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Socio-Transactional Impact of Recency, Frequency, and Monetary Features oN Customers' Behaviour in Telecoms' Churn Prediction

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ABSTRACT: Due to the increasing competitiveness in telecom's market, it has now become more necessary for operators to start building personal relationship with customers for targeted retention strategies. Achieving this goal requires the development of an effective churn prediction model that will solve the problem of churn misclassification, which is persistent in current churn prediction models. With several existing segment-oriented churn prediction models failing to harness the power of associative networking provided by telecoms users, churn prediction accuracy remains unguaranteed while targeted decision support is not enhanced. Here, the research introduced the Customer's Influence Degree (I) to the existing Recency, Frequency, and Monetary (RFM) values as an additional predictive factor, towards determining the churn class of a customer. The essence is to utilise the socio-transactional affinities of customers' direct dependent to targeted communication nodes through customers RFM analysis to determine the dominance of a customer in the community. The newly introduced predictive factor helped to minimise churn misclassification rate through appropriate reclassification of customers who were wrongly classified as churner or non-churner when using the existing RFM churn scores only.

Keywords: Churn Prediction; Recency; Frequency; Monetary; Customers Influence Degree; Socio-Transactional Network; Decision Support.

1. INTRODUCTION

On a daily bases, the number of companies competing for the same customer especially in telecoms industry are increasing. As such, the higher the number of competitors, for instance in Telecoms Company, the higher the rate of customer churn [1]. By this, customers choose in-between numerous service providers, with capacity to switch rights and privileges from a service provider to another based on reason(s) best known to them without permission or prior notification. When this happens, a company could be losing customers to competitors> however, the goal of every organization is to avoid customer loss [2]. Thus, the process of changing to another service provider from the current one is called churning [3]. No doubt, in recent times, organizations are more updated to know that the exit of a customer, is a step to loosing resources spent to acquire such and future revenue such customer can accrued to the organisation. It is more cost effective and highly profitable to retain an existing customer than acquiring a new one [4]. These resources may include but not limited to cost of publicity, production, distribution and discounts. By this challenge, different churn prediction techniques have emancipated over the years for the purpose of retaining more customers [5]. The various techniques like linear regression, Naïve Bayes, Decision Tree, Random Forest, and Boosting algorithms among others were designed to analysis the customer behaviour for appropriate churn classification [6, 7]. By these algorithms, trade-off in selecting

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appropriate model through rough set theory was used as a data mining technique for customer churn prediction. Although different categories of customers either as prospect, responder, active or churner exhibits different behaviour. By customer behaviour, we mean recognising the particular operational service modules customers are utilising, and by how often. For instance, the frequency of calls, calls length or duration, intervals between calls, data exchange worth, etc. could be clustered by the telecom's giant for appropriate customer churn classification. Although, not every customer behaviour in the transactional dataset is fit for churn prediction, the introduction of appropriate feature selection techniques whose goal is to extract optimal feature set from the entire transactional records of different customers has been helpful for different churn classification [8]. Among several others feature selection techniques, **[9]** presented a semi supervised data centric mode, which clustered highly relevant, with low redundant feature subset in feature engineering for churn prediction. However, due to the dynamic nature of customers' behaviour, here, we consider the transactional network in telecommunication as a social network where two or more customers are connected for social engagements. For instance, a social relationship can be established through voice call duration cum frequency etc. between customers in a given period. Recency, Frequency and Monetary (RFM) Model is a behaviour-based churn predictive model, which analyses customer behaviour overtime to make informed predictions [10]. By this, customers are segmented into distinct churn groups where personalise services are provided with closer monitoring of customers with churn potentials. Thus, patterns to look out for in each RFM segments could include but not limited to (1) When last did a customer made a purchase, (2) How often has the customer made a purchase over a period? (3) How much has the customer spent over the period? While, the telecommunication industry has helped to foster a digital community between subscribers via calls and SMS exchange, its impact on churn prediction techniques has not been adequately harnessed. This is because the existing RFM model; being segment based, does not consider the social network structure of the transactional records, which can be used to determine the churn class of a customer in the same community. Thus, with raising strategic competitive market models, this research suggested that customer's loyalty value, retention potency, and churn prediction should not only leveraged on segment driven models but also on the connection and association relationship (nodes and edges) that exist between customers. To this end, in section 2, related works in RFM model for churn prediction were presented while the concept of the developed customer's influence degree is discussed in section 3. Thereafter, the research developed model as an extension of RFM is showcased in section 4 before sample experiments and model evaluations were discussed in section 5. The research work was concluded in section 6.

