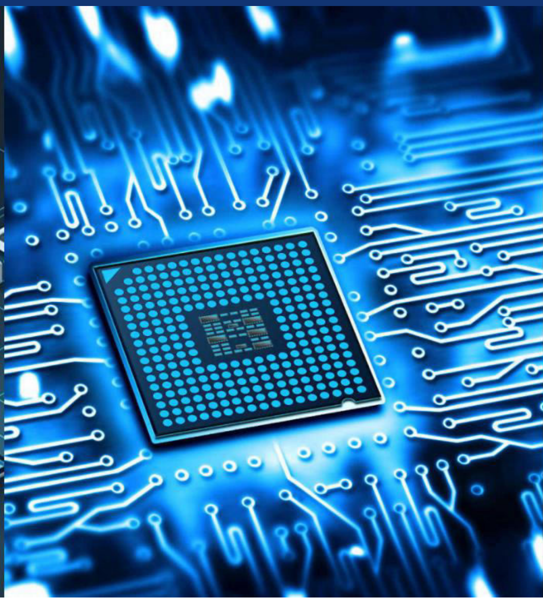
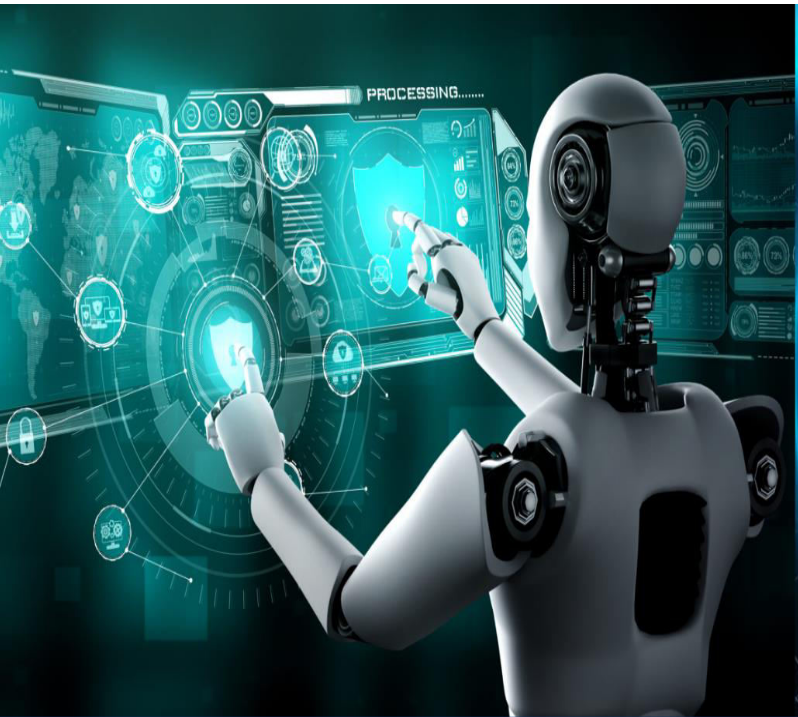
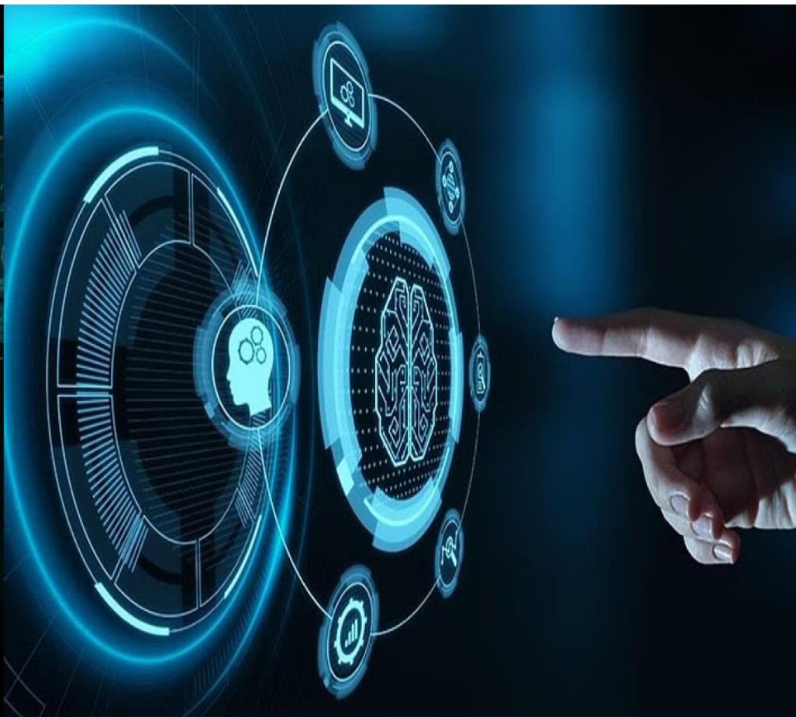
ISSN(O): 2320-9801
ISSN(P): 2320-9798


