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Leveraging RFM Analysis and MOORA for Strategic Credit Decisions

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Abstrak. *Credit risk management is crucial for the sustainability of businesses, particularly in industries dealing with perishable goods such as pharmaceutical distribution. This research aims to enhance credit risk assessment by integrating Recency, Frequency, Monetary (RFM) analysis with the Multi-Objective Optimization on the basis of Ratio Analysis (MOORA) method. By analyzing six months of sales transaction data from a pharmaceutical distributor, an ETL process was conducted to consolidate data from customer, sales transaction, billing, payment, and product tables. Four key components—Recency, Frequency, Monetary, and Payment Timeliness—were normalized and weighted to calculate overall performance scores using MOORA. The research reveals that customers with higher Frequency and Monetary scores, recent purchase activity, and timely payments are identified as low-risk candidates. The top five customers were ranked based on their comprehensive scores, demonstrating the effectiveness of the combined RFM-MOORA approach. The results indicate that leveraging detailed customer behavior metrics can significantly improve credit risk management, reduce bad debts, and optimize credit allocation. This methodology supports data-driven, strategic decision-making, fostering stronger business relationships and financial stability. Future research should consider integrating advanced machine learning techniques and expanding data sources for even more precise risk predictions*

Kata kunci: *Credit Risk Management, RFM Analysis, MOORA Method,Pharmaceutical Distribution*

INTRODUCTION

Credit risk management is a critical challenge faced by many industries, particularly those dealing with perishable goods. In sectors like pharmaceutical distribution, managing credit risk effectively is essential to ensure business sustainability. Pharmaceutical distributors, supplying to pharmacies and drug stores, often face significant difficulties in handling credit transactions (Milanesi et al., 2020). Besides cash transactions, a substantial portion of sales occurs on credit, exposing distributors to the risk of bad debts (Höck et al., 2020; Yang et al., 2021). Consequently, finding effective strategies to mitigate credit risk becomes imperative for maintaining a healthy financial state.

The distribution of pharmaceuticals entails unique characteristics distinct from other sectors (Janatyan et al., 2021). The products distributed have relatively short shelf lives, necessitating meticulous inventory and financial management (Ahmad et al., 2021; Janatyan et al., 2021). Credit transactions offered to pharmacies and drug stores add complexity to operations, as the distributor must ensure timely credit repayments to maintain a healthy cash flow. In this context, RFM analysis can be employed to assess customers' creditworthiness based on their purchasing patterns.

RFM analysis is a customer segmentation technique that measures three key dimensions: recency (how recently a customer made a purchase), frequency (how often they purchase), and monetary value (how much money they spend) (Liao et al., 2022; Wan et al., 2022). By leveraging existing sales data, distributors can calculate RFM scores for each customer. Based on these scores, customers can be categorized into three primary segments: Champions, Loyalists, and Potential Loyalists (SABUNCU et al., 2020; Wan et al., 2022). Champions are customers who frequently make large purchases and have recently transacted. Loyalists are customers who consistently make purchases, whereas Potential Loyalists are those who exhibit a high potential for loyalty based on their purchasing patterns.

By categorizing customers through RFM analysis, pharmaceutical distributors can identify customers with low and high credit risk. The RFM scores are then integrated into the decision support system to assist the distributor in making more informed credit decisions. This system will provide recommendations on customers' creditworthiness based on their RFM scores, thereby minimizing the risk of bad debts (Rahim et al., 2021). For instance, Champions might be granted higher credit limits due to their demonstrated good payment patterns, while Potential Loyalists may require further evaluation before being granted substantial credit.

In research of a pharmaceutical distributor (namely XYZ for anonimity), the implementation of RFM analysis and a decision support system offers significant advantages. Distributors can proactively manage credit risk by understanding customers' purchasing behaviors (Ernawati et al., 2021). Consequently, the company can maintain a stable cash flow and reduce potential losses due to bad debts. This implementation not only enhances operational efficiency but also strengthens business relationships with pharmacies and drug stores through fair and data-driven credit assessments.

