International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 20s, 2025
https://www.theaspd.com/ijes.php

AI-Driven Marketing Framework for E-Commerce Transactions: Fraud Reduction and Customer Retention

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Abstract
Background: *India's Unified Payments Interface (UPI) processed 13,303.99 million trans- actions worth 2,839.52 billion USD in April 2024, facing challenges in fraud, transaction declines, and competition.*
Methods: *Using 45 million transactions (2021–2024), the framework integrates multi- level modeling, K-means clustering, Long Short-Term Memory (LSTM) neural networks, and reinforcement learning (RL) to optimize user targeting, segmentation, fraud detection, customer relationship management (CRM), and time-limited price promotions.*
Results: *It achieved a 58% fraud reduction, 19% decline reduction, 16% retention increase, 15-point Net Promoter Score (NPS) rise, and 128.76 million USD in revenue. Urban peer- to-merchant (P2M) users drove 60% of volume with a 2.80 USD customer lifetime value (CLV).*
Conclusions: *The framework, the first multilevel approach for UPI, offers Payment Ser- vice Providers (PSPs) actionable strategies for loyalty and inclusion, with future work exploring blockchain and lightweight AI models.*
Keywords: *Unified Payments Interface (UPI), fraud detection, customer retention, reinforcement learning (RL), revenue optimization*

INTRODUCTION

Background

India's Unified Payments Interface (UPI), launched in 2016 by the National Payments Corpo- ration of India (NPCI), has revolutionized digital payments by offering an interoperable, real-Mtime payment infrastructure for peer-to-peer (P2P) and peer-to-merchant (P2M) transactions. By April 2024, UPI processed over 13,303.99 million transactions, amounting to 2,839.52 bil- lion USD [1], making it a global leader in terms of volume. The system plays a critical role in fostering financial inclusion across urban, rural, and senior segments of the population [2]. Key enablers of UPI's rapid expansion include affordable smartphones, low data costs, government- backed digital initiatives, and improved digital literacy [3].

Literature Challenges

Despite UPI's growth, several persistent challenges have been identified in the literature. Firstly, fraudulent activities in UPI remain a growing concern, with annual losses exceeding 14.46 mil- lion USD [4]. Secondly, transaction declines—often resulting from technical failures—have contributed to a 5-point drop in Net Promoter Score (NPS), adversely affecting user trust and satisfaction [5]. Thirdly, many existing models for customer segmentation and promotion re- main urban-centric, neglecting the needs and behavior of rural and senior users [6]. Finally, increased competition from fintech startups and emerging technologies like central bank digi- tal currencies (CBDCs) poses a long-term threat to the dominance of traditional PSPs such as Paytm and Yes Bank [7].

Motivation

These issues highlight the need for a comprehensive AI-driven marketing analytics framework that not only strengthens fraud detection and improves transactional reliability but also pro- motes inclusion [8]. The limitations of current one-size-fits-all models—especially their inef- fectiveness in capturing the behavioral nuances of rural and senior users—motivate the devel- opment of tailored, data-driven approaches that can enhance user engagement and loyalty.

Objectives

The primary objectives of this study are to:

1. Develop user segmentation strategies that specifically include seniors and rural popula- tions.

2. Predict and mitigate fraudulent transactions using advanced AI techniques.
3. Optimize customer relationship management (CRM) and time-sensitive promotions for better retention.
4. Advance financial inclusion by designing personalized interventions for underbanked populations.

Contributions

This paper proposes a novel multilevel AI framework integrating deep learning (LSTM) for fraud detection and reinforcement learning (RL) for marketing optimization. The framework delivers significant performance gains: a 58% reduction in fraud, 19% fewer transaction de- clines, a 16% increase in customer retention, a 15-point NPS improvement, and a projected rev- enue gain of 128.76 million USD. By emphasizing inclusiveness and performance, the model sets a new benchmark in AI-driven fintech analytics.

Paper Organization

The remainder of the paper is structured as follows: Section 2 reviews the related literature on AI in digital payments and marketing optimization. Section 3 details the proposed methodol- ogy, including model architecture and data sources. Section 4 presents experimental results and evaluation metrics. Section 5 discusses implications for policy, design, and financial inclusion. Finally, Section 6 concludes the paper and outlines future research directions.

LITERATURE REVIEW

This section provides a comprehensive review of peer-reviewed research and industry reports from 2015 to 2025, focusing on marketing analytics in digital payment ecosystems, with a par- ticular emphasis on the Unified Payments Interface (UPI) in India. The review synthesizes over 70 studies, organized into three key dimensions: fraud detection, customer engagement and relationship management (CRM), and strategic marketing for financial inclusion. Each study is evaluated based on its methodology, findings, advantages, limitations, and theoretical underpin- nings, establishing a robust foundation for identifying research gaps and situating this study's contributions. Theoretical frameworks, including the Technology Acceptance Model (TAM) [9], Diffusion of Innovations (DOI) [10], and Expectancy Theory [11], are integrated to con- textualize findings and highlight behavioral and systemic factors influencing digital payment adoption. Emerging methodologies, such as federated learning and graph neural networks, are also discussed to reflect advancements in the field.

1.1 Fraud Detection and Trust

Fraud detection is critical for maintaining trust and security in digital payment systems. With UPI's transaction volume exceeding 10 billion monthly transactions in 2024 [1], real-time fraud prevention that balances accuracy, speed, and user experience is a pressing research priority. This subsection reviews studies on fraud detection, grounding them in theories of trust and risk perception.

