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The RFMRv Model for Customer Segmentation Based on the Referral Value

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ABSTRACT

The development of social networks provides numerous venues for customers to share their views, preferences, or experiences with others. Thus, the Referral programs have become the most valuable forms of marketing. Additionally, studies have emphasized the positive impact of referral programs on consumers' intentions to purchase products or services, which increases the need for considering referral value as part of customer value. Hence, this study analyzed customers' behavior in social media by extending the RFM model and proposing a new RFMRv model in which Rv is the referral value of customers. First, the customer graph of invitations was used to calculate customers' referral value. Then, the K-Mean algorithm was used to cluster customers based on the CRISP-DM methodology. Finally, the CLV for each cluster was calculated. The results indicated that the referral-acquired customers are more valuable than other customers and proved that the RFMRv model provides better clustering and valuation.

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1. Introduction

The advent of social media and websites in the modern era has greatly increased overall community interaction, making social media the most important marketing medium of the 21st century (Tania et al., 2023). Social networks have played an important role in helping customers find information and make purchasing decisions (Fu & Pang, 2022), and the main methods of marketing products and services in traditional media are no longer effective for attracting the consumers' attention (Su et al., 2023). Therefore, social networks are considered to be one of the most important communication platforms for the dissemination of brand information, since they have interactive properties that enable cooperative, collaborative and knowledge-sharing activities (Tania et al., 2023). The use of social networks provides feedback to obtain information about consumer preferences, perform brand building activities and maintain good customers' relationships (Tania et al., 2023; Mason et al., 2021; Wibowo et al., 2020). Companies incur costs for marketing campaigns as these have a major impact on business growth (Tania et al., 2023).

Word of mouth (WOM) is a powerful way to spread the word as it is believed to be the idea of personal contact (Tania et al., 2023). Marketers are aware that choosing the best marketing plan often depends heavily on consumer experience (Leung et al., 2022; Rosário & Raimundo, 2021). The first thing customers do to make a better decision is to look for information about the brand. These steps help customers get to know the brand better and increase brand awareness and knowledge so that it can help customers make the right purchasing decision (Tania et al., 2023). The literature has established the importance of positive and negative information shared by consumers in business success, performance or growth of companies (Rodríguez-Torrico et al., 2023). WOM researchers relate the likelihood of sharing positive and negative WOM to confirmation of consumer expectations, such that consumers are more likely to share positive WOM (negative WOM) after an interactive experience if they (not) meet their expectations (e.g. Nam and Kanan, 2020; Rodríguez-Torrico et al., 2023). Katz and Lazarsfeld (2017) found that the effect of word of mouth on brand switching is four times greater than the effects of face-to-face selling and twice the effect of radio advertising. There is evidence that the customer's social network is more effective in attracting new customers than any other source (Sivathanu & Pillai, 2014). Satisfied customers attract new customers through positive WOM advertising by recommending a service or product to them (Rodríguez-Torrico et al., 2023; Costa et al., 2018; Xevelinakis, 2015). Customers are exposed to a large number of ads through various mediums. As the information increases through the large number of advertisements, it becomes more difficult for customers to make marketing decisions. They therefore try to obtain reliable information about the products they intend to buy because they want to reduce their perceived risk. For this reason, WOM is considered to be one of the most useful information sources for consumers as it contains the opinions and experiences of former customers on brands and products or services (Evans & Erkan, 2015).

The impact of WOM on customers purchase intentions has long been known (Rodríguez-Torrico et al., 2023). However, the advent of social networking has brought a new perspective to electronic word of mouth (eWOM) that enables users to connect to their existing networks on the Internet. In contrast to other online platforms, social networks allow users to share their opinions and experiences about products or services with acquaintances that refer to people they already know (Nuseir et al., 2023; Tania et al., 2023). These networks offer companies the opportunity to use eWOM (Mason et al., 2021; Hajipour & Esfahani, 2019; Moran & Muzellec, 2017; Heninng-Thurau et al., 2010). Therefore, marketers try to leverage the customer-to-customer relationships (Falcetti, 2019) through referral programs as a sustainable method to attract new customers to promote their products and services (Sciandra, 2019; Wang et al., 2018). It has also been shown that referred customers have higher engagement and retention rates than non- referred customers (Gershon & Jiang, 2022; Falcetti, 2019), and are more profitable than others (Xevelinakis, 2015). Therefore, many companies use referral reward programs on their social platforms to encourage customers to recommend their products or services to their friends and family (Belo & Li, 2022; Yuan & Peluso, 2021; Jiang et al., 2020; Sciandra, 2019; Wirtz et al., 2019; Orsingher & Wirtz, 2018). However, studies have shown that customers do not have equal value and that referrals and high lifetime value customers are not necessarily the same as customers with high referral value customer (Costa et al., 2018; Xevelonakis, 2015; Kumar et al., 2010a). In order to maximize the company's profitability, both measures are necessary to better understand of customer behavior (Xevelonakis, 2015; Kumar et al., 2010a). It provides a comprehensive view of each customer's value by considering the customer's income their behavior in relation to the dissemination news about brands, products and services (Costa et al., 2018).

Although in many industries customer referrals are the primary source of acquiring new customers in many industries, the value of customer referrals is largely ignored (Xevelinakis, 2015) and identifying a customer on a social network, further impacting their social connections, remains an issue (Roelens et al., 2016). This is often due to the difficulty of measuring social influence (Xevelinakis, 2015). Therefore, customer segmentation based on their behavioral value and referral values would help companies to identify their valuable customers group (Mensouri et al., 2022; Tabianan et al., 2022; Hanafizadeh & Paydar, 2013). The most widely used customer segmentation model is RFM (Recency, Frequency, and Monetary) (Huang et al., 2020), which predicts the next movement of customers based on their past transactions (Doğan et al., 2018).

