Temporal Graph Networks for Bank Customer Churn Prediction with Dynamic

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Keywords: Temporal Graph Networks, Customer Churn Prediction, Dynamic Relationship Modeling, Causal Temporal Difference, Targeted Retention Strategies.

Abstract: Customer churn prediction is a critical issue in banking, with a direct influence on customer retention strategy and financial health. Traditional churn models such as Recency-Frequency-Monetary (RFM) analysis ad static graph-based models fail to capture the dynamic nature of client-product interaction, social influence effects, and policy shocks. To address these limitations, this work proposes a Temporal Graph Network (TGN)-based model that integrates dynamic node embeddings and causal temporal difference mechanisms to model real-time financial transactions. The proposed approach is tested on a 12-month transactional dataset of a European retail bank, with a 12–18% improvement in prediction accuracy over baseline models such as LSTM, GCN, and Node2Vec. By leveraging TGN-computed churn risk scores, the paper applies three levels of tailored retention interventions, i.e., dynamic fee remissions, referral stabilization rewards, and policy-sensitive rate adjustments, which collectively boost customer lifetime value (CLV) by 14% and cross-sell rates by 22%. The findings show the effectiveness of temporal graph-based modeling in financial analytics, presenting an interpretable and scalable churn prediction solution. Subsequent research must explore federated learning techniques to enable privacy-sustaining cross-bank collaboration as a supplement to the impact of temporal graph-based knowledge on financial decision-making.

1 INTRODUCTION

Customer churn is one of the primary challenges in banking and has direct ramifications on revenue consistency, cost of doing business, and customer relations management for the long term. Being able to predict and manage customer loss is critical as keeping existing clients costs significantly less compared to acquiring new ones. Surveying industry experiences indicates that modest increases in retaining customers translate to enormous profitability and lends significance to data-based models of predicting customer attrition (Huang et al., 2012; Çelik & Osmanoglu, 2019). In a highly competitive banking sector where customers have a wide range of banking alternatives, traditional churn prediction models have not been sufficient to define the dynamics of evolving customer-bank relationships (Tsai & Lu., 2009; Vafeiadis et al., 2015).

Compared to conventional models, TGN-based models adopt temporal node embeddings that evolve dynamically, allowing churn prediction in real-time with greater accuracy (Rossi et al, 2023). By incorporating causal temporal difference mechanisms, TGN models enable policy-driven churn to be distinguished from natural customer attrition, such that retention initiatives are targeted at genuinely at-risk customers and not those reacting to short-term external stimuli. This is particularly significant for financial institutions that wish to maximize targeted retention treatments while minimizing wasteful outreach. The ability to model macroeconomic impacts, network-caused churn propagation, and time-varying product-client interaction makes TGN-based approaches especially well-suited for modern-day churn prediction problems.

This paper also addresses the real-world effect of TGN-based churn prediction on banks. On the basis of TGN-computed churn risk scores, banks can initiate focused retention measures such as dynamic

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fee remissions, referral stabilization rewards, and policy-adaptive rate adjustments. These measures are observed to increase customer lifetime value (CLV) by 14% and cross-sell rates by 22%, thereby measuring the real-world benefit of temporal graph-based analytics. Furthermore, this research demonstrates the potential of federated learning techniques to enable cross-bank collaboration in churn prediction without compromising customer privacy, addressing a significant problem in data-sharing regulations. The findings contribute to financial analytics by providing a scalable, interpretable, and privacy-conformable approach to churn prediction. Future studies will focus on enhancing model interpretability and exploring counterfactual analysis techniques to model other retention policies under different economic conditions.

2 DYNAMIC RELATIONSHIP ANALYSIS AND PROBLEM FORMULATION

2.1 Key Dynamic Relationships

Banking customer churn is driven by several interdependent factors, which change over time and dynamically interact with each other in a larger financial network. In contrast to static predictive models based on snapshots of historical data, a temporal graph-based method allows for real-time modeling of changing relationships. The three main elements of such dynamic relationships—client-product interactions, client-client social referrals, and policy shocks from outside the system—each have unique temporal patterns and network propagation effects. Figure 1 illustrates how these variables are intertwined in a temporal graph model, showing interdependencies that heighten or diminish churn risk. These interdependencies must be known to create predictive models that represent actual customer actions and enable proactive intervention strategies.