2. RELATED WORKS IN CHURN PREDICTION MODEL

Over the years, data mining methods as a process were used for finding unknown patterns in huge data sets [11] like the telecoms data. The telecoms data among others contained data like customer profiling, calling pattern, and network data, which are spawned regularly by the operators. Through the historical records of customers, there exist a probability to identify customer's mind-set on either to leave a service provider or not. This task is an instance of data mining tasks, which concentrates on categorising unknown cases grounded on a set of known samples [12], the methods are applicable for fraud detection, churn prediction among others. Based on this, [13] by using a neural network model, developed a data mining solution to predict churners. [14] also tracked customers and their behaviour against churn through a simple data mining model. [15] developed a behaviour-based churn prediction system in telecommunication with artificial neural network approach while [16] also indicated that in a busy dataset, the accuracy of churn prediction is enhanced when compared to other classifiers. However, only customer service usage information was used for its prediction. Consequently, to achieve better churn prediction, Recency-Frequency-Monetary (RFM) model, which had been used in digital marketing [17] was introduced for effective churn management. Its proper analysis as helped companies to detect important customers with likelihood to positively act on retention offers. These analytical approaches are being used by organisations as a system for breaking customers on recency of purchase, purchasing frequency, and monetary worth. The concept of RFM was incorporated into marketing reviews [18] to define RFM sequential pattern towards developing a novel algorithm. Thus, RFM model has be practically utilised in areas like on-line businesses [19], commercial organisations and government organisations [20]. Also, it has been used in travel industries [21], marketing industries [22], while telecommunication industries are not left behind. In achieving the RFM goal, several methods have been considered. Reference [23] with the goal of improving Customer Relationship Management (CRM) combined weighted RFM model into K-Means algorithm for enterprise solutions. [24] adopted K-Means method and RFM model in the value analysis of the customer to consolidate long term customers loyalty. A hybrid method, which incorporated kernel induced fuzzy clustering techniques was used to effectively cluster customers while enlisting outliers by [25]. The process also included robust possibilistic clustering method and robust fuzzy clustering method for customer segmentation. In addition, RFM model was extended to RFMTC model by introducing two addition parameters; (1) the time since first purchase and (2) churn probability. The technique can estimate the expected total number of times a customer will purchase in the near future. Also, determine the likelihood that the customer will purchase at the next interval. However, there are still problem of misclassification because the community structure of customers was not considered during churn classification rather than clustered historical patterns of individual customers. Thus, before discussing the proposed churn prediction model in section 4. In section 3, an overview of the newly introduced factor, the customer influence degree, which measures the power of influence of a customer in a community, is discussed.

3. CUSTOMER'S INFLUENCE DEGREE IN RFM MODEL

While behavioural variables are customers attitudes or responses to product brands. Similarly, specific customer descriptions contain geographical, demographical and psychographic variables. To fully utilise the services provided by telecoms operator globally, beyond segmental analysis of customer database using Recency, which describes the break between the period wherein the latest consuming behaviour was executed, and present; Frequency, which explains how often does some customers make purchase within a given period and Monetary, which refer to the cumulative amount a particular customer spent over a period. To discover a customer's influence degree, the transactional dataset is represented as networks, with vertices for individuals and edges describing relations between them. Nodes in networks are closely interrelated groups, which are usually denoted to as network communities, or module [26–28]. The process of analysing the network allows us to understand its structure and properties. Hence, as represented in figure 1, through network analysis, a customer importance can be quantified by measuring the degree of relative associations between the dependant nodes and the targeted node. Here, targeted node is the customer in concern, whose churn class is about to be predicted while dependant nodes are customers with social tie with the targeted node. Intermittently, every customer can function as either a targeted node or dependant node as the situation may be.

