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ІНФОРМАЦІЙНІ ТЕХНОЛОГІЇ

INFORMACION TECHNOLOGY

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AFFINITY ANALYSIS MODELS OF TRANSACTIONAL AND BEHAVIORALCUSTOMER DATA FOR PERSONALIZED CONTENT GENERATION IN B2B E-COMMERCE SYSTEMS

О. Арсірій, Д. Іванов. **Моделі афінітивного аналізу транзакційних і поведінкових даних клієнтів систем B2B електронної комерції для створення персоналізованого контенту.** Зростання фінансової значущості та структурної складності сегмента ринку систем B2B електронної комерції, а також необхідність підвищення його ефективності зумовило актуальність проведення системного аналізу існуючих моделей афінітивного аналізу транзакційних і поведінкових даних для обгрунтування шляхів їх адаптації з метою підвищення персоналізації товарного, інформаційного та рекомендаційного контенту системи B2B електронної комерції. На основі порівняння E-commerce System B2B та B2C за основними показниками встановлено специфіку B2B E-commerce System для пояснення концепції транзакцій «Бізнес-для-бізнесу» та зроблено висновок щодо орієнтації товарного, інформаційного та рекомендаційного контенту на раціональні рішення, великі обсяги закупівель та довгострокові партнерські відносини. Проаналізовано моделі афінітивного аналізу які базуються на алгоритмах та структурах даних Apriori, FP-Growth, а також Eclat та визначено їх недоліки щодо аналізу транзакційних і поведінкових даних B2B-клієнтів. Проаналізовано шляхи підвищення персоналізації товарного, інформаційного та рекомендаційного контенту системи B2B електронної комерції за рахунок використання моделей афінітивного аналізу транзакційних і поведінкових даних. Розроблено елементи концептуальної моделі комерційної активності B2B для персоналізації контенту на базі понять афінітивного аналізу із врахуванням великих обсягів, індивідуальних цін та поведінкових сценаріїв оптових покупок. Розроблено структуру концептуальної моделі для аналізу комерційної активності B2B. Визначено складові групи показників для комплексної оцінки ефективності персоналізації контенту B2B, яка базується на розробленій концептуальній моделі комерційної активності B2B.
Ключові слова: електронна комерція, системи B2B, транзакційні та поведінкові данні, афінітивний аналіз, асоціативні правила, Apriori, FP-Growth, Eclat, метрики якості

O. Arsirii, D. Ivanov. **Affinity Analysis Models of Transactional and Behavioral Customer Data for Personalized Content Generation in B2B E-commerce Systems.** The growing financial significance and structural complexity of the B2B e-commerce market segment, coupled with the necessity to enhance its efficiency, have necessitated a systematic analysis of existing affinity analysis models for transactional and behavioral data. This study aims to justify the adaptation of these models to improve the personalization of product, information, and recommendation content within B2B e-commerce systems. Based on a comparative analysis of B2B and B2C e-commerce systems across key indicators, the specific characteristics of B2B systems are established to define the "Business-to-Business" transaction concept. The study concludes that product, information, and recommendation content must prioritize rational decision-making, large-scale procurement volumes, and long-term partnerships. The paper analyzes affinity analysis models based on Apriori, FP-Growth, and Eclat algorithms and data structures, identifying their limitations regarding the analysis of B2B customer transactional and behavioral data. Furthermore, it explores pathways for enhancing content personalization by leveraging these models. A key contribution of this research is the development of conceptual model elements for B2B commercial activity. This model for content personalization is built upon affinity analysis concepts while accounting for wholesale purchase characteristics, such as large volumes, individual pricing, and specific behavioral scenarios. The structure of the conceptual model for B2B commercial activity analysis is established. Finally, the study defines a comprehensive set of metrics to evaluate the effectiveness of B2B content personalization, based on the proposed conceptual model.
Keywords: B2B e-commerce, personalization, affinity analysis, transactional data, behavioral data, sequential patterns, conceptual modeling, Apriori, FP-Growth, Eclat, quality metrics

Introduction

The relevance of conducting affinity analysis, also known as association rule mining, of transactional and behavioral data of customers of B2B e-commerce systems to create personalized content in B2B e-commerce systems is due to the financial significance and structural complexity of this market segment, as well as the need to improve its efficiency.

