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A method for B2B customer classification based on the utility-weighted temporal profile in E-commerce systems

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ABSTRACT

Purpose: The study addresses the problem of predictive content personalization in business-to-business e-commerce systems, where classical recommendation and segmentation approaches demonstrate limited effectiveness due to the financial heterogeneity, cyclic purchasing behavior, and long-term nature of customer interactions. The purpose of the research is to develop a method for classifying business-to-business customers based on a utility-weighted temporal customer profile, which makes it possible to generate more relevant and timely predictive offers. **Objectives:** The proposed method is designed as the third stage of an analytical pipeline that extends utility pattern mining and temporal analysis of stable purchasing cycles. **Methods:** At the first stage, financially significant product patterns are identified using the Utility Pattern Growth approach. At the second stage, the temporal stability of repeated purchases is assessed through inter-purchase time intervals and the coefficient of variation. At the third stage, the obtained pattern-level results are aggregated into an integrated customer profile that combines the average purchasing cycle, cycle stability, and average transaction value. These features are normalized and used for customer clustering, after which customer classes are integrated into the mechanism for determining an individual communication trigger window. **Results:** The experimental validation was performed on historical transactional and behavioral data from the business-to-business e-commerce platform "Baza Vzuttya" for the period from two thousand twenty-two to two thousand twenty-five. The comparative experiment included four recommendation scenarios: a baseline frequency-based approach, a utility-weighted approach, a utility-temporal approach, and an integrated approach with customer classification. The results show a consistent increase in recommendation conversion from three point nine one percent in the baseline scenario to fifteen point nine one percent in the integrated scenario. At the same time, the number of generated recommendations decreased from nine hundred and twenty to two hundred and twenty, which indicates a reduction in irrelevant communications. The integrated scenario achieved the highest average revenue per recommendation, amounting to six thousand nine hundred and nine point zero nine hryvnias. **Conclusions:** The obtained results confirm that the proposed method improves the accuracy, timeliness, and economic validity of personalized predictive offers in business-to-business e-commerce systems.

Keywords: Data mining; B2B e-commerce systems; classification methods; content personalization; recommendation systems; transactional-behavioral data

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INTRODUCTION

The current stage in the development of global and domestic digital business is characterized by rapid and large-scale growth of the business-to-business e-commerce segment (B2B e-commerce) [1], [2], [3]. Both globally and within the Ukrainian domestic market, the volumes of transactions between enterprises through specialized digital platforms demonstrate double-digit annual growth rates [1], [2]. At the same time, an analysis of the architectural solutions of modern e-commerce systems shows that this growth is predominantly extensive [1], [2]. It is ensured by scaling cloud capacities and increasing communication-channel bandwidth, whereas the analytical tools used for customer interaction remain technologically limited [1], [2].

The main reason for this methodological gap is that existing intelligent recommender systems and content personalization algorithms [4], [5] deployed on B2B platforms were historically developed and optimized for the specifics of the mass retail market (B2C). Built on the principles of frequency analysis, collaborative filtering [6], [7], and the discovery of classical association rules and sequential patterns [8], [9], these systems are oriented toward emotional, high-frequency purchases and averaged behavioral patterns of the mass consumer. The direct transfer of B2C technologies to the B2B segment ignores the fundamental properties of business interaction: the rationality of decision-making by counterparties, the long customer life cycle, uneven cyclicality, and, most importantly, the critical differentiation of goods according to their financial utility for enterprise turnover [3], [10], [11]. As a result, classical recommendation modules demonstrate low relevance and generate excessive information noise (spamming) instead of providing accurate and timely predictive offers for inventory replenishment. This creates an urgent need to develop specialized data mining methods adapted to the conditions of the B2B segment [3], [12].

LITERATURE REVIEW AND PROBLEM STATEMENT

Existing personalization tools in e-commerce systems rely primarily on recommender systems, association rule mining, and sequential pattern mining. [6], [8], [9] However, their direct use in B2B platforms is limited because B2B purchases are rational, financially heterogeneous, cyclic, and connected with long-term customer relationships. Therefore, the application of classical FP-Growth and related frequency-based methods [13], [14], [15] leads to several methodological gaps: financial blindness of binary models, combinatorial growth under weighting, temporal blindness, identification discreteness, and the absence of differentiated customer interaction strategies [3], [12], [16].

To address these limitations, the authors previously proposed a two-stage analytical pipeline for mining transactional-behavioral B2B data [3], [10], [11]. The first stage is based on a utility-weighted transaction model and the UP-Growth method. [17], [18], [19] In this model, a transaction is treated not only as a set of items but also as a carrier of financial value: the utility of an item is calculated through its quantity and individual price, while the transaction utility and Transaction-Weighted Utilization (TWU) are used to identify financially significant itemsets. This makes it possible to select product patterns that are important for business turnover rather than merely frequent combinations.