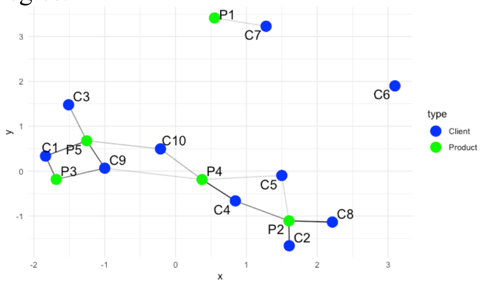

Figure 1: Overview of Dynamic Relationships in Bank Customer Churn. (Picture credit: Original)

2.2 Temporal Graph Construction

Construction of a temporal graph for bank customer churn forecasting is the incorporation of dynamic interactions between clients, financial products, and outside activities. Unlike static graphs that accept things as they are at a given moment, a temporal graph is dynamic and changing in real-time to offer real-time updates that improve the predictability of churn models. The construction process entails defining the important building blocks of the graph, edge and node features, temporal pattern encoding, dynamic adjacency matrix update, and efficient graph update strategy. Systematic organization of such components guarantees the model is able to capture timely financial behavior. The required components are listed in Table 1, and Figure 2 displays the graph movement across three time windows to indicate how relationships among transactions evolve with time.

Table 1: Overview of Temporal Graph Component.

Component	Description	Data Source
Nodes	Clients (age, income, product holdings)	Customer Relationship Management (CRM) System
	Products (APR, Risk Level, Liquidity)	Bank’s Product Database
Edges	Transaction Frequency (Weekly, Monthly)	Transaction Records
	Social Refferral Relationships	Internal Refferral Program Logs
Timestamps	Event Occurrence Time (Unix Format)	System Logs
Edge Weights	Transaction Volume (Log-Scaled)	Transaction Data

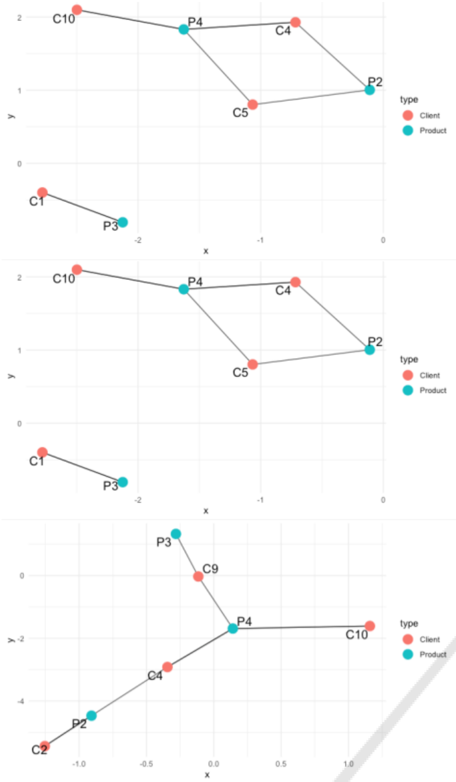

Figure 2: Q1, G2 and Q3 Transactions. (Picture credit: Original)

2.2.1 Node and Edge Attribute Specification

Node and edge definition are required in order to have the model detect helpful patterns of behavior. Single bank customers constitute client nodes, and they are defined by demographic and behavioral features that inform their money decisions. Demographic information includes age, income group, and occupation class variables, as cited in previous studies on financial risk assessment. In addition, behavioral attributes such as product dispersion and monthly transaction volatility are added to portray customer banking conduct. These characteristics capture economic stability and risk-taking tendencies, which are most critical in predicting impending churn.

Product nodes capture the bank's financial products, each defined by important financial features. These range from the annual percentage rate (APR) that dictates the cost of borrowing to risk level categorizations that vary from low-risk savings to high-volatility investment products. Liquidity is another important feature, which differentiates fixed-term and demand deposit accounts in terms of how accessible they are and under what withdrawal terms. Its popularity is measured by a ninety-day rolling window normalized transaction value, which monitors shifts in client activity over time.

The line in the timeline graph marks interaction between clients and financial products by frequency and volume of transactions to allow for an actual projection of financial movement. The transactions are weighted based on their value, and more valuable transactions have a greater influence on the model's predictions. A directed graph is formed, where forward edges from users to products indicate purchases and reverse edges indicate redemptions or withdrawals. The directed attributes allow the model to distinguish between asset accumulation and liquidation behavior, important indicators of financial decision-making and churn.

