Boliubash, N. M., & Khodzitskyi, O. M. (2024). Dynamic updating of association rules in intelligent e-commerce recommendation systems. *Actual Issues of Modern Science. European Scientific e-Journal, 35*, __-__. Ostrava: Tuculart Edition, European Institute for Innovation Development.

DOI: 10.47451/inn2025-01-02

The paper is published in Crossref, ICI Copernicus, BASE, Zenodo, OpenAIRE, LORY, Academic Resource Index ResearchBib, J-Gate, ISI International Scientific Indexing, ADL, JournalsPedia, Scilit, EBSCO, Mendeley, and WebArchive databases.

Nadiia M. Boliubash, Candidate of Pedagogical Sciences, Associate Professor, Department of Intelligent Information Systems, Petro Mohyla Black Sea National University. Mykolaiv, Ukraine.
ORCID: 0000-0002-2274-2422
Oleksandr M. Khodzitskyi, Master's Student, Faculty of Computer Science, Petro Mohyla Black Sea National University. Mykolaiv, Ukraine.

Dynamic updating of association rules in intelligent e-commerce recommendation systems

Abstract: The accumulation of large volumes of digital content in e-commerce necessitates implementing intelligent recommendation systems in their web platforms, which contribute to increasing financial profits by enhancing the efficiency of e-commerce. Among the methods used for generating forecasts in recommendation systems, Association Rule Mining (ARM) is widely applied. ARM uncovers hidden relationships between objects in large datasets. Many algorithms have been proposed for updating association rules in recommendation systems using incremental association rule mining. This approach involves rerunning the search algorithm on a modified transaction database instead of the entire database. However, dynamic updating of association rules in e-commerce systems remains an unsolved task that requires further development. The study object is the process of updating association rules in e-commerce recommendation systems. The study aims to develop and describe a method for dynamically updating association rules in an e-commerce recommendation system, which is implemented using the Apriori algorithm. The Apriori algorithm is based on finding association rules for frequent itemsets and is static and highly complex. In this work, dynamic updating of found association rules to ensure their relevance is proposed through periodic scanning of a portion of the database that contains transaction records from the past three months. The database is updated by adding new products and removing those that have been discontinued during this period. The proposed approach was implemented in actual operational conditions in an e-commerce system engaged in the retail sale of animal supplements. The study of the effectiveness of the developed intelligent recommendation system showed that its use was accompanied by an increase in the number of products sold, the average purchase value, and the conversion rate.

Keywords: e-commerce system, intelligent recommendation system, association rule, support, confidence, Apriori algorithm, dynamic update of associative rules, incremental association rule mining.

Abbreviations:

ARM is Association Rule Mining,

$DELI$ is Difference Estimation for Large Item sets,

FUP is Fast Update,

$IncA$ is Incremental Apriori,

$UWEP$ is Update with Early Pruning.

Introduction

The high pace of informatization in modern society is accompanied by the accumulation of large volumes of digital content in e-commerce. This complicates the satisfaction of users' needs for obtaining necessary information about available products and services and drives the development of technologies related to searching and providing personalized recommendations. Implementing intelligent recommendation systems in the operations of online stores significantly enhances the effectiveness of commercial activities in the online sales sector. It contributes to increasing customer loyalty by saving time and providing a personalized approach to product recommendations (*Naresh & Suguna, 2021*).

For developing an intelligent e-commerce recommendation system that generates personalized recommendations for users when making product selection decisions, the choice of methods aimed at selecting products to ensure optimal forecasting is crucial. Collaborative, content-based, and hybrid filtering methods are distinguished among the main approaches used for forecasting in recommendation systems (*Falk, 2019*; *Boliubash & Zheltobriukhov, 2024*). However, the algorithms that implement these methods have many issues: cold start, sparsity of the user-item matrix, scalability, and changes in user interests (*Fayyaz et al., 2020*; *Jannach, 2022*).