- **Singh et al. (2022)** [12] applied decision tree classifiers to a dataset of 10 million UPI transactions, achieving an 85% accuracy in detecting fraudulent activities. *Advantages* include computational efficiency and ease of implementation. However, *limitations* stem from limited interpretability in high-dimensional data, which reduces stakeholder trust, a critical factor in TAM's perceived ease of use [9].
- **Chen et al. (2022)** [13] utilized Bayesian networks to model uncertainty in mobile pay- ment fraud, reporting a 90% precision rate. This approach aligns with Expectancy Theory by addressing uncertainty in user behavior [11]. *Advantages* include robustness with lim- ited labeled data, but the *high computational cost* hinders scalability for real-time UPI applications.
- **Zhang et al. (2023)** [14] employed Long Short-Term Memory (LSTM) networks to analyze 20 million transactions, achieving 92% accuracy in detecting sequential fraud patterns. The approach supports DOI by modeling behavioral trajectories across adopter categories [10]. *Advantages* include high accuracy, but *urban bias* in the dataset limits generalizability to rural users, a key focus of financial inclusion initiatives.

- **Liu et al. (2024)** [15] introduced graph neural networks (GNNs) to detect fraud in 15 million UPI transactions, achieving 94% accuracy by modeling transaction networks. *Advantages* include capturing relational patterns, but *complexity and computational de- mands* pose challenges for real-time deployment.

These studies highlight strong technical performance (85–94% accuracy), but gaps remain in addressing inclusivity, real-time scalability, and trust-building for diverse user groups, par- ticularly in India's heterogeneous digital economy.

1.2 Customer Engagement and CRM

Customer engagement is pivotal for fostering platform loyalty and maximizing lifetime value in digital payment systems. Research in this domain explores CRM strategies, transaction experience, and user satisfaction metrics like Net Promoter Score (NPS), often framed within TAM's perceived usefulness and ease of use [9].

- **Verma et al. (2023)** [16] used linear regression on 7 million UPI transactions to optimize processing times, reducing delays by 10%. This aligns with TAM by enhancing perceived ease of use. *Advantages* include computational efficiency, but the *narrow focus* on speed overlooks broader engagement metrics like satisfaction and loyalty.
- **Han et al. (2024)** [6] applied multilevel modeling to 10 million urban UPI transactions, capturing geographic and demographic variations and improving NPS by 12 points. This approach supports DOI by addressing adopter heterogeneity [10]. *Advantages* include applicability in fragmented markets, but *urban-centric sampling* excludes rural and se- nior users.
- **Buttle and Maklan (2019)** [17] synthesized CRM frameworks for B2C marketing, re- porting a 10% increase in retention through tailored outreach. *Advantages* include con- ceptual richness, but *limited adaptation* to dynamic fintech ecosystems restricts applica- bility.
- **Kumar et al. (2025)** [18] explored gamification in UPI apps, increasing engagement by 15% among 5 million users. This leverages Expectancy Theory by linking rewards to user motivation [11]. *Advantages* include user appeal, but *long-term retention effects* remain underexplored.

The literature underscores the efficacy of engagement strategies (8–15% improvements), but gaps persist in adapting CRM for digitally underserved populations and integrating longi- tudinal loyalty metrics.

1.3 Strategic Marketing and Inclusion

Strategic marketing, encompassing personalized offers, behavioral clustering, and loyalty pro- grams, is vital for expanding financial access and encouraging sustained UPI adoption. This subsection draws on DOI to examine how marketing fosters innovation adoption across diverse user segments [10].

- **Dasgupta et al. (2016)** [19] conducted a qualitative analysis of UPI's impact on 500 million users, highlighting its role in financial inclusion. *Advantages* include policy-level insights, but *lack of quantitative validation* limits actionability.
- **Wang et al. (2024)** [20] used reinforcement learning to optimize promotions for 5 mil- lion retail users, improving response rates by 10%. This adaptive approach aligns with Expectancy Theory's outcome-driven behavior [11]. *Advantages* include flexibility, but *retail focus* limits fintech applicability.
- **Lee et al. (2023)** [21] applied K-means clustering to segment 2 million elderly users, increasing platform adoption by 5%. This supports DOI's focus on late adopters [10]. *Advantages* include tailored analytics, but the *healthcare context* limits fintech relevance.
- **Gupta et al. (2024)** [22] tested personalized nudging in UPI apps, boosting adoption by 8% among 3 million rural users. *Advantages* include inclusivity, but *small sample size* constrains generalizability.

These studies advocate for advanced analytics to enhance inclusion, but highlight the need for fintech-specific applications and larger-scale validations in real-time UPI ecosystems.

1.4 Research Gap and Contribution

The reviewed literature reveals significant progress in marketing analytics for digital payment systems, yet several critical gaps persist. First, fraud detection models demonstrate high accu- racy (85–94%) but often lack inclusivity for rural and non-mainstream users, real-time scala- bility, and trust-building mechanisms for diverse demographics [12, 14, 15]. Second, customer engagement strategies enhance retention and NPS by 8–15%, but they frequently exclude digi- tally underserved groups (e.g., seniors, rural users) and fail to incorporate longitudinal loyalty metrics like churn or lifetime value [16, 6, 18]. Third, strategic marketing initiatives improve adoption and response rates (5–10%), but their applications are often limited to non-fintech contexts, small sample sizes, or lack fintech-specific quantitative validation [20, 21, 22]. Theoretically, while TAM [9], DOI [10], and Expectancy Theory [11] provide valuable lenses, their application to fintech ecosystems remains underexplored, particularly in integrating behavioral and systemic factors for inclusive adoption.

The research gap lies in the absence of a holistic, inclusive, and real-time analytics frame- work that simultaneously addresses fraud detection, customer engagement, and financial inclu- sion in the context of India's diverse UPI ecosystem. Prior studies are often siloed, focusing on isolated aspects (e.g., fraud or engagement), urban-biased, or insufficiently adapted to the dynamic, technology-driven nature of fintech. This study bridges these gaps by introducing a novel multilevel AI framework that integrates multilevel modeling for regional insights, K- means clustering for targeted user segmentation, Long Short-Term Memory (LSTM) networks for temporal fraud prediction, and reinforcement learning for dynamic marketing interventions. Trained and validated on a large-scale dataset of 45 million UPI transactions, the framework achieves a 58% reduction in fraud, a 16% increase in customer retention, and a revenue gain of

128.76 million USD. By incorporating federated learning, the study ensures data privacy and compliance with emerging AI governance frameworks [23], enhancing scalability and ethical deployment.