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The relevance of conducting affinity analysis, also known as association rule mining, of transactional B2B e-commerce systems is due to the financial significance and structural complexity of this market segment, as well as the need to improve its efficiency. The critical importance of effective B2B personalization is confirmed by the enormous financial volumes of this segment. The global B2B e-commerce market, estimated at $11.54 trillion in 2024, significantly exceeds the B2C market ($6.55 trillion). Its projected growth to $60.62 trillion by 2034 indicates that even a slight increase in the effectiveness of customer interactions through personalization will have a multi-trillion-dollar economic impact [1]. At the same time, it has been established that traditional affinity analysis models are focused on data mining, aimed at identifying hidden relationships and patterns between different elements (goods, events, actions) in large data sets, particularly in transaction databases developed for the B2C segment of e-commerce. They are focused on emotions, impulse purchases, and a simple user experience, which is not effective enough for B2B [2]. Since B2B purchases are rational, high-value, and driven by the need for ROI (return on investment), there is an urgent need to analyze and adapt existing models to address B2B challenges such as: the complexity of the buying center (Buying Center), where the decision to purchase a product or service is made not by one person, but by a group of people or departments within the purchasing organization, individual pricing conditions, data sparsity (rare but large orders) and the need for long-term partnerships [3]. This creates a need to adapt and modernize affinity analysis models that can work effectively in a B2B environment to create truly relevant and rationally justified content (product, informational, recommendatory).

Therefore, conducting a systematic analysis of existing models that use transactional data to identify affinity rules and typical purchasing patterns and behavioral data to understand purchasing scenarios and the needs of different roles in the client company of a B2B e-commerce system is a pressing task.

Literature review and problem statement

In [3], a B2B e-commerce system is defined as a comprehensive online platform or set of interrelated technological solutions designed to carry out commercial transactions, exchange information, and automate business processes between two or more legal entities (enterprises) To explain the concept of "Business-to-Business" (B2B) transactions, let's use Figure 1.

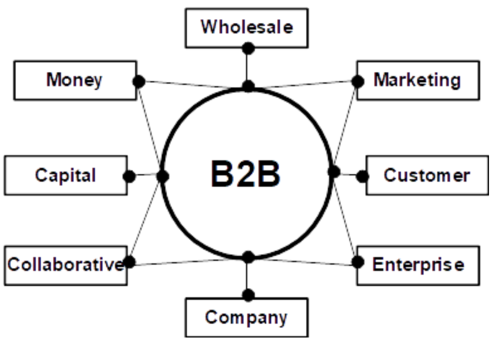

Fig. 1. B2B Transaction Conceptual Scheme

It is known that B2B transactions are the exchange of goods, services, or information between two or more companies [1]. According to the concept of transactions (Fig.1), the first aspect is wholesale trade. This business model allows retailers to purchase products at a lower price and resell them to consumers at a markup. Another important concept is marketing. B2B marketing strategies focus on building relationships with other businesses rather than individual consumers. This often involves a longer sales cycle and more complex decision-making processes.

In a B2B context, the customer is another business rather than an individual. These business customers have different needs and purchasing behaviors compared to individual consumers. B2B companies must understand the specific needs and challenges of their business customers in order to provide valuable solutions. The main customers in B2B transactions are enterprises or corporations. These enterprises require reliable solutions to support their complex operations, making them a key target market for B2B companies. A company represents enterprises involved in B2B transactions, ranging in size from small startups to large corporations.

Their interaction forms the basis of the B2B ecosystem. Collaboration is a key element of B2B relationships. Enterprises often work closely together to achieve common goals. This collaborative

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approach promotes long-term partnerships and innovation. In B2B, capital refers to various objectives, such as investing in new technologies, expanding operations, or acquiring other companies. Access to capital is crucial for B2B companies to remain competitive. Finally, the Money block represents financial transactions that occur between businesses. In B2B, these transactions can be large and complex, involving different payment methods and terms. Effective cash flow management is important for the financial health of B2B companies [1, 2, 3].

Thus, a B2B e-commerce system (B2B E-commerce System) is a comprehensive online platform or set of interconnected technological solutions designed to carry outcommercial transactions, exchange information, and automate business processes between two or more legal entities (enterprises) [3]. This system is a digital environment that enables seller organizations to present their product, information, and recommendation content (catalogues, price lists, terms of cooperation) to other buyer organizations for their production, commercial, or resale needs. Table 1 shows the results of a comparative analysis of B2B and B2C e-commerce systems based on key indicators. Thus, modern B2B e-commerce systems operate in a highly competitive Internet environment, where the quality of content determines the speed and accuracy of meeting the needs of wholesale customers. For the B2B model, the content of the online platform is created with a focus on rational decisions, large purchase volumes, and long-term partnerships [4].