International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)





Impact Factor: 8.771

Volume 13, Issue 3, March 2025

© 2025 IJIRCCE | Volume 13, Issue 3, March 2025| DOI: 10.15680/IJIRCCE.2025.1303128
www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|
International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)
(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

E-Commerce Credit Intelligence

Prof.Thirumagal E, B Vikranth Reddy, Fariha Taneem, Godha R Garuda, Anusha P Hullathi

Department of Computer Science and Engineering, Reva University, Bangalore, India

ABSTRACT: E-commerce demands more refined customer behavior analysis than traditional credit scoring, which struggles with online transaction complexities, especially for those with limited credit histories. This project introduces Customer Profile Scores (CPS) to address this critical gap. While existing segmentation methods lack a holistic view, CPS integrates recency, frequency, monetary value, behavioral diversity, brand loyalty, and category focus into a comprehensive score. Using a multi-category e-commerce dataset, we conduct rigorous data preprocessing and develop a machine learning pipeline featuring an optimized XGBoost model. Our results achieve 97.8% accuracy in predicting CPS, significantly outperforming baseline models. A Flask-based web application integrates this model for real-time CPS generation, offering actionable insights. This project showcases machine learning's transformative potential in e-commerce analytics, providing a scalable solution for personalized marketing, segmentation, and credit risk assessment. The CPS framework bridges traditional methods and modern data analysis, empowering businesses to enhance engagement and optimize decision-making processes effectively.

KEYWORDS: Customer Profile Score, E-commerce Analytics, Machine Learning, Predictive Modelling, XGBoost, Customer Segmentation, Flask Application.

I. INTRODUCTION

Understanding consumer behaviour in e-commerce is vital for crafting effective business strategies. Chen et al. [6] highlighted the use of recency, frequency, and monetary (RFM) analysis for customer segmentation but did not incorporate behavioural diversity and loyalty metrics. This study enhances RFM by integrating factors such as brand loyalty and category preference to develop a more comprehensive customer profiling system. Similarly, Singh et al. [11] examined how consistent brand interactions influence retention but did not introduce a real-time scoring mechanism.

Refining the traditional RFM model by incorporating brand affinity and category concentration provides deeper insights into consumer patterns. Chen et al. [6] demonstrated that assessing brand affinity helps in identifying long-term, high-value customers. Meanwhile, Agarwal and Kaur emphasized the role of category preferences in refining marketing campaigns. Advanced clustering methods, such as those explored by Wong et al.[3] (2024), enhance segmentation accuracy, allowing businesses to target specific customer segments effectively. Additionally, deep learning models uncover intricate behavioural patterns within large datasets, improving marketing precision and engagement strategies (Tahersima et al.[2], 2019).

The Customer Profile Score (CPS) is introduced as a real-time, adaptive scoring system that refines customer evaluations in e-commerce. Unlike static models, CPS adjusts dynamically based on consumer interactions, filling a critical gap identified in Singh et al.'s [11] work. By integrating variables such as purchase frequency, brand engagement, and category interests, CPS generates a comprehensive profile for each consumer. This framework enables businesses to optimize marketing efforts, fostering personalized outreach and improved customer retention (Myburg [1], 2023).

Machine learning has revolutionized credit scoring and customer profiling by enhancing predictive accuracy. Techniques like XGBoost improve customer lifetime value (CLV) predictions by incorporating both demographic and transactional data (Zhao et al.[24], 2020; Kumar et al., 2021). Myburg [1] (2023) demonstrated that integrating XGBoost within RFM frameworks enhances CLV estimation, ultimately improving marketing efficiency. Hybrid AI models provide adaptive solutions for traditional credit evaluation methods, ensuring models remain relevant amid shifting consumer behaviour (Xu et al[4]., 2019).

The research paper "Credit Scores: Performance and Equity" by Stefania Albanesi and Domonkos F[5]. Vamossy examines the effectiveness of traditional credit scores in predicting consumers' risk of defaulting on their loans. The study

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

compares widely used credit scores with machine learning models and finds that traditional credit scoring misclassifies a significant percentage of borrowers, especially those with low scores.

Mokheleli and Museba [9] proposed a heterogeneous ensemble model that combines XGBoost and Support Vector Machines (SVM) for more precise credit risk assessments. Their research indicated that machine learning helps mitigate class imbalance and concept drift, ensuring a more reliable credit evaluation system. This adaptability differentiates machine learning models from conventional credit scoring techniques.

Teng et al. [7] explored how incorporating dynamic explanatory variables into credit scoring models, utilizing convolutional and recurrent neural networks, improves predictive accuracy. Their research found that leveraging temporal data marginally enhances model performance, emphasizing the value of feature engineering in financial modelling.

