



A Study on Customer Satisfaction Analysis of Mobile Payment (UPI) Applications

Submitted by:

**Vaishnavi Ravindra Shirke, Neeraj Nitin Shelar ,Vivek Harish Kamble
Omkar Kalyan Shingade**

MBA (BA Specialization) Semester- 4

Under the Guidance of :

Prof. Gayatri Deokate

Assistant Professor

Department of Management Studies Zeal Institute of Management & Computer Application

Savitribai Phule Pune University Year 2026

How to Cite this Article:

Shingade, O. K., Shirke, V. R., Shelar, N. N. & Kamble, V. H. (2026). A Study on Customer Satisfaction Analysis of Mobile Payment (UPI) Applications. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(05).
<https://doi.org/10.55041/ijcope.v2i5.427>

License:

This article is published under the terms of the Creative Commons Attribution 4.0 International License (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author(s) and the source are credited.

© The Author(s). Published by International Journal of Creative and Open Research in Engineering and Management.



<https://doi.org/10.55041/ijcope.v2i5.427>

Abstract

The rapid proliferation of mobile payment services, particularly those utilizing the Unified Payments Interface (UPI), has transformed the digital financial ecosystem by enabling instantaneous, round-the-clock transactions. As the user base for these applications expands, customer satisfaction (CSAT) emerges as a critical determinant of platform retention, loyalty, and overall market competitiveness. This paper explores the application of advanced business analytics techniques to holistically measure and predict customer satisfaction within UPI applications. By integrating predictive modeling, natural language processing (NLP), and causal inference, this study proposes a comprehensive framework designed to overcome the limitations of traditional, low-response survey methods. Through a hypothetical evaluation pipeline, we demonstrate how combining unstructured user feedback with structured transactional metrics can yield actionable insights for service providers. Ultimately, this research highlights how data-driven decision support systems can enhance digital resilience, optimize user experience, and drive continuous usage in the highly competitive mobile payment industry.



Introduction

Mobile payment architectures have fundamentally altered the mechanics of personal and commercial finance, shifting consumer behavior away from traditional banking toward decentralized, smartphone-driven platforms. The rising popularity of mobile payments can be heavily attributed to the widespread use of smartphones and the convenience of mobile applications (Ajao et al., 2023). Within this landscape, the Unified Payments Interface (UPI) has emerged as a dominant protocol, facilitating immediate bank-to-bank transfers via mobile devices. As these payment ecosystems grow, ensuring robust customer relationship management becomes a leading business strategy in a highly competitive environment (Devi & Rajagopalan, 2011). Service providers must constantly monitor operational metrics such as transaction failure rates, app latency, and user interface responsiveness to maintain high levels of consumer trust. Consequently, analyzing customer satisfaction is no longer just a retroactive assessment but a proactive necessity to ensure continuous user engagement.

The primary problem addressed in this paper is the accurate measurement and enhancement of customer satisfaction in high-velocity UPI applications. The scope of this study encompasses the analytical techniques required to interpret both quantitative transaction logs and qualitative user feedback. In a digital environment where users expect instantaneous results, even minor service disruptions or security concerns can drastically diminish satisfaction and prompt users to abandon the application. Mobile payment users must exhibit a degree of digital resilience to continue using the service after adverse events, such as transaction failures or potential fraud (Alhassan & Butler, 2021). Therefore, the precise identification of pain points through continuous analytics is vital. This requires a transition from basic descriptive statistics to sophisticated decision support systems that can pinpoint the exact causes of customer dissatisfaction and recommend actionable interventions.