Recommendation provision based on association rule mining uses a fundamentally different approach. An association rule $X \rightarrow Y$ is an implication of the form "if X," then Y", where X is the selected product or products (condition, an antecedent in the form of itemsets), and Y is the product or products that customers typically purchase together with the selected one (a consequence in the form of itemsets). Based on association rule mining, recommendation generation is performed when selecting a product for the cart based on analyzing a database of transactions previously made by other customers (*Lobur et al., 2017*). Well-known algorithms for Association Rule Mining include Apriori and its modifications, Eclat, DHP, AprioriTID, McEclat, and MsApriori (*Satyavathi et al., 2019*). The Apriori algorithm is based on two processes:

(1) discovering frequent itemsets whose support is more significant than a predefined threshold value;

(2) generating strong association rules from the discovered frequent itemsets whose confidence exceeds a predefined threshold value.

However, the Apriori algorithm is static. Therefore, in e-commerce systems, there is an issue with updating the discovered rules, which has not yet been fully resolved.

The study object is the process of updating association rules in e-commerce recommendation systems.

The implementation of recommendation systems among large retailers is one of the factors driving the rapid growth of global online sales. However, this approach is not sufficiently represented in smaller online retail stores, and the existing recommendation algorithms do not always meet users' needs, which requires further improvement.

The study aims to enhance the effectiveness of e-commerce in the product sales sector by developing a recommendation system for an online store. It incorporates effective methods for searching and dynamically updates association rules to generate personalized recommendations for users using the Apriori algorithm.

Dynamic updating of already discovered association rules is very complex because the range of products available for sale changes over time. Reapplying the Apriori algorithm results in the discovery of rules, some of which may no longer be relevant. Another issue with updating association rules in e-commerce systems is the increasing computational complexity of their search caused by the accumulation of many transactions. There are various approaches to dynamically updating the transaction database during the lifecycle of recommendation systems, aimed at generating rules based on newly added transactions and updating existing rules in a shorter time frame (*Naresh & Suguna, 2021*; *Satyavathi et al., 2019*). Incremental approaches, in particular, are worth noting, as they involve updating association rules by scanning only a portion of the transaction database rather than the entire dataset. However, their implementation in e-commerce systems has not been sufficiently researched and requires further development.

Overview of information sources

Thanks to significant improvements in the ARM process, practical algorithms have recently emerged that demonstrate the automatic updating of generated association rules. Most proposed algorithms focus on minimizing database scanning and incremental association rule mining (*Satyavathi et al., 2019*; *Santoso, 2021*). The proposed approaches use variable threshold values for support and confidence (*Aqra et al., 2019*). This also addresses the issue of re-scanning previously mined databases and allows for acquiring knowledge that meets several thresholds without restarting the process, thereby reducing processing time.

Incremental association rule mining updates already mined rules using newly added transaction records in the database (*Figure 1*). The analysis of incremental association rule mining revealed the following approaches.

The FUP algorithm updates rules gradually based on changes to the database (when new transactions are added), generating a candidate set on each iteration subordinated to frequent itemsets already mined in previous iterations (*Han et al., 2022*). The FUP2 algorithm is an extension of the FUP algorithm, which supports incremental ARM for new record insertions and deletions of existing records.

The DELI algorithm, when updating the database, uses a sampling method to decide whether a new set of association rules needs to be generated or not (*Satyavathi et al., 2019*). If the evaluation is low, it considers the old rule set a good approximation of the new set. It waits for additional changes to be made to the database and applies the DELI algorithm again. If the evaluation is high, the FUP2 algorithm is applied to generate a new set of rules. DELI is more efficient than FUP2.

The algorithm utilizing negative borders improves the performance of algorithms based on FUP by using the concept of negative borders (*Thomas et al., 1997*). When generating frequent itemsets related to database growth, it scans the entire database only when the itemsets is beyond the hostile border.

The UWEP algorithm is another type of incremental ARM based on early pruning (*Ayan et al., 1999*). Early pruning helps avoid unnecessary processing of certain records by focusing only on incremental updates. The IncA algorithm is a new version of the Apriori algorithm, which scans incoming transactions and updates itemsets based on this data (*Driff & Drias, 2017*). This saves time and memory.