The results from the RFM analysis are translated into scores that form the foundation for implementing the Decision Support System (DSS) using the Multi-Objective Optimization on the basis of Ratio Analysis (MOORA) method. MOORA is a robust multi-criteria decision-making technique that helps in evaluating and ranking options based on multiple criteria (Brauers & Zavadskas, 2006). In this case, the criteria are derived from the RFM analysis, which provides a comprehensive view of customer behavior and creditworthiness (Ernawati et al., 2021). The integration of MOORA into the DSS allows

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for a systematic and quantitative approach to assess the risk and decide on the credit limits for each customer.

The four components of the RFM analysis that serve as the basis for the DSS calculations include recency, frequency, monetary value, and a composite RFM score. Recency measures how recently a customer made a purchase, providing insights into their current engagement with the distributor. Frequency captures how often a customer makes purchases, indicating their consistency and loyalty. Monetary value assesses the total expenditure of a customer, reflecting their overall value to the business. The composite RFM score is a weighted sum of these three components, offering a holistic evaluation of the customer's behavior and potential risk.

By incorporating these RFM components into the MOORA method within the DSS, the system can objectively rank customers based on their creditworthiness. This approach ensures that decisions regarding credit limits are data-driven and consider multiple aspects of customer behavior. For instance, a customer with high recency, frequency, and monetary scores would likely receive a higher credit limit compared to one with lower scores, thus minimizing the risk of bad debts and optimizing the credit management process. This integration enhances the distributor's ability to make informed, fair, and strategic credit decisions, ultimately improving financial stability and operational efficiency.

The selection of the MOORA (Multi-Objective Optimization on the basis of Ratio Analysis) method over other DSS techniques is driven by its robustness, simplicity, and effectiveness in handling multi-criteria decision-making problems (Linggadewi & Budihartanti, 2020; Wicaksono, 2023). MOORA stands out due to its ability to process multiple conflicting criteria simultaneously, which is essential in credit risk assessment where factors such as recency, frequency, and monetary value need to be considered together. Unlike more complex methods like Analytic Hierarchy Process (AHP) (Khan et al., 2019; Kharisma et al., 2021), MOORA offers a straightforward computational process that reduces the cognitive load on decision-makers. This simplicity does not come at the expense of accuracy; MOORA provides precise and reliable rankings that are critical for making informed credit decisions.

Another advantage of MOORA is its flexibility and adaptability to various decision-making scenarios (Miç & Antmen, 2021; Stanujkić et al., 2013). It has been successfully applied in numerous fields, including supply chain management, finance, and healthcare (Zavadskas et al., 2014), demonstrating its versatility and effectiveness. Research indicates that MOORA can handle large datasets efficiently, making it suitable for the dynamic and data-intensive environment of pharmaceutical distribution. Studies such as Brauers and Zavadskas (2006) have shown that MOORA consistently outperforms other multi-criteria decision-making methods in terms of ease of implementation and decision quality (Brauers & Zavadskas, 2006). By leveraging MOORA within the DSS, the pharmaceutical distributor can ensure that credit risk assessments are both rigorous and manageable, leading to better financial outcomes and operational stability.

Thus, the objective of this research is to develop a robust Decision Support System (DSS) that integrates Recency, Frequency, Monetary (RFM) analysis with the Multi-Objective Optimization on the basis of Ratio Analysis (MOORA) method to enhance credit risk management for a pharmaceutical distributor. By leveraging RFM scores to evaluate customer creditworthiness and employing the MOORA method for systematic and precise ranking, the DSS aims to minimize bad debt risks, optimize credit limits, and improve financial stability and operational efficiency. This comprehensive approach ensures data-driven, fair, and strategic credit decisions, ultimately strengthening business relationships with pharmacies and drug stores.