Table 1

Comparison of E-commerce System B2B and B2C by key indicators

B2B (Business-to-Business)	B2C (Business-to-Consumer)
Target audience	
The number of buyers is smaller. They include other companies, startups, enterprises, large corporations, government agencies, and non-profit organizations.	A large number of buyers are individual consumers
Transaction value	
High cost, higher volumes, lower frequency.	Low cost, lower volumes, higher frequency.
Purchase motivation	
Rational: focused on business efficiency, cost reduction, profit increase, long-term goals.	Emotional/Impulsive: focused on satisfying personal needs, desires, based on price, brand, trends.
Duration of the decision-making process	
Longer and more complex: involves multiple stakeholders, negotiations, possible testing, contracts.	Shorter and simpler: often a single solution, a quick purchase.
Sales cycle	
Long (from 1 to 6 months).	Short (from 1 to 6 days).
Features of customer relations	
Long-term partnerships: emphasis on building trust, support, tailor-made solutions.	Short-term, transactional.
Features of marketing	
Focus on logic, values, ROI, personalized offers, direct sales, content marketing.	Focus on emotions, image, advertising, social networks, promotions, convenience.
Payment Methods	
Sophisticated methods (lines of credit, invoices, bank transfers, deferred payments). Higher security priority.	Fast and convenient methods (credit/debit cards, mobile wallets, electronic payments).
Product/Service Customization	
High degree of customization, specialized solutions.	Standardized “ready-made” products.

However, in [5, 6], attention is focused on the situation where the vast majority of e-commerce platforms use static methods of content formation based on fixed rules or universal recommendations for individual customers. This approach does not take into account purchasing patterns, the specifics of the wholesale customer’s business, seasonality, or dependencies between products. This limits the effectiveness of the service and reduces the likelihood of repeat purchases [7, 8]. Resolving such issues requires a systematic analysis of existing models, methods, and technologies for affinity analysis of customer transaction and behavioral data in order to modify them to improve the personalization of product, information, and recommendation content in B2B e-commerce systems.

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It is known that modern algorithms for data analysis to create associative rules (Association Rule Mining) are aimed at finding frequently repeated combinations of goods or events in customer transactions. That is, such algorithms are based on the concept of frequent itemsets, which occur in multiples and are related to the concept of frequency. The method of searching for association rules (AR) using frequent itemsets consists of two steps: finding the most frequent itemsets and using them to generate ARs that meet the conditions of minimum support and confidence, and then using the resulting purchase and behavioral data to create personalized content in the B2B e-commerce system.

It is known that to search for frequent sets of elements, the following algorithms are used: the Apriori algorithm [9], which performs a search of candidates with subsequent rejection of unpopular sets, the FP-Growth algorithm, which builds an FP-Tree for further search without generating candidates [10], and the Eclat algorithm, which searches for popular sets by intersecting pre-built TID lists [11].

Based on information from literary sources, let us consider the advantages and disadvantages of popular affinity analysis algorithms in more detail.

The model for searching for frequent sets of items (Frequent Itemsets) in transactional databases through iterative generation of candidates and their testing is based on the Apriori algorithm.

The main idea of the algorithm is based on the a priori property of Apriori Property— that is, any subset of a frequent set of items must also be frequent.

The algorithm works from the bottom up (from shorter sets to longer ones), using frequent sets found in the previous step to generate candidates for the next one. At the same time, those candidate sets that are guaranteed not to be frequent are pruned [9].

According to the FP-Growth (Frequent Pattern Growth) model, a compact data structure called an FP tree (Frequent Pattern Tree) is constructed, and based on this, a recursive search for frequent patterns is performed [10]. In this case, the generation of candidates and exhaustive search, unlike Apriori, are replaced by a search for possible combinations of goods or behavioral patterns in the FP tree.

According to the Eclat (Equivalence CLAss Transformation) model, the search for frequent item sets in transactional and behavioral data uses intersections of transaction identifier lists (TID lists), as opposed to enumerating candidates in Apriori or constructing trees in FP-Growth. [11]. The main idea behind Eclat is to store a list of transaction identifiers.

