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DEVELOPING HYBRID RECOMMENDATION SYSTEMS: UKRAINIAN DIMENSION

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ABSTRACT

The lack of a consistent strategy to product recommendations, as well as the range of effective techniques to offering suggestions, are reflected in the variety of current recommendation systems. The study presents the original recommendation system, which delivers suggestions based on content and collaborative techniques and addresses the major issues in this field. The focus of the paper is hybrid recommendation systems in e-commerce on the market with a low level of implementing recommendation systems techniques. The market of recommendation systems in Ukraine, their main features are analysed. The methodology to developing hybrid recommendation systems that is relevant to the needs of Ukrainian e-commerce market is proposed. The hybrid recommendation system includes recommendation systems in four categories: Personalized recommendation, Best buy, News, Recommendation according to the survey. The alternative approach to product evaluation in proposed recommendation systems based on a combination of Wilson, Bayes, and Hacker methods is used. It is shown that this approach can be successful for recommendation systems in Ukraine. The concept's utility for users is the creation of more customised recommendations that are more attractive to them, taking into account a broader set of variables, for example, the time of publishing, the percentage of favourable comments, and personal preferences.

Keywords: recommendation system, hybrid recommendation system, product evaluation, model, e-commerce, Ukraine

JEL classification: C5, D2, M3, O1

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INTRODUCTION

A company's ability to compete becomes more challenging as the number of e-commerce firms grows. To address this issue, recommendation systems (RSs) are being actively developed to address instances when users' choices are unknown. Gaining hybrid recommendation systems (HRSs) is a significant advancement. Modern RSs are designed to solve a specific problem (for example, a cold start or a long tail of products). However, the extent of product evaluation in recommendation systems is still lacking. The characteristics of certain types of RSs (content-based, collaborative filtering, hybrid) and the aim that the assessment should give guide evaluation approaches. There is a need to develop an alternate evaluation methodology that takes into account the unique characteristics of the RSs. As a result, the focus of this research is on developing a novel model of product evaluation in RSs for e-commerce.

According to research of the most popular e-commerce sites in Ukraine, just a few of the most basic algorithms are implemented. In most situations, websites solely use direct user information (history of purchases, products viewed and products, which are added to the wish list). Other suggestions are based on data gathered from the company's whole customer base. Improving the forms and models of product evaluation is a critical job for Ukraine's existing e-commerce business.

The goal of this research is to provide an alternative strategy to developing product evaluation in HRSs, as well as to present a model of such a recommendation system that is relevant to the demands of the contemporary e-commerce market in Ukraine.

The following tasks are formed in accordance with the purpose:

- define the essential elements of current HRSs;
- highlight the features and constraints of the development of RSs in Ukraine;
- build an effective alternative product evaluation model;
- outline the methodology of an RS that employs the suggested method.

MATERIALS AND METHODOLOGY

1. 1. Features of modern recommendation systems and approaches to their evaluation

RSs are tools for automatically generating recommendations for services and products based on a study of the personal needs of website users. The main areas of use of referral systems today are marketing and ranking the results of search queries in search engines, although their application can be much wider. These systems allow to detect groups of similar users or objects, they can be used as alternative methods of searching for information on the Internet because they allow detecting of objects that cannot be found by traditional search algorithms. RSs are software used to predict which objects (products, websites, movies, news, etc.) will be of interest to the user, based on the information collected about him. Depending on the strategy of data determination, proposal frameworks are classified as content-based methods; collaborative methods and hybrid methods (Meleshko et al., 2018).

Content RSs include working with a specific user profile. For the recommendations of a particular element, many descriptions of the properties of previous elements are considered, as well as their evaluations, preferences, tags, keywords. The result is an evaluation of the level of pertinence, which decides the level of client intrigued within the subject. Studies Woldan et al. (2021), Barolli et al. (2021), Dat et al. (2021) are given to the issues of utilizing this sort of RSs.

