: 978-1-7281-6387-1.

Abidov, A., Rasulev, D., Otabayev, N., & Jumaniyozova, M. (2025). Modeling the probability of online service delivery in mass service systems. In *Proceedings of the 9th International Conference on Future Networks and Distributed Systems (ICFNDS '25)* (pp. 459–468). https://doi.org/10.1145/3789692.378975

Nursaidov, N., et al. (2025). Zero-click guardrails for classroom AI: A policy-compiled ethics kernel with pre-execution adjudication. In *Proceedings of the 9th International Conference on Future Networks and Distributed Systems* (pp. 771–777). https://doi.org/10.1145/3789692.3789793

Proofreader: Xondamir Ismoilov

Layout and Designer: Oloviddin Sobir ugli

2026. № 5

To publish articles in this journal, you may submit articles, advertisements, stories, and other creative materials through the following links. Materials and advertisements are published on a paid basis.

You may subscribe to the journal at any time using the following details. Once subscribed, please send a screenshot or photo of your payment confirmation to our Telegram page @iqtisodiyot_77. Based on this, we will send the latest issue of the journal to your address each month.

Our address: Tashkent city, Yunusobod district, 19th block, House 17.