(TID lists) for each item where that item occurs and to find frequent itemsets by intersecting these lists.

The results of comparisons of the considered associative rule search algorithms are shown in Table 2.

Table 2

Advantages and disadvantages according to the principle of operation of algorithms for searching associative rules

Principle of operation	Advantages	Disadvantages
	Apriori	
Candidate generation	Simple, classic	Slow on large sets
	FP-Growth	
FP Tree	Fast, no candidates	More difficult to implement
	Eclat	
Crossing TID lists	Simple, fast on small data	Requires a lot of memory on big data

A study of B2B e-commerce systems and existing affinity analysis algorithms (Apriori, FP-Growth, Eclat) revealed a significant gap between theoretical methods for identifying patterns and their practical effectiveness in a B2B environment. That is, the algorithms are effective for searching for associations in large transactional databases of B2C systems where transactions are homogeneous. At the same time, they are not adapted to the specifics of B2B because they do not take into account the sparsity and structural complexity of data in B2B transactions and, as a result, do not provide a rational justification for recommendation decisions to B2B managers.

Thus, to improve the effectiveness of B2B systems, it is necessary to adapt and expand affinity analysis models. This should be done by integrating transactional (financial) and behavioral (scenario) data with subsequent classification of customers, which determines the purpose and objectives of this study.

The aim and objectives of the research

The purpose of this study is to conduct a systematic analysis of existing models of affinity analysis of transactional and behavioral data to substantiate ways to adapt them to increase the personalization

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of product, informational and recommendation content of the B2B e-commerce system. The objectives of the study include:

– analysis of ways to increase the personalization of product, informational and recommendation content of the B2B e-commerce system through the use of models of affinity analysis of transactional and behavioral data;

– development of elements of a conceptual model of B2B commercial activity for personalization of content based on the concepts of affinity analysis, taking into account large volumes, individual prices, and behavioral scenarios of wholesale purchases;

– development of a conceptual model structure for analyzing B2B commercial activity in content personalization systems;

– identification of components for a comprehensive assessment of the effectiveness of B2B content personalization, which is based on the developed conceptual model of B2B commercial activity.

The research materials and methods

Analysis of ways to increase personalization of B2B content. Increasing the personalization of content in B2B e-commerce systems requires a shift from emotionally-oriented B2C methods to rationally informed decisions that directly affect the efficiency, profitability, and operating costs of the client. Affinity analysis is a key tool for achieving this goal, as it allows you to identify not only the fact of the purchase, but also the logic and sequence of purchasing decisions.

Let's consider the possibilities of affinity analysis models for transactional data creation for *creating B2B commodity content* [12].

Classical affinity analysis, applied to transactional data (invoices, bulk orders), traditionally focuses on finding frequent sets (Apriori, FP-Growth, and Eclat). In a B2B system, this model should be adapted to form product content in the form *of complex offers* by integrating financial and quantitative metrics [12]. For example*, the formation of "Wholesale* Bundles", when transactional analysis reveals associative rules, where instead of frequency (Support), the *total cost* or *margin of the* set dominates:

If {Item A, Item B}, then {Item C}→

This allows the system to offer not just related products, but complex purchasing solutions that, from the customer's point of view, optimize logistics and reduce overall costs (for example, offer of specialized fasteners and tools when ordering a large batch of building materials).

Another example of product content creation is the *personalization of the price offer* when associative rules can be applied to define individual conditions, i.e.:

If {The customer belongs to the "Premium" class,
Orders Product A monthly},
then {10% discount on Product B}→

The system generates not just a general promotion, but a personalized investment plan for the client, showing how the inclusion of associated products will allow them to obtain more favorable wholesale prices.

Consider using consistent templates to create *B2B recommendation content*. Sequential Pattern Mining (SPM) works with behavioral and temporal data, identifying cycles and sequences of events, which allows you to predict the next logical step of a B2B client, which will be the basis for creating recommendation content [13]. For example, forecasting replenishment of stocks (Restock Prediction). SPM detects the typical time interval between orders for certain sets of products.

If {Order Winter Shoe Collection}, then {Order Skincare Products (After 6 Weeks)} →

At the same time, the system will generate a recommendation notification a week before the predicted date, reminding the client of the need to replenish the stock. This increases loyalty because the system acts as an assistant in managing the customer's inventory.