Despite the critical importance of CSAT, existing measurement approaches in the mobile payment sector remain largely insufficient for two primary reasons. First, traditional CSAT metrics rely heavily on post-transaction surveys, which suffer from drastically low response rates that average only a small fraction of the user base, thereby leading to biased and inaccurate average satisfaction values (Manderscheid & Lee, 2024). This limited response rate skews the perceived performance, as the silent majority's satisfaction levels remain unknown and unanalyzed (Manderscheid & Lee, 2024). Second, conventional predictive models often fail to capture the causal relationships between specific service improvements and user satisfaction. While many business intelligence dashboards highlight correlations, they do not utilize advanced causal analysis methodologies to demonstrate how improvements in specific digital aspects directly elevate overall customer satisfaction (Mirthipati, 2024). Without establishing causality, app developers may waste resources on interface changes that do not meaningfully impact user retention or sentiment.

To address these gaps, this paper introduces a comprehensive business analytics framework tailored for UPI applications. The core contributions of this study are outlined as follows:

- First, this paper proposes a multi-modal business analytics architecture that combines unstructured natural language processing of user reviews with quantitative transaction data to construct a bias-resistant predictive model for customer satisfaction.
- Second, it introduces a structured evaluation methodology utilizing causal inference techniques to isolate and measure the specific impact of UI/UX and backend server improvements on the overall sentiment of mobile payment users.

Related Work

Drivers of Mobile Payment Acceptance and Security

The foundational literature on mobile payments largely focuses on the initial drivers of technology adoption and the architectural security required to maintain user trust. Research indicates that performance expectancy, social influence, trust, and network externalities are crucial drivers of mobile payment acceptance, particularly in emerging markets where smartphone penetration is rapidly increasing (Ajao et al., 2023). However, adoption alone does not guarantee long-term usage, especially when platforms become targets for financial fraud or suffer from frequent technical outages. To combat these vulnerabilities, researchers have proposed secure mobile payment architectures



that leverage the advanced capabilities of modern smartphones, such as multi-factor authentication and biometrics, to verify various aspects of a payment and ensure transaction legitimacy (Alamleh et al., 2023). Furthermore, post-adoption behavior is heavily influenced by a user's digital resilience; analyzing the relationship between individual digital resilience and post-event behavioral patterns enables service providers to promote the continuous use of mobile payments even after adverse incidents (Alhassan & Butler, 2021). While these studies provide excellent frameworks for understanding user onboarding and security, they often lack a continuous, analytics-driven mechanism for measuring day-to-day customer satisfaction, a gap this current study aims to fill.

Predictive Analytics and Causal Models for Customer Satisfaction

Predicting customer satisfaction in service industries has increasingly relied on sophisticated machine learning and causal inference methodologies. In high-volume environments like corporate call centers, analysts face challenges with ordinal, subjective, and highly skewed survey data, which has led to the development of Graph Neural Networks (GNN) that consider the relative scores among batches of interactions rather than isolated events (Kanchinadam et al., 2021). Similarly, addressing the bias caused by low survey response rates is critical; recent methods have been introduced to accurately replicate the distribution of survey CSAT responses using predictive models, ensuring that the inferred metrics do not suffer from sampling noise (Manderscheid & Lee, 2024). Beyond mere prediction, causal analysis has been employed in sectors like the airline industry to examine the specific impact of digital service improvements on customer satisfaction, proving that data-driven decisions can enhance market competitiveness (Mirthipati, 2024). The strength of these predictive and causal models lies in their ability to uncover hidden patterns and correct statistical biases. However, their primary weakness is that they are often domain-specific (e.g., call centers or airlines) and require adaptation to handle the micro-transactional, high-frequency nature of UPI applications, which is the specific focus of this proposed research.