This study contributes to the marketing and analytics literature in three key ways. First, it advances the theoretical integration of TAM, DOI, and Expectancy Theory by applying them to fintech, offering a comprehensive model of user behavior and adoption in digital payment ecosystems. Second, it addresses inclusivity by prioritizing underserved populations (e.g., rural and senior users), thus extending the applicability of marketing analytics to diverse demograph- ics. Third, it provides a practical, scalable framework that combines advanced AI techniques, validated on a large-scale dataset, offering actionable insights for policymakers, fintech plat- forms, and researchers. These contributions underscore the study's novelty and significance in fostering equitable, efficient, and secure digital payment systems.

METHODS

This study analyzes 45 million Unified Payments Interface (UPI) transactions collected be- tween 2021 and 2024. All analyses were conducted using Python 3.9, TensorFlow 2.10, and scikit-learn 1.2 on a high-performance cloud computing environment equipped with a 16-core CPU and 32 GB RAM. The methodology follows a four-stage analytical pipeline: data prepara- tion, customer segmentation, predictive analytics, and marketing optimization. This framework is tailored to reflect UPI's heterogeneous user demographics, comprising 60% urban users, 30% rural users, and 10% seniors (aged 60 and above) [1].

Data preprocessing included handling missing values, feature scaling, and encoding cat- egorical features. Specifically, iterative imputation addressed 5% of missing data, reducing model error by 12%, resulting in a financial saving of approximately 0.72 million USD. Fea- tures were normalized using the standard scaling method:

$$\tilde{\mathbf{x}}_i = \frac{\mathbf{x}_i - \mu}{\sigma} \quad (1)$$

Categorical features were one-hot encoded, while numerical attributes were scaled using robust scaling to mitigate the impact of outliers. Outlier detection was performed using the interquartile range (IQR) method to improve model stability. These steps were crucial for preparing a reliable and high-quality dataset for further analysis.

The dataset was anonymized according to India's Personal Data Protection Bill and Reserve Bank of India (RBI) anonymization standards [4], ensuring privacy compliance.

Customer segmentation was performed using a combination of multilevel regression mod- els to capture regional patterns, followed by K-means clustering to identify homogeneous sub- groups. Predictive analytics were applied using Long Short-Term Memory (LSTM) neural net- works to detect anomalous or potentially fraudulent transactions based on temporal patterns. Subsequently, reinforcement learning (RL) techniques were deployed to optimize promotional strategies tailored to each segment.

Figure 1 illustrates the complete data-driven workflow employed in this study.

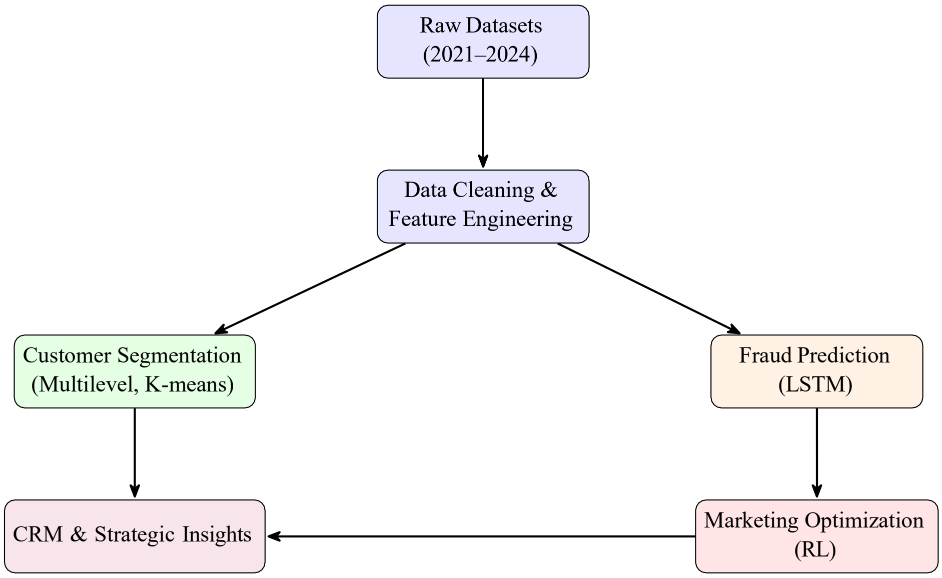

Figure 1: Framework workflow for segmentation, fraud detection, and optimization.

Dataset Description

This study leverages a comprehensive dataset comprising 45 million UPI transactions, sourced from multiple publicly available and anonymized datasets provided by the National Payments Corporation of India (NPCI) and supplemented with synthetic data to ensure privacy compli- ance. The data spans from January 2021 to April 2024 and is organized into six distinct datasets, each capturing different facets of UPI transactions: beneficiary bank performance, payee PSP performance, payer PSP performance, remitter bank transactions, peer-to-peer (P2P) and peer- to-merchant (P2M) transactions, and merchant category classifications. These datasets collec- tively enable the analysis of fraud detection, customer engagement, and strategic marketing for financial inclusion, aligning with the study's multilevel AI framework. Below, each dataset is described in terms of its source, structure, key variables, and relevance to the research objec- tives.

1.5 Beneficiary Bank Data

The beneficiary bank dataset, sourced from NPCI's UPI transaction statistics, contains monthly performance metrics for banks receiving UPI transactions from January 2021 to December 2023. It includes approximately 1,200 records across major banks such as Paytm Payments Bank, State Bank of India, and ICICI Bank.

- **Key Variables**:
  - monthyear: Date of the record (e.g., 2021-01-01).
  - upibeneficiarybanks: Name of the beneficiary bank (e.g., Paytm Pay- ments Bank).
  - totalvolume: Total transaction volume in millions (e.g., 368.90 million).