Another example of recommendations is possible scenarios for the behavior of the Buying Center. Sequential analysis is applied to the actions of different employees of the buying company.

If {View specifications by Engineer}, then {Request final price by Financier}→

That is, when the engineer has reviewed the characteristics, a recommendation notification is automatically generated to the financier in the form of an ROI calculation or a special price list for this product, speeding up the sales cycle.

Consider the use of transactional and behavioral data to create *information content in a* B2B system. Informational content in B2B includes not only technical characteristics, but also conditions, reports, and analytics [14]. Thus, affinity analysis of transactional data is used to provide personalized analytics. For example, the system compares the customer's buying behavior with typical patterns of their industry or segment.

If {Customer does not buy Product B, but his competitors buy Product B together with A},
then {Send Analytical Report on Product B and its benefits}→

Automatically generated informational content is rationally reasonable, as it appeals to lost profits or competitors' best practices.

Analysis of sequential patterns can detect behavioral anomalies preceding churn of customers (Churn), which is essential for risk management:

If {Drastic Volume Reduction, Old Invoice Loading},
then {Search for New Suppliers (Outlook)}→

These triggers personalized communication aimed at retaining customers, such as offering special, customized terms of cooperation.

Thus, affinity analysis adapted to B2B metrics such as cost, volume, time, behavioral scenario is necessary to transform a B2B E-commerce system from a simple catalog into an intelligent assistant that provides rationally reasoned, proactive, and personalized content.

Development of elements of a conceptual model of B2B commercial activity. Taking into account the fundamental concepts of affinity analysis, such as transaction, sequence, sequential pattern, and associative rule, as well as metrics for assessing the quality of their construction, we will determine the elements of the B2B model of commercial activity. For B2B, this is one wholesale order placed by a buyer company, which includes several commodity items (Stock Keeping Unit SKU) and financial conditions. The SKU has a unique alphanumeric code used by the business (seller, distributor, retailer) for internal identification, tracking, and inventory management [12].

Then, formally*, the commodity item* (element) is defined as:

$$I = \{i_1, i_2, \dots i_n\}, \tag{1}$$

where I is the set of all commodity items i_k (SKU), available for order in the B2B system. *The transaction T* is *a logical unit of work* that occurs at a single point in time t, is a subset of *I*, that is, $T \subseteq I$ is defined by the set of tuples of the total number *m*:

$$T = \{t_1, t_2, \dots t_m\}. \tag{2}$$

Each element of the transaction t_j is a tuple, which describes the purchased or executed element, taking into account its quantity (Quantity) q_k and cost p_k:

$$t_j = \langle i_k, q_k, p_k \rangle, \tag{3}$$

where i_k – Commodity item identifier (SKU), $i_k \in I$; p_k – individual price (Price) per unit applied for this client (takes into account his discounts and purchase volume).

A sequence s_j in B2B is a time-ordered activity log of a single customer (or Buying Center), consisting of a set of *T transactions* that occurred at different points in time:

$$s_j = \left\langle T_{t_1}, T_{t_2}, \dots,\ T_{t_k} \right\rangle, \tag{4}$$

where T_{t_i} – it is a B2B transaction (1) that occurred at a point in time t_i. At the same time, we have time ordering $t_1 < \dots < t_k$.

Association Rule (AP) in B2B reflects the simultaneous presence of goods, services, or actions within the same transaction *T* (1) Let *I* be the set of all elements (SKU/services/actions), and *A* and *B* be two sets of elements, such that $B = A \subset I$, $B \subset I$, $A \cap \varnothing$. The associative rule is formulated in the form

$$AR = A \rightarrow B, \tag{5}$$

i.e. – *if a* set of elements *A* is present in a wholesale order (Transaction), *then* there is a high probability that a set of elements *B* is present in the same order.

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The *Sequential Pattern* (SP) in B2B reflects the time-ordered occurrence of transactions or behavioral events (3) that form the chain of customer activity. Let S be the set of all B2B sequences of customers s_j (3), α and β – two sequences of transactions or events $\alpha = \langle T_{t_a} \rangle$, $\beta = \langle T_{t_b} \rangle$.

