

Customer segment model with the purchase recency, frequency and monetary amount

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Abstract: This paper utilizes customer transaction data to segment customers based on their purchase recency, frequency, and monetary amount. By employing an empirical approach, a stochastic model is proposed to predict customer segmentation into categories such as new, active, potential, and lost. The model also constructs indices for customer equity and loyalty. This approach allows companies to practically analyze and categorize their customers, calculating the probability of segment characteristics. The study highlights the importance of customer segmentation in strategic planning, emphasizing the role of RFM (recency, frequency, monetary amount) analysis in identifying high-value customers and optimizing marketing strategies. The proposed model integrates customer equity and loyalty metrics, providing a comprehensive framework for businesses to enhance customer relationship management and targeted marketing efforts. The empirical data from a credit card customer database in Taiwan demonstrates the model's effectiveness in segmenting customers and predicting their behavior, offering valuable insights for businesses to allocate resources strategically and maximize revenue potential. This research contributes to the field by presenting a robust method for dynamic customer segmentation, applicable across various industries.

Keywords: *purchase frequency, recency, monetary amount, RFM, customer loyalty*

JEL Classification: M31

Rad dostavljen: 07.03.2025.

Rad prihvaćen za objavljivanje: 03.04.2025.

1. INTRODUCTION

In a contemporary business environment, identifying high-value customers and implementing effective marketing strategies are critical components of strategic planning (Kumar & Philip, 2022; Xiao, 2022; Huang, 2021a). Customer segmentation, particularly through the analysis of transaction data such as purchase recency, frequency, and monetary value (RFM), has emerged as a widely adopted method in data-driven marketing. The RFM model enables businesses to categorize customers based on behavioral patterns, thereby facilitating targeted marketing campaigns and optimizing customer relationship management. Several studies (Krishnan & Nair, 2022; Ahang, Imani, Abbasi, Ghaffari & Mehdi, 2022; Rogić, Kaščelan & Đurišić, 2022; Nguyen, Loi, Ngo, Tu & Le, 2022; Chou & Chang, 2022; Huang, 2021b; Rungruang, Riyapan, Intarasit, Chuarkham & Muangprathub, 2024) have expanded upon the traditional RFM framework, integrating it into various marketing applications such as promotional targeting (Ernawati, Baharin & Kasmin, 2022), bank customer classification (Heikal, Rialialie, Rivelino & Supriyono, 2022), and product recommendation (Xian, Keikhosrokiani, XinYing & Li, 2022).

Heikal et al. (2022) applied the RFM model to segment bank customers based on loyalty levels, leveraging Structural Equation Modeling to examine the impact of customer transaction behavior on average balance classification. Similarly, Imani, Abbasi, Ahang and Ghaffari (2022) introduced an enhanced RFM model by incorporating a customer price index (RFM-CPI), demonstrating improved segmentation accuracy through a two-step algorithm. Their findings suggest that integrating additional customer value metrics can enhance the predictive power of the RFM model.

Beyond traditional applications, Ernawati et al. (2022) extended the RFM model by incorporating spatial analysis for targeted marketing within university service providers. By combining K-means clustering with Geographic Information System (GIS) methodologies, their study

revealed that spatially informed customer segmentation outperformed customer lifetime value (CLV)-based segmentation in terms of predictive accuracy and targeted marketing efficiency. Additionally, Xian et al. (2022) proposed a hybrid model by integrating RFM with k-means clustering and association rule mining to enhance customer segmentation and improve product recommendation systems.

Customer equity and loyalty are fundamental determinants of long-term business success. Customer equity represents the aggregate financial value derived from a company's entire customer base, influenced by acquisition, retention, and expansion strategies. Integrating RFM analysis with customer equity metrics enables businesses to identify their most profitable customers and allocate resources strategically to maximize revenue potential. Research by Stormi, Lindholm, Laine and Korhonen (2020) and Ernawati, Baharin and Kasmin (2021) underscores the significance of customer equity in sustaining competitive advantage across various industries.