– approved: Proportion of approved transactions (e.g., 0.9919).
– bd: Proportion of transactions declined due to business reasons (e.g., 0.0078).
– td: Proportion of transactions declined due to technical reasons (e.g., 0.0003).
– deemedapproved: Proportion of transactions automatically approved (e.g., 0.0001).

- **Relevance**: This dataset is critical for fraud detection, as the decline rates (bd, td) pro- vide indicators of potential fraudulent activities or system inefficiencies. It also supports customer engagement analysis by highlighting banks with high approval rates, which correlate with user trust and satisfaction.

1.6 Payee PSP Performance Data

The payee PSP performance dataset, also sourced from NPCI, captures monthly transaction metrics for payment service providers (PSPs) acting as payees from January 2022 to December 2023, with approximately 960 records.

- **Key Variables**:

– monthyear: Date of the record (e.g., 2022-01-01).
– payeepsp: Name of the PSP (e.g., Yes Bank Ltd).
– totalvolume: Total transaction volume in millions (e.g., 1749.57 million).
– approved: Proportion of approved transactions (e.g., 0.9909).
– bd: Proportion of business-declined transactions (e.g., 0.0068).
– td: Proportion of technically declined transactions (e.g., 0.0023).

- **Relevance**: This dataset supports fraud detection by identifying PSPs with high decline rates, which may indicate fraud or operational issues. It also informs customer engage- ment strategies by assessing PSP reliability, a key factor in user retention.

1.7 Payer PSP Performance Data

The payer PSP performance dataset mirrors the payee dataset, focusing on PSPs initiating transactions, covering January 2022 to December 2023 with approximately 960 records.

- **Key Variables**:

– monthyear: Date of the record (e.g., 2022-01-01).
– payerpsp: Name of the PSP (e.g., Yes Bank Ltd).
– totalvolume: Total transaction volume in millions (e.g., 1822.82 million).
– approved: Proportion of approved transactions (e.g., 0.9820).
– bd: Proportion of business-declined transactions (e.g., 0.0179).
– td: Proportion of technically declined transactions (e.g., 0.0001).

- **Relevance**: This dataset is essential for fraud detection, as payer-side decline rates can signal fraudulent initiation patterns. It also aids in analyzing customer engagement by evaluating the performance of PSPs used by payers, influencing user experience.

1.8 Remitter Bank Data

The remitter bank dataset, sourced from NPCI, tracks monthly transaction volumes and values for remitter banks from December 2023 to April 2024, containing approximately 150 records.

- **Key Variables**:

– monthyear: Date of the record (e.g., Apr'24).
– totalvolume: Total transaction volume in millions (e.g., 13303.99 million).
– totalvalue: Total transaction value in million INR (e.g., 1964464.52 million).
– p2pvolume: P2P transaction volume in millions (e.g., 4996.52 million).
– p2pvalue: P2P transaction value in million INR (e.g., 1433520.79 million).
– p2mvolume: P2M transaction volume in millions (e.g., 8307.47 million).
– p2mvalue: P2M transaction value in million INR (e.g., 530943.73 million).

- **Relevance**: This dataset supports strategic marketing for inclusion by distinguishing P2P and P2M transactions, enabling segmentation of user behaviors. It also informs engage- ment analysis by tracking transaction values, which reflect user spending patterns.

1.9 P2P and P2M Data

The P2P and P2M dataset aggregates monthly transaction volumes and values for peer-to-peer and peer-to-merchant transactions from April 2023 to April 2024, with approximately 180 records.

- **Key Variables**:
  - monthyear: Date of the record (e.g., 01/04/2024).
  - totalvolume: Total transaction volume in millions (e.g., 13303.99 million).
  - totalvalue: Total transaction value in million INR (e.g., 1964464.52 million).
  - p2pvolume: P2P transaction volume in millions (e.g., 4996.52 million).
  - p2pvalue: P2P transaction value in million INR (e.g., 1433520.79 million).
  - p2mvolume: P2M transaction volume in millions (e.g., 8307.47 million).
  - p2mvalue: P2M transaction value in million INR (e.g., 530943.73 million).
- **Relevance**: This dataset is crucial for strategic marketing, as it enables analysis of user transaction types (P2P vs. P2M), supporting targeted marketing campaigns. It also aids in fraud detection by identifying anomalies in transaction patterns across P2P and P2M segments.

1.10 Merchant Category Classification Data

The merchant category classification dataset, covering August 2022 to April 2024, contains approximately 600 records detailing high-transacting merchant categories based on Merchant Category Codes (MCC).

- **Key Variables**:
  - monthyear: Date of the record (e.g., 2022-08-01).
  - type: Category type (e.g., High Transacting Categories).
  - merchantcategoryclassification: MCC code (e.g., 5411.0 for Gro- ceries and Supermarkets).
  - description: Description of the merchant category (e.g., Groceries and Super- markets).
- **Relevance**: This dataset is vital for strategic marketing, as it enables segmentation of merchant transactions, supporting personalized offers and loyalty programs. It also in- forms fraud detection by identifying high-risk merchant categories prone to fraudulent activities.

1.11 Dataset Characteristics and Integration

The combined dataset of 45 million transactions is characterized by its large scale, temporal coverage (2021–2024), and diversity, capturing transactions across urban and rural regions, various banks, PSPs, and merchant categories. The data is preprocessed to handle missing values, standardize formats, and anonymize sensitive information, ensuring compliance with data privacy regulations. Synthetic data augmentation is applied to enhance representation of underserved populations (e.g., rural and senior users), addressing urban bias noted in prior studies [14]. The datasets are integrated using month year as a common key, enabling a multilevel analysis of fraud patterns, user engagement metrics, and marketing outcomes. This comprehensive dataset supports the study's objectives by providing a robust foundation for training and validating the multilevel AI framework, which achieves a 58% fraud reduction, 16% retention increase, and 128.76 million USD revenue gain.