A consistent pattern is formulated as follows:

$$SP = \alpha \Rightarrow \beta. \quad (6)$$

That is, if at a given moment in time t_a the client performed event or set of transactions α, then there is a high probability that at the next moment in time t_b, $t_a < t_b$ the will perform event or set of transactions β. The symbol "$\Rightarrow$" is used to emphasize the temporal sequence.

Let us define quality metrics that characterise the relationship between sets of goods established using APs constructed during affinity analysis.

Support for AP shows how often the set $\{AB\}$ appears in the general database of B2B transactions D. Then, for AP $A \to B$, *support* $S_{AR}(A \to B)$ looks like:

$$S_{AR}(A \to B) = S_{AR}(AB) = \frac{|\{TD \mid ABT\}|}{|D|}, \quad (7)$$

where $|\{TD \mid ABT\}|$ – total number of transactions containing A and B, $|D|$ – total number of transactions in the B2B database.

Confidence AP $A \to B$ shows the probability that if a customer bought A, they will also buy B in the same transaction. This is a direct measure of the predictive value of set A for the sale of B within a single wholesale order. D. Then for AP $A \to B$ *confidence* $C_{AR}(A \to B)$ looks like:

$$C_{AR}(A \to B) = \frac{S_{AR}(AB)}{S_{AR}(A)}. \quad (8)$$

For B2B systems, the quality assessment (Support, Confidence) AP should take into account not only the number of transactions $|D|$, but also the total financial value or volume of elements A and B in these transactions, i.e. it should be *Weighted* according to definition (3).

Lift shows how often the set $\{A \cup B\}$ appears more frequently than expected if A and B were independent. Then, for $A \to B$, *Lift* $L_{AR}(A \to B)$ looks like this:

$$L_{AR}(A \to B) = \frac{C_{AR}(A \to B)}{S_{AR}(A)} = \frac{S_{AR}(AB)}{S_{AR}(A) S_{AR}(B)}. \quad (9)$$

If $L_{AR} > 1$, then there is a positive correlation (rational sense) in joint purchasing; if $L_{AR} < 1$, then there is a negative correlation (substitute goods). This is a key metric for B2B, as it excludes trivial rules that are common simply because of the high overall popularity of one of the goods.

Leverage measures the difference between the actual frequency of joint occurrence of sets A and B and the frequency that would be expected if A and B were completely independent of each other. Then for $A \to B$ *Leverage* $Le_{AR}(A \to B)$ looks like this:

$$Le_{AR}(A \to B) = S_{AR}(AB) - S_{AR}(A) S_{AR}(B). \quad (10)$$

If $Le_{AR} = 0$, then elements A and B are independent. Their joint appearance in orders is purely coincidental. If $Le_{AR} > 0$, there is a strong logical connection between the elements, i.e. they appear together more often than expected. This indicates a strong logical connection. In B2B, this is a signal for creating bundles or joint logistics. If $Le_{AR} < 0$, then the items appear together less frequently than expected. This may indicate that the products are competitors or substitutes.

Conviction shows how often AP (5) gives incorrect predictions. It measures the dependence of set A on set B. Then, for $A \to B$, Conviction $V_{AR}(A \to B)$ looks like this:

$$V_{AR}(A \to B) = \frac{1 - S_{AR}(B)}{1 - C_{AR}(A \to B)}. \quad (11)$$

A high V_{AR} value indicates that the rule is very strong, and set A really "forces" B to appear. This is useful for filtering rules when A is very popular.

Without going into too much detail, let us define the quality metrics that characterise the relationship between sequential *SP* patterns (6). They apply to the sequence base *S* when event β occurs after event α:

Support for SP

$$S_{SP}(\alpha \Rightarrow \beta) = \frac{\left|\{s \in S \mid \textit{precedes}\ \beta \text{ in sequence s}\}\right|}{|S|}. \tag{12}$$

Confidence SP

$$C_{SP}(\alpha \Rightarrow \beta) = \frac{S_{SP}(\alpha \Rightarrow \beta)}{S_{SP}(\alpha)}. \tag{13}$$

Lift for SP

$$L_{SP}(\alpha \Rightarrow \beta) = \frac{S_{SP}(\alpha \Rightarrow \beta)}{S_{SP}(\alpha) S_{SP}(\beta)}. \tag{14}$$

Leverage for SP

$$Le_{SP}(\alpha \Rightarrow \beta) = S_{SP}(\alpha \Rightarrow \beta) - S_{SP}(\alpha) S_{SP}(\beta). \tag{15}$$

Conviction for SP

$$V_{SP}(\alpha \Rightarrow \beta) = \frac{1 - S_{SP}(\beta)}{1 - C_{SP}(\alpha \Rightarrow \beta)}. \tag{16}$$

As a practical example, we will provide the form of associative rules and sequential patterns built for *Wholesale B2B Portal* [7].