Customer lifetime value (CLV) is another essential metric that complements RFM analysis, providing insights into the long-term revenue potential of individual customers (Andriana & Mardiani, 2025; Lewaaelhamd, 2023). CLV is instrumental in guiding marketing resource allocation, enabling businesses to develop personalized engagement strategies and optimize retention efforts. Studies by Monalisa, Nadya and Novita (2019) and Anitha and Patil (2022) demonstrate that integrating CLV with RFM segmentation enhances the precision of customer profiling, leading to improved customer engagement and loyalty.

Furthermore, customer loyalty, which is closely linked to both customer equity and CLV, reflects a customer's likelihood of repeat purchases and brand advocacy (Andriana & Mardiani, 2025; Molaei, Abbasimehr & Rahsepar Fard, 2025). High-loyalty customers contribute significantly to business stability and long-term growth, necessitating targeted retention strategies (Lewaaelhamd, 2023). Advanced segmentation techniques, such as those introduced by Christy, Umamakeswari, Priyatharsini and Neyaa (2021) and Daoud, Amine, Bouikhalene and Lbibb (2015), incorporate loyalty indices to refine traditional RFM models, ensuring that businesses can tailor marketing efforts to foster customer commitment effectively.

This study offers a practical business case in which customers are segmented based on their transaction data, specifically recency, frequency, and monetary amount. Through this segmentation process, four key customer characteristics—active, new, potential, and

lost—are identified. The distinct traits of each segment are thoroughly described, providing insights into customer behaviors. Furthermore, a stochastic model is proposed within the RFM framework to enhance segmentation accuracy. This model maps customer characteristics onto a two-dimensional coordinate system based on customer equity and loyalty. The proposed approach allows businesses to predict the probability of a customer belonging to a specific segment, thereby enabling more targeted marketing and customer retention strategies.

2. THE BUSINESS CASE STUDY: RFM ANALYSIS AND CUSTOMER CHARACTERISTICS SEGMENT

2.1. Literature review on RFM applications

RFM-based segmentation has been widely utilized across various industries (Akter, Roy, Rahman, Mohona & Ara, 2025; Suh, 2025). Several studies have extended its application by integrating advanced clustering techniques or predictive modeling methods (Lee, Na, Rhim & Kim, 2025; Shu, Llorens-Marin, Carrasco & Romero, 2025). For instance, Ahang et al. (2022) implemented a decision-tree-based approach to refine RFM segmentation, achieving improved customer differentiation. Similarly, Nguyen et al. (2022) developed an RFM-CLV hybrid model to optimize business-to-business (B2B) supplier classification, demonstrating its potential beyond traditional retail settings.

Huang (2021a) examined RFM-based segmentation in different service industries, highlighting the variability in segmentation effectiveness across sectors. Furthermore, Huang (2021b) proposed a novel CLV calculation model incorporating interpurchase time and retention rates, illustrating an alternative to RFM-based classification.

Birant (2011) introduced an early exploration of RFM data mining techniques, demonstrating how segmentation can be effectively applied across various industries. Sabuncu, Türkan and Polat (2020) further analyzed customer profiling with RFM, emphasizing its role in targeted marketing strategies. Aggelis and Christodoulakis (2005) examined customer clustering using RFM, providing an early perspective on segment differentiation.

Stormi et al. (2020) investigated the role of RFM segmentation in product-oriented services and business development, demonstrating its effectiveness in manufacturing industries. Ernawati et al. (2021) re-

Table 1: The groups of RFM analysis

Group	G1	G2	G3	G4	G5	G6	G7	G8
Sample size	634	637	702	702	579	579	701	702
Qultiria	(1,1,1)	(1,1,2)	(1,2,1)	(1,2,2)	(2,1,1)	(2,1,2)	(2,2,1)	(2,2,2)

Source: Author

viewed data mining methodologies for RFM-based segmentation, offering insights into its evolving applications.

Monalisa et al. (2019) explored the relationship between customer lifetime value and RFM, presenting a categorization framework for long-term customer engagement. Additionally, Anitha and Patil (2022) applied RFM with K-means clustering to examine customer purchase behavior, reinforcing its use in behavioral segmentation.