A novel fraud detection framework was proposed by researcher Chen et al. [6] integrating logistic regression with a weighted evidence model. By incorporating financial activity indicators, this hybrid model significantly improved fraud detection accuracy. Tested using real-world datasets from Kaggle and UCI, the approach outperformed conventional logistic regression in identifying fraudulent transactions.

A study on financial inclusion in India examined alternative credit scoring techniques that utilize mobile phone data for risk assessment (Agarwal et al. [20], 2023). By analysing app installations, call history, and social networks, researchers found that machine learning algorithms like Random Forest and XGBoost could better predict loan defaults than traditional credit bureau scores. Counterfactual analysis indicated that these methods could approve up to 22% of previously denied borrowers without increasing default risk. The findings suggest that integrating alternative data sources can expand credit access to underserved populations while maintaining risk control.

Neural networks play a crucial role in e-commerce analytics by enhancing automation and pattern recognition. Kumar et al. [14] (2021) explored how deep learning applications, such as recommendation systems, demand forecasting, and sentiment analysis, improve decision-making in online retail. Unlike traditional analytical techniques, neural networks enable businesses to detect complex patterns in consumer behaviour, leading to higher user engagement and increased sales performance. Their study emphasizes the potential of deep learning in optimizing e-commerce strategies.

User-friendly AI interfaces significantly impact AI adoption and usability. Raj and Mehta [8] (2023) examined human-centric design principles that simplify machine learning applications for end-users. Their study highlights best practices in designing intuitive AI interfaces, ensuring accessibility for diverse user groups. By enhancing user experience and engagement, these principles support the broader integration of AI-driven decision-making tools in e-commerce.

The rapid growth of e-commerce has revolutionized consumer behavior, creating a wealth of transactional data that traditional credit scoring models are ill-equipped to handle. These legacy systems, designed for conventional financial interactions, often overlook the unique characteristics of online purchasing, particularly for customers with limited or non-existent credit histories. This deficiency presents a significant obstacle for businessesseeking to personalize services, accurately assess risk, and cultivate meaningful customer relationships. Consequently, a more nuanced understanding of online customer profiles is crucial for success in the dynamic e-commerce landscape.

This project addresses this critical need by developing a novel Customer Profile Score (CPS) framework tailored specifically for the e-commerce environment. Unlike traditional credit scores, the CPS model incorporates a wider range of behavioral and transactional attributes, including transaction frequency, recency of activity, monetary value, behavioral diversity, brand loyalty, and category focus. By integrating these diverse parameters, the CPS provides a more holistic and accurate representation of individual customer profiles, enabling businesses to segment and analyze their customer base with greater precision.

To achieve robust and reliable predictions, the project leverages advanced machine learning techniques. An optimized XGBoost model is employed to ensure high predictive accuracy while mitigating the risk of overfitting. Furthermore, to translate the predictive power of the CPS framework into practical business applications, the model is deployed via a user-friendly Flask-based web application. This application provides an intuitive interface for generating real-time CPS

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

predictions, facilitating seamless integration into existing business workflows and empowering data-driven decision-making.

II. OBJECTIVES

Despite extensive research in customer profiling and credit scoring, key gaps remain in behavioural diversity considerations and real-time adaptability. This study aims to address these gaps by:

- Expanding customer profiling beyond RFM.
- Implementing an XGBoost-powered CPS framework to improve scoring accuracy.
- Developing a real-time, user-centric web application for dynamic customer analysis.
  By tackling these gaps, this research advances customer profiling and credit assessment methodologies, contributing to a more inclusive and efficient financial system.