LITERATURE REVIEW

The Multi-Objective Optimization on the basis of Ratio Analysis (MOORA) method was developed by Professor Brauers and Professor Zavadskas in the early 2000s as a robust multi-criteria decision-making tool (Brauers & Zavadskas, 2006). The primary goal was to create a method that could handle complex decision-making scenarios with multiple, often conflicting criteria. The method gained recognition for its simplicity, versatility, and effectiveness, quickly becoming a preferred choice for researchers and practitioners in various fields. MOORA's widespread use in research can be attributed to its robust and straightforward approach to multi-criteria decision-making (Zavadskas et al., 2014). One of its key strengths is the ability to normalize and weigh criteria, allowing for direct comparison across different units and scales (Miç & Antmen, 2021). This flexibility makes it applicable to a wide range of decision-making problems, from supply chain management to finance and healthcare. Additionally, MOORA's computational simplicity reduces the cognitive load on decision-makers, facilitating easier and quicker implementation without sacrificing accuracy (Wicaksono, 2023). Its ability to provide clear and interpretable rankings based on multiple

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criteria has made it a valuable tool in both academic research and practical applications, ensuring its continued relevance and popularity in the field of decision science.

The RFM (Recency, Frequency, Monetary) analysis is a time-tested marketing tool that originated in the direct marketing industry. Its roots can be traced back to the 1960s when marketers began seeking more effective ways to segment customers based on their purchasing behaviors. The concept was popularized by Bult and Wansbeek (1995), who demonstrated its effectiveness in predicting future customer behaviors and improving targeted marketing strategies (Aslantaş et al., 2023). RFM analysis simplifies customer segmentation by focusing on three critical dimensions: how recently a customer made a purchase (Recency), how often they make purchases (Frequency), and how much they spend (Monetary) (Chavhan et al., 2022; Wan et al., 2022). These three metrics provide a comprehensive view of customer engagement and value, making it easier for businesses to tailor their marketing efforts.

In contemporary marketing management, RFM analysis has evolved to become an essential component of customer relationship management (CRM) systems (Rahim et al., 2021). It is widely used to identify high-value customers, optimize marketing campaigns, and enhance customer retention strategies (Aslantaş et al., 2023; Wu et al., 2020). Businesses leverage RFM scores to classify customers into various segments, such as 'Champions', 'Loyal Customers', and 'At Risk' customers, allowing for more personalized and effective marketing initiatives (SABUNCU et al., 2020; Wan et al., 2022). For instance, 'Champions' who have made recent, frequent, and high-value purchases might be targeted with loyalty rewards and exclusive offers, while 'At Risk' customers, who have not purchased recently, might receive re-engagement campaigns. The simplicity and effectiveness of RFM analysis in providing actionable insights have cemented its role as a fundamental tool in marketing analytics and strategy development (Rahim et al., 2021).

METHODS

In this research, the data collection process begins with gathering sales transaction data from the pharmaceutical distributor over the past six months. This period provides a substantial dataset to capture recent customer behavior and transaction patterns, which are critical for accurate RFM analysis. The data sources include several interconnected tables:

the customer table, sales transaction table, billing table, customer payment table, and product table. Each table contains specific details that, when combined, offer a comprehensive view of the distributor's interactions with its customers.

To prepare the data for analysis, an ETL (Extract, Transform, Load) process is implemented. The extraction phase involves retrieving relevant data from the respective tables. The transformation phase includes denormalizing the data, which involves combining and restructuring the normalized tables into a single, comprehensive dataset (Prajapati & Mary, 2022; Przysucha et al., 2023). This step is essential to streamline the data and ensure all necessary information is accessible in a unified format. For instance, customer details from the customer table are combined with transaction records from the sales transaction table, payment information from the payment table, billing details from the billing table, and product information from the product table. This denormalized dataset allows for more efficient analysis and processing.

Once the data is denormalized, it is loaded into the analytical framework where RFM analysis is conducted. The denormalized data set includes key variables such as customer ID, transaction dates, transaction amounts, billing dates, payment dates, and product details. Each variable plays a crucial role in calculating the RFM scores. Recency is determined by the most recent transaction date, frequency by the number of transactions within the six-month period, and monetary value by the total amount spent by each customer. This comprehensive dataset is then used to generate RFM scores for each customer, which serve as the basis for further analysis and decision-making processes within the DSS framework (Chavhan et al., 2022; Ernawati et al., 2021).

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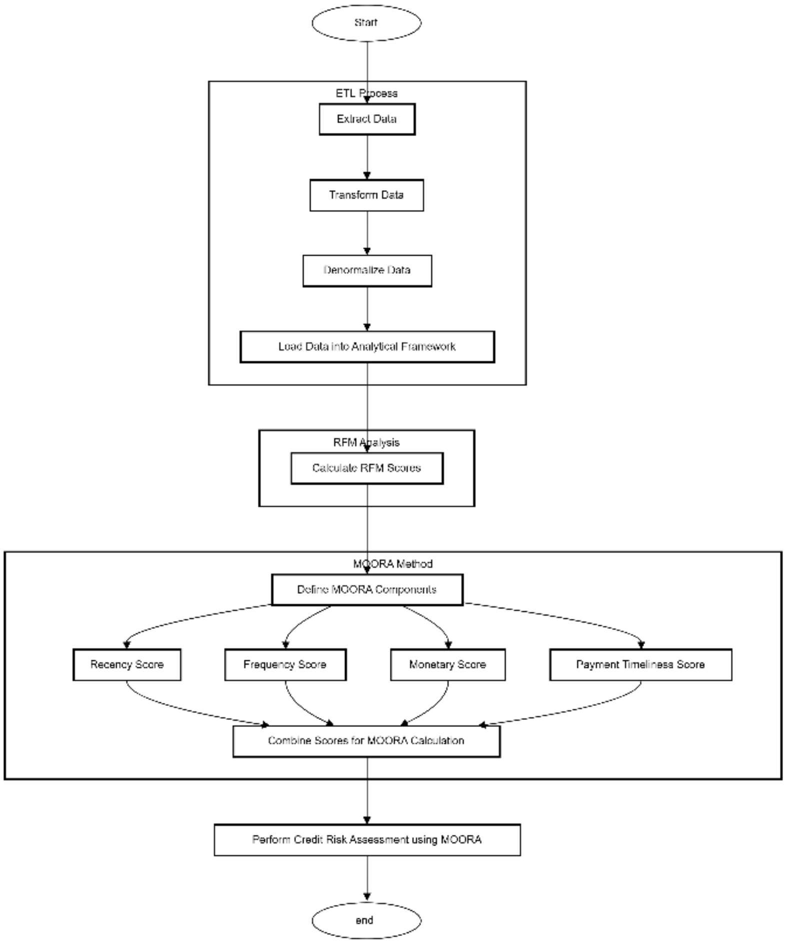

Figure 1. Workflow Diagram

Following the completion of the ETL process, the next step involves defining the four key components for the MOORA method calculations. These components are derived directly from the results of the RFM analysis and additional relevant data points to ensure a comprehensive assessment of creditworthiness. The first component is the Recency score, indicating how recently a customer made their last purchase, which helps identify current engagement levels. The second component is the Frequency score, reflecting how often a customer makes purchases within the specified period, providing insights into their loyalty and consistency. The third component is the Monetary score, representing the total expenditure of the customer, which highlights their overall value to the business. The fourth and final component is the Payment Timeliness score, calculated from the billing and payment tables, indicating how promptly a customer pays their invoices. This component is crucial for assessing the reliability of the customer in fulfilling credit obligations. Together, these four components offer a robust and multi-faceted view of each customer's behavior,

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enabling precise and effective credit risk assessment using the MOORA method within the DSS framework.

The MOORA (Multi-Objective Optimization on the basis of Ratio Analysis) method involves several systematic steps to evaluate and rank customers based on the defined criteria from the RFM analysis and additional payment timeliness score (Stanujkić et al., 2013).

Construct the Decision Matrix:

The first step is to create a decision matrix where each row represents a customer, and each column represents one of the four criteria: Recency, Frequency, Monetary value, and Payment Timeliness. The matrix entries are the scores derived from the ETL process.