Contrary to Sultana (2014) and Damm et al. (2011) who stated "*One customer's CLV is potentially similar to the CRV of the customer who made the referral*," studies have shown that customers with high customer lifetime value are not necessarily the same customers with high customer referral value (Xevelonakis, 2015). They suggested that the relationship between these two metrics may be non-linear, identifying customer profiles with low CLV and high CRV and customers with high CLV and low CRV (Costa et al., 2018; Haghighi et al., 2017; Kumar et al. 2007). This shows a debate between studies that should be addressed. However, there is little research on analyzing customers' behavior through their segmentation using the referral value along with RFM behavioral variables. Based on studies it is clear that referral behavior plays an important role in market decisions and customer purchasing behavior (Sciandra, 2019; Wang et al., 2018). Considering that many companies now use WOM-based social media marketing as part of brand communication strategies, the potential impact of eWOM communication on consumer market decision-making cannot be ignored (Chu & Kim, 2011). However, the challenge for managers is to find a way to leverage information about customers' referrals (Hanafizadeh & Paydar, 2013). This issue leads to the questions: how to use referral value along with the behavioral variables of the RFM model to attract and retain valuable customers?

to answer the proposed question, this study added customer referral value to the RFM model and studies its impact on predicting customers' behavior and promoting marketing campaigns, which is the innovation of this study. In this study, the value of customer referrals has been calculated based on real data and invitations registered from customers in the customer club. With this method, it is possible to calculate the customer's lifetime value using the financial value as well as the profit from customer referrals. The customer club is a dedicated social network for the company with the purpose of communicating more with users and involving them as much as possible, for this reason it contains important information to check the behavior of customers in the business field.

Customer segmentation based on their behavioral and referral values would help companies to identify their valuable groups of customers with distinctive features who use social networks and will help them to better target their customers and take the advantages of eWOM marketing. The research proceeds with the review of literature, then the research model and methodology are discussed. Finally, the conclusion and recommendation for future studies are explained.

2. Literature Review

2.1. Electronic Word of Mouth (E-WOM)

WOM is defined as the person-to-person verbal communication regarding a brand, product, or service between the recipient and the sender that the recipient considers non-commercial (Su et al., 2023; Hu et al., 2019). WOM communication includes "*any information about a target object (e.g., company, brand) that is transmitted from one person to another person or through some communication medium*" (Brown et al., 2005, p. 125). It is an oral or written act of conversational in a public relationship in which a person conveys his experience of using a product or service so that it can become a suggestion or recommendation to other parties as an image of the product in question (Tania et al., 2023). Researchers are increasingly recognizing the existence of a mixed WOM that contains both positive and negative WOM. This variable is essential for businesses because consumers view the WOM as one of the most reliable and trustworthy sources of information shared by impartial peers (Rodríguez-Torrico et al., 2023).

Traditional WOM marketing methods have given way to online WOM methods due to the technological advances. Before purchasing a product, consumers use the Internet to search for the product and brand and read the opinions and experiences of other consumers online (Su et al., 2023). This new form of WOM is known as electronic word of mouth or eWOM (Huete-Alcocer, 2017). EWOM is a process of dynamic and continuous exchange of information between customers about a product, service, brand or company, accessible to many individuals and organizations via the Internet (Ismagilova et al., 2020). This form of communication has gained special importance with the emergence of online platforms and is considered to be one of the most influential sources of information on the web influencing customers' behavior (Ismagilova et al., 2020; Huete-Alcocer, 2017). Numerous studies have demonstrated the impact of eWOM on consumers' purchase intentions for products or services (such as Napawut et al., 2022; Erkan & Evans, 2016; Xevelinakis, 2015). Zhao et al. (2020) also examined the impact of e-WOM on customers' purchasing behavior on social media. Their results confirmed the positive correlation between trust and the intention to purchase the products. In the same study, Nuseir (2019) highlighted the positive impact of e-WOM on online customers' purchase intentions and brand image. Another study by Chu et al. (2019) found that self-improvement and consumer engagement have increased eWOM with WeChat. The results of Maria et al. (2019) also reported that WOM advertising via brand awareness has a negligible and positive effect on purchase intent. In another study by Da Costa et al. (2018) on the impact of customer value on the WOM of a financial company in Brazil, they identified a U-shaped relationship between customer lifetime value (CLV) and WOM activity. Xevelinakis (2015) has also pointed out that WOM is a powerful factor influencing customers' buying behavior. In another study, Kumar et al. (2010a) examined business reference value (BRV) drivers as the ability of customers to persuade prospects to purchase goods or services. They identified four drivers of BRV and revealed the distinct characteristics and behavior of high BRV and CLV customers. In another study, Kumar et al. (2013) found that customer management is critical to CLV and CRV scores to maximize profits, and understanding CRV behavioral incentives could help managers target the most profitable customers with better referral marketing campaigns. Another study by Gruen et al. (2006) examined the impact of eWOM communication and knowledge sharing between customers, on customers' intention to purchase products and loyalty. Their results indicated that sharing customer knowledge influences customer's perception of product value and the likelihood of product recommendation. However, it differs from the studies of Ariesta and Zuliestiana (2019) and Kurniawati and Arifin (2015), which find that social media marketing and e-WOM have a negative impact on purchase intent. The results of Emini and Zeqiri (2021) also show that brand awareness does not mediate the relationship between social media marketing and purchase intent. This is because social media marketing is considered informal while WOM dynamics are considered through brand awareness that creates a formal impression on customers and thus does not produce meaningful results for customers despite having a positive relationship.