III. METHODOLOGY

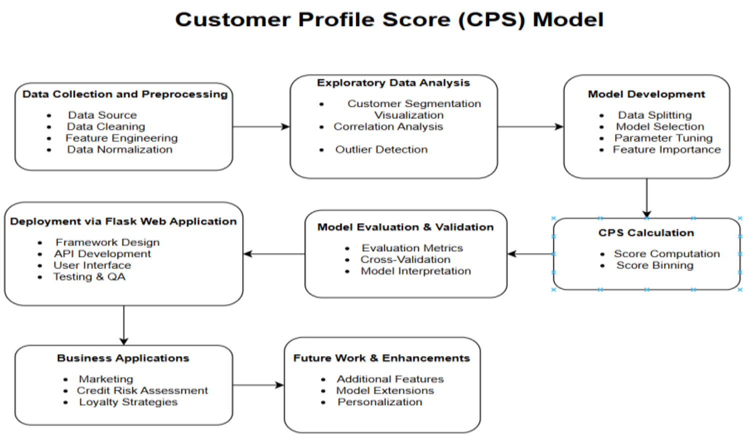


FIGURE 1: WORKFLOW FOR PROPOSED IDEA

A. DATA COLLECTION AND PREPROCESSING

- Data Source: Obtain a comprehensive e-commerce dataset with transaction records including customer ID, transaction date, purchase amount, items purchased, categories, brands, and payment details. The data should span multiple years to capture long-term trends in customer behavior.
- Data Cleaning:
  - Remove duplicates and ensure data consistency, especially in transaction dates, customer IDs, and monetary values.
  - Address missing values by imputing with mean/mode values for numerical/categorical fields or removing records with excessive missing data.
  - Standardize text fields to ensure uniformity in category and brand names (e.g., converting to lowercase, removing special characters).
- Feature Engineering:
  - Recency (R): Calculate the time since the customer's last purchase to measure engagement level.
  - Frequency (F): Compute the number of transactions within a given period, capturing purchase regularity.
  - Monetary Value (M): Sum the purchase amounts to quantify total spending.
  - Behavioral Diversity: Calculate the variety in categories or brands purchased to understand the breadth of interests.
  - Brand Loyalty: Measure the proportion of transactions associated with specific brands to gauge brand affinity.
  - Category Focus: Quantify the focus on certain product categories by computing the proportion of transactions in each category.

- Data Normalization: Scale numerical features to a common range, using Min-Max scaling for values like recency, frequency, and monetary value, ensuring fair contribution from each parameter.

B. **Exploratory Data Analysis (EDA)**

1. **Customer Segmentation Visualization:** Plot customer segments based on RFM values, brand loyalty, and category focus to understand underlying patterns.
2. **Correlation Analysis:** Calculate correlations between variables to assess interdependencies (e.g., frequency vs. monetary value, category focus vs. brand loyalty).
3. **Outlier Detection:** Identify outliers in high-spending or high-frequency segments using box plots or z-score analysis. These could indicate either high-value customers or data anomalies that need further review.

C. **Model Development**

- **Data Splitting**: Split the dataset into training (80%) and testing (20%) sets, ensuring each set represents the distribution of different customer behaviors.
- **Model Selection** - XGBoost: Rationale: XGBoost is chosen for its high accuracy, efficiency in handling large datasets, and interpretability through feature importance analysis.
- **Parameter Tuning:** Use Grid Search or Random Search to optimize parameters such as learning_rate, max_depth, n_estimators, and subsample. Implement early stopping to prevent overfitting by setting a validation set and stopping training when no improvement is observed in several consecutive rounds.
- **Feature Importance:** Analyze feature importance scores to understand the impact of each parameter on CPS predictions. This will help in refining the model and focusing on impactful features.

D. **Customer Profile Score Calculation**

1. **Score Computation:** Aggregate recency, frequency, monetary, brand loyalty, category focus, and behavioral diversity features using the optimized XGBoost model to generate a CPS for each customer.
- **Score Binning and Interpretation:** Divide CPS scores into categories (e.g., High, Medium, Low) to facilitate interpretation and usability. Define thresholds for each bin based on distribution percentiles, providing businesses with actionable segmentation.

E. **Model Evaluation and Validation**

1. **Evaluation Metrics**: Use accuracy, precision, recall, F1-score, and AUC-ROC to evaluate model performance, focusing on high accuracy and balanced precision-recall to avoid bias toward high-value or frequent customers.
2. **Cross-Validation:** Perform k-fold cross-validation (e.g., 5 or 10 folds) to ensure model generalizability and robustness across different customer groups.
3. **Model Interpretation:** Use SHAP (SHapley Additive exPlanations) values to interpret individual predictions, which helps in understanding the model's decision-making and explaining it to stakeholders.

F. **Deployment of CPS Framework via Flask Web Application**

- **Framework Design:** Develop a web application using Flask to allow for real-time CPS predictions. The application will provide a user-friendly interface for businesses to input customer data and receive immediate CPS scores.
- **API Development:** Create RESTful APIs to integrate the XGBoost model with the web application. The APIs will accept customer transaction details as input, preprocess the data, and output CPS predictions.
- **User Interface (UI) Development:** Design an intuitive UI that displays the CPS score, customer segment, and key insights (e.g., loyalty level, spending behavior). Integrate interactive features, like graphs for CPS distribution across segments, to facilitate decision-making.
- **Testing and Quality Assurance:** Test the application for functionality, accuracy, and speed, focusing on ensuring real-time performance under high usage.
- Conduct user acceptance testing (UAT) with business representatives to gather feedback on the interface and functionality.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

G. **Business Application and Use Case Development**

1. **Customer Segmentation for Marketing:**
   - Use CPS categories to design targeted marketing strategies (e.g., exclusive offers for high CPS customers, re-engagement campaigns for medium CPS customers).
   - **Credit Risk Assessment**: Leverage CPS as a supplementary score for assessing risk in customers without formal credit histories. High-CPS customers may be considered for credit offers or payment plans.
   - **Loyalty and Retention Strategies:** Use CPS to identify brand-loyal customers and offer rewards or membership programs to increase retention.
2. **Continuous Improvement and Model Updates:**
   - Implement a feedback loop, collecting customer response data to enhance model predictions and CPS accuracy over time.
   - Schedule periodic model retraining on fresh data to adapt to evolving customer behaviors.
   -