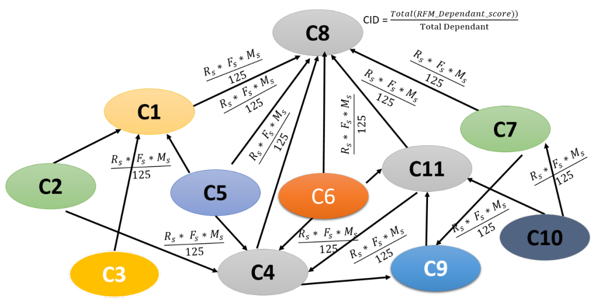

FIGURE 1. Customer Dependant and Targeted Node Analysis

Therefore, as represented in fig 1, the customer's influence degree as a factor for churn prediction answers the following questions:

1. How many dependant nodes communicate with the targeted node?
2. How recent is the communication?
3. How frequently is the communication between the dependant node and the targeted node?What is the monetary equivalency of the dependant nodes communication with the targeted node?

From fig 1, a quantile value of 5 is assigned to the RFM values of each customer. Based on this, a customer can score up to 555 but not less than 111. To obtain the RFM value of the dependant node to a targeted node, equation 1 is applied. However, in other to output the customer influence degree of the targeted node, equation 2 is applied.

$$DT_{rs} = \frac{(RFM\_Score)}{125} \tag{1}$$

Where DT_{rs} is the dependant to targeted relationship score.

$$cis = \frac{Total(RFM\_Dependent\_score)}{Total\ Dependent} \tag{2}$$

Where cis is the targeted node influence score.

Based on equation 1 and 2, the algorithm in listing 1 is used to illustrate the customer influence degree.

Algorithmic Listing 1:

From listing 1, the Recency, Frequency and Monetary values of communication between the dependant node and the targeted node were obtained and the average scores of the influence processes is obtained for each targeted node. The

ALGORITHMIC LISTING 1: CUSTOMER INFLUENCE DEGREE ALGORITHM

Input: Let c be the target node in the transactional Dataset D
Output: ci, which is the customers influence degree

1. Let x be the number of dependant nodes that are connected to the targeted customer
2. Let t_x be the number of dependant nodes that have communicated with the targeted customer in recent time. Such that the recency of a dependant node to a target node is on a scale of 1 to 5
3. Let f_x be the frequency of t_x communication with the targeted node in recent time t such that the output is on the scale of 1 – 5
4. Let m_x be the frequency of t_x communication with the targeted node in total time t such that the output is on the scale of 1 - 5
5. For (int t_x = 0; t_x <= x, t_x++){
6. If (total_dep_Rec >= 0.8)
7. ci = 1 // the higher the dependency score, the higher the customer's influence score
8.   Elseif (total_dep_Rec >= 0.6 && total_dep_Rec < 0.8)
9. ci = 2
10.   Elseif (total_dep_Rec >= 0.4 && total_dep_Rec < 0.6)
11. ci = 3
12.   Elseif (total_dep_Rec >= 0.2 && total_dep_Rec < 0.4)
13. ci = 4
14.   Elseif (total_dep_Rec < 0.2)
15. ci = 5 //customer is not to be influential cost and tends to be a churner
16. }

values were normalised to 1 because churn prediction in existing models is either o or 1. Here, the higher, the total dependency value, e.g., 0.8, the higher the customer loyalty score (1). The proportional values were assigned to derive the churn sore of customers, with customer loyalty value to churn category increases from 0 – 1. While a certain level, every customer assumes the status of a possible churner against existing methods that classify customer as either churner (1) or non-churner (0), here, five distinct influence values of ci are proposed within the range from 0 – 1. These thresholds are defined as:

1. Very influential; provided ci < 0.2
2. Moderately Influential, provided ci is >=0.2 && , < 0.4
3. Influential, provided ci is > = 0.4 && , < 0.6
4. Potential Influential provided, ci is >=0.6 && < 0.8
5. Not Influential provided, ci is > 0.8

The essence of this development is to go beyond generating RFM scores for customers in churn classification, but to also discover the direct impact of a customer in the community through dependant to targeted association and communication value analysis. With this, churn prediction is not limited to how recent a customer is in the purchase of credit, nor how frequent is a customer in purchase, or the direct monetary values a user brings to the company. However, is also relies on what the organization's gain by the existence of such customer through the values engendered by the customer's socio-transaction network. i.e., what is the impact of a customer to the existing of other members of the community transacting business with the organization? As such, a customer with a high influence factor may have a low monetary value, may have low recency and frequency value, but her existence in the community is the reason for the relevance of others. The new customer influence degree is thereby used alongside RFM to engender a new churn prediction model and the details are presented in section 4.

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4. APPLICATION OF RFMI MODEL FOR CHURN PREDICTION

By introducing the worth of a customer in the community as a factor to existing RFM model for churn prediction as presented in section 3, here, the proposed RFMI model assigns equal weights to Recency, Frequency, Monetary and Influence These factors are combined into four-digit cell to cover four equal quintile values of 25%. The goal is to go beyond the normal binary churn classification to having a wide range of churn category. This means at the end of the churn classification process, a customer can be a Churner, Potential churner, Inertia customer and Premium customer depending on the churn score of the customer between 0 and 1 using the model in figure 2 and listing 5.

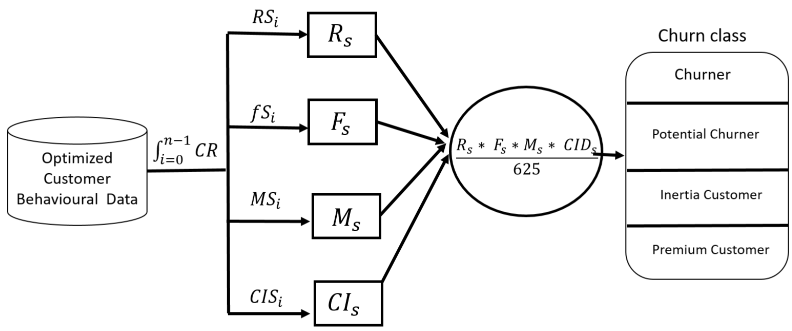

FIGURE 2. RFMI model for churn prediction

From fig 2, the analysis of customer's records by using the customer's identification number in the optimized customer behavioural dataset is to derive the Recency, Frequency, Monetary and Influence score for each customer. R_s is the recency score, F_s is the frequency score, M_s is the monetary score, CI_s is the customer's influence score. To obtain the scores for each churn factor, the recency score of each customer is obtained by measuring the interval between the previous transaction time and the analysing time (days or months). Hence, the lesser the number of days, the better the recency score. Thus, for recency score, the following condition holds as presented in listing 2

ALGORITHMIC LISTING 2: CONDITIONS OF RECENCY SCORE ALLOCATION

Input: Customer's Recency Value (in days and months)
Output: Customers Recency Score

1. If $R_{si} \geq i_5$ then $R_s = 5$
2. Elseif $R_{si} \geq i_4$ && $R_{si} < i_5$ then $R_s = 4$
3. Elseif $R_{si} \geq i_3$ && $R_{si} < i_4$ then $R_s = 3$
4. Elseif $R_{si} \geq i_2$ && $R_{si} < i_3$ then $R_s = 2$
5. Elseif $R_{si} < i_2$ *month* then $R_s = 1$

While $i_5 \ldots\ldots. i_2$ are possible period defined by an organisation for churner and non-churners, R_{si} is the Recency Score Indicator, which helps to define the Recency Score R_s.