The second stage is based on a temporal sequence model and the UT-Growth method. [9], [20], [21] For each financially significant pattern and customer, the method analyzes the sequence of purchase dates, inter-purchase time intervals, the average purchase cycle, standard deviation, and the coefficient of variation. If the purchase cycle is sufficiently stable, the system determines an active offer window and the communication trigger date in advance of the expected repeat purchase. As a result, the pipeline produces personalized triggers for specific customers, product patterns, and time windows.

Thus, compared with classical FP-Growth, the UP-Growth and UT-Growth combination changes both the criterion of significance and the nature of the result. Frequency-based mining produces global rules for an averaged customer, whereas the proposed utility-weighted temporal approach produces individualized predictive offers based on financial significance and temporal stability. Nevertheless, the output of the two-stage pipeline remains too atomic for managerial use, because it describes separate customer-pattern triggers rather than holistic customer profiles.

The traditional RFM model is widely used for customer segmentation, but in the B2B context it remains mainly retrospective. Recency fixes only the time since the last transaction, Frequency counts transactions without measuring the stability of intervals, and Monetary reflects gross historical revenue without identifying the structure of value-generating product patterns. Therefore, the problem is to move from static segmentation to dynamic customer classification based on integrated financial-temporal characteristics that can be directly used in predictive content personalization.

In this context, the term utility has methodological importance because it shifts the analysis from the binary occurrence of an item to the business value that the item creates inside a transaction. For B2B platforms, two items with the same frequency may have completely different managerial relevance if their prices, ordered quantities, and contribution to turnover differ substantially. Therefore, the use of utility-oriented pattern mining makes it possible to avoid recommendations that are statistically frequent but economically weak [22], [23], and to focus instead on product combinations that are capable of influencing revenue and replenishment decisions.

The temporal component is equally important for B2B interaction. Unlike retail purchases, business purchases are often connected with production, resale, logistics, or planned inventory replenishment. Consequently, the same product

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pattern may be useful only if the offer is generated inside an appropriate time window. A recommendation created too early may be ignored, whereas a recommendation created too late may lose its practical value because the customer has already replenished the stock or changed the supplier. For this reason, inter-purchase intervals, cycle stability, and the coefficient of variation become necessary elements of the predictive logic rather than auxiliary statistics.

However, even a utility-weighted and temporally verified trigger remains a micro-level analytical result. It answers the questions of what product pattern should be offered to which customer and approximately when, but it does not directly describe the customer as a business entity. In practice, a B2B platform needs to know whether a counterparty is financially significant, whether its purchasing behavior is stable, and whether communication with this counterparty should be more preventive or more conservative. This explains the need to aggregate pattern-level results into an integrated customer profile.

The proposed transition from a set of atomic triggers to a utility-weighted temporal customer profile also addresses the limitations of threshold-based segmentation. [24], [25], [26] In classical RFM analysis, segment boundaries are often defined by expert rules or empirical quantiles, which may be convenient for descriptive analytics but insufficient for predictive personalization. In contrast, the profile used in this study is built from the internal results of the analytical pipeline itself: the average purchase cycle reflects temporal behavior, the stability indicator reflects predictability, and average transaction value reflects financial capacity.

Thus, the problem statement is not reduced to the selection of another clustering algorithm. The central issue is the construction of features that are meaningful for B2B personalization and compatible with the previously obtained utility-temporal triggers. [3], [10], [11] The classification method must preserve the economic and temporal interpretation of the pipeline output and convert it into customer classes that can be used for managing the communication trigger window. This provides the logical basis for considering customer classification as the third stage of the overall predictive personalization pipeline.

THE AIM AND OBJECTIVES OF THE RESEARCH

The aim of this study is to develop a method for classifying B2B customers of e-commerce systems based on a utility-weighted temporal customer profile formed as a result of implementing a two-stage pipeline for analyzing B2B customer transactional-behavioral data. This made it possible to implement a three-stage pipeline for generating individual predictive offers depending on the determined customer class and to increase the final efficiency of predictive content personalization.

The research objectives are as follows:

– to conduct a systematic analysis of the capabilities of the proposed two-stage pipeline for generating personalized offers for B2B customers;

– to formalize the utility-weighted temporal customer profile as a tuple of aggregate features;

– to formalize the main stages of the B2B customer classification method, namely profile feature normalization, B2B customer clustering, and determining the size of the individual trigger window by classes;

– to develop a B2B customer classification method as an add-on to the two-stage analytical pipeline;

– to conduct an experimental study of content personalization efficiency in an e-commerce system through the implementation of a three-stage pipeline for generating individual predictive offers based on the B2B customer classification method.