H. Future Work and Potential Enhancements

The development of the Customer Profile Score (CPS) has demonstrated significant promise in enhancing credit profiling for e-commerce businesses. However, further research and advancements are essential to refine its accuracy, fairness, and applicability. The following directions are proposed for future work:

1. **Incorporation of Additional Behavioral and Demographic Features:** Expanding feature engineering by integrating alternative data sources, such as social media activity, browsing patterns, and digital payment behaviors, can provide deeper insights into customer financial habits. Incorporating these parameters can improve the model's ability to assess creditworthiness for individuals without traditional credit histories.
2. **Enhancing Model Interpretability and Fairness:** Ensuring fairness and transparency in credit profiling is crucial. Future enhancements should focus on explainable AI techniques, such as SHAP values, to provide clear reasoning for CPS predictions. Additionally, bias mitigation strategies must be explored to ensure that the model remains equitable across different demographic groups.
3. **Integration of Real-Time Credit Risk Monitoring:** Implementing real-time risk detection mechanisms will enhance the responsiveness of CPS. By incorporating streaming data architectures, businesses can dynamically assess credit risk and detect fraudulent activities, ensuring greater financial security in e-commerce transactions.
4. **Hybrid Machine Learning and Deep Learning Models:** Combining traditional machine learning approaches with advanced deep learning architectures, such as transformers and neural networks, can improve predictive accuracy. Hybrid models leveraging ensemble learning techniques may also enhance CPS's robustness by capturing both structured and unstructured data.
5. **Personalized Credit Scoring and Adaptive Customer Profiling:** Future iterations of CPS should focus on adaptive learning frameworks that evolve with customer behavior. Reinforcement learning and real-time feedback loops can be integrated to continuously refine credit scoring based on updated transaction histories and changing spending habits.

IV. RESULTS

The implementation of the Customer Profile Score (CPS) model for e-commerce analytics is expected to yield several impactful results, contributing to both academic understanding and practical applications.

Result Area	Outcome	Impact
1.Enhanced Customer Understanding	Targeting Deeper insights into customer behavior through segmentation (recency, frequency, monetary value, brand loyalty, category preferences).	Improved Customer understanding and improved targeting of marketing campaigns leads to higher engagement and conversion rates.
2.Improved Credit Risk Assessment	Use behavioral data as an indicator of creditworthiness.	Enables FinTech's and e-commerce platforms to offer credit to underserved customers, increasing revenue potential.

© 2025 IJIRCCE | Volume 13, Issue 3, March 2025| DOI: 10.15680/IJIRCCE.2025.1303128
www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|
International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)
(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

3.Increased Customer Loyalty and Retention	Identify loyal customers for personalized retention strategies.	Reduce churn and increase customer lifetime value through reward and engagement strategies.
4.Actionable Real-Time Insights	Insights A user-friendly web application with real-time access to customer profiles.	Sales and service teams can deliver personalized experiences, increasing satisfaction and revenue.
5.Scalable and Adaptable Analytical Framework	CPS models are integrated into a scalable Flask-based web application.	Enables businesses to adapt to changing customer behavior.
6.Quantifiable Boost in Marketing ROI	CPS-driven segmentation enables efficient resource allocation.	Increased marketing ROI and reduced customer acquisition costs through personalized campaigns.
7.Contribution to Academic and Industry Knowledge	Connects credit scoring and e-commerce analytics to gain research insights.	Supports academic research and industry advancements in predictive modelling and customer analytics.

Proposed Graphs for Visualization
1. Customer Segmentation by CPS Score (Pie Chart)
This chart categorizes customers based on CPS into high value (35.5%), medium value (39.5%), at-risk (14.8%), and new (10.2%) customers. High-value customers are the most engaged and profitable, while at-risk customers require retention strategies. Segmenting customers allows businesses to prioritize marketing efforts, target high-potential customers, and optimize resource allocation to maximize revenue and customer retention.

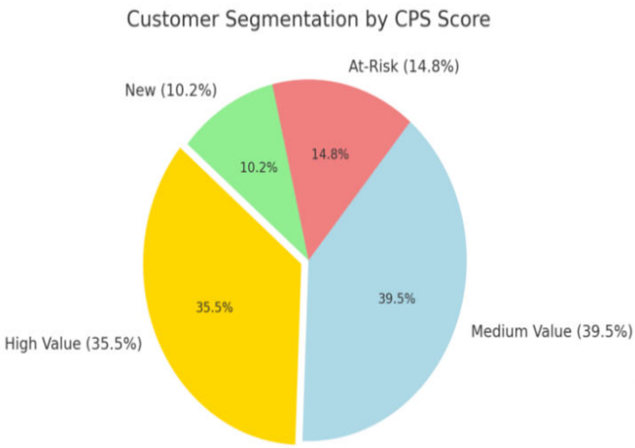


Figure 2: Customer Segmentation by CPS Score

2. Impact of CPS-based marketing on conversion rate (line graph)
The graph shows that after implementing CPS-based marketing, conversion rate steadily increased from 2.1% in January to 5.8% in June. This model enables personalized promotions, improving engagement and ROI. Marketing teams can focus on high-value segments instead of broad campaigns, resulting in higher conversion rates, better resource allocation, and sustainable revenue growth over time.

