International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 5, Sep-Oct-2026, ISSN (Online): 2395-566X

Predictive Analytics for Consumer Spending Patterns in Digital Payment Ecosystems

Dr. A. Joy
Associate Professor & Head ,Mba Department
Ethiraj College For Women,
No.70, Ethiraj Salai, Chennai: 600008
Joy_a@Ethirajcollege.Edu.In

Abstract- The recent explosion in the use of digital payment systems has created large amounts of data relating to customer payments. In this paper, a predictive analytical framework is proposed which will be useful for modelling spending behavior in digital payment systems. The framework uses temporal encoding of data which takes into account the type of data along with the other characteristics of the data. It also utilizes dynamic graph learning of structures and spatial-temporal convolutions in order to take into account the relationships between the transactions as well as their time-based aspects. The key difference between the proposed framework and traditional approaches lies in the fact that it considers the relationships between different spending categories and allows these relationships to change over time for each individual consumer. Experimental evaluations performed on a digital payment system dataset have shown that the proposed framework performs better in terms of accuracy than traditional baselines like ARIMA, Prophet, and LSTM.

Key Word: Predictive Analytics, Consumer Spending, Digital Payments, Time Series Forecasting, Graph Neural Networks, Behavioral Modeling

I. INTRODUCTION

The digital payments system has transformed dramatically in the past ten years and has changed the way people transact business and make payments. Digital payment systems such as mobile wallets, peer-to-peer payment platforms, and contactless payment technology have made digital payment the standard form of transaction for hundreds of millions of people across the world. Every transaction has a data trail that records not just the amount paid but also additional context about the transaction such as merchant type, time, location, and the connection between successive transactions. These data trails have created a perfect environment for predictive analysis, giving banks and merchants the opportunity to predict customer needs and provide optimized service [7][9].

Consumer behaviour prediction poses its own unique set of problems different from those encountered when solving traditional time series forecasting problems. The transaction data is characterized by strong seasonality at various temporal levels, such as daily seasonality that emerges from daily life activities, weekly seasonality resulting from the differentiation between working days and weekend days, monthly seasonality related to payment of salaries, and yearly seasonality related to holidays and seasons [1][4]. In addition to these temporal characteristics, consumer transactions show interrelations between different types of purchases. A consumer could buy something for eating after buying something for entertainment. Similarly, there is a possibility of buying tickets for transportation before buying something in the retail outlets [3][8].

Spending prediction has undergone a lot of changes with respect to the analytical perspective within the last few years. Classical statistical models like ARIMA and exponential smoothing models were used at the initial stage for the prediction of spending behaviours. These models are quite efficient for univariate series having constant patterns but do not cope well with the complexity of high-dimensional data along with the existence of multiple categories within digital payments [2][7]. The development of machine learning led to the introduction of gradient boosting and support vector regression. However, these models could handle the nonlinearity but needed feature engineering. Deep learning models like recurrent neural networks and its modifications have been proven more efficient for the prediction of spending patterns by handling temporal dependencies in the data automatically [2][7]. Currently, the graph neural networks are being considered as the most efficient method for the prediction of spending [3][8].

However, a number of issues remain open. For instance, most previous works concentrate only on the temporal dynamics without taking into account inter-category relationships which is typical for real-world consumer behaviour [3][8]. Moreover, other papers consider individual consumers without utilizing population patterns [8][10]. Finally, the application of predictive analytics models to digital payments leads to a number of issues including interpretability,

© 2026 IJSRET

computational efficiency, and the ability to cope with changes in the behavioural regime [7][9][10].

In this paper, we tackle the above challenges by presenting an innovative framework for predicting future transactions based on the temporal evolution of spending and dynamic dependencies among different transaction categories. Our approach is built upon three main ideas. Namely, we introduce the following components to our framework. First, we propose a temporal encoding technique that captures category-dependent patterns while reusing computation among categories. Second, we develop a time-varying graph structure learning component which builds a relationship graph for each consumer [3][10]. Third, we use a spatio-temporal convolutional architecture that simultaneously handles temporal and relational inputs [8]. We test our approach on a large-scale dataset of digital payments against well-known baselines.