Normalization of the Decision Matrix:

The next step involves normalizing the decision matrix to ensure comparability between different criteria. This is done by dividing each entry in the decision matrix by the square root of the sum of the squares of all entries in that column. The normalization formula for each element x_{ij} in the decision matrix is:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \quad \text{...(1)}$$

This step converts the scores into a dimensionless unit, allowing for direct comparison across different criteria.

Weighted Normalized Decision Matrix:

Depending on the importance of each criterion, weights can be assigned to each normalized score. If weights are to be applied, each normalized score r_{ij} is multiplied by its respective weight w_j. For this research, assume equal weights unless specified otherwise.

Calculation of the Overall Performance Score:

For each customer, the overall performance score is calculated by summing the weighted normalized scores for beneficial criteria (Frequency and Monetary) and subtracting the scores for non-beneficial criteria (Recency and Payment Timeliness). The overall performance score S_i for each customer i_i is given by:

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$$S_i = \sum_{j \in J_b} w_j r_{ij} - \sum_{j \in J_n} w_j r_{ij}$$
……………………………………..(2)

Here, J_b represents the set of beneficial criteria and JnJn represents the set of non-beneficial criteria. For this case, Frequency and Monetary are beneficial, while Recency and Payment Timeliness are non-beneficial.

Ranking the Customers:

The final step involves ranking the customers based on their overall performance scores. Customers with higher scores are considered more creditworthy and thus may be granted higher credit limits, whereas those with lower scores may be flagged for closer scrutiny or given lower credit limits.

RESULTS AND DISCUSSIONS

The first component derived from the ETL process that is included in the MOORA analysis is the *Recency score*. This score reflects how recently a customer made their last purchase, providing insights into their current engagement with the distributor. In the context of credit risk management, recency is crucial because it indicates the likelihood of continued interaction with the company. A customer who has made recent purchases is likely more engaged and, therefore, may be considered less risky. For this research, we assign a weight of 0.25 to the recency score. This weight reflects the importance of maintaining recent and active relationships with customers while acknowledging that other factors also play significant roles in creditworthiness.

The second component is the *Frequency score*, which measures how often a customer makes purchases over the specified period. This score is indicative of customer loyalty and consistency in purchasing behavior. Frequent purchases suggest a stable and reliable customer, which is essential for credit risk assessment. A customer who regularly engages in transactions is likely to have a stronger and more predictable relationship with the distributor. Therefore, we assign a weight of 0.35 to the frequency score. This higher weight compared to recency underscores the importance of consistent purchasing patterns in evaluating credit risk, as regular transactions are a strong indicator of a customer's reliability.

Both the recency and frequency scores are crucial in the MOORA method for credit risk assessment, but they serve different purposes. The recency score helps identify current

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engagement levels, which can be a predictor of near-term behavior and potential credit risk. On the other hand, the frequency score provides a longer-term view of customer behavior, indicating their loyalty and reliability over time. By giving a higher weight to frequency, we prioritize consistent purchasing behavior, which is often a stronger indicator of a customer's creditworthiness than their most recent purchase alone.

The rationale behind the proportional weighting is to balance the immediate relevance of recent transactions with the overall reliability indicated by frequent purchases. While recent engagement is important, consistent purchasing behavior over time provides a more comprehensive view of a customer’s credit risk. The assigned weights (0.25 for recency and 0.35 for frequency) reflect this balance, ensuring that the DSS gives due consideration to both immediate and historical customer behaviors. This balanced approach allows the distributor to make well-informed credit decisions, minimizing risk while fostering strong customer relationships.

The third component included in the MOORA analysis is the *Monetary score*, which represents the total expenditure of a customer over the specified period. This score is critical as it highlights the overall value a customer brings to the distributor. High monetary scores indicate customers who make significant purchases, contributing substantially to the company's revenue. For credit risk assessment, customers who spend more are typically seen as more valuable, and retaining them is crucial for the business. Therefore, we assign a weight of 0.30 to the monetary score. This weight reflects the importance of customer value in the overall assessment, ensuring that high-spending customers are recognized and given appropriate credit considerations.