2.2. Referral Reward Programs (RRPs)

Referral value (RV) estimates the average number of successful referrals a customer will have in the future (Kumar et al., 2010b). In many ways, these referrals can be thought of as no-contract sellers who receive a commission for each new customer (Song et al., 2019; Kumar et al., 2010b).

Positive referrals reduce the acquisition costs of a company. Conversely, dissatisfied customers with high penetration can generate market losses (Xevelonakis, 2015). Therefore, companies use referral marketing campaigns to harness the power of WOM and increase referrals to reach new customers (Sciandra, 2019; Wirtz et al., 2019; Orsingher & Wirtz, 2018). Referral marketing is a way of promoting products and services that are generally recommended to customers through WOM. It is one of the most reliable and cost-effective marketing strategies that attracts customers and a wide audience to purchase products and services, increasing brand awareness and ultimately sales (Guo, 2012).

As an effective marketing tool for generating referrals, referral rewards programs (RRPs) have received much attention and are used in common product marketing practices. Rewards are included in this program to induce existing customers to recommend products to potential customers, thus achieving the conversion of interpersonal social capital into economic capital (Kuang et al., 2021; Wirtz et al., 2019). The rationale behind referral programs is that companies encourage existing customers to recommend products or services to their family, friends, and acquaintances by rewarding successful referrals (Armelini et al., 2015; Chen & Fan, 2013). With the increasing number of referral marketing programs, researchers have attempted to assess their impact on company performance, profitability and cost. For example, Jung et al. (2021) evaluated the effectiveness of three incentives: selfish reward, fair reward, and generous reward in online referral programs. They showed that prosocial referral incentive schemes, i.e. fair and generous distribution schemes tend to dominate purely selfish schemes in WOM generation. In another study, Boros and Papasava (2020) examined the effectiveness of referral marketing strategy for improving of online higher education. In another study, Fan et al. (2019) studied the interpersonal effect of different types of WOM including review rating and friend referrals on consumer behavior in restaurant choice. In another study Schmitt et al. (2011) indicated that referred customers are more valuable than others. The same study of Armelini et al. (2015) reported conflicting results, stating that referred customers are no more valuable than others.

2.3. Customer Segmentation and RFM Model

Customer segmentation is the process of dividing the organization’s customers into different groups based on different geographical, demographic, cognitive and behavioral information ((Mensouri et al., 2022; Tabianan et al., 2022). An appropriate strategy for customer segmentation means providing different services for customers with different needs (Zhou et al., 2021).

Customer segmentation can be performed using various techniques and methods of data analysis. Among them, RFM (Recency, Frequency and Monetary) is known as the most popular method that measures the behavioral value of customers based on their purchase history (Tsai et al., 2013; Doğan et al., 2018). The RFM extracts customer characteristics through three behavioral indicators, which simplifies the method (Huang et al., 2020) and at the same time represents one of the weaknesses of the model (Tavakoli et al., 2018). Therefore, studies have extended RFM by adding other variables such as lifetime value (Alizadeh Zoeram & Karimi Mazidi, 2018; Mohammadzadeh et al., 2017; Beheshtian-Ardakani et al., 2018; Ansari & Riasi, 2016; Kandeil et al., 2014), time (the time interval from the first transaction in the customer's history to the last transaction in the reference time) (Mensouri et al., 2022; Hu et al., 2020), lead time (Muchlish, 2023), length (Warsito & Santoso, 2023; Ibrahim & Tyasnurita, 2022, Mahdee et al., 2022; Huang et al., 2022), length and volume (Mahfuza et al., 2022), Length of time and Periodicity (Monazam Ebrahimpour & Omidi, 2022), loyalty (Van Burg, 2020), groups of products and services (Chang and Tsai, 2011), and user lifetime, intensity and rewards (Perisic & Pahor, 2021) to this model to better analyze customers’ behavior. The results of these studies indicated that the proposed models performed better than the basic RFM to predict customers buying behavior of. Table 1 indicates the RFM evolution.

Table 1. RFM Model Evolution

Resource	Added Variable	Proposed Model
(Muchlish, 2023)	Lead Time	LRFM model
(Warsito & Santoso, 2023) (Huang et al., 2022) (Mahdee et al., 2022) (Ibrahim & Tyasnurita, 2022)	Length of time	LFRM
(Monazam Ebrahimpour & Omidi, 2022)	Length of time and Periodicity	LRFMP
(Ernawati et al., 2022)	district’s potential	RFM-D
(Perisic & Pahor, 2021)	User Lifetime, Intensity and Rewards	RFM-LIR
(Van Burg, 2020)	Loyalty	RFML
(Hu et al., 2020)	Time (The time interval from the first transaction in the customer’s history to the last transaction in the reference time)	RFMT
(Alizadeh Zoeram & Karimi Mazidi, 2018)	Customer Lifetime Value and fuzzy inference system	LRFM
(Mohammadzadeh et al., 2017)	Customer Lifetime Value	RFML
(Beheshtian-Ardakani et al., 2018) (Ansari & Riasi, 2016) (Kandeil et al., 2014)		LRFM
(Chang and Tsai, 2011)	Groups of Products and Services	GRFM

According to the studies, the researchers added various factors to the RFM and examined their effect on customers' behavior. However, despite the importance of using referral reward programs as an effective marketing strategy, to the best of the author's knowledge, there is no significant research on customers' segmentation using RFM considering referral value. Therefore, considering the effect of referral value on customer acquisition and retention, this study aims to add referral value as a new behavioral variable to the RFM to better analyze customers' behavior.

3. Methodology

This study aims to analyze customers' behavior using the RFM model, the most popular method to measure the behavioral value of customers based on their purchase history (Doğan et al., 2018; Tsai et al., 2013) and referral value. Thus the study consists of three phases: I. calculate customers' referral value using customer invitation graph; II. Customers Clustering using a developed RFM model namely RFMRv. III. Calculation of the CLV of clusters (Figure 1).

