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CUSTOMER SEGMENTATION MODELING VIA ADVANCED RFM ANALYSIS FOR DECISION-MAKING IN MARKETING

In today's e-commerce landscape, one of the key challenges is the need for effective customer segmentation to enhance the performance of marketing strategies and ensure stable customer relationships. Traditional RFM analysis - based on recency, frequency, and monetary value of purchases - is widely used in practice, but it has certain limitations, particularly the lack of consideration for customers' demographic and behavioural characteristics, which reduces segmentation accuracy.

The aim of the study is to develop and evaluate the effectiveness of the improved RFMP-DOV+AIC customer segmentation model, which combines classical RFM parameters with additional features: purchase diversity, online behaviour characteristics, and long-term customer value assessment.

The methodological basis of the study includes methods of economic and mathematical modelling, statistical analysis, clustering, and machine learning algorithms implemented in the Python environment. For empirical validation, an open dataset from the Kaggle platform was used, containing information on online store transactions.

During the research process, data preprocessing, normalization of indicators, and feature engineering for the model were carried out. Based on the K-means algorithm, customer segments were constructed and evaluated using the following metrics: SSE, Silhouette index, Calinski-Harabasz index, and Davies-Bouldin index. The consistent results of these metrics allow for a well-grounded selection of the number of clusters, ensuring internal homogeneity and sufficient distance between clusters.

The results confirmed that the extended model enables clearer customer grouping and allows for the identification of segments that consider behavioural and demographic characteristics, which are not captured by classical RFM analysis.

The practical significance of the obtained results lies in the possibility of integrating the RFMP-DOV+AIC model into CRM systems of e-commerce enterprises to optimize marketing communications, reduce customer churn, and increase customer loyalty. The proposed approach can be applied both in academic research in the field of marketing analytics and in the practical activities of companies operating in the e-commerce market.

Keywords*: RFM analysis, e-commerce, clustering, marketing analytics, personalization.*

Problem statement. The development of e-commerce is accompanied by increasing competition and growing complexity in customer retention and loyalty-building efforts. One of the most important tools in this process is consumer segmentation, which makes it possible to identify homogeneous customer groups and develop effective marketing strategies. Traditionally, RFM analysis is used for this purpose, based on three indicators: recency of the last purchase (Recency), frequency of purchases (Frequency), and the monetary value of the customer (Monetary).

However, the use of the classical RFM model has a few limitations. It does not consider consumers' demographic characteristics, their behaviour in the digital environment, their response to marketing campaigns, and other factors that directly influence customer loyalty and long-term value. This reduces segmentation accuracy and limits companies' ability to personalize communications and improve the effectiveness of marketing activities.

The need to overcome these limitations highlights the importance of developing advanced segmentation models that combine transactional, behavioural, and demographic variables, enabling the formation of more informative customer groups for practical use in customer relationship management systems.

Analysis of recent research and publications. The classical RFM (Recency, Frequency, Monetary) model is described in both scientific and applied literature [1; 2]. It is used for customer segmentation in retail and e-commerce, allowing companies to identify active and profitable buyers. However, its limitations are associated with the exclusion of behavioural and demographic characteristics [2; 3].

Modern studies propose various modifications, including the expansion of variables (e.g., discounted purchases, online channels, variety of purchased goods) and integration with clustering algorithms [4; 5]. Also common are approaches that incorporate additional variables such as LRFMV, RFM-D, etc. [6-12], or time series data [13].

Interest in the application of machine learning methods is growing [14]. In parallel, the issue of personalization is becoming increasingly relevant, as it is recognized as a key factor in enhancing the effectiveness of marketing strategies [15; 16].

Analytical reports on the development of e-commerce in Ukraine and the EU [17-21] confirm the need to implement improved segmentation approaches that consider the specifics of local markets. Thus, the literature reflects a shift from classical transactional models to more complex approaches. At the same time, there is no consensus on the optimal set of variables and clustering methods, which remains a subject of academic discussion.

Identification of previously unresolved parts of the general problem. Despite the availability of a significant body of research, the classical RFM model remains limited, as it does not fully account for customers' behavioural and demographic characteristics. Most studies focus on modifying individual parameters or applying various clustering methods, but a comprehensive approach that integrates transactional, behavioural, and socio-demographic variables into a unified segmentation system is still underdeveloped.

Another unresolved issue is the lack of a consistent approach to evaluating segmentation results. In practice, various clustering quality metrics are used, but there is no single criterion that objectively determines the optimal model.