RSs based on collaborating filtering are based on finding and analyzing past client behavior, which afterward predicts components on the likeness of the sort of appraisals given by like-minded clients to the target client. Most existing co-filtering methods rely heavily on explicit feedback. Collaborating methods can be classified into memory-based and model-based. Studies Ajaegbu et al. (2021), Nhuen et al. (2020), Shen et al. (2020) are given to the issues of utilizing this sort of RSs

HRSs combine collaborative and content methods. Based on investigating Feng et al. (2021), Schwartz et al. (2019), Chorna (2018); Kilani et al. (2018), we are able to distinguish seven essential standards that illustrate diverse ways of combining strategies in HRSs. In terms of making a HRS, a distinctive step-by-step combination of strategies of different types of proposal frameworks is conceivable to apply. The foremost common are parallel and monolithic construction (Jiang). Modern studies sure that HRSs are more effective than collaborative or content recommendation systems (Chorna, 2018; Kilani et al., 2018; Turnip et al., 2017; Stockl et al., 2020).

The system of hybrid recommendations integrates different types, which helps to overcome shortcomings and improve performance. Most advanced frameworks kill the foremost problems such as (Majjodi et al., 2019):

• Cold Start problem: a new user at the site or when adding a new item to the system. The platform has a lack of knowledges about user's interests, and he did not rate any item yet. New item that has no rates, can't be recommender to typical algoritms due to absence of reviews.

• Sparsity Problem: it is happening when a user has large matrix contain buy items or watch movies or listing for music. Sparsity evolved when the user did not rate these items. While recommender systems depend on users rating matrix users to recommend to the others.

• Scalability: it measures the ability of the system to work effectively with high performance while growing in the information. Recommender system needs to recommend items to the users without no change while the number of users increased, or the number of items increased too.

• Over Specialization Problem: Recommended item to users is based on those already known or defined by user profile only without discovering new items and other available options.

• Diversity: ensuring that the recommender results span as much as possible item space, and do not come all from the same cluster.

• Novelty: recommended items must contain new one’s items.

• Serendipity: recommended items need to be suprising for users about which user wouldn't have thought before.

• Privacy: privacy: users need to know which information needed to recommend more preferably items to him, and how it applied.

• Shilling Attacks: a malicious user or competitor enters into a system and starts giving false ratings on some items either to increase or diminish the item popularity according to own purpose.

• Gray Sheep: the opinions of a user do not equate with any group and consequently, is unable to obtain the benefit of recommendations.

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1.2. Review of the current state of development of hybrid recommendation systems

In this part, we'll look at several advanced current HRSs and discuss the need to establish a method for improving the accuracy of product evaluation models. The analysis of the provided systems allows us to assess the current condition and trajectory of RSs in general. On the other hand, an examination of these systems will aid in the development of the created model's originality.

To address the difficulties of cold start, use collaborative RS. The study (Ajaegbu et al., 2021) focuses on upgrading traditional similarity measures for co-element-based filtering to address and reduce cold start circumstances. In the direction of cold-start circumstances, the study provides an algorithm that balances three contemporary standard assessment metrics, such as cosine-based similarity, Pearson correlation similarity, and adjusted cosine similarity.

HRS with a long tail emphasis. Individual customer preferences have an impact on new product development according to research Kumar et al. (2016). To predict the rating, the study used an extension of the matrix factorization model. Models (PM-1, PM-2) are provided that show their usefulness for 1) providing individualized suggestions to users, considering the suitable taste of things with a long tail; 2) advertising items with a long tail to idiosyncratic users.

HRS based on tone and suggestions. In Chorna (2018), an RS is presented that is based on a hybrid analysis of suggestions and tonality. The F-metric is employed, which is a weighted average harmonic accuracy and completeness meter that allows the model's work to be evaluated more effectively from a broader viewpoint. The approach described in the study is more effective at identifying films that are relevant to the user.

HRS to users who are currently logged in. The study (Kilani et al., 2018) created a new RS that combines collaborative filtering and matrix factorization approaches. The RS only looks at active users and objects that are relevant to them. Novel RS use evolutionary algorithms to estimate the rates of the active user's most valued things. The considered RS for joint filtering uses neighbourhood models and hidden factor models to recommend elements for the active user (customer).

HRS is responsible for locating educational resources. With a mix of content-based filtering and cooperation filtering, the research Turnip et al. (2017) suggests an enhanced solution for the existing system of e-learning suggestions with excellent student ratings (CBF-CF-GL method). In e-commerce, for example, the method of admission for analysis of students with just high scores may be employed by selecting for analysis users with costs in a certain range that is relevant to the costs of the target user.

HRS is a visualization-based HRS combines a collapsed neural network with a Bagdanau attention mechanism for this aim. As a consequence, the approach enables the identification of locations that were particularly significant for the proposed image (Woldan et al., 2021).