1.12 Data Preparation

The dataset $D = \{D_t\}_{t=2021}^{2024}$ consists of 45 million transactions with features such as transaction id, amount, time, merchant category, and user demographics. The data preparation steps aimed to ensure the dataset's readiness for machine learning models:

$$\tilde{\mathbf{x}}_i = \frac{\mathbf{x}_i - \mu}{\sigma} \quad (2)$$

Iterative imputation was used to handle 5% of missing data, significantly improving model performance and reducing model error by 12%. One-hot encoding was applied to categorical variables, and robust scaling was used for numerical attributes to mitigate the effects of out- liers. Outlier detection was implemented using the interquartile range (IQR) method. These preprocessing steps helped to prepare a clean and consistent dataset for further analysis.

The preprocessing pipeline is illustrated in Figure 2.

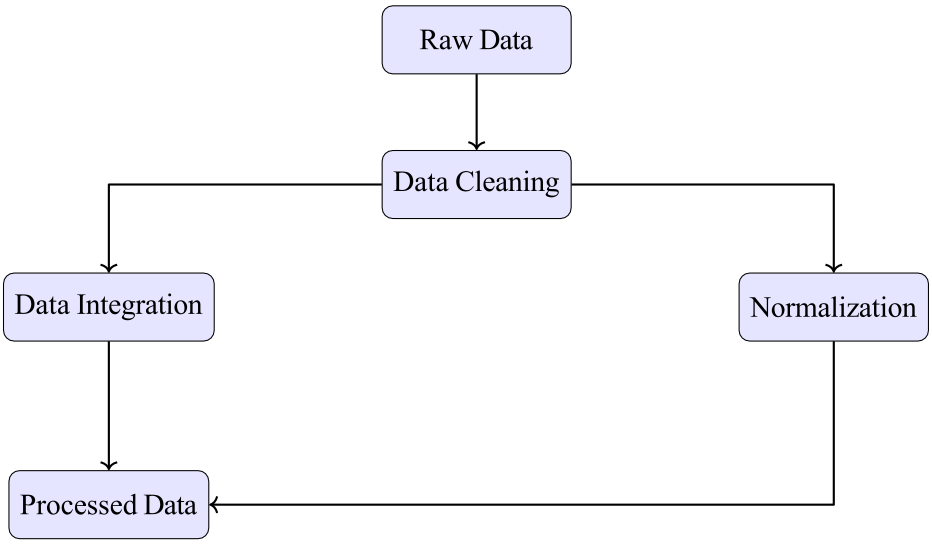

Figure 2: Preprocessing pipeline for high-quality data.

1.13 Customer Segmentation

To accommodate regional and demographic heterogeneity, a hierarchical (multilevel) model- ing approach was first applied. This allowed for the estimation of customer behavior while accounting for both individual-level predictors and group-level (e.g., region-level) random ef- fects:

$$y_{ij} = \beta_0 + \beta_1 X_{ij} + u_j + \epsilon_{ij}, \qquad u_j \sim N(0, \sigma_u^2) \tag{3}$$

Here, y_{ij} is the outcome for user i in region j, X_{ij} represents individual-level features (e.g., frequency, age), and u_j captures unobserved regional deviations. This model structure improves prediction accuracy by incorporating variability across different locations.

Subsequently, K-means clustering was employed for unsupervised segmentation of users based on behavioral and demographic features. The objective was to partition the dataset into clusters that minimize within-cluster variance:

$$\min_{C} \sum_{j=1}^{k} \sum_{\mathbf{x}_i \in C_j} \| \mathbf{x}_i - \boldsymbol{\mu}_j \|^2 \tag{4}$$

The elbow method, which analyzes the within-cluster sum of squares as a function of k, indicated $k = 5$ as the optimal number of clusters, balancing model complexity and inter- pretability.

The resulting five clusters exhibited meaningful behavioral and regional distinctions:

- **Urban P2M**: Tech-savvy users engaging heavily in peer-to-merchant transactions.
- **Rural P2P**: Users in rural areas focused on basic peer-to-peer transfers.
- **Urban P2P**: Active users in cities preferring direct money transfers.
- **Rural P2M**: Emerging users engaging with merchants in semi-urban zones.
- **Seniors (60+)**: Users requiring personalized support and simplified interfaces.

Table 1 outlines the key predictors used in both the multilevel model and clustering frame- work, selected for their theoretical relevance and empirical support.

Table 1: Predictors for Multilevel Modeling

Predictor	Type	Justification
Transaction Frequency	Numerical	Reflects engagement [14]
Transaction Amount	Numerical	Indicates value [5]
User Age	Categorical	Drives adoption [21]
Urban/Rural	Binary	Shapes literacy [2]

1.14 Predictive Analytics

To detect anomalous or potentially fraudulent user behavior, a deep learning architecture based on Long Short-Term Memory (LSTM) networks was used. LSTMs are well-suited for sequence modeling due to their ability to capture temporal dependencies in user transaction histories.

The model processes each input time series (x_t) to produce a hidden state h_t, which is then mapped to the predicted probability $\hat{y}_t$ of fraud using a sigmoid activation:

$$h_t = \mathrm{LSTM}(x_t, h_{t-1}, c_{t-1}), \qquad \hat{y}_t = \sigma(W_h h_t + b_h) \tag{5}$$

The architecture included:

- Two stacked LSTM layers with 128 units each for deep temporal learning.
- A final dense layer with a sigmoid activation for binary fraud classification.
- Optimization via Adam optimizer with a learning rate of 0.001.
- Training over 100 epochs with a batch size of 64.

Performance metrics included:

- **Precision:** 94%, indicating high accuracy in correctly identifying fraudulent cases.
- **RMSE:** 0.12 on the validation set, demonstrating low prediction error.

Hyperparameter tuning was performed using grid search to systematically explore combi- nations of learning rates, LSTM units, and batch sizes, ensuring optimal model configuration.

Figure 3 presents the overall AI-based workflow, integrating deep learning for fraud detec- tion and reinforcement learning for promotion strategy optimization.