Christy et al. (2021) introduced RFM ranking as an alternative approach to segmentation, showing its benefits in optimizing marketing efforts. Daoud et al. (2015) combined RFM with clustering techniques for online business segmentation, illustrating its applications in e-commerce. Lewaaelhamd (2023) applied machine learning models to RFM segmentation, highlighting its predictive capabilities in modern data science applications.

Wu, Chang and Lo (2009) demonstrated how RFM and K-means clustering can improve customer value analysis in retail and outfitter industries, providing practical insights for business applications.

2.2. The empirical data description

The empirical dataset used in this study is derived from the customer database of credit cards issued by Bank A in Taiwan. The database contains transaction records of 5263 customers, including the frequency of transactions during 180 days, the recency duration, and the momentary spending amount, which includes the sum of monetary, the average amount per transaction. To protect customer privacy, personally identifiable information has been removed. The available demographic information includes only customers' education levels and residential regions.

2.3. RFM analysis

The RFM analysis is conducted to segment customers into $2 \times 2 \times 2$ groups. First, customers are classified into two groups based on their recency duration. Recency refers to the time elapsed between a customer's most recent purchase and the data collection cutoff date. A longer recency period indicates that the last

purchase occurred further in the past, suggesting lower customer activity. Therefore, the recency (R) metric serves as a key indicator for assessing customer engagement levels. Based on this metric, customers are initially grouped into two categories.

Next, within each recency-based group, customers are further divided into two groups according to their purchase frequency (F). Finally, within each recency and frequency segment, customers are classified into two additional groups based on their average monetary amount (M), which is demonstrated in New Taiwan Dollars (NTD).

As a result, customers are segmented into eight distinct groups (G1 to G8), as illustrated in Table 1.

To maximize the differences among the three RFM indicators—recency, frequency, and monetary amount—and to capture the variations formed by their interactions, this study selects four customer groups, G1, G3, G5, and G8, for further analysis. G1 and G8 represent the segments with the highest and lowest contribution levels with RFM values of (1,1,1) and (2,2,2), respectively. Meanwhile, G3 and G5 correspond to (1,2,1) and (2,1,1), reflecting distinct characteristics: G3 represents customers who have made a recent purchase with low purchase frequency but high monetary value, whereas G5 consists of customers who have not made a purchase for a while but exhibit high purchase frequency and high monetary value.

To segment customers by the characteristics of RFM, it chooses four groups from G1 to G8 to represent the different traits of these four kinds of customers. The results are shown in Table 2.

Table 2: The mean of R, F, and M in G1, G3, G5, and G8

	G1	G3	G5	G8
R	7.08	7.06	56.44	64.46
F	19.00	3.97	19.86	4.89
M	287261.09	173234.31	131384.22	5390.65

Note: The database is from Bank A in Taiwan. Thus, the monetary amount is denominated in New Taiwan Dollars (NTD).

Source: Author

For G1, the average value is used as the standard for comparing observation items with other groups. The R value is 7 days, the F value is 19, and the M val-

ue is NTD 287261. From the above data, it can be seen that the G1 group not only has the lowest gap from the last purchase, but also the times and amount of consumption during the period are the highest among the 8 groups. It deserves to be regarded as the most valuable ethnic group and treated with care. If there are discounts or activities, they should be given priority and actively look for the G1 group to strengthen subsequent customer loyalty and customer value, and seize the most valuable customer.

For G3, the average value is used as the standard for comparing the observation items with other groups. The R value is 7 days, the F value is 4, and the M value is NTD 173234. As we can see from the data, it is inferred that the G3 group still has consumption recently and the average consumption amount during the period is very high. The fly in the ointment is that the number of consumptions is less. Such customers can be regarded as potential loyal customers to be developed. It is necessary to understand what causes the lower consumption frequency of the G3 ethnic group. It may be an inconvenience in living areas or a lack of incentives for consumption. Depending on the situation, give discounts or exclusive member activities to increase customer value and increase heart rate.