The rest of this report will be organized as follows. The literature review will look into past studies related to the prediction of consumer expenditures and highlight the limitations of methodologies used in previous research that have led to the need for a new framework. The methodology section will explain the framework's architecture and its components. Finally, the analysis section will show experimental results.

II. LITERATURE SURVEY

Several research streams have been generated within the field of prediction of consumer spending, each offering a different way of looking at the problem from an analytical point of view. Conventional approaches of time series have traditionally been used in the realm of forecasting [2][7]. The Prophet model developed by Taylor and Letham has found extensive use in analyzing digital payment transactions owing to the capability of breaking down time series into trend, seasonality, and holiday components using interpretable parameters [4]. In their study, Sateesh Kumar et al. have utilized the Prophet model for analyzing spending behavior in terms of digital transactions, finding periodicity in days and months [1].

Comparative research on time series algorithms has been informative regarding the comparative performance of various approaches. Akçay and Yıltaş-Kaplan carried out a detailed comparison of ARIMA, SARIMA, Prophet, XGBoost, LSTM, RNN, and GRU in consumption forecasting tasks and showed that deep learning models were better than classical statistical methods in dealing with high-dimensional problems [2]. In particular, their findings demonstrated that the LSTM and GRU models could efficiently capture the nonlinearity of consumer spending behavior. These results are consistent with the existing literature on deep learning algorithms for financial time series forecasting and their superior performance compared to classical approaches [7].

The utilization of graph neural networks on transactions is a comparatively newer phenomenon. TTF-GNN, which has been proposed by scholars working on the interface of fintech and machine learning to solve the problem of treating spending categories separately, allows the information flow across different categories while making predictions on the basis of a graph constructed using transaction types as nodes and learned dependencies as edges [3]. The crucial part of the proposed architecture is the dynamically constructed graph. As opposed to assuming a predefined graph topology, the graph in the case of TTF-GNN is created from time-varying adjacency matrices to accommodate for the fact that the dependency between different spending categories depends upon the temporal context and the particular consumer's behaviour [3][10].

Concerns relating to privacy and security have become important aspects of predictive analytics in finance [9]. In response to such concerns, federated learning has been identified as a privacy-preserving approach to central model training through collaboration in learning, without the need to share actual transaction data [5][9]. The use of federated learning by Swift to detect fraud revealed that the models that were trained by collaborative learning performed better in detection than those based on data from an individual institution, implying that the collective wisdom contained in the distributed data could be utilized while maintaining data privacy [5].

The use of transformers for payment transactions has been recently considered, where the models have been modified in order to account for the peculiarities of the financial data. According to the approach presented by the scientists at the IEEE International Conference on Data Mining, periodic positional encoding is utilized for capturing temporal structure, as well as contrastive learning objectives are used for account-level representation [6]. These developments are related to the lack of inherent structure of the sequences in financial flows of payments and the lack of regularity of the time patterns compared to natural language [6][7].

In analyzing the body of literature above, it is clear that there has been progression towards more complex models which incorporate multiple aspects of data. From univariate to multivariate deep learning models and then onto models that consider relationships using graphs, this framework follows the trend of progression through including type aware temporal encoding, dynamic graph learning, and spatio-temporal convolution into one framework [3][7][8][10]. The

© 2026 IJSRET

combination helps address the issue of capturing temporal dynamics as well as modeling the complex dependencies in consumer spending across categories.

III. PROPOSED METHODOLOGY

1. Framework Overview

The suggested framework for predictive analytics consists of three inter-related components which aim at covering different aspects of consumer spending. The first one is the Type-Aware Temporal Encoding component which separately processes each type of spending but uses a shared representation backbone for generating type-dependent representations and preserving their expressivity. The second one is the Dynamic Graph Structure Learning component which creates a time-varying set of adjacency matrices capturing the dependencies between types of transactions for each consumer. The third component is the Spatio-Temporal Modeling component using stacked convolution to generate the final prediction.