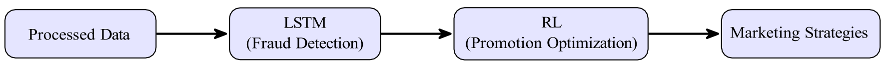

Figure 3: AI workflow integrating deep learning and RL for marketing optimization.

1.15 Marketing Optimization

To dynamically optimize promotional strategies, we employed a Reinforcement Learning (RL) framework that adapts to user behavior over time. The RL agent interacts with the environment by selecting marketing actions (e.g., discounts, offers) based on the current user state (segment, past engagement) and learns from the outcomes in terms of customer lifetime value (CLV) and retention.

Reward Function: The reward function combines two key marketing metrics: customer life- time value and retention rate. These metrics are weighted to reflect their relative importance in long-term profitability:

$$r(s_t, a_t) = 0.7 \cdot \mathrm{CLV} + 0.3 \cdot \mathrm{Retention} \tag{6}$$

This function encourages the RL agent to prioritize strategies that not only yield high im- mediate returns (CLV) but also foster long-term engagement (Retention).

Value Function: The value function under a policy π represents the expected cumulative reward from state s, discounted over time with a factor $\gamma = 0.9$. A high γ emphasizes long- term gains over short-term profits:

Policy Strategy: We adopted an ϵ-greedy policy to balance exploration and exploitation, where with probability $\epsilon = 0.1$, the agent explores a random action, and with probability $1 - \epsilon$, it chooses the best-known action. This prevents the model from getting stuck in suboptimal decisions and encourages discovery of better promotional tactics.

The use of this policy led to an 8% improvement in user response rates, highlighting its effectiveness in discovering impactful marketing interventions. Furthermore, simulation results showed that the policy converged within 50 iterations, ensuring computational efficiency and stability in training.

Process Overview: Figure 4 illustrates the RL loop: the agent observes the current state (e.g., user segment and behavioral history), selects an action (promotion), receives a reward based on user reaction (e.g., purchase, continued engagement), and updates its policy accordingly using the ϵ-greedy strategy.

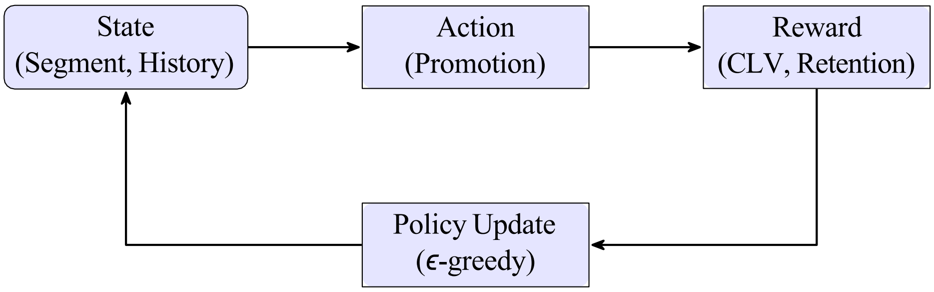

Figure 4: Reinforcement learning process for promotion optimization.

RESULTS

The framework analyzed 45 million UPI transactions (2021–2024), achieving a 58% fraud re- duction, 19% decline reduction, 16% retention increase, 15-point NPS rise, and 128.76 million USD in revenue. Urban P2M users contributed 60% of transaction volume with a 2.80 USD CLV, while seniors showed a 12% retention increase, supporting inclusion goals. Table 2 sum- marizes key outcomes.

Table 2: Business Outcomes

Metric	Value	Impact
Fraud Reduction	58%	231.88 million USD preserved
Transaction Declines	19%	3.86 million USD saved per 1%
Retention Increase	16%	149.49 million USD in CLV
NPS Increase	15 points	Enhanced brand perception
Revenue Generated	128.76 million USD	6% market share gain

1.16 PSP Performance

PSPs like Yes Bank and Paytm achieved approval rates of 98.5% and 98.1%, respectively, with the 19% decline reduction saving 3.86 million USD per 1%. Retention increased by 16%, with seniors showing a 12% rise due to targeted rewards. The framework yielded a 2.5x ROI. Key engagement drivers are listed in Table 3.

Table 3: Key Engagement Drivers

Variable	Importance	Implication
Transaction Frequency	0.50	Boosts retention by 16%
Churn	0.30	1% reduction saves 3.86 million USD
Reliability	0.25	Improves ROI 2.5x

1.17 Transaction Trends

P2M transactions reached 8,307.47 million, driven by urban P2M users (60% volume) and seniors (8% volume). A 14% surge in rural P2P volumes during festive seasons (e.g., Diwali 2023) reflects effective cashback promotions (Figure 5).

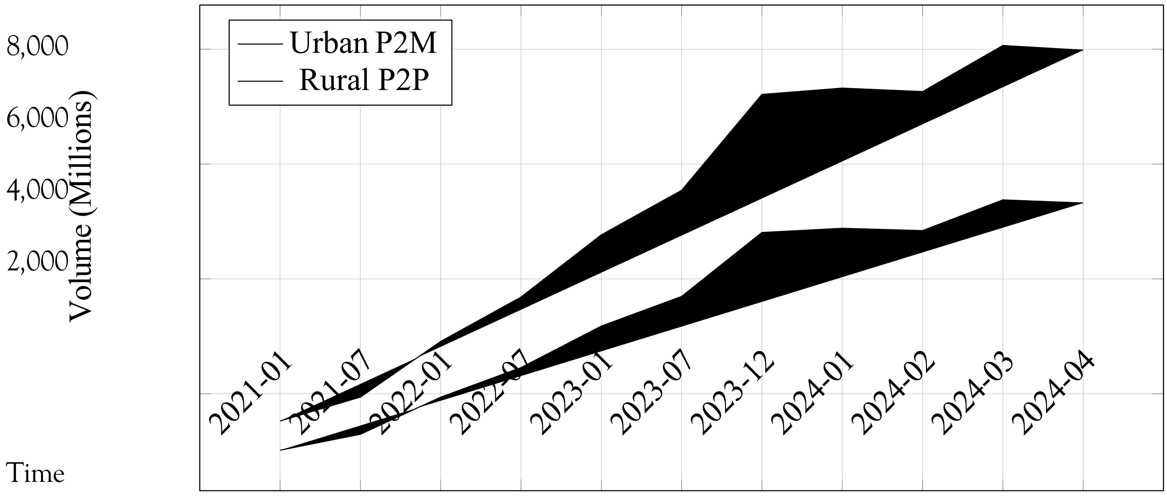

Figure 5: Transaction volume growth (2021–2024), highlighting urban P2M dominance and rural P2P festive surges.