THE RESEARCH MATERIALS AND METHODS

Based on the analysis of the authors' previous works, it can be concluded that the use of the two-stage pipeline made it possible to move from abstract frequency-based relationships to the generation of precise individual communication triggers of the form [3], [10], [11]:

$$\langle C_j, X, T_{trigger} \rangle \tag{1}$$

where $T_{trigger}$ is the calculated moment in time when the system must perform predictive content personalization, for example, send an offer for inventory replenishment.

However, the direct use of this tuple for managing the interface and content of a B2B platform has three critical practical disadvantages:

1. Extreme discreteness and atomicity of data. The trigger tuple operates at the level of a separate product/pattern X. Thus, for a large B2B customer, the system generates a set of isolated triggers for different product groups, while platform management cannot effectively interact with such atomic data. Therefore, an integrated B2B customer profile is required.

2. Strategic monotony. Due to the calculated triggers, the e-commerce system knows when and

what to offer, but it does not understand who it is dealing with in a broader business context. Segmentation of B2B customers using RFM analysis does not provide effective models for forecasting. This makes it impossible to differentiate service and account for the loyalty context, for example, to allocate priority delivery windows or special interface display conditions for the VIP segment.

3. Rigidity of time boundaries. The value $T_{trigger}$ is a discrete point. If the customer's logistics chain experiences a random shift of several days, the system records an anomaly, which makes it vulnerable to random disruptions. For flexible communication management, it is necessary to move from a trigger point to a dynamic expectation window, the width of which should depend on the customer's overall reliability class.

To overcome these disadvantages, it is necessary to aggregate the set of atomic customer triggers into a single utility-weighted temporal B2B customer profile (UW-TCP). This means moving from the micro-level of patterns to the macro-level of the customer through the transformation of the tuple of the following form: $\langle C_j, X, T_{trigger}\rangle \rightarrow \langle \bar{\mu}_j, \overline{CV}_j, \overline{U(T)}_j\rangle$. This process is considered in more detail below.

Formalization of the utility-weighted temporal customer profile. For each identified customer C_j that has a sequence of at least min_dates stable transactions of at least one utility pattern, an individual feature vector $f_j = (\bar{\mu}_j, \overline{CV}_j, \overline{U(T)}_j)$ is formed. Only those patterns that, according to the results of temporal verification, were recognized as sufficiently regular are included in this analysis, that is, they have a coefficient of variation $CV \leq \gamma$ and can be used to generate predictive triggers [27], [28], [29]. This means that the customer profile is built not on the customer's entire order history but only on those product sets for which stable temporal recurrence and economic significance for the B2B platform have been identified.

Each component of vector f_j is aggregated over all stable patterns of the customer. The indicator $\bar{\mu}_j$ characterizes the generalized average repeat-purchase cycle of the customer, that is, it reflects the typical time interval after which the customer returns to purchasing significant product sets. The indicator $\overline{CV}_j$ describes the average level of stability of such purchase cycles and makes it possible to distinguish customers with regular behavior from customers with more chaotic or situational orders.

The indicator $\overline{U(T)}_j$ reflects the average financial capacity of the customer's transactions associated with stable utility patterns and therefore characterizes the customer's economic significance for the platform. Thus, the formed vector f_j is a utility-weighted temporal profile of a B2B customer. Unlike classical retrospective segmentation indicators, this profile combines three important characteristics of purchase behavior: periodicity, stability, and financial value.

Feature 1. The average purchase cycle $\bar{\mu}_j$ characterizes the typical duration between repeated purchases of the customer's stable patterns and is defined as follows [11]:

$$\bar{\mu}_j = \frac{1}{|\mathcal{P}_j^*|}\sum_{X\in\mathcal{P}_j^*}\mu(X, C_j), \quad (2)$$

where $\mathcal{P}_j^*$ is the set of stable utility patterns of customer C_j, that is, patterns for which $CV(X, C_j) \leq \gamma$, $\mu(X, C_j)$ is the average purchase cycle of itemset X by customer C_j.

The feature $\bar{\mu}_j$ reflects the customer's planning horizon: a small value of $\bar{\mu}_j$ (less than 30 days) is typical of customers with frequent inventory replenishment, whereas a large value of $\bar{\mu}_j$ (more than 90 days) is typical of seasonal or large wholesale customers.

Feature 2. The average cycle stability $\overline{CV}_j$ characterizes the regularity of the customer's purchase behavior and is defined as follows [27-29]:

$$\overline{CV}_j = \frac{1}{|\mathcal{P}_j^*|}\sum_{X\in\mathcal{P}_j^*}CV(X, C_j), \quad (3)$$

where $CV(X, C_j)$ is the coefficient of variation of the intervals for pattern X and customer C_j.

Since only patterns with $CV < \gamma$ are included in the set $\mathcal{P}_j^*$, the value $\overline{CV}_j$ lies in the range $[0; \gamma]$. A customer with $\overline{CV}_j$ approximately equal to zero demonstrates strictly regular purchases, for example, according to a production schedule, whereas a customer with $\overline{CV}_j$ close to gamma demonstrates a moderately unstable cycle.