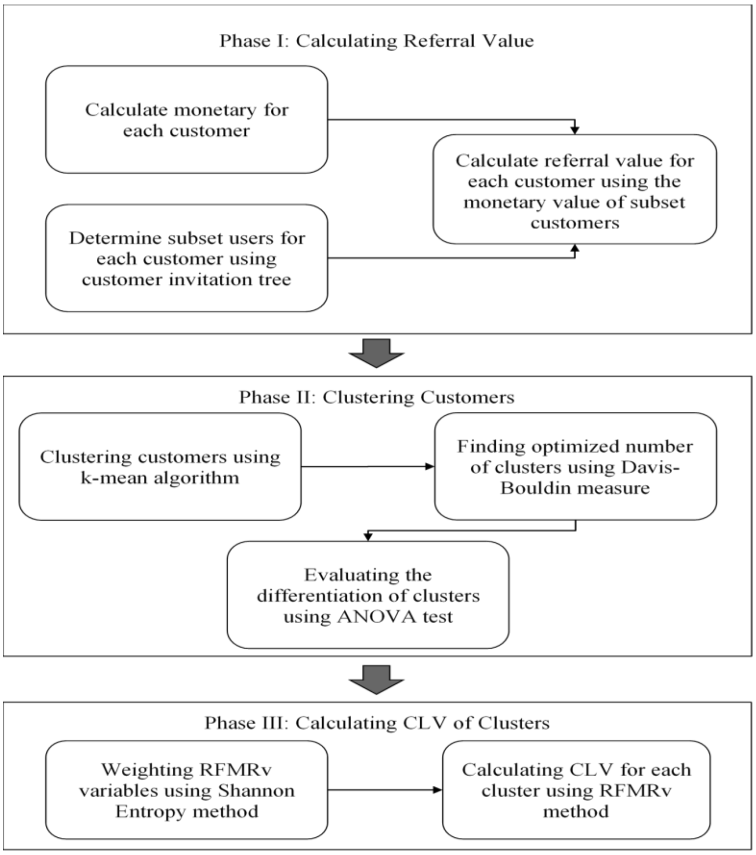


Fig. 1. The research methodology

This study is an applied work and tried to use well-known, accurate and widely used methods for customer clustering. In this regards, to calculate referral value, the subset of customers was first determined at each invitation level and the monetary value coefficient was determined. This was done using the python programming language. For this, the real data of an Iranian exchange broker was used. The studied Exchange broker provides its services through an online website. It already uses a rewarding program to increase the attractiveness of the company for customers. It also aims to increase customers' engagement by giving scores for their activities such as making transactions and inviting friends. Therefore, its database contains both transactional and referral data.

In the second phase, similar to the studies by Karki (2018), Sperkova and Feuerlicht (2016) and Sperková et al. (2015) the Cross-industry Standard Process for Data Mining (CRISP-DM), which is the widely used method in data mining projects was used to extract knowledge from customer data. It is a process model that serves as the basis for the data science process, and has six main phases in which the output of each phase is the input of the next phase (Beheshtian-Ardakani et al., 2018). The

Davies-Bouldin score was used to determine the optimal number of clusters. The Davis-Bouldin score is defined as the average similarity measure of each cluster with the most similar cluster, where similarity is the ratio of within cluster distances to between cluster distances. Therefore, clusters that are further apart and less scattered get better scores (Baarsch & Celebi, 2012). Then, clustering was performed using the K-mean algorithm, which is the most widely used method for clustering data (Liu & Shih, 2005). Finally, in the third phase, the CLV of each cluster was calculated.

The real data of the customer club of a stock brokerage company was used, which was collected from the company's database. Analysis was performed using SPSS software and modeling was performed using the RapidMiner Studio Software.

3.1. Data Gathering and Preparation

This study was conducted using the real data from 3323 customers of the customer club of one of Iran's largest stock brokerage, an investment advisory and a full-service brokerage based in Tehran, which was collected from the company database. According to the online trading rules of this brokerage, applicants will only have access to the broker's website if the validity of their information and their qualifications in relation to the use of the online trading infrastructure has been confirmed. After granting access to applicants, if one of the mentioned rules is violated, the access would be blocked with prior notice. Therefore, the possibility of making a fake account on this website is zero. Additionally, the brokerage has not provided demographic data due to the security issues.

The data collected includes one year of invitation and transaction data. The total number of financial transactions and invitations was 744947 and 3545, respectively, of which 814 customers had at least one referral activity. Data on RFM indicators including recency, frequency, and monetary value, were extracted from customers' financial transaction data using Excel software.

Data indicators included the number of customers, number of shares, and share value. The invitation data included the number of referred customers (608), number of invitations (maximum, minimum, and total), and the transactions data included the number of transactions (maximum, minimum, and total). Table 2 represents the descriptive statistics of the collected data.

Table 2. Details on data

Indicator	Minimum	Maximum	Average	Total
Number of customers	-	-	-	3323
Number of shares	1	1000000	7057.24	5257267275
Value of shares	1	1200000	18911.01	14087699025
Number of transactions	1	6208	346158	744947
Number of invitations	0	184	4.36	3545

The recency of each customer was calculated by subtracting each customer last transaction date from the last day. The minimum value represents the highest value for recency, as it indicates that the customer's last purchase occurred recently (Gupta et al., 2006). Frequency was calculated based on the number of times a customer made a purchase during the selected lifetime. The monetary value of each customer is equal to the total purchase and sale of the company, depending on the type of brokerage service.

