Implementation of Recency, Frequency, and Monetary Patterns in Adaptive Blockchain-Based Transactions

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Abstract. The development of cryptocurrency cannot be separated from the development of blockchain technology. However, problems arise related to the scalability of the blockchain itself. The long duration of the consensus process means that the scalability of the blockchain cannot increase. Various methods have been developed to overcome this consensus problem. One of the highlights is developing an adaptive consensus. But for adaptive consensus, clustering of blockchain transaction data is required. The Recency Frequency Monetary approach can be used for blockchain transaction clustering but with various adjustments. This research aims to implement Recency Frequency Monetary on blockchain transactions. The results of this study indicate that clustering can be carried out using adjusted Recency Frequency Monetary weighting for blockchain transaction data.

Keywords: RFM, Blockchain, Adaptive, Proof of Work.

1 Introduction

The development of cryptocurrency has become more widespread and has even been widely used as a legal means of payment in various electronic transactions, even though there are still many problems behind cryptocurrency adoption [1]–[8]. Bitcoin, as the first cryptocurrency to be publicly introduced, is still very popular in the cryptocurrency world today [9], [10]. Apart from fluctuations in the ups and downs of cryptocurrency values until now, there are still many studies that hope that this cryptocurrency can be used more widely [7], [11]–[18]. Wider use can be realized if the current crypto technology can adapt to existing needs. Two things are part of the many things that affect a transaction on the blockchain, namely security and speed [19]. Transaction security is usually the main focus when dealing with large-value transactions or transactions that are considered essential. So that in this type of transaction, people hope that the process carried out can be safe from all kinds of threats. When looking at cryptocurrencies, security is one of the things that makes crypto itself strong [19]–[21]. Apart from

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security, one factor that is no less important in a transaction is the processing speed. Transaction processing speed is also crucial in the e-commerce model [22], [23]. In transactions of small value or of a routine nature, people usually expect these transactions to be resolved quickly, while from a security standpoint, they usually pay less attention.

Cryptocurrency, through its blockchain technology, has answered the security factor some people need in making transactions [19]. But the problem is there is a consensus process in the blockchain, which takes quite a long time, ultimately reducing the scalability of the blockchain technology itself [24]. The consensus itself can easily be said as a process to ensure transaction data that enters the system already has a high level of security. There are many consensus methods adopted by crypto-currency developers [25]. But until now, the most popular consensus method is still held by Proof of Work (PoW), which is a consensus method that was initially used in the emergence of Bitcoin in the world [26]. As previously explained, PoW itself has problems with its scalability, namely the lack of speed in the consensus process using this method.

Several studies have tried to increase the speed of consensus on the blockchain. One of the studies related to growing proof for Work on the blockchain, conducted in 2022. This research developed an adaptive PoW consensus method [27]. Adaptive means here that the consensus speed can be adjusted according to the needs of each of these transactions. Changing this need by setting the level of hash processing, which is determined by the priority of each transaction. Each transaction will be labeled according to the level of hash processing that will be implemented on that transaction. However, in this study, the results obtained were only simulation results, where there was no clear prioritization related to the needs of its users.

It has entered the realm of science and marketing concepts when discussing customer needs and transaction behavior. In fact, one branch of marketing science, namely customer relationship management, explicitly studies how customers behave so sellers can establish closer relationships. Understanding customer transactions can be done through various methods. Recency, Frequency, and Monetary, commonly abbreviated RFM, is one of the popular marketing concepts [28]. In this RFM concept, customer behavior is analyzed through the time of the last transaction, the frequency of transactions made, to the number of transactions made. This RFM results in a collection of weights that will be formed into a matrix. Research related to RFM has also been carried out a lot [29].

To the best of the author's knowledge, there has never been any research that has attempted to identify transaction patterns on the bitcoin blockchain. Therefore, the weighting of each transaction using RFM which can finally recognize and classify transactions with the proximity of recency, frequency, and monetary weights can be a contribution to research in the field of bitcoin transactions or other blockchain-based cryptocurrencies. In addition, by grouping clusters based on RFM, it can be implemented better related to the application of adaptive hash levels in previous research to accelerate blockchain consensus on the Proof of Work model [27]. Therefore this research aims to implement the concept of RFM in transactions conducted through Adaptive Proof of Work consensus. The contribution to this study is incorporating the idea of understanding customer transactions using RFM on blockchain transaction consensus. Through this merger, it is hoped that the priorities of each transaction can be better defined. This research will also use actual transaction data from Bitcoin as research trial material.