Text Mining and Decision Support Systems

The third category of related work revolves around the use of natural language processing (NLP) and decision support systems to extract actionable business intelligence from user-generated content. With the advancement of e-commerce, the impact of business analytics and decision support systems has become a priority for enterprises seeking to gain an international competitive edge (Miah, 2022). To understand customer requirements and classify product preferences, expert systems utilizing Artificial Neural Networks (ANN) have been designed to process collected data and form appropriate rules for CRM activities (Devi & Rajagopalan, 2011). Furthermore, hybrid methodologies combining text mining and NLP are highly effective at discovering factors for customer satisfaction directly from online reviews, providing positive feedback loops for product development (Yoo et al., 2022). In internal organizational contexts, techniques like "virtual mirroring" utilize social network and semantic analysis to measure communication patterns, ultimately demonstrating that self-reflection among employees can lead to increased external customer satisfaction (Gloor et al., 2021). While these NLP and expert system approaches are powerful for extracting qualitative insights, they are sometimes disconnected from real-time operational telemetry. Our work compares to this literature by explicitly proposing the fusion of unstructured app review data with structured transactional metrics to form a unified business analytics pipeline.

Method/Approach

Proposed Business Analytics Framework

To comprehensively evaluate customer satisfaction in UPI applications, we propose a multi-layered business analytics framework that integrates both descriptive and predictive analytics. The architecture is designed to capture the dual nature of user interactions: the objective reality of the transaction (e.g., speed, success rate) and the subjective perception of the user (e.g., app store reviews, support tickets). The framework utilizes a hybrid methodology similar to those applied in the hospitality sector, mixing data mining techniques for big data analysis with natural language processing for unstructured text (Yoo et al., 2022). By leveraging these diverse data streams, the system acts as a comprehensive decision support system that not only predicts CSAT scores for users who do not fill out surveys but also identifies the root causes of dissatisfaction.

Data Collection and Preprocessing Module



The first module of the framework handles the aggregation and sanitization of disparate data sources. UPI applications generate immense volumes of telemetry data per second. We define two primary data pipelines: the Transactional Pipeline and the Feedback Pipeline. The Transactional Pipeline collects quantitative variables such as payment routing time, server timeout frequency, biometric authentication success rates, and the number of clicks required to complete a transfer. The Feedback Pipeline scrapes unstructured text from app store reviews, social media mentions, and in-app customer support chats. Because raw textual data is inherently noisy, natural language processing techniques are employed to tokenize the text, remove stop words, and perform initial sentiment polarity scoring. To address the challenge of missing CSAT surveys, the preprocessing module aligns the timestamps of user transactions with their subsequent feedback, creating a unified timeline of the customer journey.

Predictive Modeling and Causal Inference Module

The core analytical engine relies on a combination of Graph Neural Networks (GNN) and causal inference models. Recognizing that customer satisfaction is an ordinal and highly subjective metric, predicting survey scores is not a trivial task (Kanchinadam et al., 2021). We structure the user interaction data as a graph, where nodes represent users and specific transactions, and edges represent shared characteristics (e.g., same bank server routing or same device model). This allows the GNN to learn the relative satisfaction among batches of similar calls or transactions, producing more accurate predictions than standard regression models (Kanchinadam et al., 2021). Once the missing CSAT scores are imputed to replicate the true survey response distribution (Manderscheid & Lee, 2024), a causal analysis layer is applied. This layer utilizes techniques such as matching or propensity score weighting to evaluate how specific interventions (e.g., a streamlined checkout UI or faster encryption protocols) causally impact the predicted CSAT, mirroring causal frameworks proven effective in digital customer service domains (Mirthipati, 2024).

Key Design Choices and Rationale

A critical design choice in this methodology is the explicit integration of causal inference alongside traditional predictive machine learning. Traditional machine learning models can easily predict that users experiencing network delays are dissatisfied; however, they cannot mathematically prove that a newly deployed UI feature actively improved satisfaction without controlling for confounding variables like simultaneous server upgrades. Furthermore, we chose to incorporate multi-factor authentication metadata as a core feature in the predictive model. Since modern mobile payment architectures rely heavily on smartphone security features (Alamleh et al., 2023), understanding how the friction of security protocols impacts user satisfaction is paramount. By modeling the trade-off between perceived security and transaction convenience, the framework provides nuanced insights that a purely financial or technical model would overlook.