Upon obtaining the recency score of a customer, to obtain the frequency score, an analysis of how often the customers make purchases with the organization is been examined. Here, the database is organised by the total number of purchases over a period. Thus, the topmost e.g., 80% is given the value of 1 and others are allocated the values of 2, 3, and 5 respectively based on percentage. This is further illustrated in listing 3.

ALGORITHMIC LISTING 3: CONDITIONS FOR FREQUENCY SCORE ALLOCATION

Input: Customer's Frequency Value (Both single and repeated)
Output: Customers Frequency Score

1. If $F_{si} \geq i_5\%$ then frequency score = 1
2. Elseif $F_{si} \geq i_4\%$ && $< i_5\%$ then $F_s = 2$
3. Elseif $F_{si} \geq i_3\%$ && $< i_4\%$ then $F_s = 3$
4. Elseif $F_{si} \geq i_2\%$ && $< i_3\%$ then $F_s = 4$
5. Elseif $F_{si} < i_2\%$ then $F_s = 5$

While $i_5 \ldots\ldots. i_2$ are possible frequency rate defined by an organisation for churner and non-churners, F_{si} is the Frequency Score Indicator, which helps to define the Frequency Score F_s.

From the conditions in Algorithm Listing 3, a customer with low frequency has never-ending request for the product with likelihood to purchase the products recurrently. In addition to recency and frequency factors, the monetary score rating is used to determine the total amount customer spend on the organization product(s) in the given time period. Here, the higher the monetary total, the lower the churn score. Therefore, the topmost, for example, 80% is apportioned a score of 1 and the others are assigned 2, 3, and 5 respectively based on percentage as specified by respective organizations policy or rules. This is further presented in Listing 4.

ALGORITHMIC LISTING 4: CONDITIONS FOR MONETARY SCORE ALLOCATION.

Input: Customer's Total Monetary Value (Both single and repeated)
Output: Customers Monetary Score
1. If $M_{si} \geq i_5\%$ then $M_s = 1$
2. Elseif $M_{si} \geq i_4\%$ && $< i_5\%$ then $M_s = 2$
3. Elseif $M_{si} \geq i_3\%$ && $< i_4\%$ then $M_s = 3$
4. Elseif $M_{si} \geq i_2\%$ && $< i_3\%$ then $M_s = 4$
5. Elseif $M_{si} < i_2\%$ then $M_s = 5$

While $i_5 \ldots\ldots. i_2$ are possible amount defined by organizations for churner and non-churners, M_{si} is the Monetary Score Indicator, which helps to define the Monetary Score M_s.

Having obtained the monetary score for the customer, the newly introduced customer influence degree is considered. By using the algorithm in table 1, the influence score of each customer is obtained. Finally, to determine the churn class of a customer, the RFMI values obtained for each customer are presented in the format 5555, 5544, 5432, ..., 1111, which thus creates 625 (5×5×5×5) RFMI cells. Hence, the RFMI score obtained by the customer is divided by 625 to determine the churn class of a customer. This is further presented in equation 3.

$$cc_s = \frac{R_s * F_s * M_s * CI_s}{625} \tag{3}$$

Hence, where cc_s, is the customer churn score, a customer with 5555, which is equivalent to 1, is classified as churner, while a customer with 1111, is grouped as a non-churner. In essence, further classification that illustrates the new churn classification category is presented in listing 5.

ALGORITHMIC LISTING 5: A NEW CHURN CLASSIFICATION CONDITIONS.