The maximum amount of frequency and monetary value represent the best value as they represent the highest number of transactions and purchases respectively (Gupta et al., 2006). Data from customer invitations and the financial transactions for each customer were used to calculate the customer reference value.

4. Experiments and results

Phase I. Calculating Referral Value

Various studies have proposed several factors to convert the qualitative structure of referral value to a quantitative one (Guha et al., 2018). According to Cornelsen (2002), the entire monetary value of invited customers over a specified period of time must be considered as part of the referral value of referee customers. In this sense, to calculate the referral value of customers, the monetary value of all customers of the subcategories must be taken into account. To do this, the referral value was calculated recursively using the level of customers' invitation tree (considered as Wc) as a power. The referral values of invited customers were also calculated based on the set of monetary and referral values of the invited customers. This work was performed using the python programming language.

Based on this algorithm, the subcategory customers at each invitation level and a fixed coefficient of the monetary value of the invited customer to the inviting customers were determined. Each customer's subcategory was calculated by considering the relationship between each customer and their referrals as a one-way graph. Accordingly, each customer was considered as a node, and the referral between two nodes was defined as a tie. Then using a recursive function, the same operation was performed for each customer until the complete tree of invited customers was obtained. The maximum and minimum number of invitations in the given dataset was 1 and 8, respectively.

Thus, the coefficient Wc, which ranges from zero and one, decreased with increasing strength of the response function, and at each level of the invitation, the lead customer was allocated a smaller percentage of the invited customer's monetary value.. By adding these values, the referral value of this customer was calculated. Considering the customers' invitation tree, customers at each level received a certain percentage of their subcategory's monetary value. Therefore, each customer's referral value is equal to the total referral value of each customer's subcategory. According to this explanation, the referral value of customer i was calculated as equation 1:

$$RV_i = \sum_{i=1}^{n} \left[(W_C)^{i+1} \times M_{i+1} \right] \tag{1}$$

In which, W_C is the customers' impact factor, which ranges from 0 and 1; M_i is the monetary value of each subset of customers.

Phase II. Clustering Customers

In this phase, the optimal number of clusters was first determined using the Davies-Bouldin criterion. The lower value of this index is better (Davies & Bouldin, 1979). Then the mean value of indicators was calculated to verify the importance of the clusters in which each customer is clustered.

According to the results, the optimal number of clusters for the RFM (customers without referral value) and RFMRv models (customers with referral value) were 6 (value = 0.294), and 8 clusters (value = 0.297) respectively (Table 3).

Table 3. Davis- Bouldin index of RFM and RFMRv Models

Cluster	RFMRv (Rv > 0)	RFM (Rv = 0)
3	0.297	0.331
4	0.239	0.309
5	0.332	0.331
6	0.312	0.297
7	0.299	0.301
8	0.294	0.320
9	0.295	0.335
10	0.303	-

In the next step, the customers in RFM and RFMRv were clustered separately using the k-mean algorithm. In order to ensure that clusters were clearly assigned, the mean value of the indicators in each cluster was evaluated. In addition, to determine the mean value of each cluster, the total value of each cluster was divided by the number of clusters (Khajvand & Tarokh, 2011). Finally, the RFM and RFMRv data were separated into 6 and 8 clusters, respectively (Table 4).

Table 4. Indicators' Mean Value

Cluster	RFM (Rv = 0)			RFMRv (Rv > 0)		
	R	F	M	R	F	M
1	6.32	7.27	8.41	2.96	7.65	8.90
2	6.02	4.02	5.60	5.30	5.86	7.17
3	5.52	5.93	7.73	2.66	3.14	5.24
4	10.36	6.22	7.36	11.04	10.21	10.59
5	1.97	2.36	4.63	10.80	7.35	8.23
6	10.48	9.181	9.90	9.94	7.85	9.00
7	-	-	-	6.09	6.36	7.72
8	-	-	-	7.79	9.01	9.85

Clusters differentiation was then assessed using ANOVA test. According to Table 5, the significance (sig) of all indicators is less than 0.5, suggesting that the clusters have a different mean, and the accuracy and adequacy of the clusters has been confirmed.

Table 5. ANOVA Test Results

Model	Indicator	Variation Source	Sum of Square	Degree of Freedom	Mean	F	Significance
RFMRv	R	Treatment	5799.42	7.00	828.5	512.57	0.000
		Error	969.80	600.00	1.62		
		Total	6769.22	607.00			
	F	Treatment	2065.32	7.00	295.05	227.41	0.000
		Error	778.44	600.00	1.30		
		Total	2843.76	607.00			
	M	Treatment	1263.08	7.00	180.44	169.33	0.000
		Error	639.40	600.00	1.07		
		Total	1902.47	607.00			
	Rv	Treatment	1080.71	7.00	154.4	91.57	0.000
		Error	1011.61	600.00	1.7		
		Total	2092.32	607.00			
RFM	R	Treatment	28709.3	5	5741.85	3924.97	0.000
		Error	3963.01	2709	1.463		
		Total	32672.3	2714			
	F	Treatment	12864.5	5	2572.89	1927.57	0.000
		Error	3615.93	2709	1.33		
		Total	16480.42	2714			
	M	Treatment	8128.075	5	1625.61	1361.64	0.000
		Error	3234.18	2709	1.19		
		Total	11362.26	2714			

Phase III. Calculating CLV of Clusters

In this phase, the Shannon's entropy was used first to calculate the weight of the indicators. These weights were then used to calculate the CLV. Shannon's Entropy consists of four steps (Karagiannis and Karagiannis, 2020) (table 6):