The MAAP and PELICAN algorithms generate large, frequent item sets based on previously mined frequent itemsets (*Satyavathi et al., 2019*). These algorithms are similar to FUP2 but focus on maintaining minimal frequent itemsets, as the database is periodically updated. MAAP computes the most frequent itemsets using the Apriori property, while PELICAN uses a decomposition grid and a vertical database format.

Thus, the analysis of incremental ARM algorithms showed that for dynamic updating of association rules in e-commerce systems, it is advisable to apply approaches that scan only part of the transaction database rather than the entire dataset. This reduces the algorithm's computational complexity and decreases the time required for rule updates.

Materials and methods

For developing the server-side part of the e-commerce recommendation system, the MongoDB database management system, the open-source platform Node.js, the JavaScript library Mongoose, and the cloud hosting service Digital Ocean with an Ubuntu server were used. Nginx and SSL were configured on the server. HTML, CSS, JavaScript, the Vue.js framework, the Shopify e-commerce platform, and the Liquid templating language were used to develop the user interface.

The developed intelligent recommendation system was implemented into a company's web application specializing in the online sale of animal feed additives designed to help combat specific diseases. The recommendation system's main tasks are finding feed additives for animals with particular health issues and recommending their selection to customers.

A transaction database was prepared for generating and searching association rules (*Figure 2*). Scanning the entire transaction database has high computational complexity. To reduce the search space, the Apriori algorithm was chosen. However, it is static, and in real-world commercial systems, the discovered association rules must remain relevant. Recommended products are periodically removed, new ones are added, and advertised in different ways. Therefore, to solve the problem of generating up-to-date association rules and their optimal updating, the Apriori algorithm-based association rule mining was used, which allows reducing the search space by setting threshold values for support $S_{\min}(X \to Y)$ and confidence $C_{\min}(X \to Y)$ and searching for rules among frequent itemsets using incremental association rule mining.

The system includes the calculation of the following association rule metrics (*Boliubash, 2023*):

1) *Support* – is the ratio of the number of transactions containing both the condition and the consequence to the total number of transactions in the database:

$$S(X \to Y) = P(X \to Y), \quad (1)$$

where $P(X \to Y)$ is the probability of the joint occurrence of the condition and consequence;

2) *Confidence* – is a measure of the rule's accuracy and is defined as the ratio of the number of transactions containing both the condition and the consequence to the number of transactions containing only the condition:

$$C(X \to Y) = \frac{S(X \cup Y)}{S(X)}, \quad (2)$$

3) *Lift* – is the ratio of the confidence of the rule to its expected confidence, which is determined by the frequency of the consequence's appearance in the overall database (the support of the consequence of the rule):

$$L(X \rightarrow Y) = \frac{C(X \rightarrow Y)}{S(Y)}, \tag{3}$$

4) *Conviction* – compares the probability that condition X will appear in a transaction without consequence Y, assuming they are independent, to the actual frequency of X appearing without Y:

$$Conv(X \rightarrow Y) = \frac{1-S(Y)}{1-C(X \rightarrow Y)} = \frac{P(X) \times P(\overline{Y})}{P(X \cup \overline{Y})}, \tag{4}$$

where $P(\overline{Y})$ is the probability that Y will not appear in a transaction.

Discovered by the Apriori algorithm, the rules were sorted according to their lift and conviction values in the developed e-commerce system. The determination of lift $L(X \rightarrow Y)$ and conviction $Conv(X \rightarrow Y)$ metrics allows for more accurate identification of relevant rules by detecting their non-randomness, which enhances the understanding of the discovered patterns. The calculation of lift helps exclude false rules that are not frequent itemsets: rules with lift values greater than 1 are considered significant. The calculation of conviction $Conv(X \rightarrow Y)$ helps identify the condition X and consequence Y, where the relationship is random if the value is close to 1. If the conviction is greater than 1, the relationship between the condition and consequence of the association rule is not random.

To dynamically update the discovered association rules to maintain their relevance and reduce the algorithm's computational complexity, it was decided to periodically scan the transaction database, including only transactions within the most recent time interval. The size of this interval was empirically determined by scanning the actual transaction database with different intervals. Accordingly, the association rules discovered by the Apriori algorithm will be updated at a period equal to the selected interval.