For G5, the average value is used as the standard for comparison between observation items and other groups. The R value is 56 days, the F value is 19, and the M value is NTD 131384. It has been 56 days since the last purchase. It may be that the loyal customers in the past no longer have high loyalty to the brand for some reason. Reasons that caused such factors might be better service or preferential prices elsewhere. Therefore, they should be more cautious with G5 customers. With proper care, G5 is very likely to be converted into high-value customers such as the G1. Therefore, more attention should be paid to the needs of the G5.

For G8, the average value is used as the standard for comparison between observation items and other groups. The R value is 64.8 days, the F value is 4.8, and the M value is NTD 5390. From the data, it can be seen that it has been 64 days since the last consumption of the G8 group. In addition, the times of consumption during the period and the average consumption amount are the lowest in the 8 groups. The average of total consumption is only NTD 5390. It can be implied that this group of customers may be passers-by, early adopters, or have come just for a special purpose, rather than for frequent visits. For this group of customers, it is not necessary to invest too much effort. Therefore, it does not need to design exclusive

events or advertising, marketing costs in an attempt to win them over.

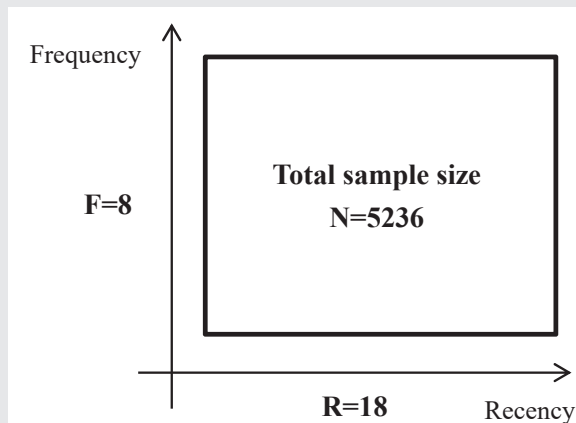
To sum up, G1 is the most valuable customer group in the analysis data, showing that this consumer group has high loyalty, and it can continue to maintain a good relationship with this customer group. The average consumption amount of G3 is high, and the frequency of the last consumption is quite close. Although the number of consumptions is less than G1, according to the monetary amount and frequency of consumption, we believe that the G3 group has the most potential to develop into a long-term customer relationship. Providing other services to this ethnic group can be quite effective.

Regarding segment G5, it can be seen that there has been a long period since their last purchase. Due to some factors, the product may not meet their expectations. Therefore, we believe that resources should be invested in more valuable customers. The average consumption amount, frequency, and times of the G8 are the lowest. We believe that the effectiveness of investing in this group of customers will be insignificant, so we are putting resources into G3.

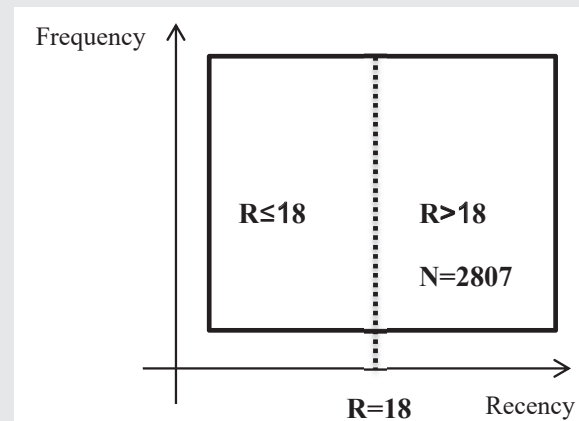
2.4. The new, active, potential, and lost characteristics in customer analysis

Building on the analysis of the characteristics of the four RFM-based segments—G1, G3, G5, and G8—this study further refines customer segmentation by mapping the recency (R) and frequency (F) indicators into two coordinate quadrants. This approach enables a more effective identification of consumer characteristics and enhances the applicability of a diversified RFM analytical model. The segmentation is based solely on the R and F indicators because, within the RFM framework, these two metrics are considered more influential than the monetary (M) indicator (Anitha & Patil, 2022). In preliminary customer segmentation, it is common practice to first determine whether a customer is still „active“ (i.e., continues to engage in transactions with the brand, as indicated by the recency of their last purchase) and to assess their transaction frequency (Stormi et al., 2020).