Indicator normalization through equation 2:

$$P_{ij} = \frac{X_{ij}}{\sum_{j=1}^{m} X_{ij}} \tag{2}$$

Each index entropy calculation through equation 3, in which k=1/ln (m):

$$E_j = -k \sum_{i=1}^{m} \left[n_{ij} \ln\left(n_{ij}\right) \right]; \qquad j = 12 \ldots n \tag{3}$$

Divergence definition through equation 4, in which d_j is the deviation degree of data:

$$d_j = 1 - E_j \qquad \left(j = 12 \ldots n\right) \tag{4}$$

Obtain the normalized weight of each indicator through equation 5, in which $w_j$is the weight of each indicator:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \qquad \left(j = 12 \ldots n\right) \tag{5}$$

Table 6. Shannon's Entropy results

	W_R	W_F	W_M	W_{Rv}	Total weight
E_i	0.1233	0.87047	0.8287	0.5713	2.3938
D_i	0.8767	0.12953	0.1713	0.4286	1.6062
W_i	0.5458	0.08064	0.1066	0.2668	1.000

After calculating the weight of each indicator, the CLV was calculated using W_i of each indicator multiplied by its normalized value through equation 6 (Shih & Liu, 2008):

$$CLV_{ci} = W_R \times R + W_F \times F + W_M \times M + W_{RV} \times RV \tag{6}$$

where CLV_{ci} is the average CLV for cluster ci (i: 1, 2… n), W_R, W_F, and W_M are the weights of R, F, and M of clusters respectively.

Then, the average CLV for each cluster was calculated (Table 7). According to Table 5, considering the CLV, in the RFM model the first cluster has the higher value, which was labeled as a high-value cluster; cluster 3 was labeled as middle-value, and cluster 4 was labeled as low-value. In the RFMRv model the fifth cluster with maximum referral value included the most valuable customers.

Table 7. The Average CLV in Each Cluster

Cluster	RFM (Rv = 0)	RFMRv (Rv >0)
1	4.93	5.22
2	4.20	5.46
3	2.68	4.12
4	6.94	10.28
5	1.76	9.09
6	7.58	9.57
7	-	6.96
8	-	7.86

Finally, the average value of each cluster was calculated based on the clusters' mean value. For this purpose, the CLV values were divided into three categories: high-value (CLV < 4.6), middle-value (4.6 ≤ CLV < 7.44) and low-value (4.6 > CLV). In the next step, each R, F, M, Rv indicator was divided into three separate categories based on their mean value. Table 8 indicates the division range of each indicator.

Table 8. Range of Segmentation for Each Cluster

Index	Low	Average	High
R	R < 5.00	5≤ R <8.02>	8.02 ≤ R
F	F < 4.98	4.98 ≤ F <7.59	7.59 ≤ F
M	M < 6.62	6.60 ≤ M < 8.6	8.6 ≤ M
Rv	Rv < 3.19	3.19 ≤ Rv < 6.37	6.37 ≤ Rv
CLV	CLV < 4.6	4.6 ≤ CLV < 7.44	7.44 ≤ CLV

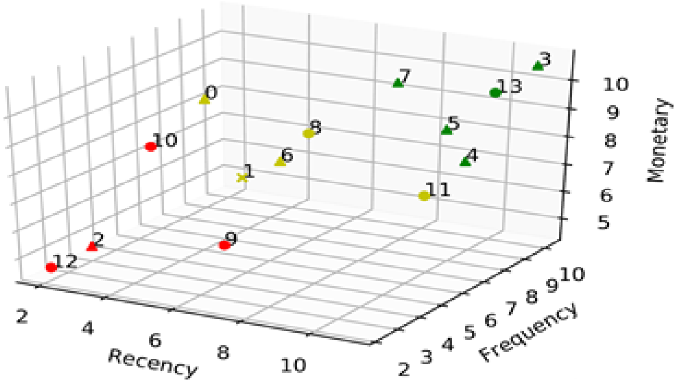
In each of these sections, there are different clusters with different indicators. The results are shown in Table 9.

Table 9. Clusters description

Cluster	CLV	Indicators division for each cluster				CLV Categorizing
		Recency	Frequency	Monetary	Referral Value	
Clusters with Referral Value						
0	5.22	L	H	H	H	Average
1	5.46	A	A	A	A	Average
2	4.12	L	L	L	H	Low
3	10.28	H	H	H	H	High
4	9.09	H	A	A	H	High
5	9.57	H	H	H	H	High
6	6.96	A	A	A	H	Average
7	7.86	A	H	H	H	High
Clusters without Referral Value						
0	4.93	A	A	A	0	Average
1	4.20	A	L	L	0	Low
2	2.68	L	A	A	0	Low
3	6.94	H	A	A	0	Average
4	1.76	L	L	L	0	Low
5	7.58	H	H	H	0	High

Note: H= High, A = Average and L = Low

Figure 2 indicates the 5-dimensional scatter plot of the clusters. Thus, the company can design different marketing programs and allocate resources based on these characteristics.



▲	$6.37 \leq R_V$	■ (green)	$7.44 \leq CLV$
•	$3.19 \leq R_V < 6.37$	■ (yellow)	$4.6 \leq CLV < 7.44$
×	$R_V < 3.19$	■ (red)	$CLV < 4.6$

Fig. 2. 5-D Scatter Plot of Clusters

5. Discussion

In each category, there are different clusters with different indicators. Following are some examples of these analyze and proposed plans for each category based on Table 4:

High-Value Customers: There are two types of customers in this category. In the first group, all the indicators are high. This cluster consists of customers who are valuable to the company because they have both high monetary value and a high WOM effect. This will generate more customers for the company. Therefore, their churn causes many casualties. Therefore, the company should target these customers and retain them through the use of loyalty programs.