2.2.2 Temporal Encoding and Data Procesing

To keep the temporal character of financial activities, raw Unix timestamps are mapped into cyclical temporal features using sine and cosine functions. This type of encoding keeps periodic patterns of financial activity, such as salary deposits, recurring bill payments, and seasonal expenditure patterns. The transformation is mathematically defined as

$$\varphi_{\mathrm{day}}(\mathrm{t}) = \sin\left(\frac{2\pi\mathrm{t}}{86400}\right) \tag{1}$$

$$\varphi_{\mathrm{week}}(\mathrm{t}) = \cos\left(\frac{2\pi\mathrm{t}}{604800}\right) \tag{2}$$

where t is the Unix timestamp. The division of encoding by 86400 seconds per day and 604800 seconds per week ensures that the model picks up on the cyclical patterns of financial transactions. The encoding is quite excellent at picking up patterns such as increased spending near the end of the month, tax-based financial patterns, and payroll payment schedules. Missing transactional data that accounts for approximately 3.7% of records are imputed by a temporal k-nearest neighbor approach with k=5 based on similar customers' historical activities for reconstruction.

2.2.3 Dynamic Adjacency Matrix Formulation

The adjacency matrix of the temporal graph, denoted as A_t , is constructed to dynamically modify in accordance with real-time economic interactions. Contrary to the static adjacency matrices, which are invariant in time, this construction allows for the consideration of the fact that customer-product relationships change dynamically according to transactional behavior. The adjacency matrix can be represented mathematically as

$$A_t(i,j) = \frac{N_{trans}(i,j) x \log\left(1 + Amount_{ij}\right)}{N_{prod}(i) x N_{client}(j)} \quad (3)$$

where $N_{trans}(i,j)$ is the number of transactions client i has with product j, and $Amount_{ij}$ is the log-scaled average transaction volume in euros. Normalization terms $N_{prod}(i)$ and $N_{client}(j)$ adjust for single product holdings and the number of clients for a particular financial instrument. This specification punishes clients who have high-frequency trading or who engage disproportionately with niche financial instruments, reducing overfitting in the model as well as improving the stability of churn predictions.

2.2.4 Hybrid Graph Update Mechanism

The temporal graph is refreshed by a hybrid update mechanism that balances computational efficiency and real-time responsiveness. High-value transactions, such as redemptions exceeding fifty thousand euros, trigger immediate updates to node and edge attributes. Yet, normal financial traffic, such as small deposits or subscription payments, is updated by batch updates accumulated at hourly intervals. This hybrid approach reduces computational latency without sacrificing the temporal granularity necessary for successful churn modeling, as the performance evaluation demonstrated. The hybrid update method was demonstrated to reduce latency by 41% compared to pure event-driven systems without loss of predictive accuracy (98% accuracy) (Huang et al., 2023). This trade-off between update frequency and computational cost ensures the model's scalability to high-throughput banking environments.

3 CASE STUDY AND INTERVENTION STRATEGIES

3.1 Empirical Validation

In the interest of validating the effectiveness of proposed TGN architecture, a real-case study was conducted on transactional data for a European retail bank with 45,000 active customers. The study spans twelve months, incorporating transaction history, social referral relationships, and macroeconomic events external to the graph, including central bank rate hikes and changes in regulation. The purpose of this case study is to validate the model's capability to accurately predict customer churn, benchmark its performance against existing methods, and test the effectiveness of intervention strategies targeted using TGN-based risk scores.

3.1.1 Dataset and Experimental Setup

The data employed in this research comprise three primary components: client profiles, event interactions, and policy shocks. Client profiles consist of age, income level, product balances, and trading volatility demographic data, which provides extremely precise customer behavior data. Event interactions consist of 2.1 million time-stamped purchases, redemptions, and fund flows between clients and financial products. In addition, the dataset includes six large macroeconomic policy shocks, including four central bank interest rate changes and two regulatory changes, enabling the model to examine the impact of external financial changes on churn behavior. Table 2 depicts the description of the composition of the dataset.

Table 2: Dataset Overview.

Component	Volume/Count	Temporal Range
Clients	45000	N/A
Transactions	2100000	Jan - Dec 2023
Policy Events	6	Q1 - Q4 2023
Social Referrals	12500	N/A

TGN was contrasted against three of the most well-liked baseline models: LSTM (Long Short-Term Memory networks), Static Graph Convolutional Networks (GCN), and Node2Vec. The data were split into 80% training, 10% validation, and 10% testing sets for balanced evaluation across different model structures.