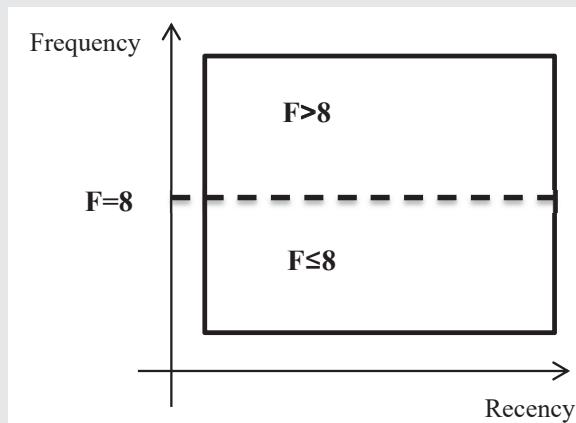
The customers are segmented into new, active, potential, and lost characteristics with frequency (number of purchases) and the median of recency (recent shopping time) in RFM analysis. Specifically, a new customer is one whose most recent purchase occurred very recently, indicating continued engagement, while their cumulative purchase frequency remains low. An active customer is characterized by a very recent last

Figure 1: The segment of characteristics in step 1

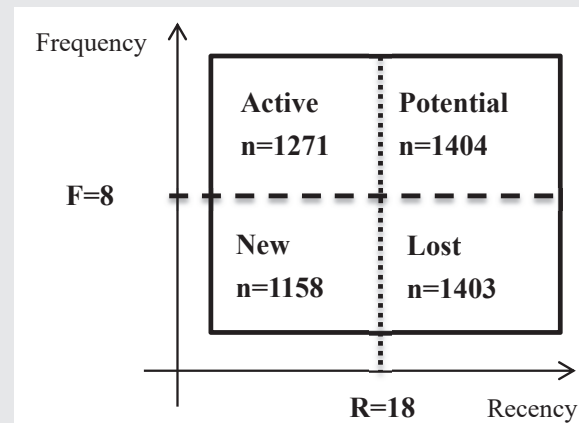
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Figure 2: The segment of characteristics in step 2

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Figure 3: The segment of characteristics in step 3

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Figure 4: The segment of characteristics in step 4

Source: Author

purchase and a high purchase frequency. A potential customer is one whose most recent purchase was made some time ago, but who has a high past purchase frequency. This segment presents an opportunity for marketing interventions to re-engage them and stimulate transactions, preventing them from transitioning into the lost customer group. It is important to note that the definition of a potential customer in this study differs from the traditional marketing concept of those who belong to the target group but have not yet made any purchases. Finally, a lost customer is identified as one who has not made a purchase for a long time and has a low overall purchase frequency.

There are four steps to make segmentation of the total sample size by the number of purchases and the recent shopping time.

- (1) The first step is to decide the threshold level of recency and frequency. We base on the RFM analysis to set the median value of R and F as $R = 18$ and $F = 8$ (please see Figure 1).
- (2) In step 2, to divide customers into two groups by the recent shopping days, $R=18$ (please see Figure 2).
- (3) For step 3, to make customer segmentation into two groups by the number of purchase frequency, $F=8$ (please see Figure 3).
- (4) In the last step, to make segmentation both by the recent shopping days $R=18$ and the number of purchase frequency $F=8$ (please see Figure 4).

Customers are first divided into two groups based on their purchase frequency: those who have made fewer than 8 purchases and those who have made 8 or more. Among those with fewer than 8 purchases, in-

dividuals who have purchased within the past 18 days are categorized as new (N) customers, totaling 1158. Conversely, those who have not purchased in the past 18 days fall into the lost (L) segment, comprising 1403 customers. The customers are divided into those who have not consumed more than 8 times, and those who are above.

