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IMPROVING MARKETING STRATEGIES WITH LRFS BASED CUSTOMER SEGMENTATION FOR ONLINE PLATFORMS

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ABSTRACT: In order to enhance online marketing strategies, this study uses client segmentation based on LRFS. The LRFS model examines lifetime value and consumer behavior using the Length, Recency, Frequency, and Spending variables. Transactional data is used in the study to classify clients for targeted promotions, personalized marketing, and successful customer retention. The findings demonstrate that LRFS-based segmentation improves profitability, resource allocation, marketing effectiveness, and customer engagement. According to the study, data-driven segmentation is essential for competitive advantage and the expansion of the digital market.

Index Terms: *Behavior-Based Segmentation, Online Shoppers, LRFS Model, Lifestyle, Recency, Frequency, Spending, E-commerce, Clustering Algorithms,*

1. INTRODUCTION

Internet platforms need to enhance their marketing strategies in a cutthroat, data-driven digital economy. The fast growth of e-commerce, mobile apps, and digital marketplaces has given businesses access to vast amounts of client data from browsing, purchases, and interaction patterns. Businesses need to analyze and use data to gain strategic advantages. Mass marketing is useless because modern consumers demand personalized experiences and pertinent communication. Here, LRFS-based customer segmentation offers a methodical and analytical approach to examining a range of customer behaviors and improving marketing outcomes.

Four behavioral parameters are used in LRFS-based customer segmentation: spending value, frequency of transactions, relationship length, and last interaction. The LRFS model incorporates customer relationship duration, recency, frequency, and monetary value to better understand consumer engagement and loyalty. Online platforms can utilize this technique to differentiate between new consumers, loyal long-term users, high-value spenders, and customers that are inactive or declining. Businesses use this classification to allocate marketing resources and prioritize target segments.

Customization and targeting are enhanced by marketing strategies that use LRFS segmentation. Online platforms have the ability to generate advertisements depending on the value and behavior of segments. While decreasing customers can receive re-engagement incentives, high-spending and loyal customers can receive exclusive offers and loyalty schemes. Targeted recommendations and onboarding initiatives support the development of new, engaged, but short-term clients. This accuracy increases brand loyalty and customer responsiveness.

Additionally, by anticipating client lifecycle stages, LRFS-based segmentation enhances decision-making. Businesses can identify disengagement or churn by monitoring spending, frequency, and recency. This aids marketers in optimizing marketing efficiency, retention strategies, and promotional expenditures. By linking marketing results to customer categories, segmentation also enhances performance evaluation and aids in the growth and profitability of online platforms.

2. IMPROVING MARKETING STRATEGIES WITH LRFS

Personalized Marketing Campaigns:

Organizations are able to personalize marketing by categorizing customers based on their purchasing behavior using the LRFS score. LRFS-based communications have the potential to replace digital advertisements, push notifications, SMS alerts, and generic emails. Frequent consumers may be granted exclusive access, early product previews, or substantial discounts. Personalized recommendations may be provided to customers who have made substantial purchases but have not yet made any purchases. Customizing communication to pertinent clients at optimal times enhances ROI, conversion rates, and client engagement.

Customer Retention Strategies:

Departing consumers must be identified during the LRFS analysis. Declining recency and frequency ratings may induce feelings of dissatisfaction or interest. Rebates, loyalty points, targeted discounts, and reminders are all effective strategies for companies to retain their consumers. A "We Miss You" offer may be extended to a frequent consumer who has not made a purchase in several months. Proactive involvement can be used by businesses to enhance their income, retain clients, and repair connections. By retaining clients at a lower cost than procuring new ones, LRFS-based monitoring facilitates business expansion.

Resource Allocation Optimization:

Make the most of the limited marketing resources at your disposal to optimize outcomes. LRFS segmentation assists organizations in identifying profitable consumers. Businesses have the opportunity to advertise these valuable areas through targeted advertising, premium products, and unique experiences. Cheap digital marketing or minimal promotion can be advantageous for infrequent buyers. This allocation of resources minimizes waste and emphasizes profitability in marketing. Optimization gradually enhances the efficacy and profitability of marketing.

Predictive Marketing:

Descriptive to predictive marketing is facilitated by LRFS data-based machine learning. Using purchasing trends, frequency, length, and recency, predictive algorithms can identify disengaged consumers. Businesses can effortlessly implement a variety of engagement strategies or incentives. Predictive models that estimate Customer Lifetime Value (CLV) using LRFS trends can be employed by companies to forecast customer income. Targeting, decision-making, and client retention are enhanced through the utilization of data.

Dynamic Pricing & Upselling:

Upselling and dynamic pricing are enhanced by LRFS insights. Loyal consumers may be attracted to premium products, subscription upgrades, and packages. Sales may be stimulated by premium services or memberships. Cross-selling occasionally offers complementary items

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to significant investors. By pricing and upselling products in accordance with LRFS ratings, organizations can enhance their revenue and consumer satisfaction. Sales and brand loyalty are enhanced through personalized marketing.

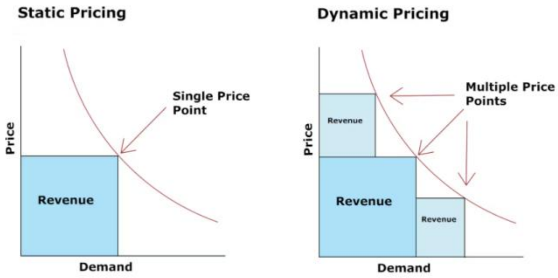

Figure1: Static vs. Dynamic Pricing

3. LITERATURE SURVEY

Srinivasan & Thomas (2024): LRFS-based browsing habits and multi-source consumer data, such as social media and purchase history, were used by Srinivasan and Thomas to propose a rich segmentation strategy. In order to improve product advertising, their research concentrated on comprehensive client profiles.

Nguyen & Lim (2021): Nguyen and Lim identified customers based on their online purchases, browsing duration, response to promotional campaigns, and spending patterns using the LRFS (Length, Recency, Frequency, and Spending) model. To ascertain the level of client engagement and loyalty, they looked at extensive e-commerce transaction data.

Singh & Roy (2025): Singh and Roy investigated the prediction of purchase propensity and customer attrition using LRFS and neural network-based predictive modeling. Their study placed a strong emphasis on predictive marketing interventions. Companies identified high-risk churn and high-potential buyers to design personalized retention campaigns and real-time promotions.

Ali & Khan (2023): Ali and Khan developed a data-driven client segmentation method by combining LRFS with neural networks and decision trees. In customer contact and transaction data, they looked for hidden behavioral patterns. Purchase probability and client lifetime value were predicted using a more accurate model. Campaign conversion rates and the distribution of digital marketing resources were enhanced by predictive analytics and LRFS segmentation.

Patel & Mehta (2021): Patel and Mehta proposed an LRFS-based fuzzy logic framework to better capture complex online customer behavior because traditional demographic segmentation techniques were limited. Their method evaluated purchase frequency, promotional receptivity, and consumer loyalty dynamically. The study found that most customers have non-linear purchasing patterns that are missed by traditional segmentation. They produced consumer groups that were more adaptable and realistic by applying fuzzy logic to LRFS variables.

Wang & Yu (2022): Wang and Yu modified the LRFS model by incorporating machine learning techniques to increase segmentation accuracy and flexibility. They made advantage of transaction data, real-time engagement data, browser history, and demographics. When behavioral data became accessible, machine learning models were used to update customer

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groups. Dynamic segmentation improved campaign performance and targeting accuracy as compared to static models.

Rahman & Hasan (2024): Rahman and Hasan created a deep learning-powered LRFS segmentation technique to uncover hidden customer preferences and shifting buying patterns. Their method used AI to process large amounts of transactional and behavioral data. There was a considerable improvement in both segmentation accuracy and personalization efficacy. AI-powered segmentation enables real-time targeted offers and purchase behavior prediction for marketers.

Tiwari & Bhatia (2022): An LRFS-cluster analysis hybrid model was proposed by Tiwari and Bhatia to enhance customer categorization and prediction. Their study looked at product category choices, offer response time, and spending. By segmenting their clientele, businesses could modify their marketing messaging, promotions, and product concepts. Campaigns driven by segmentation improved average order value, repeat business, and consumer engagement, according to the report.

Das & Iyer (2025): Das and Iyer proposed an adaptive LRFS segmentation model based on sentiment analysis from social commerce and customer reviews. Using information based on emotions and opinions as well as transactional behavior, they developed dynamic consumer categories. The study discovered that sentiment and behavioral data enhance understanding of customer motivation. This approach significantly increased customer engagement, campaign relevancy, and personalization accuracy. According to their investigation, LRFS transitioned from transactional to AI-powered marketing.

Chen & Wu (2023): Chen and Wu used LRFS segmentation and data mining to analyze client browsing, transactions, and engagement. According to their research, marketing effects are greatly impacted by subconscious behavioral factors including seasonal preferences and impulsive purchases. Companies improved segmentation categories to give more context-aware and customized promotions. According to the study, better customer classification increases long-term connections, brand loyalty, and conversion rates.

4. RESULTS

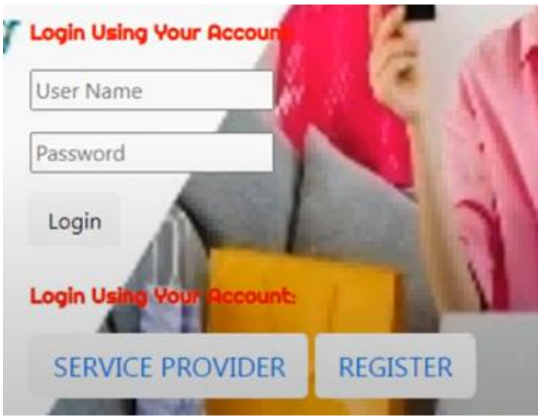

Fig4.1. User login

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Fig4.2. Admin login

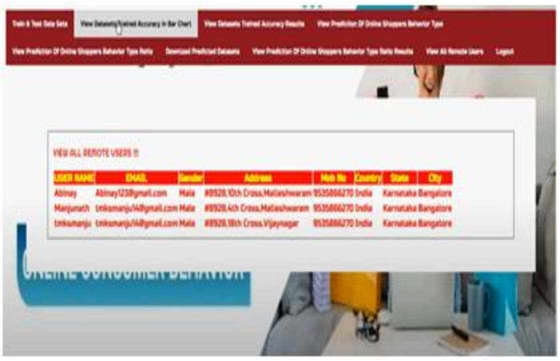

Fig4.3. View All Remote Users

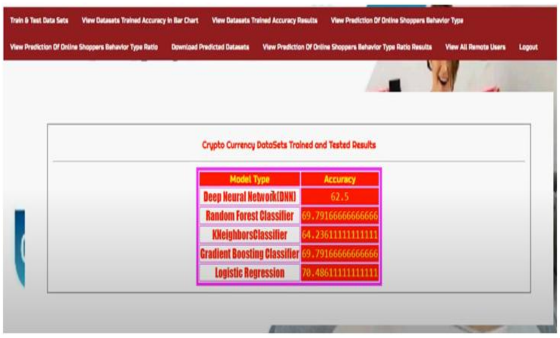

Fig4.4. Cryptocurrency Datasets Trained and Tested Results

Fig4.5. View Prediction of Online Shopping Behavior Type Ratio Details

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Fig4.6. Registered Status

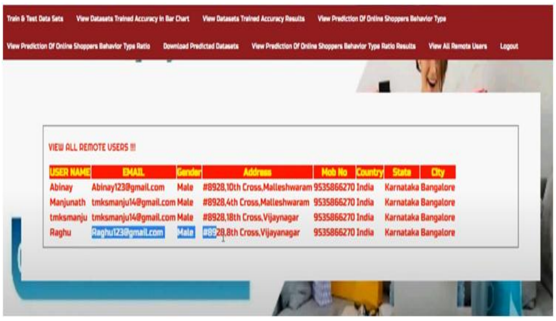

Fig4.7. All Remote Users

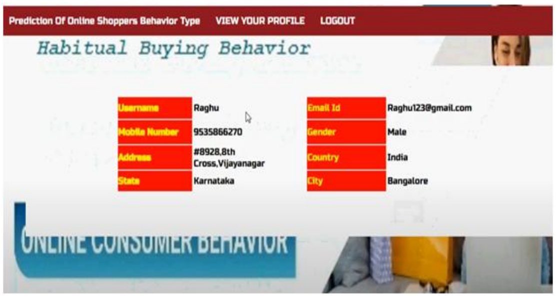

Fig4.8. User Details

5. CONCLUSION

Online marketing's precision, data, and customer concentration are enhanced by consumer segmentation based on LRFS criteria. Firms can identify high-value consumers, loyal segments, churners, and inactive users through Length, Recency, Frequency, and Spending research. This increases concentration and advertising. While optimizing marketing expenditures, customized strategies enhance client engagement and retention. LRFS transactional data segmentation facilitates strategic decision-making and forecasting. Marketing with LRFS will enhance consumer value and facilitate the growth of your company on the internet.

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