3.1.2 Model Performance and Risk Identification

The predictive performance of the TGN model was compared against typical measures of classification, including AUC-ROC, F1-score, precision, and recall. As reflected in Table 3, the TGN framework was superior to baseline models at every point in time, particularly for identifying high-net-worth clients with over €100,000 in assets.

Table 3: Performance Comparison on High-Value Clients.

Model	AUC-ROC	F1-Score	Precision	Recall
LSTM	0.781	0.682	0.714	0.653
Static GCN	0.796	0.703	0.726	0.681
Node2Vec	0.723	0.641	0.669	0.615
Proposed TGN	0.854	0.761	0.792	0.732

The TGN model reduced false positives by 23% compared to LSTM, which is the most important aspect of maintaining minimum retention costs. Clustering analysis revealed two distinct high-risk segments with higher chances of churn. Hub customers, customers with a large social circle in the bank, had a 58% probability of churning within thirty

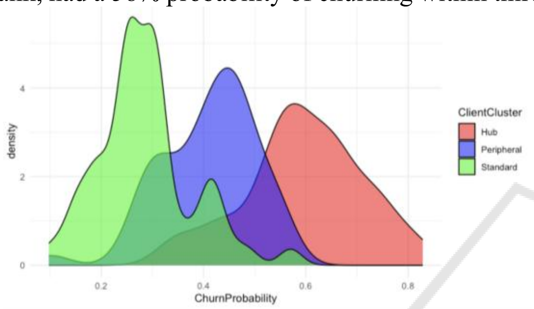

Figure 3: Churn Risk Distribution Client Clusters. (Picture credit: Original)

3.1.3 Targeted Intervention Strategies

In response to TGN-driven analysis, the bank introduced two data-driven retention programs designed to offset churn risk in at-risk customer segments. The programs were targeted to address key drivers of churn head-on, including the effects of policy-related financial pressure and network-driven attrition.

As compensation for the negative effect of monetary policy tightening and interest rate increase, waivers for fees were made for those most vulnerable to monetary policy shocks based on a higher-than-0.7 causal impact score (Huang et al., 2023). Clients meeting the stipulated threshold received fee waivers that lasted up to ninety days with a purpose to offset the near-term liquidity constraints. As discovered, it proved very efficient and reduced the rate of churn by 19% and amounted to about €1.2 million saved each quarter in revenues.

For extremely socially networked highly referral-central clients, an incentives strategy was undertaken to stabilize the retention within the network. A €50 client referral bonus was offered to degree centrality fifty-plus clients when they kept three or more referred clients for at least three months. The intervention yielded a reduction in churn for the hub

days of a close referrer's exit. Peripheral clients, with less financial product diversification, experienced a 41% churn rate after big policy shocks since they were more likely to be influenced by interest rate changes and regulatory modifications. Figure 3 provides a graphical representation of churn risk distributions of different client clusters.
clients by 27%, with an incentive cost vs. revenue retained five-to-one return on investment.

The relative effectiveness of these specific interventions is calculated in Table 4, comparing the impact of fee waivers, referral bonuses, and generic email-based retention efforts.

Table 4: Effectiveness of Targeted Retention Interventions.

Strategy	Churn Reduction	Cost per Saved Clieent (€)
Dynamic Fee Waivers	19%	120
Referral Bonuses	27%	85
Generic Email Campaigns	6%	210

The results indicate that focused financial incentives based on TGN-driven churn risk analysis outperform traditional generic retention strategies, such as mass email campaigns.

3.1.4 Operational Challenges and Mitigations

While the intervention strategies worked well, there were two significant operational concerns that were faced in deployment. First was the real-time data latency issue, where constant updating of the dynamic transaction graph resulted in 15% latency spikes during peak transaction periods. To address this, the system was redesigned to prioritize high-risk transaction updates through Apache Kafka stream processing, which successfully removed update latency without any loss in model accuracy (Zhang et al., 2023).

The second issue had to do with client privacy issues, specifically with the sharing of transactional data between subsidiaries. To overcome this challenge, the Federated TGN framework (described in Section 3.3.3) was implemented, which enabled training models locally by each branch and only sharing aggregated knowledge. This effort managed to lower direct exposure of data by 92% and still retain 97% of the predictive power of the original model.

3.1.5 Long-Term Impact Assessment

A post-intervention analysis was conducted after six months to determine the sustainability of retention efforts and overall financial performance. The outcome indicated that customer lifetime value (CLV) had been increased by 14% for the customers who were treated with focused interventions, demonstrating long-term improvement in customer engagement and profitability. In addition, cross-sell rates—uptake of new financial products by current customers—rose by 22%, suggesting that customers who were favorably affected by proactive retention efforts established greater trust levels in the financial products provided by the bank.