The second type of customers is high-value customers with low monetary value and low transactions. Despite the low transaction volume, customers in these clusters have a high volume of invitations and thus a high referral rate. Therefore, they are considered high-value customers. In addition, due to the impact these customers have on their subcategory customers; their churn can have a negative impact on customers within the network. Therefore, the company should identify and target these customers and increase their loyalty. It should also motivate these groups of customers to offer their products and thus increase the probability of sales success and profitability.

Average-Value Customers: In this category, where the referral value of most clusters is above zero, the recency is below average, and the value of other indicators is above average. There are also three types of clusters with zero reference values.

The first type has high frequency and monetary and recency less than the average. These high-transaction customers can move to high-value clusters. They are likely to drop out due to low recency, which prohibits the use of incentive programs. The second type is customers with low monetary and frequency but with high recency. The third type is customers whose all indicators are above the average. Low recency of the customers indicates that they have not been in contact with the company for a long time, which may lead to the customers churn. Since customer acquisition is costly, the company must develop appropriate strategies to retain these customers and increase their value. The customers of these groups have high monetary value to the company, but their CLV has decreased due to their lack of referrals. Therefore, companies should encourage these customers to recommend their brand and thereby attract new customers by offering incentives such as discounts or personalized offers.

Low-Value Customers: Customers in this category have the lowest value across all indicators, indicating that this group includes customers who have no particular activity in terms of transactions or in the terms of activities in the customer club. Therefore, the provision of additional products and services does not affect the company's sales rate. In addition, low recency and low frequency of customers indicate that customers are not attracted to the company, especially incentive programs, and will leave the company in the short term.

It is worth noting that if this cluster had a high recency value, it could be categorized as a high-value cluster with high WOM. This cluster does not have much monetary profit, but they have attracted new customers to the company. Due to the low recency of this cluster, there is a risk that customers will leave this cluster. However, by looking more closely at their behavior and determining the reason for their departure, the company can do more accurate planning to retain them and attract new customers. A cluster with high referral value will attract them. Since the cost of attracting new customers is high, the company should provide appropriate strategies to maintain the recency of these customers in a suitable level and to retain customers, and then increase the value of customers.

6. Conclusion

Many companies use referral marketing campaigns to harness the power of WOM advertising and attract new customers through more referrals (Buczynski, 2007). However, they encounter the challenge of finding a way to leverage information through WOM and customer referrals.. Research has shown that customers with high customer lifetime value are not necessarily the same customers with high customer referral value. Therefore, both criteria are required for effective customer management (Costa et al., 2018; Haghighi et al., 2017; Kumar et al. 2007). However, studies conducted in this area have calculated CLV value using financial value and have not considered the influence of WOM or referral value. Haghighi et al. (2017) similar study has only examined the data of one industry (a broadband Internet service industry) and the generalizability of the results is not clear. The application of the CLV and CRV orientations vary according to the industry given the degree of customer interaction and the opportunity to promote products and services in the form of up-selling or cross-selling (Dhameeth et al., 2020; Keh & Pang, 2010). In the retail and financial industry, consumers make relatively frequent visits to points of sales compared to other industries such as telecommunication. Therefore, retail, financial, and telecommunication industries use CLV and CRV orientations at the point of customer interference in differing degrees (Dhameeth et al., 2020). Furthermore, the methods used in Haghighi et al. (2017) study have not completely explained, so it is not clear how accurate the method is and how reliable the results are. Therefore, it is necessary to conduct more studies in other industries to determine the generalizability of results. Therefore, this study proposed a new RFM method namely RFMRv to cluster customers by their referral value to better cluster customers. For this purpose, the referral value was first calculated using the customer invitation graph from the customer club, and then the RFM was extended by adding the referral value index. Then, by dividing the data into two categories of customers with referral value and customers without referral value, each category will be clustered separately. In the next step, the clusters were categorized and analyzed based on customer lifetime value.

This study confirmed the positive impact of e-WOM on online customers' purchase intentions, which is consistent with the results of Nuseir (2019), Maria et al. (2019), Haghighi et al. (2017), Xevelinakis (2015) and Gruen et al. (2006). However, it inconsistent with the studies of Emini and Zeqiri (2021), Ariesta and Zuliestiana (2019) and Kurniawati and Arifin (2015), which find that social media marketing and e-WOM have a negative impact on purchase intent.

The proposed framework can help companies to identify customers who are not financially profitable but are still profitable for the business due to their positive impact on other customers. Therefore, companies can use this framework to develop appropriate programs to identify and retain these customers.

6.1. Implication for Research

This study added customer referral value to the RFM method and examined its impact as an important variable in predicting customers' behavior and driving marketing campaigns. This is the innovation of this study and contributes to the body of literature in the field. Furthermore, this study contributes to future research with empirical experiments from current eWOM studies that suggest a joint assessment of information characteristics and consumer behavior in this regard.

This study provides the assessment of the economically relevant differences between customers acquired through a referral program and customers acquired through other methods. This shows significant differences in engagement margins, customer retention and customer value. Analyze whether these differences disappear or persist over time and examine the differences in customer segments. The finding that referred customers are, on average, more valuable than other customers provides the first direct evidence for the financial attractiveness of referral programs, as well as much-needed evidence for the financial attractiveness of induced WOM in general.

The advantage of the presented framework is that in addition to calculating the customer's financial value, it also applies their value in the social network, the WOM value. This also takes into account customers who are not financially viable but have a positive impact on other customers. This study can be used as a reference for managers to delve into service management and customer experience. Proper service can be the starting point for creating and maintaining a positive customer experience. The results of this empirical study show that word-of-mouth advertising is a strong factor influencing customer purchasing behavior. With this knowledge, a company is able to segment its customers and define an appropriate strategy to increase marketing efficiency.