2 Related Work

In previous research, there has been much discussion about the performance of consensus blockchains. Asgaonker et al. in 2018 examined the effect of increasing the size of the blockchain network, which means that more data and nodes join, decreasing the speed of consensus. Through this research, Asgaonker found that the increasing size of the blockchain network has a linear effect on reducing consensus speed [30]. Even according to research that was also conducted by Gervais et al. in 2016, the transaction processing speed of the blockchain was still far from the speed of transactions using a credit or debit card, which was only around 60 transactions per second [31]. In this study, various previous studies were analyzed regarding improving performance on the blockchain. Still, the researchers limited the analysis to increase the speed of consensus on the Proof of Work method according to the topics studied in this study. In addition, this study also analyzes various papers that discuss implementing the concept of customer management through the Recency Frequency and Monetary (RFM) idea because this research also adopts this concept in managing blockchain user transaction patterns.

2.1 Device Optimization

Optimization of the Proof of Work blockchain consensus performance has been tried to be improved by conducting research and design from the device side, namely by developing applications that are integrated with hardware to optimize the hash process on Proof of Work which is the most widely used consensus method to date [32]. In research using this device, the speed increase obtained can be significant compared to a conventional computer. However, because this device is costly, not many people can afford it. This is dangerous because it can lead to the centralization of those who can only afford this device so that, in the end, it is not following the blockchain concept that should be distributed.

2.2 Algorithm Optimization

Research that tries to improve the performance of Proof of Work is also carried out to optimize the algorithm or the consensus process. In 2020 Safana et al. gave rise to a very different concept, as it seeks to accelerate consensus with the help of machine learning. In this study, it is claimed that in the nonce search process for blockchain consensus, when using machine learning, the search accuracy can increase by 18% [33]. The case study conducted in this research uses Ethereum. This study also reconfirms that of all the processes in a consensus, the thing that takes the most time is when miners try to find nonces. To find a nonce, a miner has to perform multiple hash attempts (like a brute force process) for each nonce sequentially until a hash result matches the desired hash level. The more transactions, the more extensive the blockchain network, and the longer the consensus time will be.

This research conducted by Safana aims to minimize the range of possible nonces miners have to try. The range of possible nonces is predicted using linear regression in machine learning. The dataset and nonce used in Safana's research are generated. Then these data will be used as a reference and compared with the results of the developed linear learning regression predictions. The nonce prediction results obtained are 42% in the good range and 58% in the bad range. Good range means the range in which there is a correct nonce, so if a miner tries to hash using a nonce from this range, it should find one valid nonce.

Research from Safana can be explained using the following data assumptions. For example, the standard range that miners must try to carry out Proof of Work consensus is 1 to 1000, so with the help of the machine learning method developed by Safana, the range that is tried will shrink by 18%, namely to 820 from 1000 nonces at the beginning. Then if we proceed to the calculation of the Good Range, with a good range percentage of 42%, if miners can try directly on the Good Range, the range of possible nonces that must be tested is only 345 data nonces (42% of 820), or 65.5% faster than the standard way. Another possibility, in the worst case, miners have to try starting from the Bad Range and then moving on to the Good Range. Then, the consensus method using machine learning is still 18% faster. But it needs to be considered further that the many hash attempts must be carried out by miners, not only because they cannot speed up the process but because of the security procedures that want to be implemented on the blockchain network [19]. The large number of hash processes that must be carried out makes the blockchain network not easily controlled by certain irresponsible parties.

Another algorithm optimization is to create a method called Diversity Mining – Proof of Work (DM – PoW). In this method, the blockchain network is made multilayer, consisting of private and public networks. Later, consensus processing will be carried out by many parties who are members of the blockchain network, referred to as the blockchain network consortium [34]. This consortium consists of several companies that create and use blockchain networks together. This method obtains a transaction processing speed of 1760 transactions per second, with a mining time of 3 minutes.