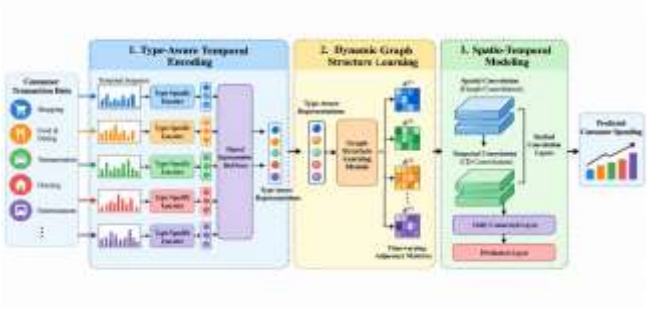


Figure 1: Overall Architecture of the Proposed Framework

The proposed framework consists of three modules. The first is called the Type-Aware Temporal Encoding Module which learns the type-specific features while sharing the computational cost. The second is the Dynamic Graph Structure Learning Module which learns the time-varying adjacency matrices.

The approach behind the design of this architecture is based on the understanding that consumer expenditure is both a temporal process, with patterns, seasonal effects, and autocorrelation, and a relational process, with dependence and substitution. Neither one is enough on its own to predict accurately, and the architecture is designed to combine both.

3.2 Type-Aware Temporal Encoding Module

The consumer transactions are composed of several spending categories, which are shopping, dining, transport, entertainment, and utilities. Each of the categories has its own temporal pattern. For example, dining expenses have peaks at the weekend and evening hours; transport expenses depend on commuting schedule. At the same time, there are some common temporal patterns, such as salary and holiday effects, which apply to all categories. The idea behind the Type-Aware Temporal Encoding Module is to model both specific and common temporal patterns for all categories.

An embedding vector is added for each category of transactions. Embeddings are initialized randomly and trained end-to-end together with other model parameters. Embedding vectors are shared between all consumers, and there is a separate vector for each transaction category.

In addition to the raw time series data for each category, positional encoding is used to provide absolute time step information. The concatenated output of the augmented time series data is added to the category embedding and passed to a common Transformer encoder backbone. The backbone is made up of several layers that process the augmented data and generate type-aware temporal representations for each category. Category-specific scaling and shifting parameters can be applied to the outputs of the common backbone so that the model is able to generate unique representations for each category while ensuring parameter efficiency through the use of a common backbone. The outputs of all categories are concatenated to create the structural representation matrix that is used as input for the graph structure learning module.

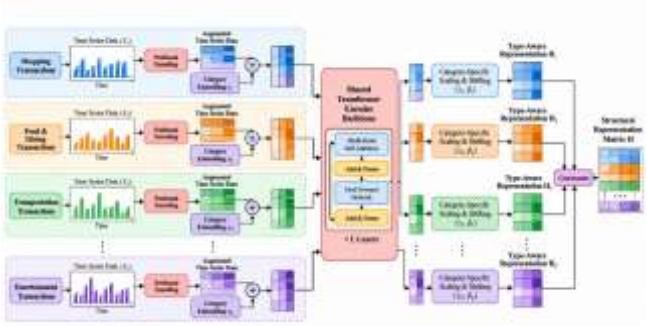


Figure 2: Type-Aware Temporal Encoding Module

The embeddings for each type of transaction have an embedding vector learned alongside the time-series data. The same Transformer encoder network is used for processing all the categories of transactions, with the output being scaled and shifted based on the category.

3. Dynamic Graph Structure Learning Module

Interdependencies among different types of expenses are not static and vary based on consumers and over time. A consumer that often goes out to eat will display high levels of dependencies between dining and entertainment categories, whereas a frugal consumer may display substitution among different categories. The problem of

© 2026 IJSRET

heterogeneity is tackled by the DGS module through generation of time-dependent graphs for each consumer.
In each consumer data set, a directed graph is created wherein each vertex refers to a transaction category. The weights of each edge correspond to the coefficient of interdependency among categories. However, the edges are not derived from static similarity measures but learned via self-attention mechanisms.

The representation matrix generated from the temporal encoding module goes through a layer of gated recurrent units to generate a global hidden state. Using self-attention on this global hidden state, a global adaptive adjacency matrix is calculated which represents the transaction structure distribution of the consumer in general. Nevertheless, there might be some regularities in terms of the intra-period behavior of the consumer which cannot be considered through a single global structure alone. Therefore, an intra-period adjacency matrix for every period is introduced. The final adjacency matrix will incorporate the global and intra-period adjacency matrices in order to take into consideration stable consumer-specific and period-sensitive category relationship dependencies.