In addition, the results confirmed that customers acquired through referrals are more valuable than other customers and proved that the RFMRv method provides better clustering and valuation. Therefore, future studies can begin with a more comprehensive perspective, by understanding the importance of consumer behavior. Finally, this study provides a further understanding of eWOM in social networks by highlighting the determinants of its media information that influence consumers' intent to purchase products and services. Validated determinants are important for both researchers in the same field and for researchers looking to purchase into different research fields.

6.2. Implications for Business

From a practical perspective, this study provides a reference framework for marketers to understand the impact of eWOM and customers' referrals in social media on consumer purchase intentions. Customer segmentation based on their behavioral and referral values helps companies to identify their valuable customer groups with distinctive characteristics that use social networks, helping them better target their customers and take the advantages of eWOM marketing.

In this study, customers were divided into three categories of low value, medium value and high value based on their value. Within each of these categories, there are clusters with different indicators from which the company can design different plans and programs according to these characteristics. Looking at the results, it is clear that many companies need to rethink their customer service strategy and make it easier for customers to report positive references about their products and services. The use of internal and external data to determine social impact and customer attitudes is becoming increasingly relevant. Negative and positive word of mouth should be considered as a relevant factor when calculating the true value of a customer referral.

Referral programs do not create higher-value customers by turning unattractive prospects into attractive ones. Instead, they help companies selectively acquire more valuable prospects and retain them for longer at a lower cost. Therefore, instead of the current "all-in" approach, companies should design and target referral programs to attract more attractive customers.

Managers must also inform their customers about their referral programs. Managers must also create the conditions for potential customers to actually become customers. One possible plan is to partner with online communities and make it easier for people to connect with a business online immediately after receiving a referral from a customer in the same community. Such awareness and facilitation efforts should selectively target customers who offer the highest value.

Referral costs are another aspect to consider when designing the referral program. Many programs offer the same reward to every referrer (Kumar et al., 2010b). However, as we show, the value of referrals can vary widely, even for the same company. Therefore, businesses can benefit from offering rewards based on the value of the customer referred.

In addition, according to the results, social networks play an important role in the presentation, communication and also the exchange of information between customers. Therefore, marketers need to shift their approaches from traditional marketing to social marketing, which is more effective in engaging with customers over the internet. They should strive to become a social enterprise. In this regard, using WOM marketing and customer referral programs as a low-risk and cost-effective method can increase brand awareness and promote the companies' products and services. It can also increase their overall reputation and sales.

Furthermore, based on the results it was pointed that referred customers are more valuable than others and will bring more sales and profits to the companies. Therefore, ignoring these customers and abandoning those leads to huge financial loss for the company. Therefore, companies can use referral programs to build long-term relationships with customers by meeting their expectations and providing them with personalized services and additional incentives. It helps businesses keep customers more satisfied and turn potentially valuable customers into loyal and even influencers. Paying attention to customers' referrals and creating loyal customers can lead to a competitive advantage. Customers who are actively involved in referral programs are more likely to stay with the organization; because they already know the brands of the companies and have tried their products. Therefore, businesses can target more profitable customers as they help a company attract more customers through their referrals. They can also avoid additional advertising and go straight to sales.

Customers' satisfaction plays an important role in the flow of information in the market. The use of referral marketing can help companies increase customer referrals to their products and services, which leads to increased customers' loyalty and thus strengthens the credibility of the company. Managers can also use the Customer Engagement Value Scale to gather information and compare their customer engagement to competing brands. This information helps managers determine if they need to change their strategic marketing plans to achieve their goals. Accordingly, managers are recommended to try to improve each service by developing specific management strategies and experience management, as well as adjusting marketing activities based on customer retention (Because some customers may not appreciate the interaction, a variety of features related to the level of Customer loyalty should be offered). Therefore the following suggestions are made:

First, to create an enjoyable experience, the service experience must be evaluated over the long term to increase customer lifetime value. Second, the service experience is not only based on customer interactions with service providers, but also needs to consider the environment in which the services are delivered. Therefore, both factors must be considered. Third, to increase customer lifetime value, steps must be taken to support the valued customer and increase customer satisfaction and loyalty so that customers are more motivated to increase the frequency or volume of their purchases.

Fourth, managers and marketers must create an environment where customers can communicate and share their experiences to increase the value of customer influence that comes from persuading other customers to share their shopping experiences. . Finally, to extend the value of customer insights, marketers can use customer insights to identify strengths and weaknesses and develop new service ideas. To do this, they can create an online forum where customers can share and discuss their opinions. In these online forums, moderators determine the topics of discussion and control the direction of conversation. In this way, marketers can create open innovation structures that encourage customer participation and collect ideas about innovations and their implementation in the organization. In this context, customers should be rewarded with brilliant new ideas to encourage greater engagement. To achieve these goals, marketers need qualified employees and managers, trained in the industry and in the use of communication technologies, as well as personalization of the service.

6.3. Limitations and Future Studies

This study has some limitations that may guide future research. The model in this study was implemented on a brokerage database, which may limit the results to one type of service. To work around this limitation, it is recommended to run this model on different databases.

Considering that many variables are effective on customers' profitability and social network effectiveness, it is recommended to consider other indicators such as customer churn and customer loyalty when segmenting customers. This helps companies better understand their customers.

The proposed approach of this study can be used and modified in other industries. Therefore, it is recommended that future research conduct the same study in other industries and compare the results.

Furthermore, the presented model could be developed using a bilinear graph of customers' relationships, which is a suggestion for future research. In addition, it is recommended that future studies use other techniques such as association rule mining to predict customer and profitability and extract useful rules.

The data-related limitation for this work is that customer demographic information of was not available due to security concerns. Therefore, it is suggested that future studies conduct the same study considering the demographic information of the customers.

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