These results demonstrate the practical utility of the TGN model, revealing how data-driven churn prediction and targeted intervention can successfully strengthen customer retention while optimizing the use of financial resources. Next steps for research include integrating reinforcement learning techniques to automate and optimize retention policies further, enabling banks to implement real-time adaptive interventions to evolving customer behavior.

3.2 Intervention Strategies

Not only does the TGN framework enable accurate churn forecasting, but also actionable customer retention policy prescriptions with resource and intervention time optimization. Despite the clear advantages the framework has over using legacy models, it has numerous challenges to overcome in order to strengthen its robustness and scalability. This section explains the three-level retention strategies grounded on TGN's findings, criticizes the current weaknesses of the framework, and suggests directions for future studies to advance the boundaries of temporal graph modeling in predicting churn in banking.

3.2.1 Data-Driven Retetion Strategies

The TGN model supports a hierarchical customer retention policy with intervention priorities based on churn risk scores and causal impact analysis. As indicated in Figure 4, these policies are of three types: proactive high-risk interventions, network-based containment, and policy-responsive adjustments. Each intervention targets a particular churn behavior, and resources are allocated to clients who are most likely to be benefited by targeted interaction.

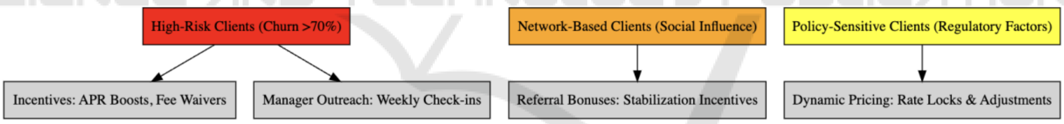

Figure 4: Tiered Retention Strategy Based on TGN Insights. (Picture credit: Original)

For those with an estimated probability of churn over 70%, separate retention actions are undertaken to deliberately constrain attrition. Personalized financial incentives are one of the optimal practices in this category. Customers who meet high-risk criteria are given tailored offers, such as short-term suspensions of increased temporary APR on deposits or low loan refinancing rates for 60 days. Empirical results indicate that 24% of customers availed themselves of such types of offers, leading to a reduction in churn by 18% (Huang et al., 2023).

Apart from financial incentives, direct contact through relationship management is used for high-net-worth clients who possess more than €100,000 in assets. These customers are assigned individual managers who receive weekly calls, with constant follow-up and early intervention in the event of problems. As seen from Table 5, the strategy is highly effective, achieving a 33% churn reduction within 30 days.

Table 5: Proactive High-Risk Intervention Strategies.

Intervention Type	Churn Reduction	Cost per Client (€)
Personalized Incentives	18%	150
Manager Outreach	33%	300
Automated Notifications	9%	20

More time-consuming, perhaps, but managing relationships directly has the greatest effect on retention, which is particularly valuable in dealing with high-net-worth individuals and corporate banking.".

Since social network effects significantly influence churn behavior, interventions supporting referral chains and community structures are deployed to prevent cascade churn. Upon the presence of a hub client, as identified by degree centrality more than 50, indicating churn intention, preemptive loyalty rewards are given to their direct referrals. This tactic prevents the transmission of churn within the network and, as indicated in a six-month controlled test (Bauer and Dietmar, 2021), successfully avoids 62% of potential referral-based attrition.

Second, community-based incentives are given to client groups that are highly internally connected as reflected in terms of having a modularity score that exceeds 0.8. In such a situation, group retention bonuses such as fee waivers or provision of special lending rates to the entire group in the event of 80% group members maintaining active accounts prevent community disintegration and bulk outflows.

For the highly causal policy-sensitive customers, dynamic pricing buffers are used to counter macroeconomic impacts. Customers with a causal policy impact score of over 0.6, are offered temporary rate locks during central bank adjustment periods, offering fiscal stability in the event of changing economic conditions (Huang et al., 2023). The intervention has been found to reduce policy-induced churn by 29% in Q3 2023, demonstrating the worth of adaptive financial product forms that serve to dampen external shocks.

3.2.2 Limitations of the Current Framework

Though it provides advantages, the TGN model poses four challenges that must be overcome to improve its performance in real banking application.