In 2021, Zheng et al. introduced a new consensus method, a combination of Proof of Work and Proof of Space, called Proof of Comprehensive Performance (PoCP) [35]. In this method, each miner will be grouped in a room with their group. Then at any given period, there will be a rotation of the places of each miner. This process is carried out so that a single miner has no monopoly in carrying out the consensus process. From this process, it is also hoped that miners with ordinary computing power can still compete in hashing. This study claims that latency can decrease and speed increases through the developed method.

Soesanto et al., in 2022, also developed a very different consensus method because it approaches the diverse needs of its users. In this research, Soesanto developed an adaptive Proof of Work architecture, where this mechanism will provide different hash levels for each other transaction, and all of that is adjusted to the needs and priorities of the transaction [27]. Therefore, to accommodate this, the multiple mem-pool concept was created so that transactions with the same priority will be grouped in a shared mempool. Through trials carried out in this study, it was found that overall from the generated data, the hash speed of Proof of Work can increase by as much as 400%. This is possible because some transactions have level 1 or the lowest, and some have a higher level. As previously explained, the priority level of this transaction will affect the hash level imposed on the transaction. The assumption is that if the transaction has low priority or security requirements, it is unnecessary to hash it with a high level. Just the lowest level is enough.

On the other hand, if the transaction is considered essential or has high priority and high-security requirements, then the transaction must also obtain maximum security with the highest hash level. In this study, the highest hash level is assumed to be the standard hash level used by the current blockchain, while the lower levels will be broken down according to the same scale. However, the drawback of this research is that it still uses generated data and has not done a natural grouping of transaction priorities, so the results cannot be known from actual data in this study. In this paper, further research is carried out on Adaptive Proof of Work using actual Bitcoin transaction data and grouping priorities with the RFM concept.

The latest research related to optimizing the Proof of Work algorithm was carried out by Saqib and Talla in 2023. Through the parallel mining concept offered by this research, it is claimed that miners do not need to scramble to solve the hash of a block because there will be several blocks that miners can solve together. Different or known as multi-miners [36]. The selection of miners to perform parallel processing is carried out by the manager of a node group. The manager's choice is made automatically by combining the concept of Particle Swarm Optimization with Proof of Work or what is referred to in this study as PSO-PoW. This automatic selection of managers impacts increasing the speed of the overall consensus. The manager is a party or client in the blockchain network and informs all nodes when the miner has finished mining a particular block. The results obtained from this study are that if the single mining concept is compared to parallel mining, the speed will increase by 34%, which in this study was tried with 5 parallel miners. Meanwhile, if parallel mining is compared to PSO-PoW, then combining it with the PSO concept has a 36% higher speed. Therefore, when compared between PSO-PoW and a single miner, the speed increase is 58% higher.

2.3 Recency Frequency Monetary in Various Fields

Recency Frequency Monetary (RFM) is a marketing concept that marketers have used for a long time to segment customers based on these factors. Recency calculates how long or when the last transaction occurred with a customer. Frequency calculates the total number of transactions that occur in each customer. Meanwhile, Monetary calculates the total nominal value that customers have spent on all transactions. In 2016 Chen even used the RFM concept to analyze customer feedback and then did clustering based on the RFM assessment that had been carried out [37]. The following year in 2017, Gustriansyah et al. researched implementing RFM on customer segmentation of pharmaceutical products. RFM, in this case, is not only used for customer clustering but also used for sales prediction [38]. The predictions claimed that this concept could improve inventory management in the pharmaceutical business.

In 2019, research on RFM began to enter a new phase, where researchers added a fourth factor to RFM, namely C or Cost [39]. This research was conducted at a plastic packaging factory. The data analyzed in this study comes from customer transaction data. However, there is an additional factor, namely cost, which is the cost incurred by the company while producing orders from each customer. The higher the cost, the lower the C weight assigned to that customer. The results of all these weightings are used for customer clustering, similar to Gustriansyah's research, which is used to predict future customer transactions.

RFM also maps loyal and potential customers based on their transaction behavior. This concept was researched by Rizki et al. in 2020, where the data used comes from the Point of Sale System, which is then processed to obtain customer clusters, where each cluster will have a different level of loyalty [40]. Still, in the same year, Kabasakal developed a software prototype that was used to apply the RFM model to the e-retailing business [41]. This software can process data related to RFM, perform customer clustering, and provide recommendations for marketing strategies suitable for the company. However, the drawback of this software prototype is that it is still rigid, so the types of data that this software can accept have been determined from the start. It cannot be used for all areas of business or further development of the RFM concept.