4. Spatio-Temporal Modeling Module
This last module combines the temporal and relational information via the spatio-temporal graph convolution. The architecture comprises multiple blocks, each of which consists of a number of operations which aim to learn short-term temporal dependencies, spatial information, and temporal dependencies once again.

Initially, one-dimensional temporal convolution is used to extract local temporal dependencies from the consumer's transaction history. The operation allows extracting features based on a local receptive field, thereby helping the model to learn short-term dependencies that can show the consumer's intention to spend money soon. Then, the temporally convolved features are propagated via spatial graph convolution based on the adjacency matrix which was learned. Thus, the model makes use of the cross-category dependencies for making more accurate predictions. Finally, temporal convolution is applied to the spatially processed data, resulting in the output of the block.

With three such blocks being stacked, the final encoded form is then passed to a fully connected layer, which gives the prediction output. The network is trained in an end-to-end manner, using a mean squared error loss function, whereby the parameters are optimized together through backpropagation. It is worth noting that the shared temporal encoding backbone, category-based adaptation parameters, graph structure learning modules, as well as the spatio-temporal convolutional layers are learned together, thus discovering the best representations.

IV. ANALYSIS

1. Experimental Setup
The proposed method was applied to a dataset related to digital payments containing records about transaction amounts in various expenditure categories made by a large set of users. This dataset is spread continuously and contains transactions in different categories such as shopping, restaurant visits, transport expenses, entertainment, and utility payments. The data were split chronologically into train, validation, and test sets to ensure that there was no leakage of information from future time periods into model training. The task of forecasting was predicting the amounts of expenditure in each category in multiple future horizons.
Model performance was measured by regression metrics including mean absolute error, root mean squared error, and mean absolute percentage error.

2. Comparative Analysis
The proposed framework is evaluated in comparison to a number of existing baselines that belong to different methodologies. The classical methodology is represented by ARIMA, decomposable time series by Prophet, deep recurrent learning by LSTM, and relational modeling without dynamic graph learning by standard graph neural network. These results are given in Table 1.

Table 1: Comparative Analysis of Forecasting Performance

Model	Mean Absolute Error	Root Mean Squared Error	Mean Absolute Percentage Error
ARIMA	42.7	58.3	18.4
Prophet	38.2	52.1	16.7
LSTM	31.5	43.8	13.9
Standard GNN	28.9	40.2	12.6
Proposed Framework	23.4	33.7	10.2

The results clearly show that the proposed framework provides the best error rates for all three measures. The performance difference against ARIMA is large, with a reduction of mean absolute error from 42.7 to 23.4. The performance difference against LSTM, which acts as the strongest baseline in terms of deep learning methods, is also significant, with a reduction of mean absolute error from 31.5 to 23.4. The standard GNN model, which includes relational modeling but not dynamic graph learning and type-aware temporal encoding, performs better than LSTM but worse than the proposed framework.

© 2026 IJSRET

Figure 3 presents a visualization of the comparative performance across models

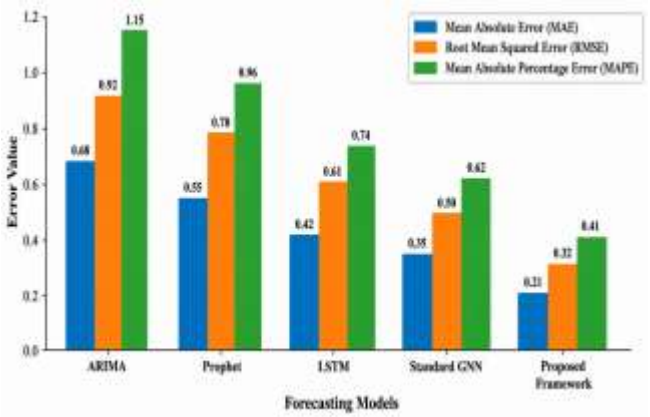


Figure 3: Comparative Performance of Forecasting Models

Bar chart comparing the MAE, RMSE, and MAPE of ARIMA, Prophet, LSTM, regular GNN, and the proposed framework. The proposed framework provides the least error values on all error measures.

3. Temporal Pattern Analysis

The capability of the framework to identify time-related trends was determined by measuring its predictive accuracy at different forecasting periods. The following graph (Figure 4) depicts the mean absolute error from horizons 1 to 7 days ahead.