Those who have spent more than 8 times in the past 180 days are further segmented according to the most recent consumption time. Those who have purchased in the past 18 days are in segment A (Active) with 1271 people. Those whose last consumption was over 18 days would be in segment P (Potential) with 1404 people.

According to the above two analyses, the four groups of RFM, respectively G1, G3, G5, and G8, can be mapped to the four segments on the four characteristics chart. It is found that the N (NEW) segment on the chart matches the target group G3, which is the most valuable 1158 customers that we have.

3. THE STOCHASTIC MODEL CONSTRUCTION

To enhance the applicability of this study's RFM-based customer segmentation concerning customer loyalty and customer equity characteristics, the four customer groups—new, active, potential, and lost—will be redefined based on these two dimensions. Finally, a stochastic model that transforms recency and frequency data into two dimensions, customer equity and loyalty, will be derived to serve as a practical marketing tool, enabling broad application across different industries and brands:

(1) Customer Loyalty Dimension. Recency values are converted into loyalty indices, where shorter recency durations indicate higher loyalty levels. It is considered recency as a random variable following an exponential distribution, allowing us to derive a cumulative distribution function (c.d.f.) and probability density function (p.d.f.) for loyalty scores.

(2) Customer Equity Dimension. Customer equity is modeled as a normal distribution, considering variations in transaction frequency and monetary value. The threshold values for loyalty (z') and equity (y') are used to define four customer segments:

- Active Customers: High loyalty, high equity;
- Potential Customers: Low loyalty, high equity;
- New Customers: High loyalty, low equity;
- Lost Customers: Low loyalty, low equity.

Based on the aforementioned definitions and the assumptions of the probability density functions, the following section will calculate the probability models for the four customer segments classified by „customer loyalty“ and „customer equity,“ respectively.

3.1. The customer loyalty dimension

To transform the recency value to loyalty index, we denote the duration of recency as the random variable t following an exponential distribution $f(t)$ with the parameter λ . The shorter the recency time, the more likely this customer is still active and has not switched to another brand. The customer who has a shorter recency time is more loyal than others who have a longer recency time. Thus, it denotes that the loyalty value is $1/t$ which translates from the recency.

It denotes that loyalty is a random variable Z , and it can calculate the cumulative distribution function (c.d.f.) of loyalty value $1/t$ as $G(z)$ in which we consider the random variable z :

$$P\left(\frac{1}{t} < z\right) = P\left(t > \frac{1}{z}\right) = 1 - P\left\{t < \frac{1}{z}\right\}$$

$$G(z) = 1 - F\left(\frac{1}{z}\right) = 1 - e^{-\lambda \frac{1}{z}}$$

Then, we can calculate the probability density function (p.d.f.) of loyalty value as $g(z)$ to differential $G(z)$:

$$\frac{d}{dz}G(z) = g(z) = -F'\left(\frac{1}{z}\right)(-z)^{-2} = f\left(\frac{1}{z}\right)\left(\frac{1}{z^2}\right) = \frac{\lambda}{z^2}e^{-\lambda \frac{1}{z}} \quad (1)$$

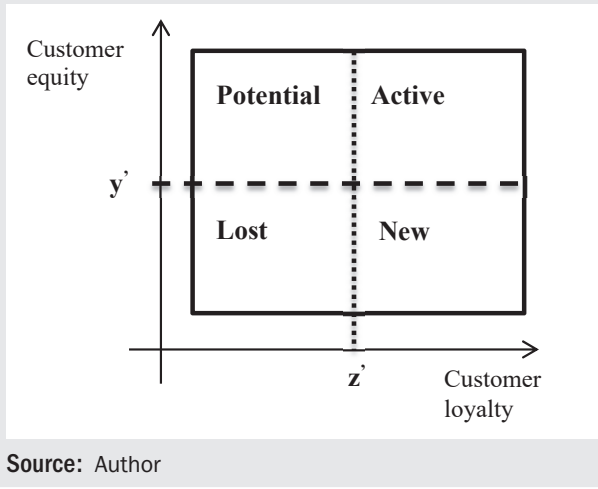
3.2. The customer equity dimension

It denotes that customer equity is a random variable Y . We consider that Y follows a normal distribution with parameters μ and σ^2 . And its p.d.f. is:

$$l(y) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(y-\mu)^2}{2\sigma^2}\right\} \quad (2)$$

We denote the threshold value z' for the loyalty variable Z and y' for the threshold value of the customer equity (customer contribution) variable Y . Then, it can divide customers into four segments with their loyalty and customer equity index (Figure 5).