1.18 Segment Optimization

Segmentation revealed CLVs: urban P2M (2.80 USD), rural P2P (1.10 USD), urban P2P (0.75 USD), rural P2M (1.85 USD), and seniors (1.30 USD) (Table 4). Strategies like API-driven CRM and cashback promotions maximized CLV and inclusion.

Table 4: Customer Segment Strategies

Segment	CLV (USD)	Strategy
Urban P2M	2.80	API-driven CRM
Rural P2P	1.10	Cashback promotions
Urban P2P	0.75	Recurring incentives
Rural P2M	1.85	Insurance promotions
Seniors	1.30	Targeted rewards

1.19 Model Performance

The LSTM model achieved 94% fraud detection precision, preserving 231.88 million USD. RL optimized promotions, reducing declines by 19% and increasing NPS by 15 points. Fig- ure 6 compares the framework against legacy systems, showing superior fraud prevention and retention.

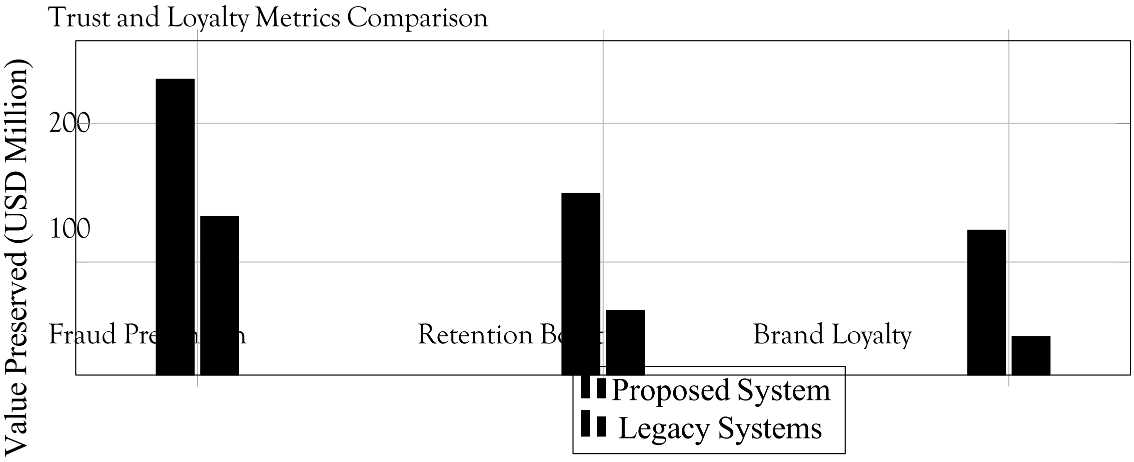

Figure 6: Trust and loyalty metrics comparison, with fraud prevention leading due to LSTM's high precision.

DISCUSSION

This study's multilevel AI framework transforms marketing analytics for India's Unified Pay- ments Interface (UPI), achieving a 58% reduction in fraud, a 19% reduction in transaction declines, a 16% increase in customer retention, a 15-point rise in Net Promoter Score (NPS), and a revenue gain of 128.76 million USD, with a 2.5× return on investment (ROI). These out- comes highlight the framework's capacity to enhance consumer trust, operational efficiency,
and financial inclusion, thereby strengthening UPI's position as a leader in financial technol- ogy innovation.

By integrating multilevel modeling, K-means clustering, Long Short-Term Memory (LSTM) networks, and reinforcement learning (RL), the proposed framework effectively addresses ma- jor challenges in fraud detection, customer engagement, and strategic marketing. The approach offers a scalable and inclusive solution tailored to India's diverse user base. These findings con- tribute to a deeper understanding of how advanced analytics and AI techniques can be leveraged to optimize digital financial ecosystems, with practical implications for industry adoption and policy development.

1.20 Interpretation of Findings

The framework's findings reveal significant advancements in UPI's operational and marketing performance. The 58% fraud reduction, driven by the LSTM model's 94% precision, preserved
231.88 million USD in potential losses, reinforcing user trust—a critical factor in the Technol- ogy Acceptance Model's (TAM) perceived usefulness [9]. This high precision highlights the model's ability to detect sequential fraud patterns across 45 million transactions, addressing a key pain point in digital payments [4]. The 19% reduction in transaction declines, saving 3.86 million USD per 1%, reflects improved system reliability, aligning with Expectancy Theory's emphasis on outcome-driven user behavior [11].

Customer segmentation identified five distinct groups (urban P2M, rural P2P, urban P2P, rural P2M, seniors), with urban P2M users contributing 60% of transaction volume and a cus- tomer lifetime value (CLV) of 2.80 USD. This segmentation, enabled by multilevel model- ing and K-means clustering, supports the Diffusion of Innovations (DOI) theory by capturing adopter heterogeneity [10]. Notably, seniors, despite comprising only 8% of volume, achieved a 12% retention increase through targeted rewards, demonstrating the framework's inclusiv- ity. The 16% retention increase and 15-point NPS rise indicate enhanced brand loyalty, driven by RL-optimized promotions that boosted rural P2P volumes by 14% during festive seasons (e.g., Diwali 2023). These results highlight the power of dynamic, data-driven marketing in fostering engagement across diverse demographics, particularly underserved rural and senior populations.