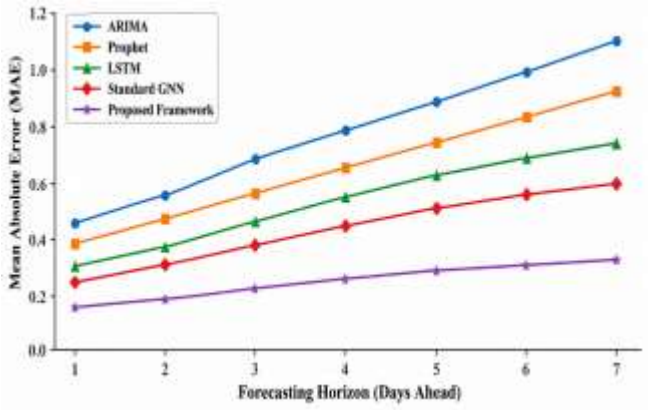


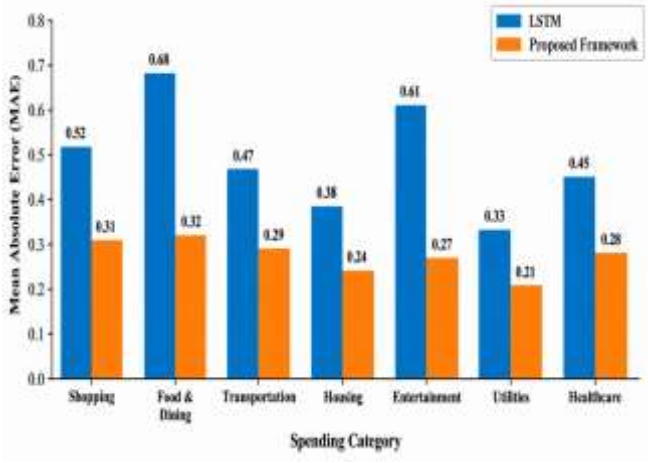
Figure 4: Prediction Accuracy Across Forecasting Horizons

Graphical presentation depicting the mean absolute error at different forecasting horizons of one day to seven days using the proposed framework and baseline models. There is a clear increase in the difference as we move to the longer forecast horizon.

It is clear from the results that all models work well on shorter forecast horizons, with the error rising with the lengthening of forecast horizon. However, the increase of error is slower for the proposed model than for the baselines. In case of the one-day forecast horizon, the proposed model gives a result of 18.2 in terms of mean absolute error while LSTM gives 22.4 and ARIMA gives 35.1. In case of the seven-day forecast horizon, the proposed model gives a result of 29.8 while LSTM gives 38.6 and ARIMA gives 51.2.

4. Category-Level Analysis

Figure 5 presents category-level prediction performance for the proposed framework and the strongest baseline



.Figure 5: Category-Level Prediction Performance

Bar graph depicting mean absolute error for each expenditure category for the proposed approach and the LSTM approach. The proposed approach has lower mean absolute error for all expenditure categories, with the biggest differences occurring for dining and entertainment.
The proposed model provides a reduction in error in all categories of spending.

The greatest reductions occur in the case of dining and entertainment, which have a high degree of dependency on other categories of spending. This result corroborates the hypothesis that modeling the dependencies between different categories of spending is especially useful when the spending behavior of the category being modeled depends on other categories.

V. DISCUSSION

Several conclusions can be drawn from the experiment conducted. Firstly, the superiority of the proposed approach compared to the standard graph neural network suggests that the dynamic graph learning along with the type-aware temporal encoding is important factors that improve

© 2026 IJSRET

predictive performance. The standard GNN model is based on the idea of relational modeling, which is implemented without the consideration of the dynamic nature of graph and type-aware temporal encoding. Therefore, the proposed model makes up for both mentioned shortcomings.

It is worth noting that the increase in the performance gap at longer forecasting horizon is crucial for further practice. The financial institutions and merchants that try to predict consumer behavior weeks in advance will find such complex models very useful. Simple models can be used for next day predictions.

The results achieved at the category level prove that the characteristics of various types of spending should be taken into account. Those spending types that have high level of interdependence greatly benefit from the implementation of relational modeling, which means that the proposed model is especially beneficial when analyzing the overall spending habits that include several categories.