Feature 3. The average transaction value $\overline{U(T)}_j$ characterizes the customer's financial capacity and is defined as follows [17], [19]:

$$\overline{U(T)}_j = \frac{1}{|\mathcal{P}_j^*|}\sum_{X\in\mathcal{P}_j^*}\overline{U(T)}_j(X, C_j), \quad (4)$$

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where $\overline{U(T)}_j(X, C_j)$ is the average value of a transaction with pattern X for customer C_j, $U(T)$ is the full transaction value.

Formalization of the main stages of the B2B customer classification method. The values of the three average features have fundamentally different scales. Therefore, direct application of the k-means clustering algorithm to features with different scales leads to the dominance of the feature with the largest absolute spread, for example $\overline{U(T)}_J$, which distorts the results. To eliminate this effect, Min-Max Scaling is applied, whereby each feature is transformed to the range $[0; 1]$ according to the following expression, where values of $\bar{\mu}_j$, $\overline{CV}_j$ and $\overline{U(T)}_J$ are used as the function values:

$$\tilde{f}_{ij} = \frac{f_{ij} - min_j(f_i)}{max_j(f_i) - min_j(f_i)}, \quad (5)$$

where $\tilde{f}_{ij}$ is the normalized value of the i-th feature for customer C_j, f_{ij} is the original value, $max_j(f_i)$ and $min_j(f_i)$ are the maximum and minimum values of feature f_i over the entire set of classified customers.

After normalization, the formed feature matrix $\tilde{F} \in \mathbb{R}^{n\times 3}$, where n is the number of customers selected by the utility-weighted temporal pipeline, is passed to the k-means clustering algorithm [25-26]. According to the algorithm, the total within-cluster variance is minimized by the following expression:

$$J = \sum_{l=1}^{K} \sum_{C_j \in \mathcal{C}_l} \|\tilde{\mathbf{f}}_j - \boldsymbol{v}_l\|^2, \quad (6)$$

where J is the objective function (total within-cluster inertia), $K = 3$ is the number of clusters, $\mathcal{C}_l$ is the set of customers belonging to the l-th cluster, $\boldsymbol{v}_l$ is the centroid of the l-th cluster, $\|\cdot\|$ is the Euclidean distance in the normalized feature space.

As a result of clustering, each B2B customer in the e-commerce system is assigned a value of coefficient k of the previous section, which determines the date of communication trigger activation $T_{trigger}$. This value significantly affects the date assigned to the predictive offer. According to the developed two-stage analytical pipeline, coefficient k was assigned experimentally and did not depend on the B2B customer cluster.

After the clustering procedure, it becomes possible to determine the width of the communication trigger window $window_j$ in the trigger activity verification formula more reasonably according to the following expression:

$$window_j = WINDOW \times k_j, \quad (7)$$

where $WINDOW$ is the width of the base trigger window in days, k_j is the coefficient assigned to customer C_j based on the determined class.

Identification of classes after the clustering stage is performed automatically according to the $\overline{U(T)}$ value of the centroid; that is, the cluster with the highest $\overline{U(T)}$ value is recognized as the premium class, while the cluster with the lowest value is regarded as belonging to the economy class.

Development of the B2B customer classification method. Considering the above formalizations of obtaining the features of the utility-weighted temporal profile of a B2B customer, their normalization, as well as clustering and identification procedures for classifying B2B customers in order to integrate the results into the communication trigger generation system, the stages of the B2B customer classification method are defined. The list of method stages is given in Table 1.

It should be noted that the developed method functions exclusively as an add-on to the UP-Growth and UT-Growth methods proposed by the authors and does not require any additional data. The new features $\bar{\mu}_j$, CV_j and $\overline{U(T)}_J$, which make up the utility-weighted temporal profile of a B2B customer, are aggregates of already available intermediate results. This makes the B2B customer classification method the third stage of the pipeline for generating predictive offers for B2B customers. In this case, one can speak of the computational efficiency and architectural integrity of using this pipeline in an e-commerce system.

The difference between the developed B2B customer classification method and standard RFM analysis is fundamental: instead of using retrospective indicators (recency, frequency, amount), a utility-weighted temporal profile of the B2B customer is created based on the characteristics of forecast cycle, stability, and financial capacity, which is then used to determine customer classes for their integration into the communication trigger generation system [24], [30].

This provides a meaningful link between the customer class and the interaction strategy through a mathematically substantiated assignment of the trigger window width according to customer value, rather than through a subjective definition of segmentation thresholds as in standard RFM analysis.