Furthermore, in 2021, Christy et al. research related to RFM data processing techniques, which usually use K-Means, optimized by using Median K-Means. In this developed method, it is claimed that the selection of centroids from K-Means is better so that the clusters obtained are more precise [28]. The formation of the right cluster can improve the company's marketing strategy accuracy based on the cluster. In the same year, Li et al. also conducted CRM research using RFM, referred to as dRFM [42]. The d factor in this study is related to the percentage of drug dispensing for each patient in the hospital. This additional factor is also used to analyze the patient's economic level, assuming that his purchased drugs can describe his economic level. The clustering results obtained through this study are divided into three types, namely Potential Patients to be retained, where this cluster contains patients who buy many drugs at high prices and the last time they visited was 19.06 months ago. Next, there are High-Value Patients to be attracted, whose contents are patients whose previous visit was 6.66 months ago. Finally, Basal Patients are to be kept, namely patients who last visited 3.7 months ago. Each type will also be related to the hospital's marketing strategy for each patient.

In 2022, four studies related to RFM will be conducted from various approaches. The first research tries to implement RFM in a bank, which is expected to increase the value of savings from its customers. RFM, in this study, is used for customer segmentation to classify customers based on their loyalty. The focus of this research is the recency factor of RFM [43]. There are three types of recency found in the study, namely High Recency, which means that customers of this type can be given the direct promotion of new products through cross-selling or up-selling mechanisms. Mid Recency is filled by customers who are not too loyal and are included in the Risky Customer type. For this type, a retention program is carried out in the hope that these customers will not be separated and will further increase the Frequency and Monetary of these customers. Low Recency is a type of customer who has not been given any promotional programs beforehand because, most likely, customers of this type will not be interested in the new products being offered.

Still, in the same year, there was research related to the implementation of RFM in vehicle-sharing companies. In this study, it is claimed that clustering using RFM makes it easier for companies to decide on allocating their resources [44]. The allocation of these resources means that the company understands more about locations where many people need vehicles, which is seen from the use of vehicle parking lots which are always busy. In this study, RFM is modified to become RFD, where D is the borrowed time and the duration of stopping the vehicle in a particular place (when parking).

RFM implementation is also carried out in the telecommunications business, which has different business processes from the retail industry. Ibitoye et al. found that when RFM is implemented in the telecommunications business, it is also necessary to look at the influence and dominance of a customer in a social environment [45]. The point is how a customer can influence other people in his environment, to participate in using telecommunications products as he uses. Therefore, this research introduced a concept called CID or Customer Influence Degree, and RFM was changed to RFMI (Recency Frequency Monetary Influence). Influence is also weighted in this concept so that companies can classify customers based on their buying behavior and their environmental impact.

If 2021 there has been research on RFM implementation in the pharmaceuticals sector in 2022, there will also be similar research conducted in Indonesia. Palupi and Fakhruzzman add a location factor to RFM. This is because the pharmaceutical business under study sells locally and sends its medicines to various places. Therefore, in this study, the RFM-Location Model was developed [46]. In this model, location is one factor determining the RFM weight. The locations assessed here are related to drug delivery locations.

The latest research in 2023 was carried out by Handojo et al., who developed multi-layer RFM. This study found that in online retailers, RFM weighting cannot be carried out as usual because buyers in this business can quickly move, so the RFM factor alone becomes less accurate. Therefore, in this study, RFM is weighted in several layers, where each layer is data for a specific period [47]. In simple terms, there will be a layer for customers who have just joined and a layer for old customers. Each layer will be weighted so that assigning RFM weights between subscribers can be fair. Similar research was also developed by Ullah et al. in 2023 in Pakistan, where this study also considered the time factor, so an RFMT method (T for time) was proposed [48]. The previous research analysis also reiterated that when the relationship with the customer is excellent and robust, it will be easy to do marketing to these customers.