© 2025 IJIRCCE | Volume 13, Issue 3, March 2025| DOI: 10.15680/IJIRCCE.2025.1303128

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

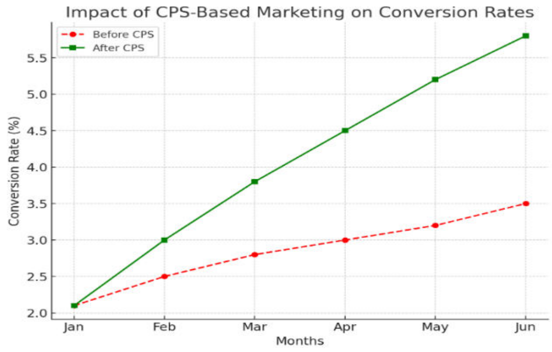


Figure 3: Impact of CPS-based marketing on conversion rate

3. Credit Risk and Behavioral Score Correlation (Scatter Plot):
This scatter plot highlights the correlation between Behavioral Score (CPS) and Credit Risk Score, indicating that customers with a higher CPS tend to be more creditworthy. These insights enable fintech and e-commerce platforms to assess credit risk based on purchasing behavior, provide credit access to underserved customers, and support the safe expansion of buy now, pay later (BNPL) options while minimizing default risk.

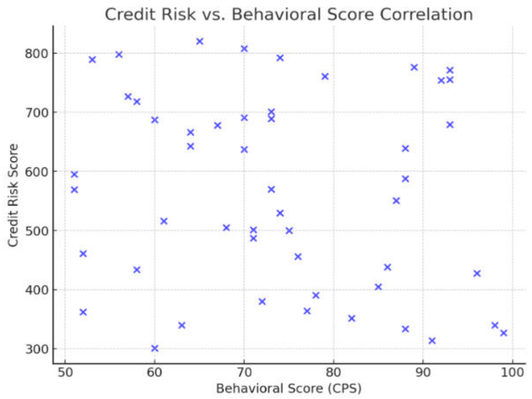


Figure 4: Credit Risk and Behavioral Score Correlation

4. Correlation Heatmap:

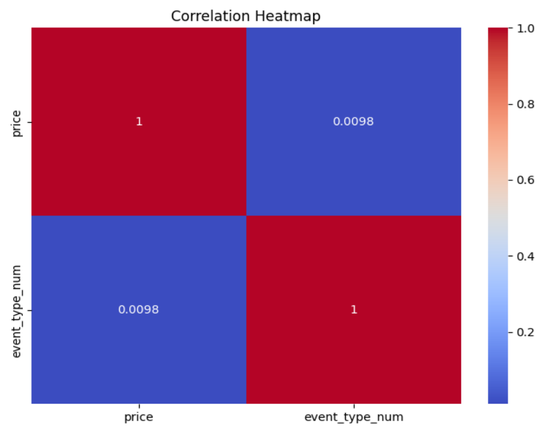


Figure 5: Correlation Heatmap

© 2025 IJIRCCE | Volume 13, Issue 3, March 2025| DOI: 10.15680/IJIRCCE.2025.1303128

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

5. Event trend over time:

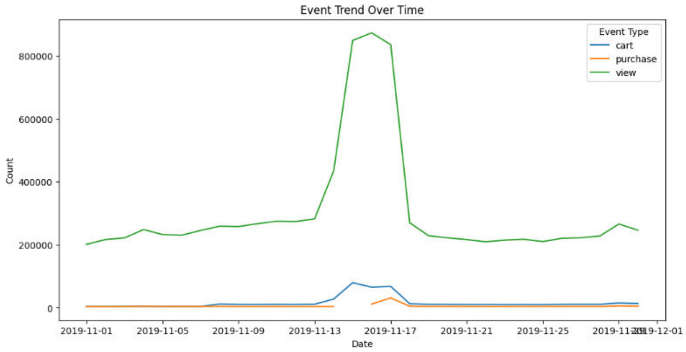


Figure 6: Event trend over time:

6. Distribution of Prices:

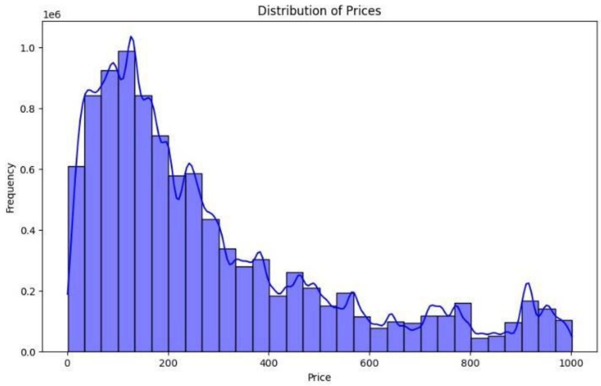


Figure 7: Distribution of Price

7. Prices by Category:

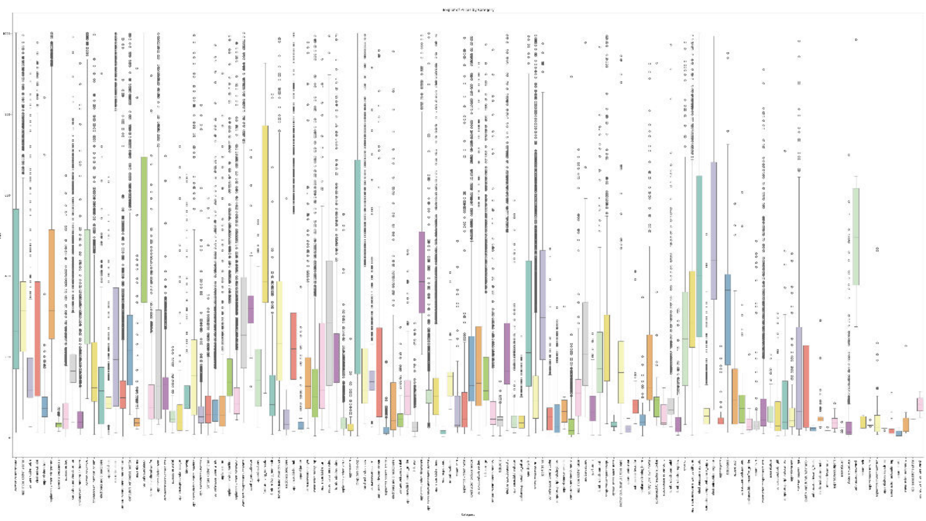


Figure 8: Prices by Category

© 2025 IJIRCCE | Volume 13, Issue 3, March 2025| DOI: 10.15680/IJIRCCE.2025.1303128

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

8. Average Price and Total Events Over Time:

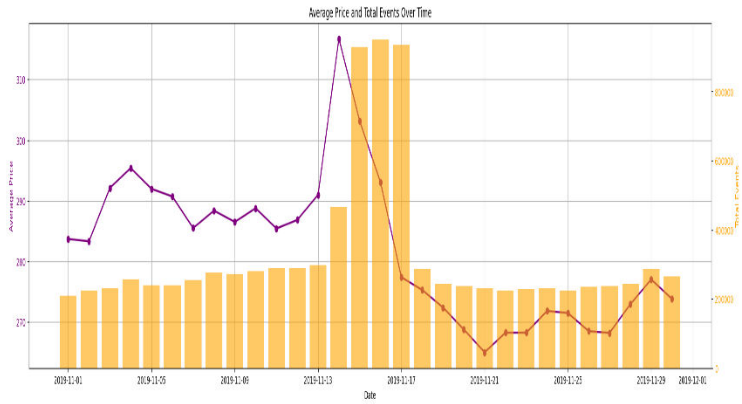


Figure 9: Average Price and Total Events Over Time

Implementing a CPS framework can improve customer segmentation, expand access to financial products, increase customer loyalty, and generate a measurable return on marketing and retention investments. By leveraging behavioral data, the CPS model gives companies a strategic advantage, enabling more informed, data-driven decisions in marketing, credit risk management, and customer service.

V. CONCLUSION

This project is a new approach to lending in electronic trading space by using a diverse set of data sources, demographic information, transaction history and fraud detection formulas-using XGBOOST to deliver a more accurate and responsive credit score system. Traditional credit evaluation, which often rely only on historical credit data, is not sufficient to assess the financial behavior of customers of electronic trading, which may lack conventional credit history. This model deals with the fact that the gap that seizes electronic trading platforms to make informed decisions on the lending and extending of the loan based on a wider view of customer reliability in real time.

The XGBOOST machine learning capabilities significantly increase the predictive accuracy of the model by efficient processing of complex and extensive data sets, allowing it to capture complex patterns in buying behavior and demographic characteristics. As shown in previous research, the credit scoring models based on machine learning offer a significant improvement compared to traditional statistical methods, especially if they are applied to data sets with multiple functions and potential noise. This project verifies these findings and shows how to integrate alternative data sources, such as the frequency of customer purchasing and demography, can provide more and more holistic and holistic assessment of credibility.