Associative rule (Product):

{Women's trainers Art. 403, Men's trainers Art.
510}→{Comfort insoles set}.

Associative rule (Product + Service):

{Order over 1000 pairs} → {60-day credit line provided}.

Sequential pattern (Seasonality):

<Order for winter boots> → <Order for salt protection products (in 2 months)>.

Sequential pattern (Forecasting):

<Request for individual price for new collection,
Receipt of technical documentation>→<Placing main wholesale order (within 14 days)>/

Development of a conceptual model structure for analysing B2B commercial activity Let us present the structure of the conceptual model of B2B commercial activity in the form of a three-level hierarchy – "Entities, Relationships, Metrics".

The first level of entities contains data objects. It is the foundation of the conceptual model, which transforms "raw" data into structured information. The entity level consists of:

– Sets of commodity items *I* (1), where i_k *(SKU)* is an atomic unit of analysis;

– Transactions *T* (2), which are a logical grouping of goods taking into account volume and personal price (rational context);

– Client sequences S (3), which are a chronological chain of transactions that reflects the customer life cycle.

The second level of logical connections contains the so-called analytical vectors. Due to the establishment of such ties, data is converted into knowledge about behavior. The second level is based on:

– vectors of associative rules *AR* (5), which describe the presence of horizontal relationships, i.e. commodity items t_j (3), which are purchased together. This is the basis for "commodity personalization" and the formation of bundles;

– vectors of sequential SP patterns (6), which describe vertical (temporal) relationships s_j (4), i.e. what follows what. This is the basis for "predictive personalization", recommendation content, and management of replenishment cycles.

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The third level of evaluation and validation contains quality metrics, the values of which are tools for selecting the most significant rules or patterns that make economic sense, namely:

– *Support S* (7) and (12) characterizes the scale of the rule or pattern;

– *Confidence C (*8) and (13) characterizes the reliability of the prediction against a rule or pattern;

– *Lift L* (9) and (14) elevator characterizes the degree of connection between transactions or patterns, taking into account its non-triviality and intellectual novelty;

– *Leverage Le* (10) and (15) characterizes the value of absolute benefit/weight of a rule or pattern for a business;

– *Conviction V* (11) and (16) characterizes the resistance of a rule or pattern to random fluctuations.

Thus, the proposed conceptual model of B2B commercial activity allows formalizing complex multifactorial processes of interaction between the supplier and the client. It combines static associative relationship analysis to optimize product content and dynamic sequential pattern analysis for proactive demand forecasting. Its development provides a mathematical basis for the automated personalization of product, recommendation, and informational content of the B2B platform.

Identifying the components for a comprehensive assessment of the effectiveness of B2B content personalization

Taking into account the identified ways to increase the personalization of product, informational and recommendation content of the B2B e-commerce system, the elements and structure of the conceptual model for analyzing B2B commercial activity have been developed, a comprehensive assessment of the effectiveness of content personalization in B2B e-commerce systems has been proposed, which combines four groups of indicators.

Group 1 contains indicators for determining the quality of analytics (*Model Performance*) of Q_{analyt} and is based on previously developed metrics for *AR* and *SP,* namely:

– Average *Lift* (L_{avg}), determines how non-trivial and useful connections the system finds. Time accuracy ($T_{accuracy}$) determines for sequential patterns how accurately the system predicted the date of the next order (deviation Δt);

– Inventory Coverage determines what percentage (%) of all SKUs participate in the generated personalized offers.

Group 2 contains indicators for determining technological efficiency (Engine Performance) Q_{tech} to assess the system's ability to work with large amounts of data in real time, namely:

– Generation speed (latency) – the time it takes to form a recommendation block when loading a page (should not exceed 100…200 m/s);

– Freshness – the time it takes for a new customer transaction to be reflected in the update of their affinity profile;

– Scalability – the ability of affinity analysis algorithms (Apriori, FP-Growth, and Eclat) to process a growing number of transactions without an exponential increase in memory consumption.