Additionally, in the context of the Ukrainian e-commerce market, there is a shortage of applied research aimed at testing improved segmentation models and adapting them to the specifics of the local environment.

Article objectives. The purpose of the article is to develop and implement an improved customer segmentation model to support marketing decision-making based on extended RFM analysis, considering digital, social, and demographic factors.

To achieve this goal, the following tasks were set:

- to systematize known modifications of the RFM analysis model;
- to develop an extended RFMP-DOV+AIC model and justify the choice of variables;
- to prepare the data and conduct a descriptive analysis of the sample;
- to apply cluster analysis to form customer segments;
- to interpret the results and provide managerial recommendations;
- to assess the effectiveness of the model in comparison with traditional methods;
- to outline directions for the practical implementation of the model in marketing activities.

Research methodology. The methodological basis of the research is the development and testing of an extended customer segmentation model - RFMP-DOV+AIC. The proposed model includes not only the traditional RFM parameters - Recency (R), Frequency (F), and Monetary (M) - but also additional variables:

- PromoScore (P) - customer response to marketing campaigns;
- DiscountPurchases (D) - the number of purchases made with a discount;
- OnlineRatio (O) - the share of online purchases in the total number of transactions;
- Diversity (V) - the diversity of product categories;
- Demographic indicators - age (A), income (I), and number of children (C).

The selection of these variables is driven by the need to overcome the limitations of the classical RFM model, which does not account for behavioural and demographic factors. As a result, the RFMP-DOV+AIC model forms a multidimensional customer profile, enhancing clustering accuracy and increasing the practical value of the results for marketing decision-making.

The study was conducted using the Marketing Campaign Dataset [22], which contains socio-demographic characteristics of customers and information about their purchase behaviour. Data cleaning, sample formation, and descriptive analysis were performed to identify key patterns.

Cluster analysis was carried out using the K-means algorithm to form customer segments, enabling the identification of homogeneous consumer groups. The optimal number of clusters was determined based on the following metrics: SSE, Silhouette index, Calinski-Harabasz index, and Davies-Bouldin index. The sequence of research stages is presented in Figure 1.

The advantages of using the RFMP-DOV+AIC model are that it combines classic transactional indicators with behavioural and demographic characteristics, which allows you to obtain more informative segmentation results. Unlike the basic RFM approach, this model considers customer reaction to promotions, propensity to online shopping, diversity of the consumer basket and socio-demographic profile. This provides increased clustering accuracy, allows you to identify groups of customers with clearly expressed behavioural patterns and increases the practical value of the results for customer relationship management systems. In addition, the model creates opportunities for developing targeted marketing strategies and integration into CRM, which helps reduce customer churn and increase their long-term loyalty.