Figure 5: The segment of characteristics with customer equity and loyalty



To determine the likelihood of each segment, we apply the stochastic model equations. The probability mode of each segment is as follows:

(1) new customer segment

$$\begin{aligned}
 &P(Z > z' \cap Y < y' | R = r, M = m) \\
 &= \left\{ 1 - \int_0^{z'} g(z | R = r) dz \right\} \cdot \int_0^{y'} l(y | M = m) dy \\
 &= \{1 - G(z')\} \cdot \Phi\left(\frac{y - y' - \mu}{\sigma}\right) = e^{-\lambda \frac{1}{z'}} \cdot \Phi\left(\frac{y - y' - \mu}{\sigma}\right)
 \end{aligned}$$

(2) active customer

$$\begin{aligned}
 &P(Z > z' \cap Y > y' | R = r, M = m) \\
 &= 1 - \int_0^{z'} g(z | R = r) dz \cdot \int_0^{y'} l(y | M = m) dy \\
 &= \Phi\left(\frac{y - y' - \mu}{\sigma}\right)
 \end{aligned}$$

(3) potential customer

$$\begin{aligned}
 &P(Z < z' \cap Y > y' | R = r, M = m) \\
 &= G(z') \cdot \left\{ 1 - \int_0^{y'} l(y | M = m) dy \right\}
 \end{aligned}$$

$$= \left(1 - e^{-\lambda \frac{1}{z'}} \right) \cdot \left\{ 1 - \Phi\left(\frac{y - y' - \mu}{\sigma}\right) \right\}$$

(4) lost customer

$$\begin{aligned}
 &P(Z < z' \cap Y < y' | R = r, M = m) \\
 &= \int_0^{z'} g(z | R = r) dz \cdot \int_0^{y'} l(y | M = m) dy \\
 &= G(z') \cdot \Phi\left(\frac{y - y' - \mu}{\sigma}\right) \\
 &= \left(1 - e^{-\lambda \frac{1}{z'}} \right) \cdot \Phi\left(\frac{y - y' - \mu}{\sigma}\right)
 \end{aligned}$$

These stochastic model equations are according to the defined equations (1), (2), and the difference segment, which is demonstrated in Figure 5.

4. CONCLUSION

This study demonstrates the effectiveness of using the RFM (recency, frequency, monetary amount) model for customer segmentation, providing a practical approach for businesses to identify and categorize their customers based on transaction data. The proposed stochastic model enhances the traditional RFM framework by incorporating customer equity and loyalty dimensions, offering a more comprehensive understanding of customer behavior and value. The RFM analysis divides customers into eight distinct groups based on their recency, frequency, and monetary amount, allowing businesses to identify key customer characteristics such as active, new, potential, and lost customers. The empirical data from the credit card customer database in Taiwan shows that these segments can be effectively used to tailor marketing strategies and improve customer relationship management. Integrating customer equity and loyalty into the RFM model provides a deeper insight into customer value, with customer equity representing the financial value derived from the entire customer base and loyalty reflecting the likelihood of repeat purchases and brand advocacy. The stochastic model uses exponential and normal distributions to calculate the probability of a customer belonging to each segment, allowing businesses to predict customer behavior more accurately.

The study highlights the importance of targeted marketing strategies for different customer segments, suggesting that active customers should be prioritized for exclusive offers and loyalty programs, potential customers require incentives to increase their spending frequency, new customers need personalized engagement to convert them into loyal customers, and lost customers may not warrant significant marketing investment but can be re-engaged through specific campaigns.