Group 3 contains indicators for determining commercial effectiveness (Business Impact) Q_{comm}, such as key indicators for the business of the B2B platform owner, namely:

– Conversion Rate (CVR) – The indicator of the effectiveness of converting information content into actual purchases is defined as the ratio of the number of successful orders to the number of personalised sessions on the B2B platform;

– Average Order Value (AOV) – an indicator of the quality of commercial content, characterising the ability of a B2B platform to encourage customers to purchase comprehensive solutions and defined as the increase in the average customer spend (Δq Δp) thanks to AR bundles;

– Churn Rate Reduction (CRR) – An indicator of the quality of recommendation content, characterising the ability of a B2B platform to retain customers through a sense of "partner support" and defined as a reduction in customer churn thanks to proactive SP recommendations;

Group 4 contains indicators for determining customer value (Q_{cust}). These indicators measure:

– Time-to-Purchase (TTP) – reduction in the time spent by the purchasing manager on creating a basket thanks to recommendations;

– Stock-out Prevention Rate (SPR) – percentage of cases when the system reminded the customer to replenish stocks in time, preventing the customer's business from stopping.

Taking into account the indicators from the four groups, we will define a comprehensive assessment of the effectiveness of content personalisation in B2B e-commerce systems as:

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$$E_{pers} = \omega_1 Q_{analyt} + \omega_2 Q_{tech} + \omega_3 Q_{comm} + \omega_4 Q_{cust} ,$$

where: E_{pers} –integral personalisation effectiveness index; Q – normalised values for each group of metrics; $\omega_{1...4}$ – weighting coefficients (whose sum = 1).

It should be noted that for B2B systems at the implementation stage, higher priority is usually given to the values of ω_4 (value for the customer) and $_1$ (quality of analytics), as these are the factors that build long-term loyalty.

Conclusions

Based on the system analysis and development of conceptual elements of the model, the following conclusions can be formulated:

It is shown that the growth of financial significance and structural complexity of the market segment of B2B e-commerce systems caused the need to increase its efficiency, which determined the relevance of conducting a systematic analysis of existing models of affinity analysis of transactional and behavioral data to substantiate ways of their adaptation in order to increase the personalization of product, informational and recommendation content of the B2B e-commerce system.

The conceptual scheme of B2B transactions and the comparison of the B2B and B2C E-commerce System in terms of the main indicators are defined. The specifics of personalization in B2B systems of electronic commerce are determined. It has been established that unlike B2C, where emotional factors dominate, in B2B, personalization should be based on rational calculations, ROI, and maintaining long-term partnerships.

A study of existing algorithms of affinity analysis has been carried out and a significant gap between theoretical methods of pattern detection and their practical effectiveness in the B2B environment has been identified. That is, the algorithms Apriori, FP-Growth, Eclat are effective for finding associations in large transaction databases of B2C systems where transactions are homogeneous and not adapted to the specifics of B2B because they do not take into account the sparsity and structural complexity of data in B2B transactions and, as a result, do not provide a rational justification for recommending decisions to B2B managers.

The ways to increase the personalization of product, recommendation and informational content of the B2B system are analyzed and it is shown that conducting affinity analysis adapted to B2B metrics such as cost, volume, time, behavioral scenario is necessary to transform the B2B E-commerce system from a simple catalog into an intelligent assistant that provides rationally reasoned, proactive and personalized content.

A conceptual model of commercial activity has been formed. The model integrates time-ordered sequences of transactions and behavioral events, which makes it possible to formalize the work of the "Buying Center" of the client company.

Affinity analysis metrics have been adapted. The use of weighted indicators of support and reliability, taking into account the financial value of orders, is proposed. Differentiation of metrics for associative AR rules and sequential SP patterns allows you to clearly separate static relationships between goods and the dynamics of purchasing cycles.

Ways of practical implementation are proposed. It is determined that the use of affinity analysis models allows automating the generation of personalized price proposals, bundles for logistics optimization and proactive notifications about the need to replenish the client's warehouse stocks.

The foundations for creating a comprehensive assessment have been developed. Groups of indicators (analytical, technological, commercial and client) have been established, which together allow measuring the effectiveness of the implemented personalization system through an integral index.

Thus, the study creates the necessary theoretical basis for transforming B2B e-commerce systems from passive catalogs to intelligent decision support systems, which increases customer loyalty and the cost-effectiveness of the platform.

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