Input: Let cc_s, be the churn score
Output: Customer's Churn Class
1. If cc_s, = 0 && cc_s, <= 0.25 then, the customer is a premium customer
2. If cc_s, > 0.25 && cc_s, <= 0.50 then, the customer is an inertia customer
3. If cc_s, > 0.50 && cc_s, <= 0.75 then, the customer is a potential churner
4. If > 0 75 && <= 1 0 then, the customer is a churner

By using the assigned RFMI behaviour scores, customers are classified into portions where their worth and constraints can be analysed further. Thus, the RFMI model goes beyond identifying when customer transact business, how often customers perform the transaction and how much is the customer's total transaction to determining the importance, impact or gains the customer is bringing or may bring to the organisation in the nearest future through associative network that exist between a customer and other members of the community. The scores obtained is used to improve the predictability of churn via customer's behavioural segmentation, for enhanced retention decision support where necessary.

5. EVALUATIONS AND EXPERIMENTS

Here, the research presented 20 sampled customers records is represented in table 1. The score for each customers are obtained using algorithm listing 2, 3, and 4 while the customers influence degree is obtained using algorithm listing 1.At first, the RFM score for each dependant customer is calculated before identifying the customers influence degree for each respective customers using the total RFM score of the dependent node. Thereafter, the new churn value for the customer is obtained.

From table 1, by direct value approximation, in RFM, 95% of the customers are churners while 5% are non-churners. However, in RFMI, 85% are non-churners while 15% are churners. These results as further illustrated in the figure 4 to 6 justifies our research goal that a customer is presumed loyal until such transaction activities are disconnected from the

Table 1: 20-sampled customer recorded.

Customer ID	Recency	Frequency	Monetary	CID	RFM score	RFMI Score
C1	5	5	5	2	1	0.4
C2	4	5	5	3	0.8	0.48
C3	5	5	4	3	0.8	0.48
C4	5	5	4	4	0.8	0.64
C5	5	4	5	5	0.8	0.8
C6	5	5	4	3	0.8	0.48
C7	5	4	4	4	0.64	0.512
C8	5	5	5	1	1	0.2
C9	5	5	4	1	0.8	0.16
C10	5	4	5	1	0.8	0.16
C11	5	5	5	1	1	0.2
C12	5	5	4	3	0.8	0.48
C13	5	5	5	4	1	0.8
C14	5	5	4	3	0.8	0.48
C15	5	5	5	3	1	0.6
C16	5	4	5	3	0.8	0.48
C17	5	5	5	2	1	0.4
C18	5	3	5	2	0.6	0.24
C19	5	5	4	2	0.8	0.32
C20	5	5	2	2	0.4	0.16

associative network of community members either voluntarily or involuntarily. i.e., customers should not be assumed a complete churner based on direct contribution to an organization. But until such is completely disassociated from the transaction network of the organization's social community.

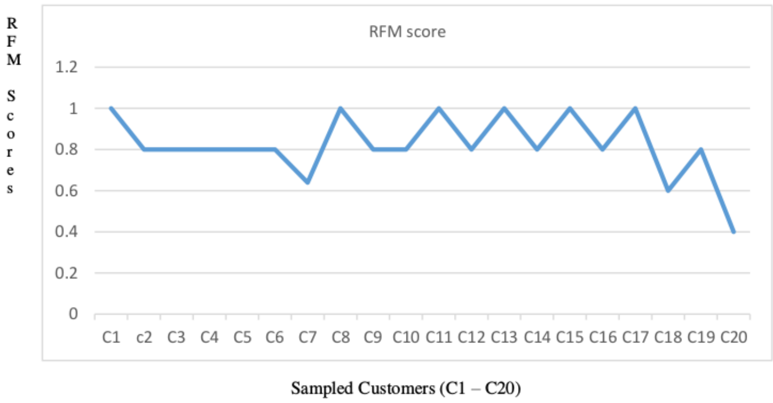

FIGURE 3. Customer's RFM Churn Value

However, with the introduction of Customers influence degree, the obtained customer's influence degree as a great impact on the churn score for respective customers. This is further presented in figure 5:

In fig 6, the evaluation of the two approaches is presented for evaluation. We observed that the customer influence degree as a significant impact on the RFM with range of 0% to 80% depending on the customer's influence degree score.