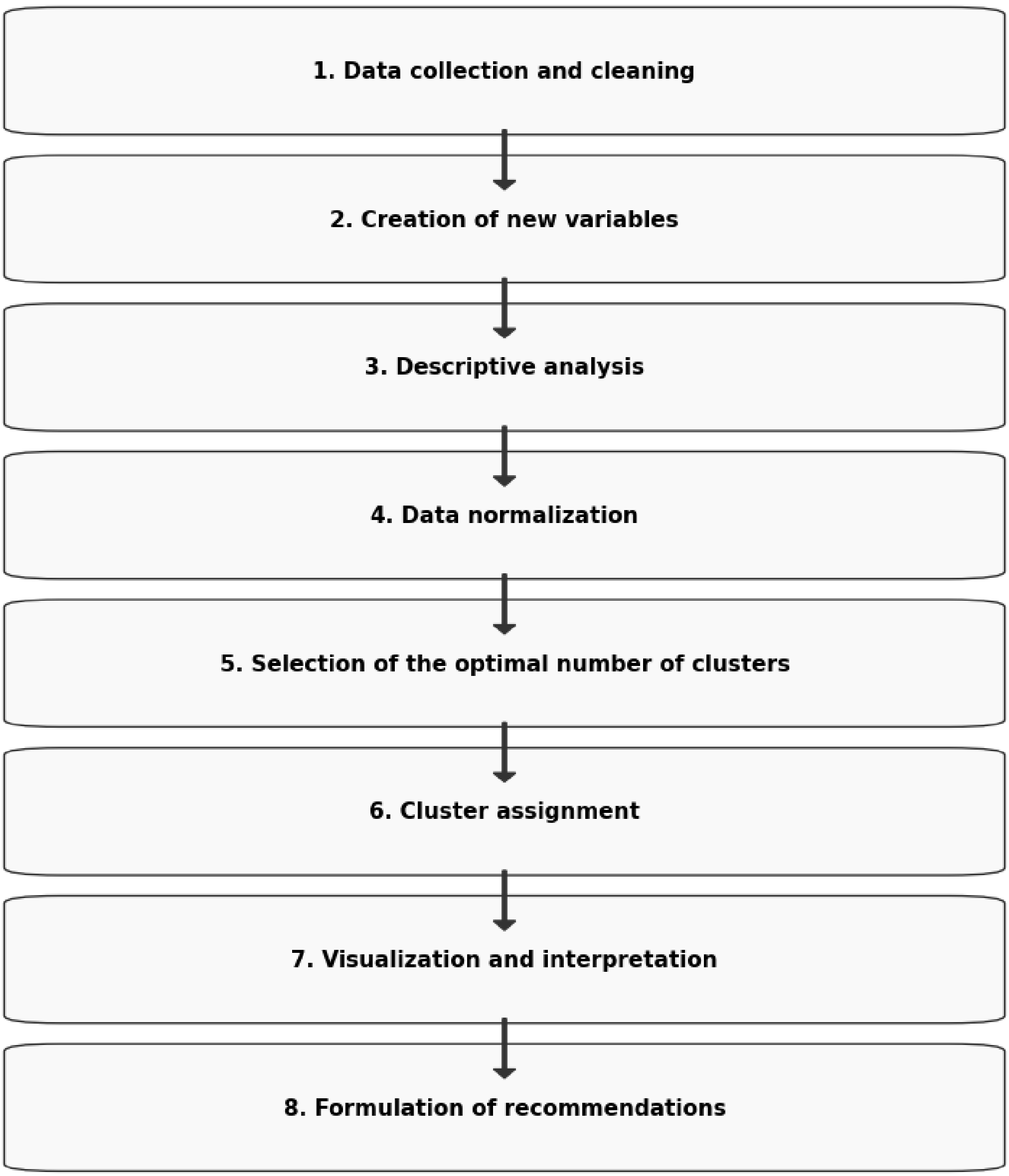

Figure 1. Algorithm for customer segmentation using the RFMP-DOV+AIC model

Source: developed by the authors based on [6–12]

Research Results. At the first stage, an analysis of existing modifications of the RFM model presented in scientific and applied research was conducted. To systematize approaches to segmentation, the main types of RFM models were generalized and summarized (Table 1).

Table 1.

Comparative Characteristics of RFM Analysis Variants and Their Practical Application

Model Name	Additional Parameters	Key Advantages	Potential Limitations	Recommended Areas of Application
RFM (base)	–	Easy to implement, requires only transactional data	Ignores customer tenure, purchase diversity, and volume	Basic analysis across most sectors
LRFM	L – Length (customer tenure)	Allows consideration of the duration of customer interaction	Not applicable for short-term interactions	Subscription services, banking, e-commerce
RFMT	T – Time interval between purchases	Accounts for the regularity of purchasing activity	Requires detailed transaction history	Services with regular sales
RFM-D	D – Diversity	Assesses the breadth of customer interests	Requires product assortment classification	Hypermarkets, retail with a wide product range
LRFMV	V – Volume of purchases	Enables identification of wholesale customers and comparison of purchase volumes	Requires quantitative measurement of products in transactions	B2B segment, wholesale supply
LRFMS	S – Satisfaction	Considers service quality as a factor of loyalty	Requires feedback or survey data	Services where customer experience is critical
RFM+DP	DP – Discount Proportion	Allows assessment of customer price sensitivity	Requires data on all types of discounts	E-commerce, loyalty programs
RFM-C	C – Social Influence	Identifies customers with referral activity	Data on social connections is not always available	Online communities, brand marketing

Source: *developed by the authors*

The analysis results indicate that although existing RFM model modifications partially incorporate additional characteristics, they do not offer a comprehensive approach to customer segmentation. This served as the foundation for developing an improved RFMP-DOV+AIC model, which integrates transactional, behavioural, and demographic variables. This approach enables the construction of a multidimensional customer profile and allows for more accurate segment differentiation.