The fourth component is the *Payment Timeliness score*, derived from the billing and payment data. This score measures how promptly a customer pays their invoices, which is a direct indicator of their reliability in fulfilling credit obligations. Timely payments are crucial for maintaining a healthy cash flow and reducing the risk of bad debts. Customers who consistently pay on time demonstrate financial responsibility and lower risk for the distributor. Given the critical nature of payment timeliness in credit risk management, we assign a weight of 0.10 to this score. While it is essential, we assign a slightly lower weight compared to other factors to maintain a balanced view, acknowledging that payment behavior, while crucial, should be considered alongside other aspects of customer engagement and value.

By assigning these weights—0.25 to recency, 0.35 to frequency, 0.30 to monetary, and 0.10 to payment timeliness—we ensure that the total weight sums to 1. This balanced distribution reflects the comprehensive nature of credit risk assessment, where multiple factors must be considered to make informed decisions. The slightly higher weights for frequency and monetary scores emphasize the importance of consistent purchasing behavior and customer value, while the recency and payment timeliness scores provide essential context about recent engagement and reliability.

Table 1. Weight for Each Component

Component	Description	Weight
Recency	Time since the last purchase	0.25
Frequency	Number of purchases in the specified period	0.35
Monetary	Total expenditure over the specified period	0.30
Payment Timeliness	Promptness of customer payments	0.10

This proportional weighting strategy allows the Decision Support System (DSS) to provide a nuanced evaluation of each customer's creditworthiness. By considering a mix of historical and recent behaviors, along with financial responsibility, the DSS can generate robust and data-driven recommendations. This approach ensures that credit limits and terms are aligned with the overall risk profile of each customer, thereby minimizing the risk of bad debts while fostering valuable customer relationships.

Table 2. Initial Data

Customer ID	Recency	Frequency	Monetary	Payment Timeliness
C1	2	15	12000	5
C2	5	12	9500	7
C3	1	20	15000	3
C4	3	10	8000	4
C5	4	8	7000	6
C6	7	9	7500	8
C7	6	14	11000	7
C8	2	18	14000	5
C9	3	7	6000	4
C10	5	11	8500	6
C11	4	13	10500	5
C12	6	6	5500	7
C13	1	19	14500	2
C14	2	16	12500	3
C15	5	12	9500	6
C16	3	9	7000	5
C17	4	7	6000	4
C18	2	11	8500	5

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Customer ID	Recency	Frequency	Monetary	Payment Timeliness
C19	6	8	6500	7
C20	7	5	5000	8

The table 1 provides the raw scores for Recency, Frequency, Monetary, and Payment Timeliness for top 20 customers. These scores are the initial data points used to perform normalization as part of the MOORA method. Each customer is assigned a unique ID and their corresponding scores in each of the four components are listed. Recency is measured in months since the last purchase, Frequency is the number of purchases made in the last six months, Monetary represents the total amount spent in currency units, and Payment Timeliness is the average number of days taken to pay invoices.

These raw scores will be normalized to ensure comparability across different criteria. The normalization process will involve transforming these scores into dimensionless values by dividing each score by the square root of the sum of the squares of all scores in the respective column. This step is crucial to balance the impact of each criterion in the overall assessment and to facilitate the subsequent steps of the MOORA method, ultimately leading to the ranking of customers based on their creditworthiness.

Weighted Normalized Decision Matrix

In this step, the normalized values are multiplied by their respective weights to create the weighted normalized decision matrix. The weights assigned to each component are as follows: Recency (0.25), Frequency (0.35), Monetary (0.30), and Payment Timeliness (0.10).

The weighted normalized decision matrix is calculated by multiplying the normalized values of each criterion by their respective weights. This step adjusts the relative importance of each criterion according to the assigned weights, ensuring that the final decision-making process reflects the strategic priorities of the business. So, weighted normalized decision matrix forms the basis for calculating the overall performance scores in the subsequent step, where the benefits and non-benefits are aggregated to determine the final rankings of the customers based on their creditworthiness.