Table 1. **Description of the stages of the B2B customer classification method**

Step	Action description	Input data	Result
1	Obtaining a list of personalized triggers of the form $\langle C_j, X, T_{trigger}\rangle$	UT-Growth results ($CV \leq \gamma$)	Set $\mathcal{P}_j^*$ for each customer C_j
2	Calculating features according to expressions (2)-(4)	$\mathcal{P}_j^*$, values of μ, CV, and $U(T)$	Feature matrix $\mathbf{F} \in \mathbb{R}^{n\times 3}$
3	Normalization according to expression (5)	$\mathbf{F}$	Normalized matrix $\tilde{\mathbf{F}}$
4	k-means clustering according to expression (5), $K = 3$	$\tilde{\mathbf{F}}$	Cluster labels for each customer C_j
5	Cluster identification by centroid values $\overline{U(T)}$	Cluster centroids	Classes: Premium / Standard / Economy
6	Determining the coefficient k_j according to the identified class	Cluster labels	Dictionary $C_j \rightarrow k_j$
7	Calculating the width of the individual window according to expression (7)	k_j, $WINDOW$	$window_j$ for each customer
8	Checking trigger activity with the individual $window_j$	T_{last}, μ, $window_j$	Final list of predictive offers

***Source*: compiled by the authors**

RESULTS OF THE RESEARCH AND THEIR DISCUSSION

The proposed B2B customer classification method was experimentally evaluated as the third component of the utility-weighted temporal pipeline for predictive offer generation. The study used historical transactional-behavioral data from the «Baza Vzuttya» B2B e-commerce platform for 2022-2025. The dataset contained 106,378 product-item rows corresponding to 29,352 B2B orders, 2,525 customers, 56,197 unique SKUs, and a total order amount of UAH 416,277,239.52. By year, the dataset included 7,666 orders in 2022, 8,326 in 2023, 7,587 in 2024, and 5,773 in 2025. The temporal distribution of order amounts is shown in Fig. 1.

At the order level, the average transaction amount was UAH 14,182.24, the median amount was UAH 7,320.00, the average number of SKUs per order was 3.62, the median was 2 SKUs, and the maximum number of SKUs in one wholesale order was 252. Before the experiments, the data were cleaned, unified by type, transformed from order lines into transactions, grouped into customer histories, filtered for excessively long transactions, and chronologically ordered. A time-based split was then applied in an 8:2 ratio: the training sample contained 22,826 orders and the test sample contained 5,707 orders.

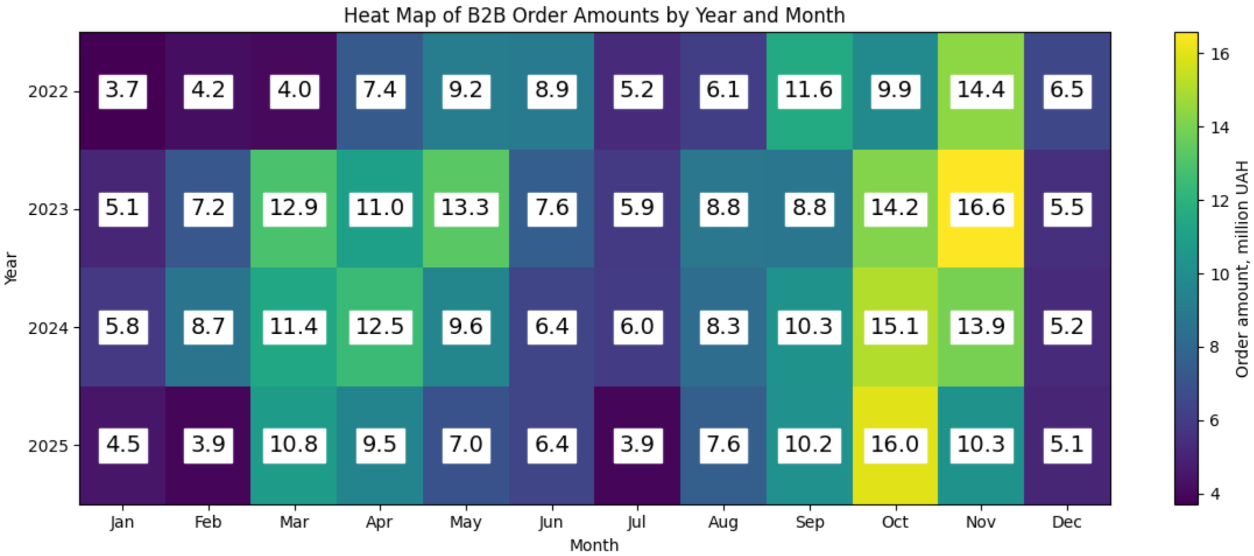

Fig. 1. **Heat map of B2B order amounts by years and months, million UAH**
***Source*: compiled by the authors**

Recommendation effectiveness was evaluated by a compact metric system that combined behavioral and economic indicators. A recommendation was considered successful if the corresponding customer purchased the recommended product set or its relevant part within the test horizon. The evaluation included recommendation conversion, covered revenue, average revenue per recommendation, the share of covered test transactions, and the share of covered test revenue.