The proposed model was tested using the Marketing Campaign Dataset [22], which covers the period from July 30, 2012, to June 29, 2014 and includes data on 2,240 customers. After data cleaning and removal of technical records, the final sample consisted of N = 2,209 observations. To ensure the validity of the analysis, the data were normalized, date formats were unified, and outliers were removed.

Additionally, an aggregated variable PromoScore was introduced, calculated as the sum of a customer's positive responses to five marketing campaigns (AcceptedCmp1–AcceptedCmp5). Descriptive statistics confirmed the heterogeneity of the customer base (Table 2). The mean Monetary value was 606.66, with a median of 396.00 and a maximum of 2,525, indicating the presence of a small group of high-spending customers who are strategically important for the business.

Table 2.

Descriptive Statistics

Variable	Count	Mean	Std. Dev	Min	25%	Median	75%	Max
Recency	2209.00	353.48	202.39	0.00	180.00	356.00	529.00	699.00
Frequency	2209.00	12.56	7.21	0.00	6.00	12.00	18.00	32.00
Monetary	2209.00	606.66	602.75	5.00	69.00	396.00	1047.00	2525.00
PromoScore	2209.00	0.74	1.45	0.00	0.00	0.00	1.00	6.00
DiscountPurchases	2209.00	2.32	1.92	0.00	1.00	2.00	3.00	15.00
OnlineRatio	2209.00	0.33	0.12	0.00	0.25	0.33	0.40	1.00
Diversity	2209.00	5.43	0.92	2.00	5.00	6.00	6.00	6.00
Age	2209.00	34.09	11.70	7.00	26.00	33.00	44.00	63.00
Income	2209.00	52221.80	25193.00	1730.00	35196.00	51373.00	68487.00	666666.0
Children	2209.00	0.95	0.75	0.0	0.00	1.00	1.00	3.00

Source: *developed by the authors*

The Recency and Frequency indicators also showed significant dispersion: some customers made purchases regularly, while others completed only one transaction with a long-time gap. PromoScore and DiscountPurchases had low average values but high maximums, suggesting the existence of a narrow segment of promo-sensitive customers.

In terms of the demographic profile, many customers belonged to the 26–44 age group, while income distribution was asymmetric, indicating the presence of both low- and high-income segments.

The correlation analysis (Figure 2) revealed a strong positive relationship between Frequency and Monetary (r ≈ 0.82), reflecting the expected link between purchase frequency and total spending. A significant correlation was also observed between Income and Monetary (r ≈ 0.67), indicating that higher-income customers tend to spend more.

Meanwhile, PromoScore and DiscountPurchases demonstrated a moderate level of interdependence (r ≈ 0.44), suggesting that customers who respond positively to marketing campaigns are also more likely to take advantage of discounts.

At the same time, the correlations between OnlineRatio–Age and PromoScore–OnlineRatio were weak, which supports the inclusion of these variables in the model. Their low correlation with other features indicates that they contribute unique information and help reduce the risk of multicollinearity.