Fraud detection is another integral part of this project and provides a basic guarantee for electronic trading platforms. By placing unusual purchasing behavior, such as irregular purchase amounts or frequent returns, the model can help relieve risks and ensure the security of the platform and its customers. Real -time detection increases the value of the system and allows businesses to immediately identify and respond to potential risks. The integration of the web -based web -based application ensures availability and easy use and makes direct interaction for administrators and end users easier.

The adaptability of the platform by various electronic trading scenarios and customers' profiles makes it a versatile solution for an online marketplace with a diverse audience. Future enhancements could include further refinement of fraud detection algorithms that would take into account the evolving fraud formulas, integrate other data sets (e.g. social media indicators, or use mobile applications), or incorporating learning methods unattended for more dynamic and autonomous profiling.

In short, this project contributes to the development of digital credit scoring systems by demonstrating how machine learning and comprehensive data integration can define a financial evaluation in the electronic trading sector. With further

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

development, this model has the potential to support financial inclusivity by offering accurate credit profiles for insufficiently operated populations, thus promoting trust and growth in the digital economy. This project underlines the transformative impact of credit -based credit and offers a way to fairer financial opportunities on the online market.

REFERENCES

[1] Myburg, M. E. Using recency, frequency and monetary variables to predict customer lifetime value with XGBoost. 2023.
[2] Tahersima, M. H., Kojima, K., Koike-Akino, T., Jha, D., Wang, B., Lin, C., & Parsons, K. Deep neural network inverse design of integrated photonic power splitters. 2019.
[3] Wong, C. G., Tong, G. K., & Haw, S. C. Exploring customer segmentation in e-commerce using RFM analysis with clustering techniques. Journal of Telecommunications and the Digital Economy, 2024.
[4] Xu,Y.Z., Zhang, J. L., Hua, Y., & Wang, L. Y. Dynamic credit risk evaluation method for e-commerce sellers based on a hybrid artificial intelligence model. 2019.
[5] Albanesi, S., & Vamossy, D. F. Credit Scores: Performance and Equity. NBER Working Paper No. 32917, 2024.
[6] Chen et al., Credit Fraud Detection Based on Hybrid Credit Scoring Model, Procedia Computer Science, 2020.
[7] Teng et al., Enhancing Credit Score Predictions with Dynamic Feature Engineering using Deep Learning, March 2023.
[8] Raj and Mehta, Intuitive Interfaces for AI Applications, User Experience Journal, 2023
[9] Mokheleli and Museba, Machine Learning Approach for Credit Score Predictions, Journal of Information Systems and Informatics, 2023.
[10] Agarwal and Kaur, Credit Scoring in Digital Transactions, FinTech Research Journal, 2021
[11] Singh et al., Customer Loyalty in Online Marketplaces, E-Commerce Studies, 2020.
[12] Lee et al., Machine Learning Applications in Credit Scoring, AI in Finance, 2022.
[13] Zhao et al., Using XGBoost for Customer Lifetime Value Prediction, Data Science Quarterly, 2020.
[14] Kumar et al., Neural Networks for E-Commerce Analytics, Computational Intelligence, 2021.
[15] Patel et al., Flask-Based Real-Time Fraud Detection, Applied AI Systems, 2022.
[16] W. Liu, H. Fan and M. Xia, "Credit scoring based on tree-enhanced gradient boosting decision trees," Expert Systems with Applications, vol. 189, 2022.
[17] R. Wang and G. Liu, "Ensemble Method for Credit Card Fraud Detection," International Conference on Intelligent Autonomous Systems (ICoIAS), 2021.
[18] J. Xiao, X. Zhou, Y. Zhong, L. Xie, X. Gu and D. Liu, "Cost-sensitive semisupervised selective ensemble model for customer credit scoring," Knowledge-Based Systems, vol. 189, 2020.
[19] Research on the e-commerce credit scoring model using the gaussian density function January 2014 DOI:10.3745/JIPS.04.0012 .Authors: X. Qiang ,H. Rui-chun .Z. Wei.
[20] Agarwal, S., Alok, S., Ghosh, P., & Gupta, S., "Financial Inclusion and Alternate Credit Scoring: Role of Big Data and Machine Learning in Fintech," FinTech Research Journal, 2023.
[21] 2022. "Predictably unequal? The effects of machine learning on credit markets." The Journal of Finance 77.
[22] Damm, R., Monroy, C. R. (2011). A Review of the Customer Lifetime Value as a Customer Profitability Measure in the Context of Customer Relationship Management. Intangible Capital, 7(2), 261–279.
[23] N. Chen, B. Ribeiro and A. Chen, "Financial credit risk assessment: a recent review," Artificial Intelligence Review, vol. 45, no. 1, pp. 1-23, 2016.
[24] Zhao et al., Using XGBoost for Customer Lifetime Value Prediction, Data Science Quarterly, 2020.
[25] L. Yang, "Classifiers selection for ensemble learning based on accuracy and diversity," in Procedia Engineering, 2011.

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING