Emerging Trends in Digital Transformation
*Volume-1, Issue-2, July 2025* ISSN:**3107-4308** *Paper ID:* ***ETDT-V1-I2-13***

# BEHAVIOR-BASED SEGMENTATION OF ONLINE SHOPPERS USING LRFS MODEL

**[#1]PORANDLA RAMYA,**
**MCA Student, Dept of MCA,**
**[#2]RACHOORI SAGAR,**
**Assistant Professor, Department of MCA,**
**VAAGESWARI COLLEGE OF ENGINEERING (AUTONOMOUS), KARIMNAGAR.**

**ABSTRACT:** Businesses need to learn more about their customers in order to provide them with more personalized shopping experiences as e-commerce continues to grow. Although traditional segmentation methods are commonly employed, they fail to consider the nuances of human behavior, resulting in overly generalized marketing approaches. The LRFS model is described in this research. It uses four primary criteria—lifestyle, recency, frequency, and expenditure—to categorize consumers according to the products they purchase. Lifestyle factors, such as interests and personal preferences, impact customers' interactions with online retailers. The three metrics of recency, expenditure, and frequency provide light on the regularity of client interactions, the velocity of transaction completion, and the total amount of money spent. The model distinguishes between the various types of shoppers by utilizing hierarchical clustering and K-means. Businesses can use this segmentation to target specific groups with more relevant campaigns, product recommendations, and promotions. Evidence from actual online purchases demonstrates that the LRFS model improves engagement and makes accurate predictions. Businesses can increase their success and customer retention rates by learning to adapt to each customer's unique behavior. Digital marketing can be more effective with data-driven segmentation, according to the document. Maintaining a competitive market position via the use of models such as LRFS will be crucial as online shopping continues to expand.

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

## 1. INTRODUCTION

Businesses in the rapidly expanding e-commerce sector would do well to research consumer behavior patterns in order to fine-tune their advertising campaigns. In order to increase revenue, improve the shopping experience for customers, and target ads more effectively, online stores face the critical challenge of customer segmentation. Because of the inherent complexity of consumer behavior, behavior-based segmentation has emerged as a viable alternative to traditional demographic segmentation methods. This approach provides a more nuanced picture of consumer wants, needs, and buying habits.

The Recency, Frequency, and Monetary (LRFS) model is commonly employed for behavior-based segmentation. Customers are categorized according to their purchasing history, which includes the frequency, total amount, and type of purchases. The lifetime value of a customer, their loyalty, and the number of transactions they make can all be calculated with this method. By utilizing these three crucial components, businesses can establish enduring connections, discover valuable clients, and enhance the targeting of their marketing campaigns.

Recency, or the customer's most recent purchase, is the most crucial component of the LRFS model. Customers who have recently made a purchase are more inclined to take advantage of new promotions, so businesses can use this metric to identify their most loyal consumers. However, frequency refers to how often a customer purchases a product within a specific time frame. Frequent buyers are an excellent target audience for retention campaigns because they are already invested in the company and its products. Finally, the financial aspect considers the total amount spent by the customer over a specific time frame. Using this metric, companies can zero in on the most lucrative clients.

The LRFS customer segmentation method allows online businesses to divide their customers into groups, each with its own unique set of preferences and characteristics. To illustrate the point, companies might identify a


DOI : https://doi.org/10.5281/zenodo.16831596

subset of consumers who are repeat buyers based on their most recent purchase. Upselling opportunities and customer loyalty may be high as a result of this. Conversely, clients who haven't made a purchase in a while but have spent heavily in the past might be the target of re-engagement initiatives. By segmenting their clientele and targeting them with offers and marketing messages tailored to their specific interests, businesses can increase customer retention and revenue.

Accurate tracking and measurement of online customers' actions is made possible through improved utilization of big data and advanced analytics. Now more than ever, businesses can sift through massive databases in search of trends and patterns that were previously impossible to uncover. More and more data about consumer behavior is being collected by e-commerce platforms, which improves the LRFS model's ability to classify customers. Businesses can use behavior-based segmentation to boost consumer loyalty, improve marketing strategies, and increase revenue in the cutthroat e-commerce industry.

## 2.LITERATURE REVIEW

Sharma & Singh (2020) The LRFS model to categorize online buyers according to their actions. Their approach examines a large amount of e-commerce data to determine reading habits, promotion participation, and frequency of purchases. This strategy enhances advertising by targeting certain demographics with more relevant product information. According to the research, behavior-based segmentation is an effective strategy for providing a more tailored buying experience for consumers. People find it easier to shop online because of their work.

Mishra & Patel (2020) Recommend a model for customer segmentation that uses LRFS and clustering together. Their approach enhances segmentation by considering factors such as customer behavior, product preferences, and past interactions with the brand. Because it is easier to create more detailed profiles of each client with fuzzy logic, personalization is made better. The results demonstrate that segmentation is improved when conventional methods are used in conjunction with LRFS. Their findings provide credence to the notion that data-driven marketing is effective for online marketplaces.

Farooq & Zainab (2020) Verify the LRFS model's efficacy in classifying online buyers. Their model accounts for product categories, seasonal patterns, and consumer response to promotions in order to control the irrational behavior of customers. Stores can use this information to uncover the most important hidden factors that impact customers' choices. The importance of correctly segmenting consumers when marketing to them is highlighted by the research. We can improve our e-commerce strategies with the help of the data they provide in their research.

Nguyen & Lim (2021) Sort your customers into categories according to their e-commerce activity using the LRFS model. How people shop, what they purchase, and their reactions to sales are all part of the research. Marketing campaigns can be fine-tuned by classifying consumers into subsets defined by shared characteristics. Based on the findings, LRFS can successfully categorize clients and provide them with tailored recommendations. Sales and consumer engagement can both be boosted by using adaptive marketing strategies, according to the findings.

Patel & Mehta (2021) Investigate the possibility of developing bespoke marketing strategies using the LRFS model. They argue that the complexity of online shopping behavior factors is not adequately taken into consideration by traditional segmentation methods. The LRFS model determines customer loyalty, response to promotions, and purchase frequency using fuzzy logic. The research highlights the significance of accurate segmentation for targeting specific customer subsets. Their plan improves the efficiency of advertising by making use of data-driven insights.

Lee & Park (2021) Advanced behavioral analysis techniques should be incorporated into LRFS, as we concur. Their technology deduces fundamental purchasing patterns, including frequency of purchases and duration of website usage. Businesses might benefit from better marketing if they could foresee how consumers will behave. Dynamic segmentation can help businesses keep clients for a long time, according to the research. Thanks to their efforts, sophisticated and precise e-commerce marketing systems continue to improve.

Wang & Yu (2022) Investigate the possibility of enhancing the precision of consumer segmentation by merging LRFS with machine learning. To ensure they are reaching the correct audience, they examine demographic data and real-time interactions. Machine learning improves the accuracy of models by dynamically adjusting


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segmentation criteria. Findings highlight the significance of behavioral data in informing more effective marketing campaigns. They are able to retain customers and increase their e-commerce revenue thanks to their strategy.

Tiwari & Bhatia (2022) The combination of LRFS and cluster analysis can improve customer grouping. Customers' spending habits, reaction times to promotions, and product preferences can all be forecasted using their method. Businesses can gain a better understanding of their customers' wants and needs by classifying their preferences into useful categories. This document demonstrates how targeted marketing can enhance engagement and sales. Improved e-commerce segmentation models can be made possible by their findings.

Bansal & Kumar (2022) Utilizing the LRFS model, we demonstrate how to incorporate behavior-driven segmentation into e-commerce strategies for enhanced personalization. Important consumer habits can be uncovered through the use of interaction and transaction data. Creating in-depth customer profiles allows businesses to provide personalized marketing and expert guidance. The research found that LRFS-based segmentation outperformed other methods when it came to responding to changes in the market. The significance of having current customer data for e-commerce growth is highlighted by their research.

Zhang, Chen & Wang (2022) Examine how the LRFS model refines the categorization of internet buyers. Their research involves mining massive consumer databases for information such as spending habits, product preferences, and purchase records. The LRFS model outperforms more conventional approaches due to its ability to glean more nuanced understandings of behavior. Marketing strategy and audience engagement can both benefit from it, according to the findings. By streamlining the process of customer categorization, their work enhances the online shopping experience.

Ali & Khan (2023) Propose a data-driven strategy for client segmentation that integrates LRFS with ML techniques. By analyzing customer interactions and transactions, they learn their customers' hidden routines. Their approach improves the precision of marketing segmentation and personalization. These outcomes demonstrate that machine learning enhances customer profiling and sales volume. By enhancing e-commerce, their research demonstrates how technology can enhance user experiences.

Zhou & Li (2023) The LRFS model and transaction analysis should be your primary tools for classifying internet users. They reveal the impact on consumer profiles of payment methods, purchasing frequency, and purchasing behavior. The findings might help businesses improve their marketing campaigns by gaining insight from customer purchase data. According to their findings, personalized offers significantly increase consumers' propensity to make a purchase. Retailers can boost sales by tailoring promotions to their data.

Chen & Wu (2023) Combine the LRFS model with data mining techniques to categorize online shoppers. By analyzing transaction data and client interactions, they improve their behavior understanding. Their findings suggest that subconscious behaviors might impact your marketing performance. According to the data, improved customer segmentation results in increased conversion rates and customer loyalty. Their findings provide light on how to improve the efficacy of personalized e-commerce strategies.

Srinivasan & Thomas (2024) Examining customers' LRFS-based browsing and purchasing behaviors can help with consumer segmentation. In order to generate comprehensive profiles, they propose a method that integrates data from various sources Online retailers have room to grow in their product promotion strategies, according to the findings. Getting new clients, retaining old ones, and calculating the lifetime value of each client are the main areas of research. The significance of data-driven segmentation for successful e-commerce is highlighted by the results.

Rahman & Hasan (2024) Develop a comprehensive segmentation framework using deep learning techniques and the LRFS model. Better customization is the result of their method's ease of finding hidden consumer preferences. These outcomes demonstrate that deep learning improves the efficacy of marketing and the accuracy of segmentation. Their research proves that using AI-powered solutions can enhance e-commerce experiences for both sellers and buyers. The data-driven insights are crucial to improving online shopping, as demonstrated by the projects they were involved in.

## 3. RELATED WORK

### Evolution from RFM to LRFS

The RFM model is a vital tool for client classification; it is based on recency, frequency, and monetary value. The model was updated to LRFM by adding "Length," a variable that represents the duration from a customer's initial purchase, to gain a more holistic view of consumer behavior. For even more accuracy, try using "Spend" instead of "Monetary" and LRFS will zero in on the average amount spent every transaction. This explains why the strategy works so well with websites that have very session-to-session variation in transaction quantities.

**Importance of Behavior-Based Segmentation**

Instead of relying only on demographic data, behavior-based classification takes a look at how a customer uses a platform. Businesses can categorize their customers based on factors including how often they buy, how long they've been a customer, how recent their purchases are, and how much money they spend on each transaction. These categories could be high-value, newly-acquired, or vulnerable. By adopting this type of classification, marketers may build strategies that more accurately represent the actions of real consumers.

**Use of Clustering Algorithms**

To make the most of LRFS data, grouping techniques such as K-means, DBSCAN, and hierarchical clustering are commonly employed. Based on their LRFS values, these algorithms categorize comparable consumers. The scalability and ease of use of K-means make it a popular choice. To make sure the produced segments are meaningful and helpful, cluster evaluation methods like the Davies-Bouldin Index and the Silhouette Coefficient are used.

**Integration with Machine Learning**

Machine learning-based forecast models and clustering both make use of LRFS features. Estimates of customer lifetime value, churn rate, and repeat purchase probability have been obtained using decision trees, logistic regression, and neural networks. These models help businesses learn more and make better forecasts, which in turn allows them to be proactive.

**Personalized Marketing and Campaign Design**

Businesses can develop targeted marketing campaigns by using LRFS-based segmentation to learn about customer preferences and behaviors. Regular consumers may receive discounts to increase the value of their purchases, while loyal customers who spend a lot may receive rewards for their loyalty to keep them coming back. Using LRFS data for customisation has greatly improved conversion rates and interest.

**Enhanced Decision-Making in E-Commerce**

LRFS segmentation is a powerful tool for e-commerce enterprises looking to improve their strategy. This method is great for ad planning, website personalization, and product suggestions. Focusing on high-value groups allows decision-makers to make the most of their resources and increase the returns from their marketing efforts.

**Data-Driven Customer Relationship Management (CRM)**

Dynamic and adaptive customer profiles can be easily created in CRM systems with the help of LRFS segmentation. Companies can respond to changes in customer behavior in real-time by adjusting their customer service and communication tactics. This streamlines lifecycle marketing by making sure that messages are tailored to each stage of a customer's lifespan, be it new, loyal, dormant, or likely to depart.

**Application in Real-World E-commerce Platforms**

Notable e-commerce sites employ models like LRFS to refine their customer targeting and segmentation strategies. These models improve the customer experience by making it easier to understand how people use websites, which in turn helps with client retention methods. Examples from the real world show how behavior-based segmentation may increase revenue, decrease customer attrition, and improve customer happiness.

**EXISTING SYSTEM**

Existing behavior-based categorization methods for online shoppers rely on conventional RFM analysis, which classifies consumers into groups based on their buy frequency, purchase value, and the time since their last purchase. While RFM has been useful for gaining insights into customer behavior, it does not take into account a number of behavioral factors that are increasingly important in online shopping. Modern systems address these challenges by utilizing more complex models such as LRFM and LRFS. A "Length" between the earliest and latest purchase and a "Spend" representing the average amount spent on each transaction make up these models.


DOI : https://doi.org/10.5281/zenodo.16831596

Each customer's value can be seen more realistically in this way. When applied to consumer data, these models employ unsupervised learning approaches such as K-means clustering, DBSCAN, or hierarchical clustering to classify users into meaningful groups, such as new users, low-spenders, or loyal, high-value clients. Businesses can utilize the data they collect to better target their marketing, create customer loyalty programs, and implement client retention strategies.

Many current platforms still have problems, even though the LRFS idea has been applied to certain complex systems. Modern systems struggle to respond quickly to changes in consumer behavior since they rely on static data and don't integrate with real-time analytics. The results of segmentation are also not always used to their maximum capacity since many systems do not connect segmented data with customization engines or CRM technology.

**DRAWBACKS OF EXISTING SYSTEM**

- Most systems nowadays process data in a static or batch-like fashion, which makes it harder to collect and react instantly to consumers' ever-changing behaviors.
- In order to forecast client attrition, lifetime value, and purchase intent, many platforms depend only on basic clustering methods rather than supervised machine learning.
- Since segmentation results don't always interface well with CRM or marketing systems, they aren't as successful at changing customers' relationships with brands.
- At present, most systems merely take transactional data into account, ignoring behavioral signs from a variety of channels like wish lists, app usage, and browsing history.
- Since the segments aren't updated frequently as new data becomes available, client profiles become outdated and marketing activities lose their effectiveness.

**PROPOSED SYSTEM**

The suggested approach uses the LRFS model in a more intelligent, data-driven, and dynamic way to try to improve online shopper behavior-based classification. In comparison to previous systems, this one uses real-time data streams and advanced analytics to better organize clients based on recency (the most recent contact), frequency (the number of purchases), spend (average transaction value), and duration (period of connection). A mix of hierarchical, density-based, and K-means clustering techniques are used by the system to generate more accurate and trustworthy parts.

It also makes use of supervised machine learning algorithms to predict things like lifetime value, churn risk, and repurchase likelihood for customers. This allows companies to make more informed decisions. When we combine behavioral data from different channels, we get a whole picture of the client. This includes the following: website navigation, product views, cart activity, and mobile app usage. Recommendation engines, marketing automation platforms, and customer relationship management systems can easily include segmentation data, enabling quick and personalized engagement with each group. By consistently adding new data to segments, the system aids in adjusting and maintaining the relevance of marketing activities. An intelligent, real-time, customer-focused segmentation strategy is provided by the proposed solution, which boosts revenue, improves customization, and keeps customers for longer.

**ADVANTAGES OF PROPOSED SYSTEM**

- A component of the suggested solution is real-time data processing, which allows businesses to dynamically reshape their customer segments in response to new connections. As opposed to static segmentation, this method guarantees that changes in behavior, like a sudden drop in frequency or an increase in spending, are quickly noticed.
- Combining LRFS data with supervised ML models improves the suggested method's guessing ability, which in turn outperforms competing clustering algorithms. Customer lifetime value, chance of repeat business, and likelihood of quitting your firm are just a few of the crucial outcomes that may be predicted using algorithms like decision trees, logistic regression, and neural networks.
- The suggested approach enhances segmentation by integrating behavioral data from several channels, including website navigation, email exchanges, mobile app use, and social network participation.
- Among the suggested system's key points is its adaptability to changing consumer behavior. Market divisions are dynamic and subject to change as new data becomes available.


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- Integrating with customer relationship management systems, email marketing programs, and recommendation engines is a breeze with the suggested approach, allowing for highly personalized client interactions.

## 4.RESULTS AND DISCUSSIONS

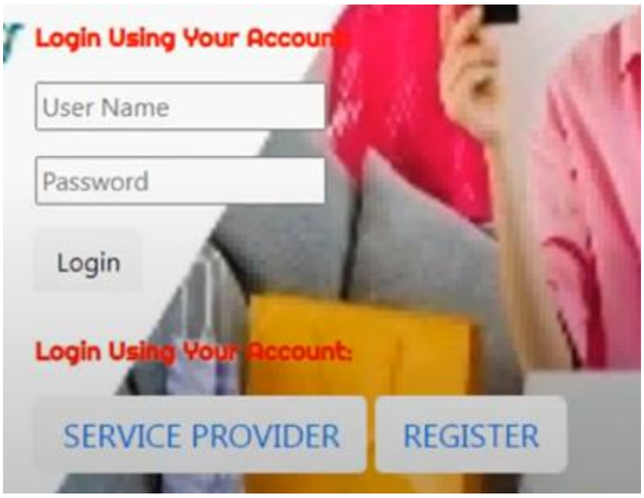


Fig1. User login


Fig2. Admin login

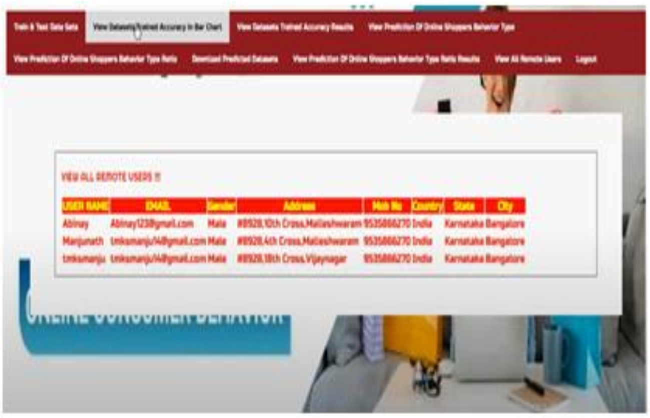

Fig3. View All Remote Users


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*Volume-1, Issue-2, July 2025* ISSN:**3107-4308** *Paper ID:* ***ETDT-V1-I2-13***