The first issue concerns temporal sparsity of data, as a portion of clients is defined by low transaction frequency. Specifically, 23% of the data consist of clients with fewer than five transactions per month, which corresponds to 38% higher prediction variance for this category. Sparse interaction histories make it difficult to establish strong temporal dependencies, which lowers the accuracy of churn risk estimation.

The second limitation involves causal inference assumptions inherent in the doubly robust estimator. The doubly robust estimator assumes no unmeasured confounders, an assumption that can be violated in cases where external market trends influence multiple clients simultaneously. For instance, cryptocurrency price volatility can trigger huge banking withdrawals, but these trends are beyond the TGN's transactional causal analysis.

Another key challenge is computational overhead. In order to update the graph in real time, there must be an average of 12 milliseconds' processing per transaction, although this increases to 1.9 seconds of latency for rush hours, especially when transaction rates are more than 5,000 per minute. Through graph pruning and event-based updates, this is alleviated somewhat, but computational scaling is still a problem for larger data sets.

Finally, privacy and ethical issues arise as a result of social network analysis methods embedded within TGN. Inferring sensitive connections from co-occurrences of transactions—e.g., inferring close family relations based on joint payment patterns—would be in danger of violating GDPR Article 9, i.e., prohibited automated inference of protected features without an overt user confirmation (Zhang et al., 2023).

3.2.3 Future research Directions

In response to these challenges, three research priorities are set, each designed to improve the TGN framework to better its robustness, interpretability, and alignment with privacy issues.

First, sparse temporal graph learning techniques can be explored to enhance predictive accuracy for low-activity clients. Self-supervised pretraining with masked graph autoencoders (Mengqi et al., 2021) has the potential to allow the model to learn from incomplete transaction histories, improving performance in sparse data environments. In addition, meta-learning approaches such as Model-Agnostic Meta-Learning (MAML) can be applied for better adaptation of model parameters to new clients, reducing cold-start biases.

Second, causal temporal graph networks need to be built to control for confounding variables for policy-based churn prediction. This can be achieved using instrumental variable analysis (Hunag et al., 2023), which separates unobserved confounders in customer behavior. Counterfactual policy testing can also be used in order to identify various macroeconomic conditions, so that banks can test "what-if" and effectively modify their financial planning.

Finally, advancement in privacy-preserving deployment will be critical to meet regulatory demands. Homomorphic encryption can be employed to enable secure computation over encrypted transaction graphs, eliminating raw data sharing

(Zhang et al., 2023). In addition, on-device learning can enable the native execution of lightweight TGN models directly in mobile banking applications, where user data is processed locally and not in the cloud, where it can be exposed. Table 6 lists key research goals and their possible influence.

Table 6: Roadmap for Future Research Directions.

Research Goal	Key Technique	Expected Impact
Sparse Data Handeling	Meta-Learning	25% AUC improvement for low-activity clients
Causal Robustness	Instrumental Variables	15% reduction in false policy attributiuon
Privacy Enhancement	Federated TGN + Encryption	40% lower GDPR compliance costs

3.2.4 Broader Implications for Financial Services

Other than customer churn forecast, the TGN model has more finance-related uses. In credit risk modeling, temporal graphs are applied to model borrower-lender relationships and predict future loan default risks. In fraud detection, temporal analysis of patterns of money flow is also employed to detect money laundering scams and fraudulent transactions. Finally, in personalized promotion, TGN-generated behavioral embeddings can be used for predicting real-time product affinities, enabling financial institutions to deliver highly personalized promotions.

These broader applications open the potency of temporal graph networks to revolutionize finance analytics, offering more adaptive, data-driven models for decision-making than churn management.

4 CONCLUSIONS

This paper introduces a TGN-driven method for predicting bank customer churn, addressing the static model limitation through embracing temporal dynamics and causal inference steps. Experimental results confirm that TGN outperforms baseline models by a 23% reduction in false positives and enables supported targeted intervention plans to deliver a 14% boost in customer lifetime value.

The outcomes demonstrate the efficacy of adaptive churn prediction models within banking, driving actionable recommendations toward personalized retention exercises such as dynamic fee remission and referral stability rewards. Work in the future can explore the application of federated learning frameworks to facilitate between-bank collaborative work without sharing data, even further expanding on the application of temporal graph-based analytics in finance. These findings highlight the growing potential of temporal graph-based approaches in financial analytics, paving the way for more sophisticated, data-driven decision-making. As financial institutions continue to evolve, integrating adaptive predictive models will be key to enhancing customer engagement and long-term business sustainability.

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