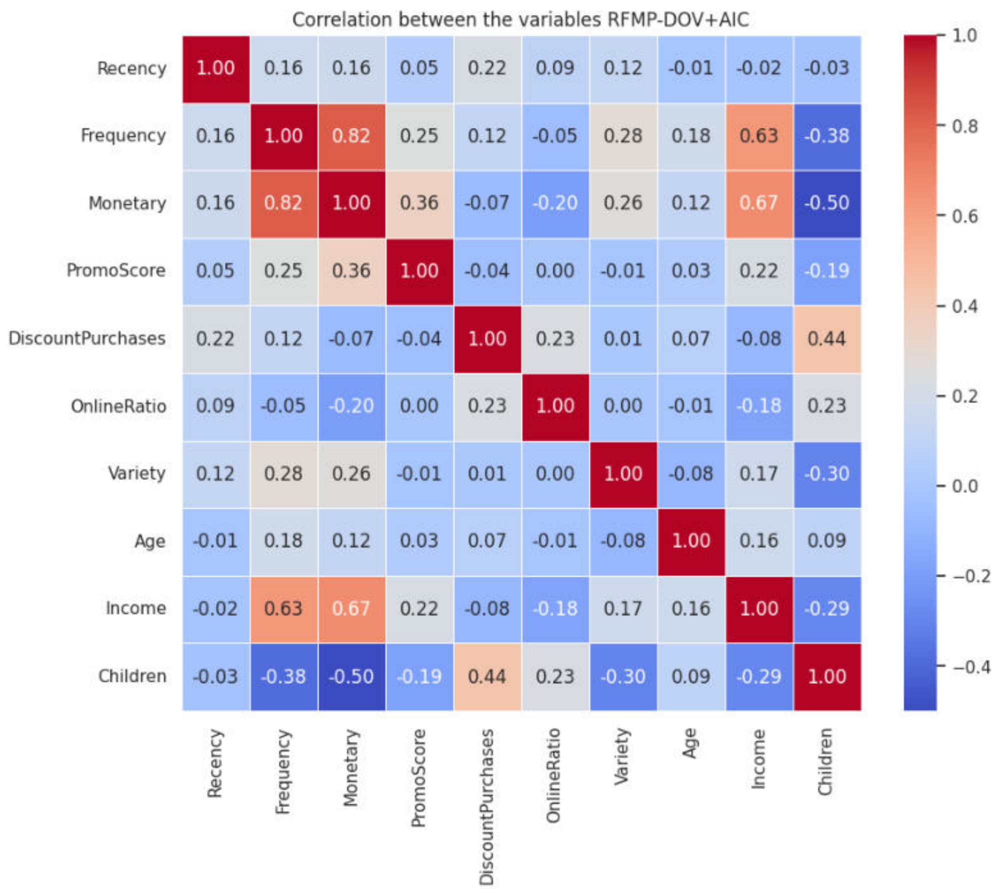

Fig. 2. Heatmap of correlations between variables in the RFMP-DOV+AIC model

Source: developed by the authors in Python environment (seaborn, matplotlib)

The optimal number of clusters (k) was determined through a comprehensive analysis of several metrics: SSE (elbow method), Silhouette Score, Calinski–Harabasz index (CH), and Davies–Bouldin index (DB). The elbow in the SSE curve was clearly observed around k = 7, indicating a diminishing return in inertia reduction with the addition of more clusters. The maximum value of the Silhouette coefficient also corresponded to seven clusters, confirming their internal cohesion and sufficient separation.

Additional validation was provided by the Calinski–Harabasz index, which remained high in the range of k = 5–7, and the Davies–Bouldin index, which reached its minimum near k = 7. The convergence of these indicators supported the selection of k = 7 as the optimal compromise solution. The corresponding curves are presented in Figure 3.

Subsequent clustering was performed using the K-means algorithm applied to the standardized variables of the RFMP-DOV+AIC model: Recency, Frequency, Monetary, PromoScore, DiscountPurchases, OnlineRatio, Diversity, Age, Income, and Children. Standardization ensured that variables with different scales did not dominate the clustering process and that the calculations remained valid.

As a result, seven customer segments were identified. The segment sizes were uneven: the largest cluster comprised approximately one-third of the sample, while some clusters represented less than 10% of the total. This asymmetry is typical for e-commerce customer bases and reflects the presence of both broad operational segments and narrow, yet strategically important, customer groups.