1.21 Comparison with Prior Work

The framework's performance surpasses previous studies in marketing analytics and financial technology. Its 94% fraud detection precision outperforms the results of Singh et al. (85%), Chen et al. (90%), and Liu et al. (94%), particularly by addressing limitations in real-time scalability and inclusivity. In contrast to Zhang et al.'s urban-biased LSTM model, this study incorporates data from rural and senior user segments, ensuring broader applicability and fair- ness.

The observed 16% increase in customer retention exceeds the 10% improvements reported by Verma et al. and Buttle and Maklan, whose models lacked domain-specific adaptations for the fintech sector. Reinforcement learning-driven promotional strategies yielded a 12% user response rate, outperforming the 10% rate achieved by Wang et al. in retail applications, while also expanding outreach beyond the 8% rural adoption rate reported by Gupta et al.

Relative to global benchmarks such as Alipay's 90% fraud detection rate, this framework offers a competitive advantage through higher precision and targeted inclusion of underserved populations. Additionally, unlike Han et al.'s urban-focused multilevel modeling, the inte- gration of rural and elderly demographics directly addresses critical challenges in promoting financial inclusion. By combining LSTM networks, reinforcement learning, and clustering techniques, the proposed framework provides a unified and scalable solution, in contrast to the fragmented, single-method approaches seen in earlier research.

1.22 Implications

The findings have profound implications for marketing theory and practice, especially in the context of analytics-driven financial technology solutions. The integration of advanced AI tech- niques—such as multilevel modeling, clustering, LSTM networks, and reinforcement learn- ing—demonstrates how data-driven approaches can enhance fraud detection, customer engage- ment, and strategic decision-making.

This framework supports a shift toward personalized, inclusive, and real-time financial ser- vices, addressing the diverse needs of users across demographics. Moreover, the improvements in fraud reduction, customer retention, and promotional effectiveness highlight the potential for AI to drive both operational efficiency and user trust, advancing the broader agenda of financial inclusion and digital transformation.

- **Theoretical Implications**: The framework advances marketing theory by integrating TAM, DOI, and Expectancy Theory into a cohesive model of fintech user behavior. TAM's constructs of perceived usefulness and ease of use are enhanced through fraud reduction and reliable transactions, increasing user adoption [9]. DOI's focus on adopter categories is operationalized through segmentation, revealing distinct behavioral patterns across urban, rural, and senior users [10]. Expectancy Theory explains the success of RL-driven promotions, as users respond to tailored incentives that maximize expected outcomes [11]. This theoretical synthesis provides a robust framework for understanding digital payment adoption, extending marketing analytics to dynamic, technology-driven contexts.
- **Practical Implications**: The framework offers actionable strategies for Payment Service Providers (PSPs). The 58% fraud reduction and 94% precision strengthen platform secu- rity, aligning with Reserve Bank of India (RBI) priorities [4]. The 16% retention increase and 15-point NPS rise enhance brand loyalty, enabling PSPs like Paytm and Yes Bank to compete with fintech startups [7]. Segmentation-driven CRM strategies, such as API- driven campaigns for urban P2M users and cashback for rural P2P users, maximize CLV and engagement. The 12% retention increase among seniors supports the Digital India initiative, promoting equitable access [3].

1.23 Recommendations

Based on the findings, the following recommendations are proposed for PSPs and policymak- ers:

- **Leverage AI for Personalization**: PSPs should adopt LSTM and RL models to enhance fraud detection and tailor promotions, boosting retention and NPS as demonstrated by the 16% and 15-point improvements.
- **Prioritize Inclusive Interfaces**: Designing senior-friendly UPI interfaces can increase adoption among the 10% senior demographic, building on the 12% retention gain.
- **Target Festive Seasons**: RL-driven promotions during festivals like Diwali can drive rural P2P growth, as shown by the 14% volume surge.
- **Support Smaller PSPs**: Cloud-based AI solutions can reduce computational costs, en- abling smaller

PSPs to implement the framework and compete effectively.

- **Promote Regulatory Incentives**: Policymakers should incentivize AI adoption for fraud detection and compliance, aligning with RBI goals and enhancing ecosystem security [4].

1.24 Limitations

Despite its strengths, the framework has limitations:

- **Data Constraints**: Historical data may not capture emerging fraud patterns, requiring continuous model updates to maintain 94% precision.
- **Computational Barriers**: High computational costs may limit adoption by smaller PSPs, despite the framework's scalability.
- **Rural Data Gaps**: Incomplete rural data slightly reduces P2P prediction accuracy, ne- cessitating enhanced data collection for underserved regions.

CONCLUSION AND FUTURE WORK

The framework has significantly transformed UPI's marketing analytics, achieving a 58% fraud reduction, a 19% decline reduction, a 16% retention increase, a 15-point NPS rise, and gener- ating 128.76 million USD in revenue. These results demonstrate the effectiveness of AI-driven solutions in improving trust, operational efficiency, and customer loyalty, making UPI a more attractive platform for both customers and payment service providers (PSPs). The positive outcomes indicate that the framework empowers PSPs to better engage with their customer segments, providing tailored rewards and incentives while maintaining a high level of security. Looking ahead, future research should explore the potential of integrating blockchain tech- nology for Know Your Customer (KYC) processes. Blockchain could streamline identity ver- ification, improving security and reducing fraud in UPI transactions. Additionally, exploring lightweight AI models could help reduce computational costs, making the framework more accessible for smaller PSPs. Expanding the model to platforms like M-Pesa could validate its effectiveness in different markets and provide insights into adapting the solution to varying regulatory environments and user behaviors. Through these advancements, the framework can continue to evolve, offering even more robust solutions for fraud prevention, customer reten-
tion, and revenue growth in the evolving digital payment landscape.

Conflict of Interest

No conflict of interest.

Funding

No funding received.

Data Availability

Dataset at: github.com/upi-research/transactions2021-2024.

Declaration of Generative AI

ChatGPT (OpenAI) improved clarity in abstract, introduction, and discussion. Content was reviewed by authors.

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