Results

The recommendation system, developed using the approaches described above, was implemented in the operation of the e-commerce system for selling animal feed additives. The threshold values for support and confidence were selected so that the company could promote new products to the market.

The developed intelligent recommendation system generates association rules by selecting products that are frequently bought together, based on the set threshold values for support $S_{\min}(X \rightarrow Y)$ and confidence $C_{\min}(X \rightarrow Y)$ (*Figure 3*). The metrics for the generated association rules are calculated (*Figure 4*). Based on association rule mining, recommendations are generated when selecting items for the shopping cart based on the analysis of transaction data from previous purchases made by other customers.

Scanning the transaction database with different intervals showed that the most optimal update period for the association rules is every three months. Therefore, to generate the rules, it was decided to consider only the most recent transactions from the last three months. Subsequently, new transactions will be considered, and new association rules will be generated every three months. Implementing this approach significantly reduced the computational complexity of the algorithm and considerably shortened the time needed to search and update the association rules.

In the recommendation system, custom events were set up to track how many times a product appeared in the recommendations, how many purchases were made, and how many users showed interest in the product. The Figure 5 (*Figure 5*) shows information about each product added to the cart via the recommendation system. Monitoring the operation of the recommendation system revealed that its implementation led to an increase in revenue generated from sales due to the more significant number of company products purchased through the provided recommendations.

Custom events were also set up to track how many times each product was displayed in the recommendations, how many purchases were made, and how many users were interested in the product (*Figure 6*, *Figure 7*). This allows for tracking sales conversion and making decisions regarding optimizing the company's marketing strategy based on the analysis conducted. An analysis of the impact of the recommendations on customer product selection showed that 55% of the recommended products were chosen and purchased by the customers (*Figure 8*).

Thus, applying the described approaches to the dynamic update of association rules in the e-commerce recommendation system has enhanced and improved customer service, expanded the customer's shopping cart, stimulated online sales in the e-commerce platform, and ensured high conversion rates for the online store.

Discussion

Providing personalized recommendations in the context of rapid growth in digital content volume requires identifying methods that offer high forecasting accuracy regarding users' intentions and preferences and optimal flexibility in their interaction with the recommendation system. The research has shown that incremental ARM algorithms can be used in real-time applications, ensuring automatic rule updates without the need to rescan the entire database. The incremental database is sufficient for creating new rules and updating the existing ones that have been generated. However, the ability of these algorithms to work with data with Big Data's characteristics remains unexplored. There are also incremental mining algorithms based on patterns. This highlights the need for further development in researching the effectiveness of their application in electronic commerce systems.

Conclusion

The analysis of recommendation provision in electronic commerce systems showed that the widely used method for forecasting users' potential preferences when selecting products is the search for association rules using the Apriori algorithm. It was found that dynamic updating of association rules in e-commerce systems is a problem that has not yet been fully resolved, as the algorithm is static and highly complex. In contrast, the product and service assortment in e-commerce systems changes over time.

The research established that incremental association rule mining algorithms significantly reduce rule update time and computational complexity by scanning only a part of the database related to new transaction records rather than the entire database.

To improve the commercial activity of a company engaged in the online sale of animal feed additives, an intelligent recommendation system was developed based on the Apriori algorithm using incremental ARM. Recommendations were provided based on association rules generated by the Apriori algorithm, sorting according to lift and conviction values. The recommendation system scans the transaction database every three months for dynamic updating of association rules. To reduce computational complexity and find up-to-date rules, the new scan covers only transactions made during the new three-month period, not the entire database. Implementing the developed intelligent recommendation system in the company's web application was accompanied by an increase in profit due to a rise in the number of products sold through the provided recommendations.

Thus, the research revealed that implementing an intelligent recommendation system based on the Apriori algorithm, using Incremental Association Rule Mining, significantly enhances the effectiveness of commercial activities in online sales.

Conflict of interest

The authors declare that there is no conflict of interest.