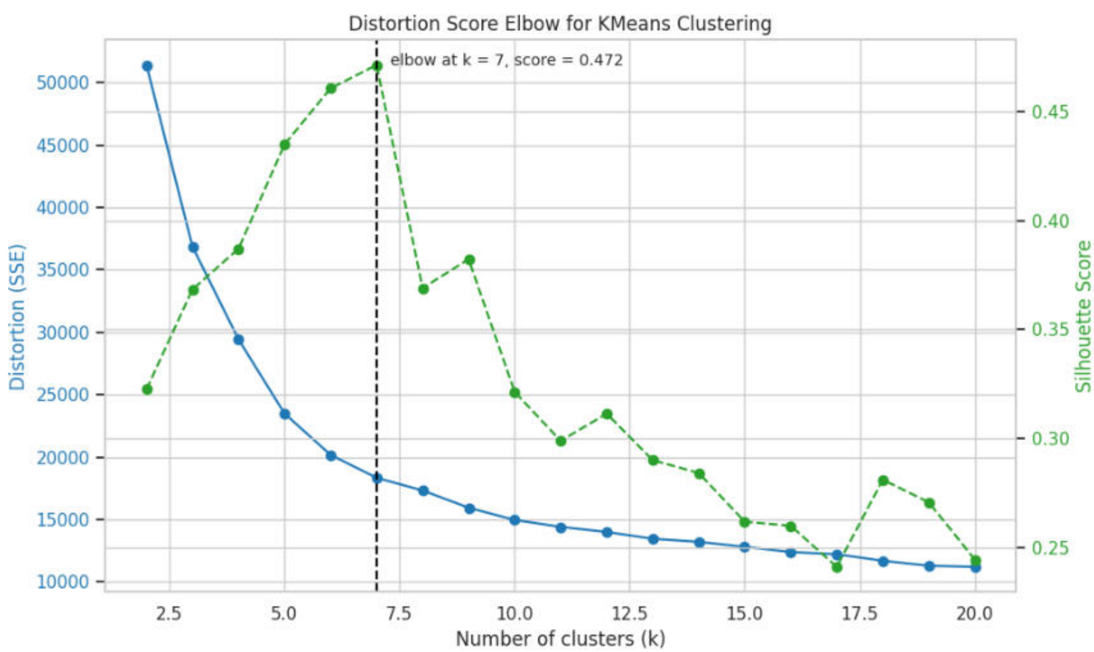

Fig. 3. Elbow Method and Silhouette Score Method

Source: developed by the authors in Python environment (seaborn, matplotlib)

Seven clusters were described based on the average values of the model variables and visualizations; for each, key attributes and marketing management directions were identified:

Segment 1: high-value loyal customers. The highest Monetary and Frequency values, a short period since the last purchase, medium or high PromoScore. Loyalty programs, premium services, and personalized incentives are recommended.

Segment 2: loyal customers with an average level of spending. High frequency of purchases and average spending. PromoScore confirms sensitivity to promotions, which opens opportunities to increase the average check through cross-selling and bundled offers.

Segment 3: new active customers. Low frequency and value of purchases, usually the first or second transactions. The main task is to convert them into regular customers through welcome bonuses and incentives for repeat purchases.

Segment 4: frequent thrifty buyers. Often buy low-cost goods, focusing on promotional offers (high PromoScore). It is advisable to increase the average check using combined promotions and bonus programs.

Segment 5: active online customers. High frequency and a significant share of online transactions. These are younger or technologically active consumers for whom digital tools are effective: email marketing, push notifications, mobile applications.

Segment 6: passive ("dormant") customers. A long period without purchases, low Frequency, Monetary value, and PromoScore. Reactivation campaigns and additional analysis of the reasons for churn are needed.

Segment 7: low-value irregular customers. Low frequency and spending, high Recency. These are occasional buyers who are not a strategic priority but can be attracted using mass incentive tools.

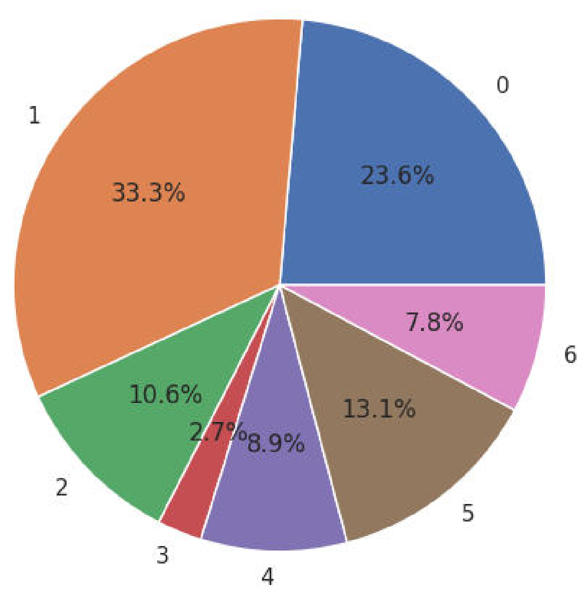

Fig. 4. Share of Customers in Each Cluster

Source: developed by the authors in Python environment (seaborn, matplotlib)

Thus, the application of the RFMP-DOV+AIC model made it possible to distinguish segments with different behavioral patterns and to form a basis for targeted marketing strategies.

Conclusions. As a result of the study, the feasibility of using the extended customer segmentation model RFMP-DOV+AIC, which combines transactional, behavioral, and demographic characteristics, was substantiated. Unlike traditional approaches, this model allowed us to account not only for classic indicators of purchasing activity but also for additional parameters that reflect consumer response to promotions, propensity for online shopping, variety of purchased goods, and the socio-demographic profile of customers. This ensured the formation of more expressive and methodologically sound segments.