The comparative experiment included four scenarios. Scenario S_0 represented a baseline frequency-based approach, where recommendations were formed only from frequent itemsets. Scenario S_1 added the financial weight of product patterns. Scenario S_2 additionally verified temporal recurrence of purchases. Scenario S_3 implemented the full integrated approach, in which the communication window was adapted according to the B2B customer class determined from the utility-weighted temporal profile. Together, these scenarios provide a step-by-step comparison of the baseline, utility-weighted, temporal, and fully integrated recommendation logic.

The experimental results confirm the cumulative effect of the proposed pipeline components.

The baseline scenario S_0 generated the largest number of recommendations (920), but its conversion rate was only 3.91 %, which indicates the limitations of purely frequency-based association logic in B2B personalization. Scenario S_1 reduced the number of recommendations to 760 and increased conversion to 5.39 %, confirming the importance of utility weighting for selecting economically significant product patterns. Scenario S_2 reduced the recommendation set to 260 but increased conversion to 12.69 %, showing that temporal verification acts as a strong quality filter and improves the timing of predictive offers.

The best result was achieved by the integrated scenario S_3. It generated 220 recommendations, of which 35 were successful; conversion reached 15.91 %, and the average revenue per recommendation was UAH 6,909.09. Compared with S_0, the number of recommendations decreased by 700, while the number of successful interactions remained almost unchanged. This means that the proposed approach reduces irrelevant customer contacts and manager workload while preserving the practical effectiveness of communication (Fig. 2).

Figure 2 shows that the largest conversion gain is obtained after the inclusion of temporal verification, while customer classification provides an additional improvement by adapting the communication window to the customer type. Overall, the results demonstrate that predictive offer effectiveness in B2B e-commerce depends on the joint use of frequency relations, financial significance, purchase-cycle stability, and customer class.

From a practical standpoint, scenario S3 is the most appropriate for implementation in a B2B platform. It focuses not on the maximum number of recommendations but on a smaller and more relevant set of predictive offers. Therefore, the proposed classification method is not only an analytical add-on to UP-Growth and UT-Growth, but also a practical tool for reducing communication noise and increasing the economic return of personalized content.

The preprocessing stage was important because the initial dataset was not a ready transaction matrix. Each order could include several product rows, and therefore the analytical representation had to be reconstructed at the transaction level. This made it possible to calculate the financial contribution of each product item, form product sets for pattern mining, and preserve the chronological order of customer behavior. The time-based split was used instead of a random split because predictive offers must be validated against future purchases rather than against randomly selected past observations.

The yearly distribution of orders also shows that the dataset is sufficiently heterogeneous to test the proposed approach. The platform includes customers with different purchase volumes, different numbers of ordered SKUs, and different degrees of regularity. This heterogeneity is typical for B2B commerce and is one of the reasons why a single global recommendation rule is insufficient. The same association may have different practical value for different customer groups, especially when purchase cycles and order amounts vary significantly.

The selected metrics were intended to reflect not only prediction accuracy but also business usefulness. [5], [6] Recommendation conversion shows whether a generated offer is confirmed by future behavior, whereas covered revenue and average revenue per recommendation show whether the recommendation is economically meaningful. This is essential for B2B platforms because a recommendation system that produces many formally correct but low-value offers may increase informational noise without improving business performance.