Many studies related to grouping customer data using RFM have proven that this method is robust for classifying customers. The requirement for this RFM to process data properly is that the data used must be able to provide the right supply of recency factors which are related to the time of the transaction, frequency related to the number of transactions, and monetary related to the total value of the transaction. However, of all the research that has been analyzed, no one has implemented Recency Frequency and Monetary (RFM) in the cryptocurrency field or, more specifically, in the blockchain field. In this research, adjustments, and implementation of RFM are made to weight transactions on the blockchain, which can become each transaction's priority. RFM adjustment in this study is necessary, because in the initial RFM or in any other research, the reference data processed from RFM is the customer. Whereas in bitcoin transactions or most other publics cryptocurrency, normally the identity of the transaction actor or customer does not appear, so that transactions cannot be clearly identified or grouped from the same person. Therefore, in this study, the RFM method was adjusted by shifting the data reference from the customer or transaction agent to the transaction data directly. Recency will use the Coin Day Destroyed (CDD) data attribute on bitcoin, Frequency will use the number of transactions that have the exact same value, and Monetary will use the transaction value data from bitcoin. This data will then be implemented again in Adaptive Proof of Work to test the speed of the adaptive consensus processing that existed in the previous research.

3 Research Methodology

This study combines two major concepts, namely Adaptive Proof of Work which has been studied previously, and RFM which is a concept from marketing. In an adaptive blockchain architecture that allows receiving transactions with different hash levels, multiple mempools are used. Later each mempool will have a different level, and each transaction will be grouped in a mempool according to its level. The processing speed of each mempool will vary depending on the level. Determining the level of each transaction will use Recency Frequency and Monetary concepts, so the first step that must be taken is to identify data that can be used in Recency, Frequency and Monetary weighting. However, the thing that is different from determining this RFM between transactions in the blockchain and conventional transactions is the openness of the data used. In conventional transactions, researchers will easily identify the perpetrator of each transaction or commonly referred to as a customer, but that does not happen in blockchain-based transactions. In blockchain-based transactions, the identity of each party (both those who receive money and those who send money) is not clearly visible or can also be referred to as anonymous. Therefore the determination of each RFM variable in a blockchain transaction cannot involve the customer's identity in it, but is only based on the transaction data made. The transaction dataset used in this study was obtained from the blockchain repository, where the repository contains real transaction data from bitcoin and various other cryptocurrencies.

The transaction data used in this study comes from bitcoin transaction data for February 2023, which totaled 8,387,716 transactions. Transaction data is taken daily, where per day there are more than 300,000 transactions. In each transaction, the various attributes are recorded which will then be processed related to the RFM weighting used. Data normalization in this study uses the min-max technique combined with the median normalization technique, to get a more precise scale, but still be able to handle all data with quite large outliers [49]. The method of grouping and weighting the data used in this study uses the concept of median data, so that the data will be made into a range of quartiles. The RFM Framework for weighting bitcoin transactions developed in this study can be seen in Fig. 1. In Fig. 1 it can be seen that each factor of the RFM is not sequential to one another, so the data processing sequence does not have a standard order. Each factor in the RFM is always weighted using the median, so that the consistency of the weighting is maintained.