Overall, RFMI model showcased the importance of associative network between customers by minimising churn classification error rate for effective and targeted decision support. With customers not existing in isolation, the community has a significant contributed on each customer's churn prediction.

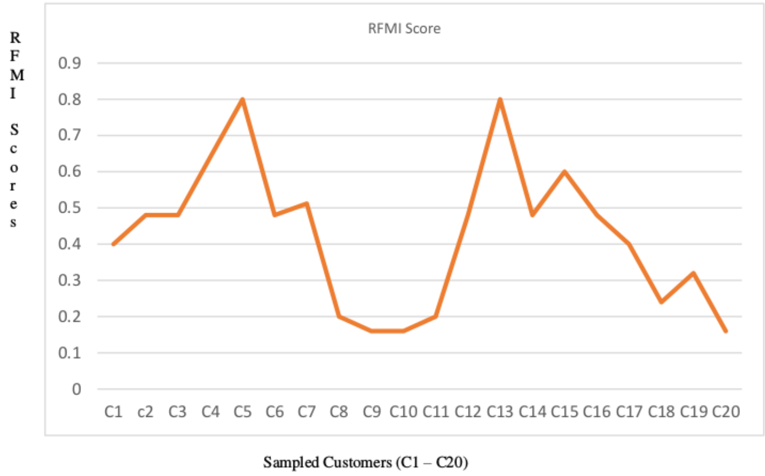

FIGURE 4. RFMI customers churn score.

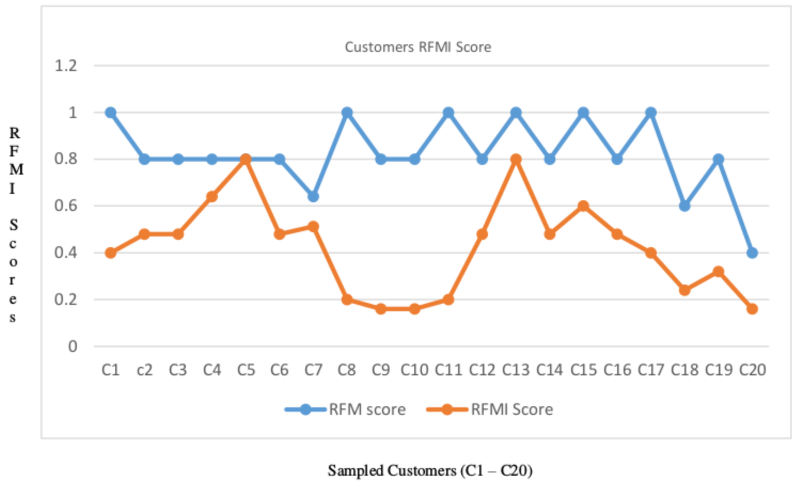

FIGURE 5. RFM vs RFMI

6. CONCLUSION

If churn prediction should be categorised strictly on RFM, there are chances that a higher-value customer of today may decline in loyalty in the near future, or even not a customer anymore. By this, a customer with higher frequency of product purchase may drop or stop purchase due to different reasons. When this two happens, the monetary value of a customer with lower recency and frequency score may also decrease. Hence, the research introduced a socio-transactional network dependent variable to test for the strength/ influence of a customer among members of the community. The essence is to see what contribution the based-on recency, frequency and monetary values isan organisation gaining through the existence of a targeted customer. Therefore, a customer with low recency, frequency and monetary score, but with high CID may not be classified totally as churner. Hence, there is an improvement in the customer churn prediction when compared to the existing RFM models.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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