References

Aqra, I., Ghani, N., Maple, C., Machado, J., & Safa, N.S. (2019). Incremental algorithm for association rule mining under dynamic threshold. *Applied Sciences*, *9*(24), 5398. https://doi.org/10.3390/app9245398

Ayan, N. F., Tansel, A. U., & Arkun, M. E. (1999). An efficient algorithm to update large itemsets with early pruning. *Proceedings of the 5th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 287-291. https://dl.acm.org/doi/10.1145/312129.312252

Boliubash, N. M. (2023). *Data Mining*. Mykolaiv: Petro Mohyla Black Sea State University. (In Ukrainian). https://dspace.chmnu.edu.ua/jspui/handle/123456789/1461

Boliubash, N., & Zheltobriukhov, O. (2024). A Chat-bot for providing recommendations for watching videos based on matrix factorization models. *Information Technology and Society*, *1*(12), 20-30. https://doi.org/10.32689/maup.it.2024.1.3

Cherednichenko, O., Yanholenko, O., Ivashchenko, O., & Matvieiev O. (2020). Models of recommendations formation in the intelligent e-commerce systems. *Information Processing Systems*, *1*(160), 32-39. (In Ukrainian). https://doi.org/10.30748/soi.2020.160.04

Driff, L. N., & Drias, H. (2017). An efficient incremental mining algorithm for dynamic databases. In: R. Prasath, A. Gelbukh. (Eds). *Mining Intelligence and Knowledge Exploration. MIKE 2016. Lecture Notes in Computer Science*, 10089. https://doi.org/10.1007/978-3-319-58130-9_1

Falk, K. (2019). *Practical recommender systems*. Shelter Island, NY: Manning. https://www.simonandschuster.com/books/Practical-Recommender-Systems/Kim-Falk/9781617292705

Fayyaz, Z., Ebrahimian, M., Nawara, D., Ibrahim, A., & Kashef, R. (2020). Recommendation systems: Algorithms, challenges, metrics, and business opportunities. *Applied Sciences*, *10*(21). https://doi.org/10.3390/app10217748

Han, C., Yu, W., Li, X., Lin, H., & Zhao H. (2022). A new fast algorithm for library circulation data mining based on FUP. *Scientific Programming for Fuzzy System Modeling of Complex Industry Data*. https://doi.org/10.1155/2022/1683099

Jannach, D. (2022). Evaluating conversational recommender systems: A landscape of research. *Artificial Intelligence Review*, *56*(3), 2365-2400. https://doi.org/10.1007/s10462-022-10229-x

Lobur, M., Stekh, Yu., & Shvarts, M. (2017). Building association rules for predicting recommendations in collaborative recommender systems. *Collection of scientific works of the UAP*, *2*(32), 82-86. (In Ukrainian). http://nbuv.gov.ua/UJRN/Kk_2017_2_15

Naresh, P., & Suguna, R. (2021) IPOC: An efficient approach for dynamic association rule generation using incremental data with updating supports. *Indonesian Journal of Electrical Engineering and Computer Science*, *24*(2), 1084-1090. http://doi.org/10.11591/ijeecs.v24.i2.pp1084-1090

Santoso, M. H. (2021). Application of association rule method using Apriori algorithm to find sales patterns case study of indomaret tanjung anom. *Brilliance: Research of Artificial Intelligence*, *1*(2), 54-66. https://doi.org/10.47709/brilliance.v1i2.1228

Satyavathi, N., Rama, B., & Nagaraju A. (2019). Present State-of-The-ART of Dynamic Association rule mining algorithms. *International Journal of Innovative Technology and Exploring Engineering*, *9*(1), 309-316. https://www.ijitee.org/portfolio-item/a4107119119/

Thomas, S., Bodagala, S., Alsabti, K., & Ranka, S. (1997). An efficient algorithm for the incremental updation of association rules in large databases. In *KDD'97 Proceedings* (pp. 263-266). https://cdn.aaai.org/KDD/1997/KDD97-055.pdf