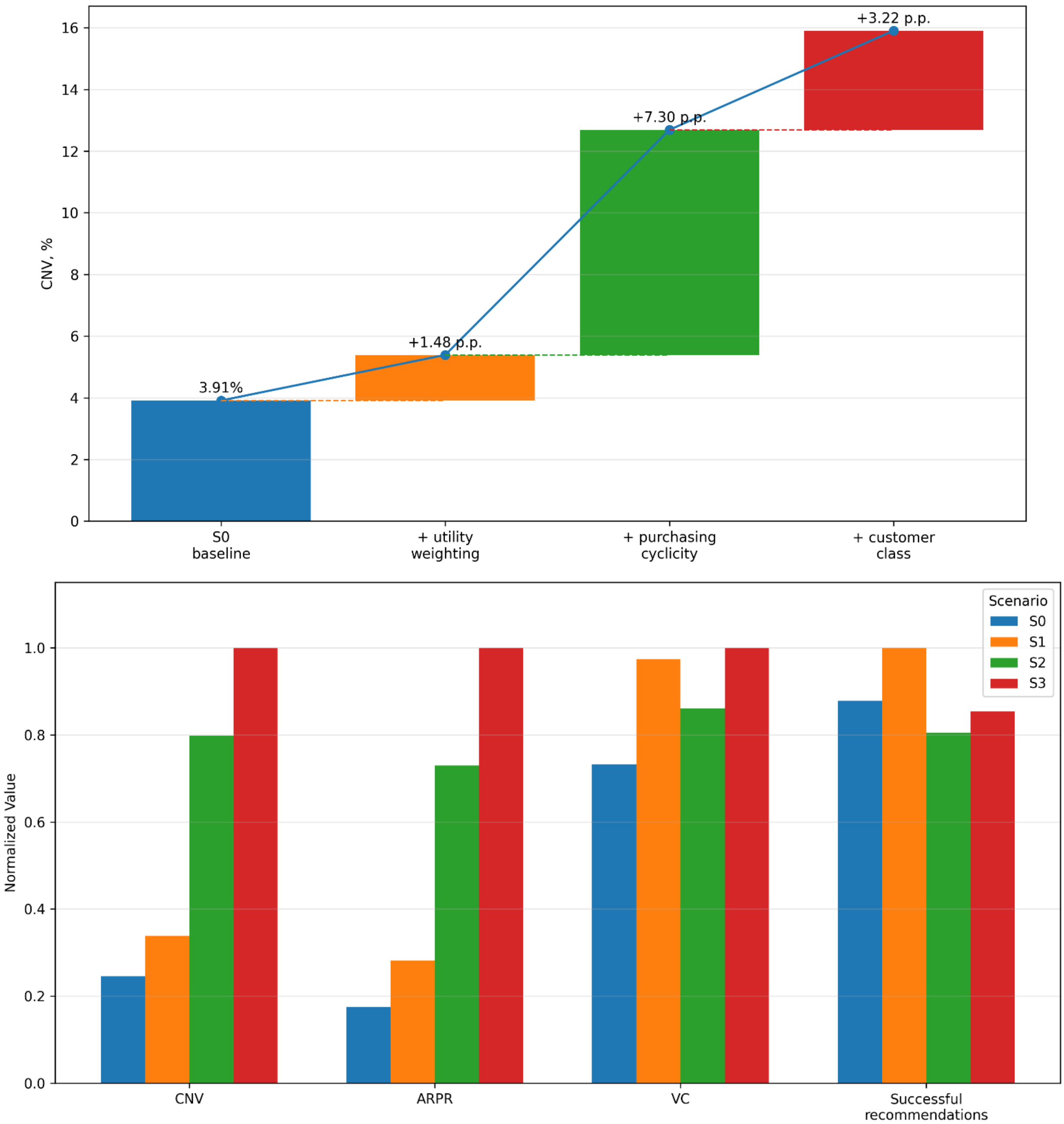

Fig. 2. **Comparison of recommendation approach scenarios by conversion growth and key efficiency metrics**

***Source*: compiled by the authors**

The comparison of S_0 and S_1 demonstrates the effect of adding financial utility to the mining procedure. [17], [18], [19] The number of recommendations becomes smaller, but the system begins to prioritize product combinations that contribute more to turnover. This result supports the assumption that frequency alone is not sufficient criterion for B2B personalization. In wholesale transactions, a less frequent product pattern may be more important than a frequent one if it is associated with higher order value or strategically significant stock replenishment.

The transition from S_1 to S_2 produced the largest conversion increase, which confirms the methodological role of temporal verification. [9], [20], [21]. This result means that many economically significant patterns are not necessarily useful at every moment. Their recommendation value depends on the expected phase of the customer purchase cycle. By filtering patterns through inter-purchase stability, the system excludes cases where the customer behavior is too irregular for reliable trigger activation.

The additional improvement achieved in S_3 is smaller than the improvement obtained after temporal verification, but it has important practical meaning. Customer classification does not replace product pattern and time-window analysis; rather, it adjusts the communication strategy according to the overall customer profile. Premium, standard, and economy classes can be used to assign different trigger-window widths and different levels of preventive communication, which makes the recommendation process more flexible for managerial use.

Therefore, the experimental results show that the proposed method improves the quality of personalization through selectivity rather than through increasing the number of offers generated. In applied B2B conditions, this is a desirable effect because every unnecessary contact with a customer consumes managerial resources and may reduce customer loyalty. The integrated scenario preserves almost the same number of successful interactions as the baseline scenario while generating far fewer recommendations, which demonstrates the practical advantage of the utility-weighted temporal profile for decision support.

CONCLUSIONS

The article develops a method for classifying B2B customers based on a utility-weighted temporal profile for generating individual predictive offers in e-commerce systems. The proposed method is the third stage of the analytical pipeline, complementing utility-weighted analysis of product patterns and temporal verification of the stability of purchase cycles.

A utility-weighted temporal profile of a B2B customer has been formalized, combining three key characteristics of purchase behavior: the average repeat-purchase cycle, cycle stability, and the average financial capacity of transactions. Unlike standard RFM analysis, the proposed approach is oriented not toward a retrospective description of the customer but toward supporting the predictive generation of offers while accounting for regularity, economic significance, and the expected moment of repeat purchase.