The application of the model demonstrated increased clustering accuracy based on the results of the Silhouette Score, SSE, Calinski–Harabasz, and Davies–Bouldin metrics, confirming its effectiveness in practical use. The resulting segments are characterized by significant heterogeneity, and their detailed analysis allowed us to identify both groups of high-value loyal customers and segments with low value that require reactivation measures. This creates a basis for the development of differentiated marketing strategies adapted to the behavioral and socio-economic characteristics of each group.

The practical significance of the study lies in the fact that the proposed model can be used as an effective tool for managing the customer base in the field of e-commerce. Its application allows not only for increased effectiveness of marketing activities but also for optimized resource allocation, focusing efforts on the most promising consumer segments. Thus, the RFMP-DOV model has proven its ability to enhance the effectiveness of personalized strategies and strengthen the competitive position of companies in a dynamic digital environment.

The results confirm the feasibility of using the improved RFMP-DOV+AIC model to increase the effectiveness of personalized strategies in the field of e-commerce.

Prospects for further research. Further development of the study should be directed towards the integration of the RFMP-DOV+AIC model into customer relationship management (CRM) systems. This will allow for automated segmentation of consumers in real time, which will significantly increase the speed and quality of management decision-making. Using the model in a CRM environment opens up opportunities for building personalized communication scenarios adapted to the specifics of each segment.

An important direction is the integration of RFMP-DOV+AIC with analytical modules of business intelligence systems, which will provide a combination of statistical analysis and data visualization, simplifying the interpretation of results for managers. Special attention should be given to developing mechanisms for automatic cluster updates as consumer behavior changes, which will allow for early detection of customer churn signals and timely application of reactivation tools.

In addition, the use of the RFMP-DOV+AIC model in combination with predictive analytics is promising, as it enables forecasting the future value of a customer and their reaction to marketing stimuli. This creates a foundation for implementing more effective loyalty programs, dynamic pricing, and personalized promotions within e-commerce.

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МОДЕЛЮВАННЯ ПРОЦЕСУ СЕГМЕНТАЦІЇ КЛІЄНТІВ З ВИКОРИСТАННЯМ РОЗШИРЕНОГО RFM АНАЛІЗУ ДЛЯ ПІДТРИМКИ ПРИЙНЯТТЯ РІШЕНЬ У МАРКЕТИНГУ

У сучасних умовах розвитку електронної комерції однією з ключових проблем є необхідність ефективної сегментації клієнтів для підвищення результативності маркетингових стратегій та забезпечення стабільності взаємовідносин із покупцями. Традиційний RFM-аналіз, що ґрунтується на показниках давності, частоти та вартості покупок, активно використовується у практиці, проте має певні обмеження, зокрема неврахування демографічних та поведінкових характеристик клієнтів, що знижує точність сегментації.

Метою дослідження є розробка та перевірка ефективності удосконаленої моделі сегментації клієнтів RFMP-DOV+AIC, яка поєднує класичні параметри RFM з додатковими ознаками: різноманітність покупок, характеристики онлайн-поведінки та оцінку довгострокової цінності клієнта.

Методологічну основу дослідження становлять методи економіко-математичного моделювання, статистичного аналізу, кластеризації та алгоритми машинного навчання, реалізовані у середовищі Python. Для емпіричної перевірки використано відкритий набір даних із платформи Kaggle, що містить інформацію про транзакції інтернет-магазину.

У процесі дослідження здійснено попередню обробку даних, нормалізацію показників та формування ознак для моделі. На основі алгоритму K-means побудовано сегменти клієнтів, які оцінено за допомогою наступних показників: SSE, індекс Silhouette, індекс Calinski-Harabasz та індекс

Davies-Bouldin. Узгоджені результати цих показників дозволяють обґрунтовано вибрати кількість кластерів, що гарантує внутрішню однорідність та відстань між кластерами. Результати підтвердили, що розширена модель забезпечує більш чітке групування клієнтів та дозволяє виокремити сегменти з урахуванням поведінкових і демографічних характеристик, що недоступно для класичного RFM-аналізу.

Практичне значення отриманих результатів полягає у можливості інтеграції моделі RFMP-DOV+AIC у CRM-системи підприємств електронної комерції для оптимізації маркетингових комунікацій, зниження відтоку клієнтів та підвищення рівня їхньої лояльності. Запропонований підхід може бути використаний як у наукових дослідженнях у сфері маркетингової аналітики, так і в практичній діяльності компаній, що працюють на ринку e-commerce.

Ключові слова: *RFM-аналіз, електронна комерція, кластеризація, маркетингова аналітика, персоналізація.*