Appendix

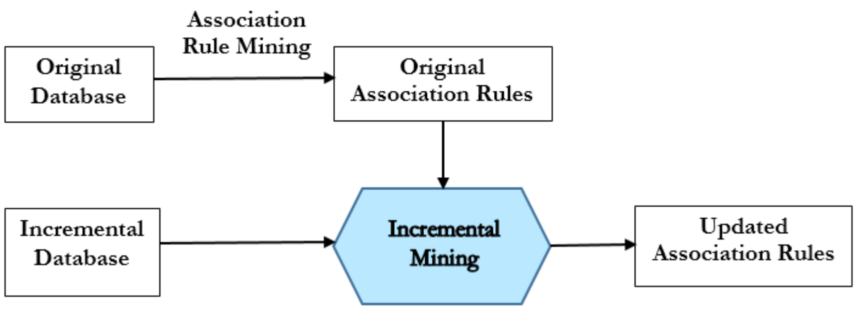


Figure 1. Process of Incremental Mining

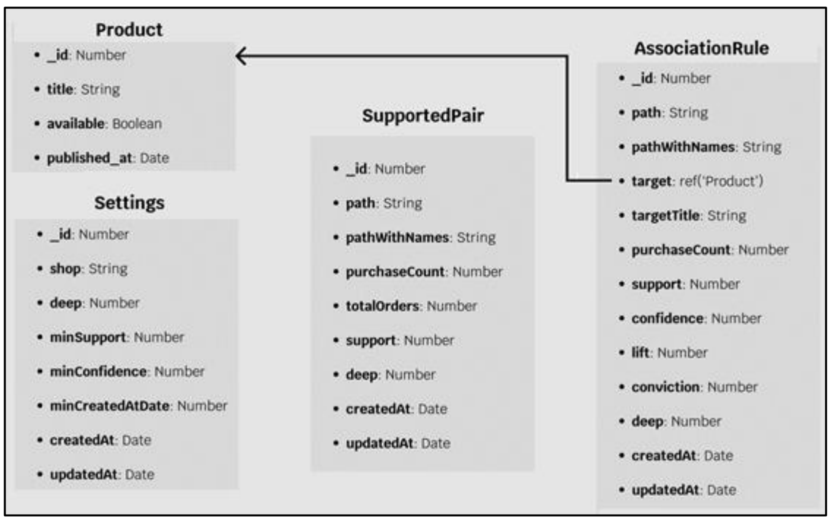


Figure 2. Architecture of the transaction database

Deep	Minimal support	Minimal confidence
2	0.40	0.55

Supported Pairs

Items set	Deep	Support
Lucky Belly	1	0.62224493557
Relax Time	1	0.84451045138
Fresh Smile	1	0.12363502326
Happy Hips	1	0.71974935110

Figure 3. Calculation of support for single-item sets

Association Rules

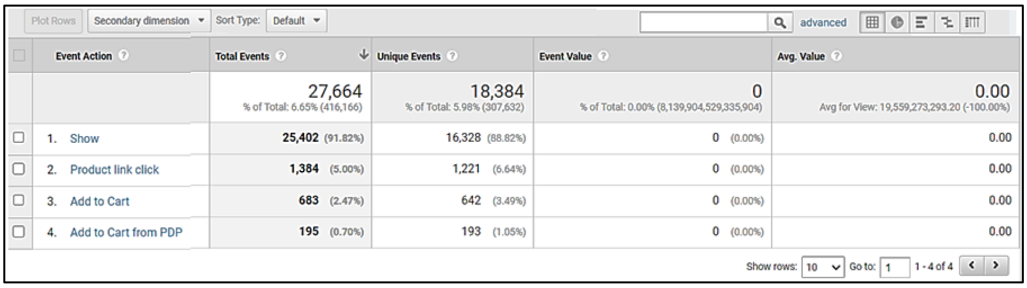
Deep	Minimal support	Minimal confidence
2	0.40	0.55

Items set	K	Confidence	Lift	Conviction
Easy Fresh -> Fresh Smile+	2	0.8435145869691682	8.747077774819811	1.0599619226450465
Easy Fresh -> Flavor Bundle	2	0.8231937172774869	2.931496303428662	1.0411289277060174
Easy Fresh -> Lucky Belly+	2	0.77545908667830134	2.4865983684815864	1.0314847517964587
Easy Fresh -> Fresh Smile	2	0.5997673072774869	2.3714454814477577	1.2398941522653337