HRS for telemetry in a web browser. The study (Lopatka et al., 2019) proposed a telemetry-aware add-on recommendation system (Telemetry-Aware Add-on Recommender), which offers Firefox users with suggestions. Three different models are employed, each based on three different data sources: the user's

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installed add-ons; use and interaction data (browser telemetry); and the user's browser language preferences. The study creates independent recommendation models for each model and uses the linear ensemble composition approach to summarize the suggestions they provide.

HRS is based on a hybrid of taxonomy and folksonomy. According to Mao et al. (2019), tag information is combined for semantic analysis of taxonomy characteristics, and an algorithm for reconciling the establishment of general similarity between components is devised. The research proposes a unique model of random sampling on a heterogeneous graph, built by user nodes, element nodes and different types of relationships - user-element, element-element.

HRS for commodity network consideration. The link between product networks formed by RSs and product rating convergence is examined in the research (Stockli et al., 2020). The study looks at how different forms of product networks affect customers' perceptions of quality between product pairings within the network. Furthermore, this study investigates whether different forms of product networks are connected to the convergence of attitudes toward items in the product network in different ways.

HRS takes into account profile similarity coefficients as well as demographic disparities. The technique of generating the similarity coefficients of user profile vectors and object profile vectors was further refined in Schwartz et al. (2019), which, unlike the basic ones, takes into account the demographic features of users, allowing forecasting predictions to be more accurate. A technique of searching for user groups has been created based on the notion of application in one approach of categorical, mixed, and numerical clustering, which adjusts to the sparseness of the user-object matrix.

HRS based on partial variation autoencoder. The study (Ma et al., 2018) devised a hybrid recommendation technique, in which the missing data is processed, and the amortized result is used for rapid forecasting. Partial Varial Autoencoder is the name of the technique (P-VAE). The method uses a new probabilistic generative model to process a different number of user ratings in principle.

HRS is used to compare product descriptions with user profiles. The study Badriyah et al. (2017) created a hybrid e-commerce recommendation system that uses content-based filtering and collaboration-filtering to determine how comparable product descriptions and user profiles are.

HRS based on partial variation autoencoder. The study (Kwok, 2019) employed the content-based approach's built-in categories with the shared filtering approach's embedding of clients. It will be sent into the new neural network as input, and it will be checked to see if it is relevant to the suggestions. The generated model may be utilized in two ways: to arrange recommendations categorized by prior methodologies, or to generate recommendations.

The paper suggests HRS, which varies from earlier models in that it improves product evaluation modelling accuracy. The suggested evaluation methodology takes into account a broader set of variables. Using the complex of recommendation systems helps to use different methods is a right way, not only together, but also in a more suitable order.

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1.3. Review of recommendation systems on e-commerce sites in Ukraine

Nowadays, the growth in the number of Internet users in Ukraine is rapidly increasing at the same time with the growth of their activity at different types of marketplaces. In general, about 67% of Ukrainian Internet users visit sites associated with e-commerce. It means that there is strong precognition to marketplaces' growth in the world and Ukraine. Although in our country there are some deterrent factors to its full developed. Suppliers single out such as (Retailers, 2021):

- 52.2% lack of tools to promote goods at marketplaces;
- 36.2% difficulties with content preparation;
- 30.4% technical integration;
- 20.3% hazard to quickly updates of price due to their volatility;
- 11.6% processing customer questions and feedback:
- 10.1% orders processing;
- 8.7% time settlements with marketplaces.

HRSs that take into account the personal preferences of users, demographic characteristics of the population, metrics for product evaluation serve as a quality tool for product promotion among users. Unlike other advertising tools, recommendation systems provide a more personalized recommendation that will provide suppliers with greater sales and better customer satisfaction. The use of simple algorithms of RSs cannot qualitatively solve the problem of product promotion.

The application and promotion of RSs partially eliminate the problem of forming a product description, as the priority is to fill the description on specific items. And in this case, the task that depends on the suppliers is to form the right set of products presented on the marketplaces.

To develop a recommendation system that is most suitable for Ukraine, an analysis of the existing results of the action of recommendation systems on the country's websites was conducted. E-commerce companies selected from the ranking of the most popular sites are taken for analysis (Figure 1). The research was conducted in two directions: for an authorized user, for an unauthorized user.