Evaluation Plan and Numbered Pipeline

To validate the effectiveness of the proposed framework, an evaluation plan will be executed using a hypothetical, large-scale dataset simulating one month of activity on a major UPI platform. The hypothetical dataset will consist of 5 million transactions, 50,000 app store reviews, and 10,000 explicitly completed CSAT surveys. The evaluation will follow a strict, numbered pipeline:

1. **Data Ingestion:** Import the hypothetical transaction logs and unstructured text reviews into a centralized data lake.
2. **Feature Engineering:** Extract latency metrics, security friction scores, and semantic sentiment scores using NLP.
3. **CSAT Imputation:** Train the GNN model on the 10,000 labeled surveys to predict the CSAT for the remaining user base, ensuring the predicted distribution matches the empirical distribution (Manderscheid & Lee, 2024).
4. **Causal Testing:** Formulate a hypothesis (e.g., "Updating the biometric API reduces checkout time and causally increases CSAT"). Apply causal inference models to compare the control group (old API) with the treatment group (new API).
5. **Performance Evaluation:** Assess the predictive accuracy of the GNN using Root Mean Square Error (RMSE) against a holdout validation set, and evaluate the causal model's confidence intervals to confirm the statistical significance of the discovered insights.



Discussion

Practical Implications and Deployment Considerations

The deployment of this advanced business analytics framework has profound practical implications for the mobile payment industry. By integrating this system into their operational backend, UPI service providers can transition from a reactive customer service model to a proactive, data-driven strategy. Near real-time identification of potentially dissatisfied customers provides organizations the opportunity to take meaningful interventions, thereby fostering ongoing customer loyalty (Kanchinadam et al., 2021). For instance, if the causal inference module detects that a specific banking partner's routing delays are significantly depressing user sentiment, the decision support system can automatically route transactions through alternative gateways. Furthermore, providing these analytics dashboards to small and medium enterprises (SMEs) that rely on UPI for e-commerce can encourage business development on an international level, as SMEs utilize these insights to optimize their own digital storefronts (Miah, 2022).

Limitations and Failure Modes

Despite the theoretical robustness of the proposed framework, several limitations and potential failure modes must be acknowledged.

- First, there is a significant risk of data sparsity and cold start problems for newly registered users. Without historical transaction data or previous survey responses, the Graph Neural Network will struggle to accurately initialize nodes, leading to low-confidence CSAT predictions for new adopters.
- Second, the reliance on Natural Language Processing for analyzing user feedback presents linguistic challenges. UPI applications, particularly in diverse markets like India or Nigeria, serve populations that use regional languages, code-switching, and local slang. Standard NLP models may fail to capture the nuances of these dialects, resulting in inaccurate sentiment classification (Ajao et al., 2023).
- Third, real-time causal inference requires immense computational overhead. Continuously recalculating causal graphs and propensity scores as millions of transactions flow through the system may introduce latency into the analytics pipeline, making immediate, automated interventions technologically unfeasible for smaller operators.

Ethical Considerations and Risks

The implementation of deep business analytics in the financial sector inherently carries substantial ethical considerations.

- First and foremost is the risk to user privacy and the potential for surveillance capitalism. By aggregating biometric authentication metadata, geolocation, and transaction histories to model satisfaction, companies amass highly sensitive datasets. If these secure mobile payment architectures are breached, the resulting identity theft and financial exposure would be catastrophic for users (Alamleh et al., 2023).
- Second, there is a risk of algorithmic bias embedded within the predictive models. If the historical data used to train the GNN predominantly reflects the satisfaction metrics of high-income, urban demographics, the model may deprioritize the pain points of rural or economically disadvantaged users. This bias could lead to product development decisions that marginalize vulnerable populations, contradicting the goal of financial inclusion.

Future Work

To further refine the analytics of mobile payment satisfaction, future research should explore several promising avenues.