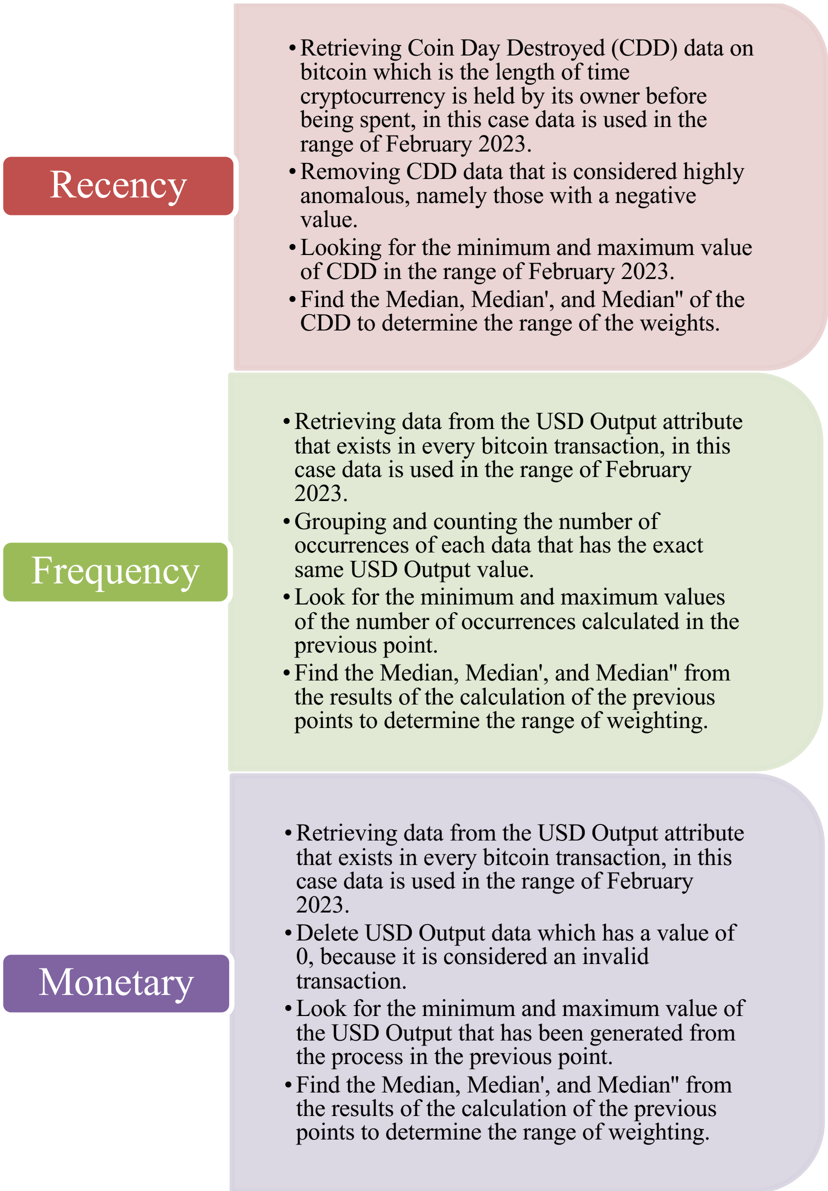

Fig. 1. RFM Framework on bitcoin transactions

3.1 Recency

Recency is a variable that shows when the last transaction was made by the customer. However, because the identity of the customer cannot be known in bitcoin, the bitcoin transaction attribute is taken, which is called CDD or Coin Day Destroyed. This CDD shows how long the cryptocurrency is stored, until it is finally spent. So the bigger the CDD, it means that the longer the crypto money is held or stored by the owner before being spent. Whereas the smaller the CDD, it means that this crypto money is only briefly held by the owner (counting from the first time the owner receives this crypto money), then immediately spends it again.

As previously explained, the concept of grouping data in this study uses median data. The first step is to clean transaction data from CDD which are outliers, namely CDD which is less than zero or negative. Through this initial step, 7,306,115 transaction data were obtained. The second step is to look for the median (M) of the data, and the median from CDD is 0.003. After that, the minimum and maximum values of the CDD were also searched and they were obtained respectively 0.0000000009 and 4,948,163. After obtaining these three values, the next step is to find M` between the minimum and median values (M) and obtain M` of 0.0003. Finally searched for M`` between the median value (M) and the maximum value, and obtained M`` of 0.045. When recapitulated, the results are as shown in Table 1 below, where these values can ultimately form the range of quartiles needed for grouping transaction data.

Table 1. Recency Range

Min	M`	M	M``	Max
0.0000000009	0.0003	0.003	0.045	4,948,163

Through this range, the weighting for this bitcoin transaction Recency variable is also defined. This weighting is divided into 4 scales, weight 1 for very high priority because in this case, people whose transactions are included in this scale, are people who rarely spend their money. Weight 2 is high priority, on this scale, customers hold their money long enough, but are still under first priority. Weight 3 is normal priority, which means that customers spend their money in a range that is considered normal, and the last weight is 4 for low priority. At the lowest priority, people spend money as soon as it is earned. Therefore the lower priority will be given the highest level of processing speed, but with the lowest level of security. Priority details can be seen in Table 2.