The segmentation characteristics of new, active, potential, and lost customers provide a structured approach for businesses across different industries. In the retail sector, companies can use these classifications to refine loyalty programs and promotional campaigns, ensuring that marketing efforts are directed toward retaining high-value customers and reactivating lost ones. In the banking and financial services industry, institutions can leverage the RFM model to assess customer creditworthiness and risk management, using stochastic modeling to predict long-term engagement and profitability. Likewise, in subscription-based businesses, firms can proactively identify potential churn risks and deploy retention strategies such as personalized discounts and exclusive content offerings.

Moreover, the stochastic model construction allows businesses to develop probabilistic forecasts of customer behavior, enhancing predictive analytics in marketing decision-making. By incorporating these models into customer relationship management (CRM) systems, companies can transition from reactive to proactive strategies, ensuring real-time responsiveness to shifts in consumer engagement patterns. The ability to anticipate changes in customer activity enhances strategic planning and fosters a data-driven approach to long-term business sustainability.

The proposed model can be applied across various industries, including retail, banking, and e-commerce, optimizing marketing efforts, allocating resources more effectively, and enhancing customer retention. Future research should focus on validating the proposed model with empirical data from different industries to ensure its reliability and generalizability, integrating additional customer value metrics such as customer lifetime value and customer satisfaction scores to enhance the predictive power of the RFM model, and using advanced clustering techniques like machine learning algorithms to improve the precision of customer segmentation. Incorporating demographic variables into the RFM analysis can provide a more holistic view of customer behavior, offering valuable insights for personalized marketing strategies.

Businesses should allocate resources strategically based on customer segmentation, develop personalized engagement strategies for different customer segments, continuously monitor customer behavior and transaction patterns, and apply the proposed model across various industries to drive long-term business success. This study provides a comprehensive framework for customer segmentation using the RFM model, enhanced by customer equity and loyalty dimensions, offering a practical approach for businesses to predict customer behavior, optimize marketing efforts, and enhance customer relationship management. Future research should focus on validating and refining the model, exploring its integration with additional metrics, and investigating its application across different industries to achieve a deeper understanding of customers and drive long-term growth and competitive advantage.

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Apstrakt

Model segmentacije potrošača zasnovan na datumu poslednje kupovine, učestalosti i novčanom iznosu kupovine

Hui-Hsin Huang

Ovaj rad koristi podatke o transakcijama potrošača u cilju njihove segmentacije na osnovu datuma poslednje kupovine, učestalosti kupovine i novčanog iznosa. Korišćenjem empirijskog pristupa, predlaže se stohastički model za predviđanje segmentacije potrošača u kategorije kao što su novi, aktivni, potencijalni i izgubljeni potrošači. Model takođe konstruiše indekse vrednosti i lojalnosti potrošača. Ovaj pristup omogućava kompanijama da praktično analiziraju i kategoriju svoje potrošače, uz izračunavanje verovatnoće karakteristika segmenata. Studija ističe značaj segmentacije potrošača u strateškom planiranju, naglašavajući ulogu RFM (eng. *recency, frequency, monetary amount*) analize u identifikaciji potrošača visoke vrednosti i optimizaciji marketing strategija. Predloženi model integriše metrike

vrednosti i lojalnosti potrošača, pružajući sveobuhvatan okvir za unapređenje upravljanja odnosima sa potrošačima i ciljanih marketing aktivnosti. Empirijski podaci iz baze korisnika kreditnih kartica na Tajvanu pokazuju efikasnost modela u segmentaciji potrošača i predviđanju njihovog ponašanja, nudeći značajne uvide za strateško raspoređivanje resursa i maksimizaciju potencijalnog prihoda. Ovo istraživanje doprinosi prethodnoj literaturi predstavljajući robusnu metodu za dinamičku segmentaciju potrošača, koja se može primeniti u različitim delatnostima.

Ključne reči: učestalost kupovine, datum poslednje kupovine, novčani iznos, RFM, lojalnost potrošača

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