- First, future work should investigate the integration of "virtual mirroring" techniques within the customer support teams handling UPI disputes. By measuring the communication patterns of support agents through semantic analysis and mirroring it back to them, platforms could potentially trigger changes in employee behavior that directly increase end-user satisfaction (Gloor et al., 2021).
- Second, the analytical framework should be expanded to study cross-border mobile payment infrastructures. As



digital economies become increasingly interconnected, understanding the network externalities and trust factors that drive international mobile payment acceptance will require more sophisticated, cross-cultural causal models (Ajao et al., 2023). Exploring how digital resilience varies across different regulatory and cultural environments will be crucial for the global expansion of these payment technologies (Alhassan & Butler, 2021).

Conclusion

In conclusion, this study underscores the immense value of applying sophisticated business analytics techniques to monitor and enhance customer satisfaction in UPI mobile payment applications. As the digital finance sector becomes increasingly saturated, relying solely on traditional survey metrics is no longer adequate due to inherent response biases and an inability to map specific platform features to overall user sentiment. By proposing a framework that integrates Natural Language Processing for unstructured review analysis, Graph Neural Networks for accurate CSAT prediction, and causal inference for isolating the impact of operational variables, this paper provides a comprehensive blueprint for platform optimization.

The integration of these advanced methodologies allows service providers to deeply understand the friction points in the user journey, ranging from multi-factor authentication delays to server timeouts. Although challenges such as computational overhead, linguistic diversity in NLP, and stringent data privacy requirements remain, the potential benefits of deploying such a decision support system are undeniable. Ultimately, continuous, data-driven analysis of customer satisfaction will not only bolster the digital resilience of users but also ensure the long-term sustainability and growth of mobile payment architectures in the global e-commerce landscape.

References

- Ajao, Qasim, Oludamilare, Olukotun, & Sadeeq, Lanre (2023). Drivers of Mobile Payment Acceptance: The Impact of Network Externalities in Nigeria. <https://doi.org/10.4236/oalib.1110240> <https://doi.org/10.4236/oalib.1110240>
- Devi, P. Isakki alias, & Rajagopalan, S. P. (2011). The Expert System Designed to Improve Customer Satisfaction. <https://arxiv.org/pdf/1112.2183v1> <https://arxiv.org/pdf/1112.2183v1>
- Alhassan, Muftawu Dzang, & Butler, Martin (2021). Digital Resilience and the Continuance Use of Mobile Payment Services. <https://arxiv.org/pdf/2108.09743v1> <https://arxiv.org/pdf/2108.09743v1>
- Manderscheid, Etienne, & Lee, Matthias (2024). Predicting Customer Satisfaction by Replicating the Survey Response Distribution. <https://arxiv.org/pdf/2411.12539v1> <https://arxiv.org/pdf/2411.12539v1>
- Mirhipati, Tejas (2024). Enhancing Airline Customer Satisfaction: A Machine Learning and Causal Analysis Approach. <https://arxiv.org/pdf/2405.09076v1> <https://arxiv.org/pdf/2405.09076v1>
- Kanchinadam, Teja, Meng, Zihang, Bockhorst, Joseph, Singh, Vikas, & Fung, Glenn (2021). Graph Neural Networks to Predict Customer Satisfaction Following Interactions with a Corporate Call Center. <https://arxiv.org/pdf/2102.00420v1> <https://arxiv.org/pdf/2102.00420v1>
- Yoo, Yongmin, Park, Yeongjoon, Lim, Dongjin, & Seo, Deaho (2022). 5-Star Hotel Customer Satisfaction Analysis Using Hybrid Methodology. <https://arxiv.org/pdf/2209.12417v1> <https://arxiv.org/pdf/2209.12417v1>
- Gloor, P., Colladon, A. Fronzetti, Giacomelli, G., Saran, T., & Grippa, F. (2021). *The impact of virtual mirroring on customer satisfaction*. *Journal of Business Research* 75, 67-76 (2017). <https://doi.org/10.1016/j.jbusres.2017.02.010> <https://doi.org/10.1016/j.jbusres.2017.02.010>