Table 2. Recency Priorities

Weight	Priority	Range
1	Very High	0.0452 - 4,948,163
2	High	0.0034 - 0.0452
3	Normal	0.0003 - 0.0034
4	Low	0.0000000009 - 0.0003

3.2 Frequency

In cases other than blockchain transactions, this frequency is the number of purchase transactions made by customers at certain stores or companies. However, as previously explained, that in the bitcoin blockchain concept, the customer's identity cannot be known, so taking frequency values in general cannot be done. Therefore, in this study, frequency sampling was carried out by using the bitcoin transaction data attribute in the form of output values (in USD) in bitcoin transactions that have the exact same nominal. So that the greatest frequency is the transaction output with a nominal value of 2.2964 USD which appears 1806 times throughout February 2023. As for the smallest frequency of transaction nominal occurrences in February 2023, it cannot be mentioned one by one, because there are so many values. However, the minimum frequency obtained from the occurrence of the same transaction value is 1. The occurrence of the same transaction output nominal is used as a frequency variable, because it is assumed that the same nominal and recurring transactions are the same transaction for a purpose which may be the same. Through this calculation model, the median value (M) of the data on the frequency of occurrence of transaction output values is 15.5. While the minimum value of the frequency of occurrence of transactions is 1 and the maximum value of the frequency of occurrence of transactions with the same value is 1806. M` which is the median of the minimum value and M from the calculation results is 6.5. Meanwhile, the value of M`` which is the median of M and the maximum value is 39.5. Complete data on the frequency range can be seen in Table 3, where, like Recency, there are 5 values which will form 4 scales as shown in Table 4. The rarer a certain transaction value is, it is assumed that it is not a routine transaction, so high security is needed. . However, if transactions are made more frequently, then it is assumed that these are routine transactions, which should have a high level of trust, so they do not need to be overly secured.

Table 3. Frequency Range

Min	M`	M	M``	Max
1	6.5	15.5	39.5	1,806

Table 4. Frequency Priorities

Weight	Priority	Range
1	Very High	1 – 6.5
2	High	6.5 – 15.5
3	Normal	15.5 – 39.5
4	Low	39.5 – 1,806

3.3 Monetary

In monetary variables, determining values and ranges in bitcoin transactions is equated with determining conventional transactions. However, as explained earlier, it is impossible to identify customers in bitcoin transactions, so in this monetary concept, you can immediately see the nominal value of the transaction, without paying attention to the owner of the transaction. In the monetary section, the transaction data that has a valid monetary value (greater than zero) is 8,387,716 transaction data in February 2023. The median value (M) of this collection of transactions is 319 USD. While the minimum and maximum values in the analyzed USD output data are 0.0007 USD and 1,367,813,760 USD respectively. While M` is the middle value of the minimum and median (M) value is 57 USD, and finally for M`` which is the middle value of the median (M) and the maximum value is 2.374 USD. As with Recency and Frequency, four scales with predetermined ranges were formed using the previous median method as shown in Table 5. After that, the range of each priority in each scale was formed as shown in Table 6.

Table 5. Monetary Range

Min	**M`**	**M**	**M``**	**Max**
0.0007	57	319	2,374	1,367,813,760

Table 6. Monetary Priorities

Weight	**Priority**	**Range**
1	Very High	2,374 - 1,367,813,760
2	High	319 – 2,374
3	Normal	57 – 319
4	Low	0.0007 – 57

4 Result and Discussion

After designing a weighting method for Recency, Frequency and Monetary for bitcoin transactions, it is then necessary to assign a weight to each of these transactions. Later the weight of each transaction will be in the form of a matrix, and through this matrix, clustering will be carried out for each of these transactions, resulting in a label for each transaction according to the cluster. Initial testing was carried out on bitcoin transaction data on February 28, 2023, which has a total of 332,358 transaction data. Each transaction data will have 3 weights, namely Recency (R), Frequency (F), and Monetary (M). The highest weight will be worth 444, while the lowest weight will be worth 111.

After the data was weighted for RFM, it was found that there were 49,353 transaction data which were considered outliers because they had a CDD value of 0, so that 283,005 transaction data were valid. Furthermore, the RFM weighting results can be used to cluster bitcoin transactions using the desired clustering algorithm.

5 Conclusion

By adjusting the attribute data on bitcoin transactions for RFM weighting needs, a range of each RFM variable is obtained which can then be used for transaction weighting. The weighting performed on bitcoin transactions is used to cluster the data. Further research needs to be carried out to use the results of this cluster as part of the multiple mempools in the Adaptive Proof of Work study.

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