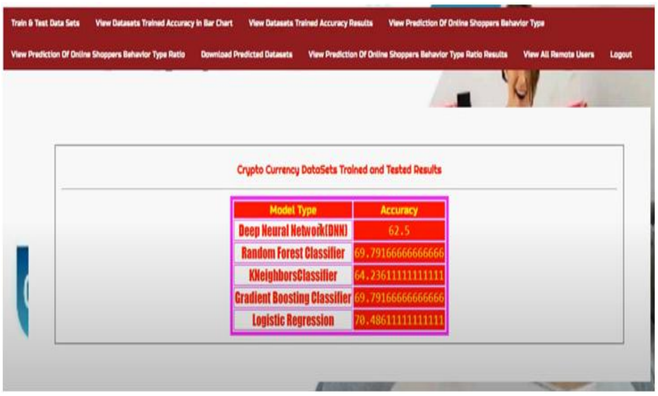


Fig4. Cryptocurrency Datasets Trained and Tested Results


Fig5. View Prediction of Online Shopping Behavior Type


Fig6. View Prediction of Online Shopping Behavior Type Ratio Details

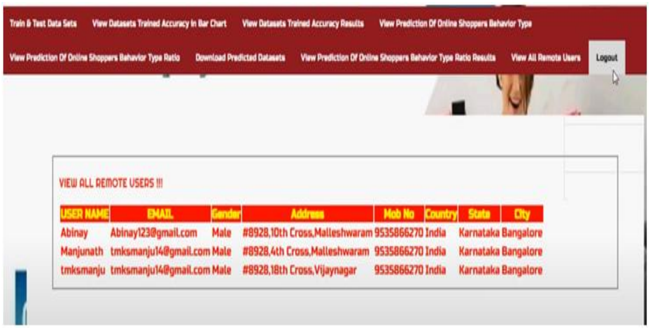


Fig7. View All Remote Users


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Fig8. Registered Status

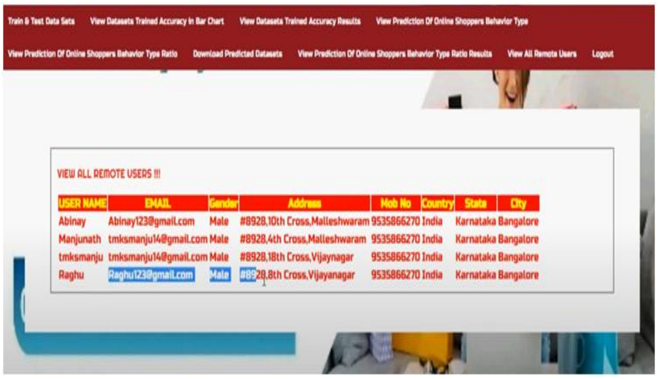


Fig9. All Remote Users

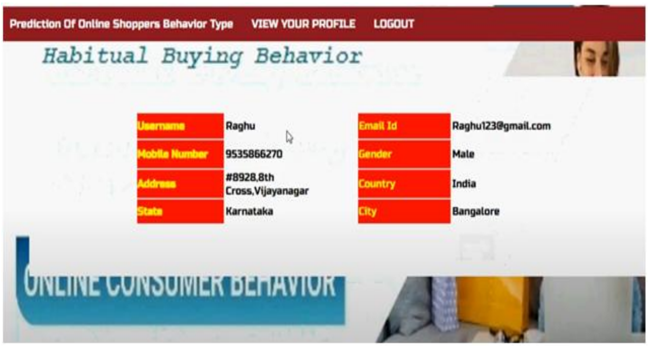


Fig10. User Details


Fig11. Enter Datasets Details Here

## 5.CONCLUSION

Finally, by using the LRFS model—an expansion of the widely used RFM model—to classify online shoppers into groups based on their behaviors, we can obtain a more thorough and realistic picture of people's actions in e-commerce settings. This model comprises Length (L), Recency (R), Frequency (F), and Spend (S). This


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complex model allows marketers and analysts to go beyond basic data by taking into account the full customer lifecycle with all of its subtleties. Factors such as a customer's length of time as a client (L), the time since their last purchase (R), the frequency with which they shop (F), and their average spending amount (S) may help businesses better characterize their clients and tailor their marketing campaigns to them. Personalized marketing may re-engage valuable customers who haven't bought from you in a while, and unique deals can be sent to loyal customers who spend a lot of money.

The LRFS method allows data-driven micro-segmentation that accurately represents real behavioral trends, in contrast to demographic segmentation that often leads to broad generalizations. In today's digital era, where customer behavior is driven by trends, seasons, and fluctuating brand loyalty, this technique is even more vital. Improved upon by machine learning methods, this paradigm may automatically recognize patterns and categorize individuals into separate groups based on their predicted behavior. Improved marketing, personalized advice, and customer retention efforts are all made possible by this astute categorization, which in turn increases conversion rates and client lifetime value.

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DOI : https://doi.org/10.5281/zenodo.16831596