Calculation of the Overall Performance Scores

In this step, the overall performance score for each customer is calculated by summing the weighted normalized scores for beneficial criteria (Frequency and Monetary) and subtracting the scores for non-beneficial criteria (Recency and Payment Timeliness).

The overall performance score for each customer is computed by aggregating the weighted normalized scores for the beneficial criteria (Frequency and Monetary) and subtracting the scores for the non-beneficial criteria (Recency and Payment Timeliness). This calculation provides a composite score that reflects each customer's overall creditworthiness, balancing the positive contributions of frequent and high-value purchases against the negative impacts of recent inactivity and delayed payments. This process is repeated for all customers, resulting in a ranking that can be used to make informed credit decisions. Customers with higher overall performance scores are deemed more creditworthy and may be granted higher credit limits, whereas those with lower scores may require closer monitoring or lower credit limits to mitigate risk.

Ranking Customers Based on Overall Performance Scores

The final step involves ranking the customers based on their overall performance scores to identify those with the lowest credit risk. Below is the table showing the top 5 customers with the highest overall performance scores, indicating the lowest credit risk.

Table 6. Top 5 Overall Performance

Customer ID	Overall Performance Score	Rank
C3	0.1555	1
C13	0.1521	2
C8	0.1060	3
C14	0.0970	4
C1	0.0839	5

The results of the RFM analysis, integrated with the MOORA method, provide a robust foundation for determining credit risk in the context of pharmaceutical distribution. By quantifying and categorizing customer behaviors through Recency, Frequency, and Monetary metrics, the analysis captures essential dimensions of customer engagement and value. The incorporation of Payment Timeliness further enriches the assessment, offering insights into customers' reliability in fulfilling their financial obligations. The final ranking of customers based on these comprehensive scores demonstrates how RFM analysis can effectively distinguish between high and low-risk customers. For instance, customers with higher frequency and monetary scores, coupled with recent purchases and timely payments, emerge as low-risk candidates, as evidenced by the top-ranked customers in the overall performance scores.

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Using RFM analysis as a basis for credit risk determination allows businesses to make informed, data-driven decisions that balance customer value with potential financial risks. This approach not only identifies the most creditworthy customers but also highlights areas where specific customers may need closer monitoring or adjusted credit terms. By prioritizing customers with strong RFM profiles and good payment behavior, businesses can minimize the risk of bad debts, optimize their credit management strategies, and enhance overall financial stability. This methodology underscores the importance of leveraging detailed customer data to inform critical financial decisions, ultimately leading to more sustainable and profitable business practices.

CONCLUSION

The implementation of RFM analysis combined with the MOORA method has proven to be an effective strategy for assessing credit risk among customers in the pharmaceutical distribution industry. The detailed evaluation of customer behavior through Recency, Frequency, Monetary, and Payment Timeliness metrics provides a comprehensive understanding of their engagement and financial reliability. The results from this analysis, particularly the ranking of customers based on overall performance scores, highlight the ability to identify low-risk customers accurately. Customers with frequent and high-value transactions, recent engagement, and timely payments emerged as the most creditworthy, demonstrating the robustness of this combined approach.

By utilizing RFM analysis as the foundation for credit risk assessment, pharmaceutical distributors can make more informed and strategic credit decisions. This methodology not only enhances the accuracy of credit risk evaluation but also supports proactive risk management, leading to reduced instances of bad debt and improved financial stability. The research confirms that integrating detailed customer behavior metrics into decision-making processes is crucial for optimizing credit management and fostering stronger, more reliable business relationships.

Future research could explore the integration of advanced machine learning algorithms with the RFM and MOORA framework to further enhance credit risk assessment accuracy. By incorporating predictive modeling techniques, such as neural networks or decision trees, researchers can potentially uncover deeper insights into customer behavior patterns and predict future credit risks with greater precision. Additionally, expanding the scope of analysis to include more diverse and dynamic data sources, such as social media

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interactions or real-time transaction data, could provide a more holistic view of customer reliability. Implementing and testing this enhanced model across different industries would validate its applicability and effectiveness, offering valuable insights for broader credit risk management strategies.

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