Figure 4. Calculation of association rule evaluations at the stage of their formation

Назва продукту	Всього покупок	Ціна продукту	Загальна сума
Easy Fresh (50% Rabatt)	232	17.49	4,057.68 €
Lucky Belly Akut (40% Rabatt)	211	17.99	3,795.89 €
Fresh Smile Probe	83	4.99	414.17 €
Lucky Belly	65	39.99	2,599.35 €
Flavor Bundle	72	19.99	1,439.28 €
Pure Genius	43	39.99	1,719.57 €
Immu Push	31	39.99	1,239.69 €
Lucky Belly+	37	49.99	1,849.63 €
Fresh Smile+	24	49.99	1,199.76 €
Easy Protect (50% Rabatt)	11	17.49	192.39 €
Forever Young	10	39.99	399.90 €
Super Protect	14	39.99	559.86 €
Lucky Belly Probe	8	4.99	39.92 €
Fresh Smile	7	39.99	279.93 €
Happy Hips	7	39.99	279.93 €
Lucky Belly Akut	5	29.99	149.95 €
Easy Fresh	2	34.99	69.98 €
Happy Hips+	1	49.99	49.99 €
Relax Time	1	39.99	39.99 €
Shiny Hair	1	39.99	39.99 €
Приблизна загальна сума доданих в кошик продуктів			20,416.85 €
Приблизна загальна сума куплених продуктів (-55%)			11,229.27 €

Figure 5. Products added to the cart via the recommendation system



	Event Action	Total Events	Unique Events	Event Value	Avg. Value
		27,664 % of Total: 6.65% (416,166)	18,384 % of Total: 5.98% (307,632)	0 % of Total: 0.00% (8,139,904,529,335,904)	0.00 Avg for View: 19,559,273,293.20 (-100.00%)
1.	Show	25,402 (91.82%)	16,328 (88.82%)	0 (0.00%)	0.00
2.	Product link click	1,384 (5.00%)	1,221 (6.64%)	0 (0.00%)	0.00
3.	Add to Cart	683 (2.47%)	642 (3.49%)	0 (0.00%)	0.00
4.	Add to Cart from PDP	195 (0.70%)	193 (1.05%)	0 (0.00%)	0.00

Figure 6. Custom recommendation events in analytics

Назва події	Всього подій	Всього унікальних подій	Відсоток подій	Відсоток унікальних подій
Відображеннь продукту в секції рекомендацій	25,402	16,328	100%	100%
Відриття продукту через секцію рекомендацій	1,384	1,221	5.45%	7.48%
Додавання продукту в кошик через секцію рекомендацій	683	642	2.69%	3.93%
Додавання продукту в кошик зі сторінки продукта, якщо на неї перейшли через секцію рекомендацій	195	193	0.77%	1.18%
Усього додавань в кошик за допомогою рекомендацій	878	835	3.46%	5.11%

Figure 7. Generalized data of custom events

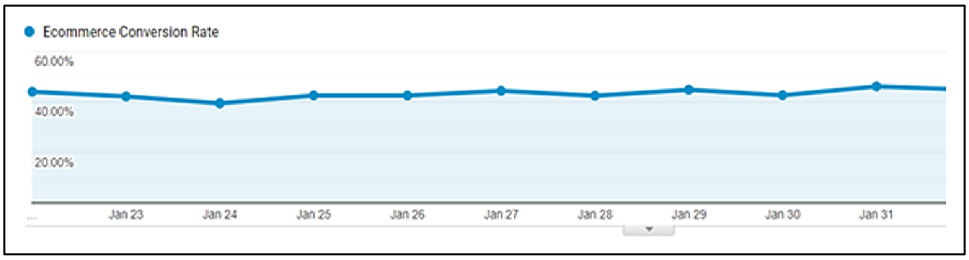


Figure 8. Analysis of the dynamics of recommended product purchases