A sequence of stages of the B2B customer classification method has been developed, including aggregation of UP-Growth and UT-Growth results, normalization of profile features, customer clustering, class identification, and determination of an individual communication window for generating predictive offers. This makes it possible to connect the customer class with the interaction strategy not through subjectively specified thresholds, but through mathematically substantiated characteristics of the customer's purchase behavior.

Experimental verification using data from the B2B platform «Baza Vzuttya» for 2022-2025 confirmed the effectiveness of the proposed approach. The comparison of four scenarios showed a consistent increase in recommendation conversion: from 3.91 % in the baseline frequency-based scenario to 5.39 % in the utility-weighted scenario, 12.69 % in the utility-temporal scenario, and 15.91 % in the integrated scenario with customer class considered. At the same time, the number of recommendations generated decreased from 920 to 220, that is, by 76.09 %, indicating a substantial reduction in irrelevant contacts.

The best result was obtained for the integrated scenario, which generated 220 recommendations, 35 of which were successful, ensured an average revenue per recommendation of UAH 6,909.09, and covered test revenue of UAH 1,520,000.00. Compared with the baseline scenario, the number of recommendations decreased substantially, while the number of successful interactions remained almost unchanged. This confirms that the proposed method improves not only recommendation accuracy but also the practical value of each communication contact with a B2B customer.

Thus, the conducted study confirms the expediency of using a utility-weighted temporal profile for classifying B2B customers and generating predictive offers. The proposed approach makes it possible to transition from mass frequency-based recommendation generation to more accurate, timely, and economically substantiated management of personalized content in B2B e-commerce systems.

Thus, the conducted study creates the necessary theoretical foundation for transforming B2B e-commerce systems from passive catalogs into intelligent decision-support systems, thereby increasing customer loyalty and the economic efficiency of the platform.

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Метод класифікації B2B-клієнтів на основі ціннісно-зваженого темпорального профілю в системах електронної комерції

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АНОТАЦІЯ

Мета: Дослідження присвячено вирішенню проблеми предикативної персоналізації контенту в системах електронної комерції business-to-business, де класичні рекомендаційні та сегментаційні підходи демонструють обмежену ефективність через фінансову неоднорідність, циклічну закупівельну поведінку та довготривалий характер взаємодії з клієнтами. Метою дослідження є розробка методу класифікації business-to-business клієнтів на основі ціннісно-зваженого темпорального профілю клієнта, що дозволяє формувати більш релевантні та своєчасні предикативні пропозиції. **Завдання:** Запропонований метод розглядається як третій етап аналітичного конвеєра, який доповнює пошук ціннісних патернів і темпоральний аналіз стабільних закупівельних циклів. **Методи:** На першому етапі фінансово значущі товарні патерни визначаються за допомогою підходу Utility Pattern Growth. На другому етапі темпоральна стабільність повторних закупівель оцінюється на основі міжзакупівельних інтервалів і коефіцієнта варіації. На третьому етапі отримані результати рівня патернів агрегуються в інтегрований профіль клієнта, який поєднує середній закупівельний цикл, стабільність циклу та середню вартість транзакції. Ці ознаки нормалізуються та використовуються для кластеризації клієнтів, після чого визначені класи клієнтів інтегруються в механізм визначення індивідуального вікна комунікаційного тригера. **Результати:** Експериментальну перевірку виконано на історичних транзакційно-поведінкових даних business-to-business платформи електронної комерції «База взуття» за період з дві тисячі двадцять другого до дві тисячі двадцять п'ятого року. Порівняльний експеримент охоплював чотири сценарії формування рекомендацій: базовий частотний підхід, ціннісно-зважений підхід, ціннісно-темпоральний підхід та інтегрований підхід із класифікацією клієнтів. Результати засвідчили послідовне зростання конверсії рекомендацій з три цілих дев'яносто одна сота відсотка у базовому сценарії до п'ятнадцять цілих дев'яносто одна сота відсотка в інтегрованому сценарії. Водночас кількість сформованих рекомендацій зменшилася з дев'ятсот двадцяти до двохсот двадцяти, що свідчить про скорочення нерелевантних комунікацій. Інтегрований сценарій забезпечив найвище значення середньої виручки на одну рекомендацію, яке становило шість тисяч дев'ятсот дев'ять цілих дев'ять сотих гривні. **Висновки:** Отримані результати підтверджують, що запропонований метод підвищує точність, своєчасність та економічну обґрунтованість персоналізованих предикативних пропозицій у business-to-business системах електронної комерції.

Ключові слова: інтелектуальний аналіз даних; B2B-системи електронної комерції; методи класифікації; персоналізація контенту; рекомендаційні системи; транзакційно-поведінкові дані

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