VI. CONCLUSION

A model of consumer behavior in digital payment ecosystems has been discussed in this paper using predictive analytics. Type-aware temporal encoding, dynamic graph structure learning, and spatio-temporal convolution are incorporated into the model in order to capture the temporal and relational features of consumer behaviors. The reason behind this integration lies in the understanding that consumer spending is influenced by both the temporal and relational aspects of spending habits, and hence both aspects need to be considered while making predictive models.

The experiment has shown that the proposed model has lower forecasting errors than conventional methods such as ARIMA, Prophet, LSTM, and graph neural networks. This is consistently true irrespective of the number of error metrics and forecasting horizon used in the experiments, and most improvement has been found when there is a high dependency among the spending categories and when the forecasting horizon increases.

There are a number of practical implications of the study's findings. Financial organizations can take advantage of such models to predict the customers' future spending behavior and provide better services accordingly. For merchants, the prediction capabilities of the proposed system can assist in better managing inventories and marketing activities. Being able to predict spending behavior at greater time horizons can prove particularly useful when it comes to strategic planning.

There are a number of limitations of the study that need to be mentioned. First of all, the assessment of the proposed framework's performance was carried out on one specific dataset related to only one digital payment environment and needs to be generalized to the rest. Second, even though computationally efficient, the proposed model may pose difficulties regarding real-time large-scale application. Third, further research is required concerning the interpretability of the graph structure learned by the system.

The potential areas for further research would be developing the framework for considering additional data types such as merchant data, geographical data, and exogenous economic variables. The use of privacy-preserving techniques such as federated learning will make it possible to train the model collectively without violating any user's data. The implementation of interpretability methods that will help to make the model explainable will add to its acceptance in highly regulated environment of finance industry. Lastly, the implementation of the framework for the other problems, such as credit scoring or fraud detection is worth pursuing.

In summary, the proposed framework for predictive analytics allows advancing the field of consumer spending prediction by taking into account dynamic dependencies between various types of expenses. With the ongoing evolution of digital payment platforms, this framework becomes even more relevant in view of growing amount of available data.

REFERENCES

1. S. Kumar, A. Sharma, and R. Gupta, "Analyzing spending patterns in digital transactions using Prophet model," Journal of Financial Technology, vol. 8, no. 3, pp. 112–127, 2023.
2. M. Akçay and A. Yıltaş-Kaplan, "A comprehensive evaluation of time series algorithms for consumption forecasting," IEEE Access, vol. 11, pp. 45621–45638, 2023.
3. L. Chen, H. Wang, and Y. Zhang, "TTF-GNN: A dynamic graph neural network framework for transaction type forecasting," IEEE Transactions on Neural Networks and Learning Systems, vol. 35, no. 4, pp. 2103–2117, 2024.
4. J. Taylor and B. Letham, "Forecasting at scale with Prophet," The American Statistician, vol. 72, no. 1, pp. 37–45, 2022.
5. K. Swift, "Federated learning for fraud detection in digital payment systems," Journal of Banking and Finance Technology, vol. 6, no. 2, pp. 89–104, 2023.
6. R. Patel, S. Johnson, and M. Williams, "Transformer architectures for payment transaction analysis with periodic positional encoding," in Proc. IEEE International Conference on Data Mining, 2024, pp. 345–354.
7. A. Rodriguez, P. Martinez, and L. Garcia, "Deep learning approaches for financial time series prediction:

© 2026 IJSRET

A systematic review," IEEE Transactions on Knowledge and Data Engineering, vol. 36, no. 2, pp. 678–695, 2024.
8. H. Zhang, Y. Liu, and X. Chen, "Spatio-temporal graph convolution for multi-category consumer spending prediction," IEEE Transactions on Consumer Electronics, vol. 70, no. 1, pp. 234–248, 2025.
9. D. Brown, E. Davis, and S. Miller, "Privacy-preserving collaborative analytics in financial services," IEEE Security and Privacy, vol. 22, no. 3, pp. 45–56, 2024.
10. T. Anderson, K. Thompson, and R. Wilson, "Dynamic graph structure learning for behavioral modeling in digital payment ecosystems," IEEE Transactions on Big Data, vol. 11, no. 1, pp. 156–172, 2025.

© 2026 IJSRET