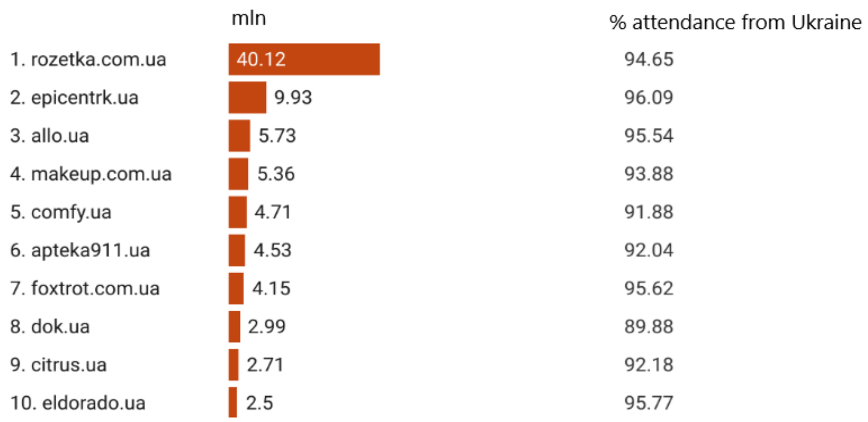

Figure 1. The most popular Ukrainian sites by number of visits, 2021

Source: Retailers (https://retailers.ua/uk/news/menedjment/12587-samyie-poseschaemyie-internet-magazinyi-avgusta-2021-goda)

The most popular e-commerce site is Rozetka (https://rozetka.com.ua). For the unauthorized user, recommendations are offered in the following categories: promotional offers, hot news, similar products from other sellers, currently in demand in the category of women's / men's rubber boots, most often added to the wish list, the most anticipated, most discussed products are now in demand. The most dubious category is "Similar products from other sellers". According to the results of the categories, it is noticeable that the user's behavior on the Internet in general and on other sites is not analyzed. It is improved to provide recommendations in the categories currently in demand in the category of women's / men's rubber boots, as it corresponds to the season and weather conditions. The last four categories are not personalized, but the available information for recommendations is still analyzed. For the authorized user, in addition to the above, the following categories are offered: last viewed products, bestsellers in the category (recently viewed), more products to choose from, recommendations based on personal views. The added categories analyze the direct behavior of the user: specific products, similar products or categories viewed by this user. In categories that are the same for authorized and unauthorized users, the recommendations are the same. In general, the site uses certain information of the general geographical group and the history of purchases, user views to provide recommendations. However, only direct information provided is used.

In second place in popularity is Epicenter (https://epicentrk.ua). The following categories of recommendations are available for the unauthorized user: product of the day, popular categories, promotions, the most interesting. The same categories are available for the authorized user. Unlike the previously analyzed site, this one provides other recommendations for categories that are the same for authorized and unauthorized users. This is due to the fact that there are no personalized categories in the list. However, the user perceives positively that in the supposedly general categories of recommendations are selected specifically for him. The analysis concludes that Epicentr is likely to use only direct information from users and geographic location.

The third most popular site is Allo (https://allo.ua/). Categories are available for unauthorized user: sales leaders, news, promotions and news, best price. For the authorized user, the "You watched" category is additional. The list of products of the previous categories remains unchanged.

An analysis of the top 10 most popular e-commerce sites in Ukraine has identified several similar trends. Sites are limited to direct user information (history of purchases, viewed products and those added to the wish list). Other recommendations are based on information collected from all consumers of the company. The Ukrainian e-commerce market has a limited number of the simplest algorithms for providing recommendations. At least such standard algorithms as users who bought the same product also bought are not taken into account; bought together; algorithms based on demographic characteristics.

E-commerce sites in Ukraine do not provide information on the indicators they track. However, the following are possible to collect within their functionality: User ID and full name; ID, name, rating, category, brand, product metadata; text and response time; price.

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RESULTS AND DISCUSSION

2.1. Conceptual foundations of recommendation systems

The lack of a consistent strategy to product recommendations, as well as the range of effective techniques to offering suggestions, is reflected in the variety of current RSs. The study presents its own recommendation system, which delivers suggestions based on content and collaborative techniques and addresses the major issues in this field.

The built recommendation system offers recommendations in four categories: "General recommendation for the user", "Personalized recommendation," "Best buy," "News," and "Survey recommendation."

In recent versions of e-commerce sites, the practice of presenting suggestions in numerous categories is popular. Amazon, for example, offers suggestions in two directions (On-site and Off-site) and 13 categories (Figure 2).

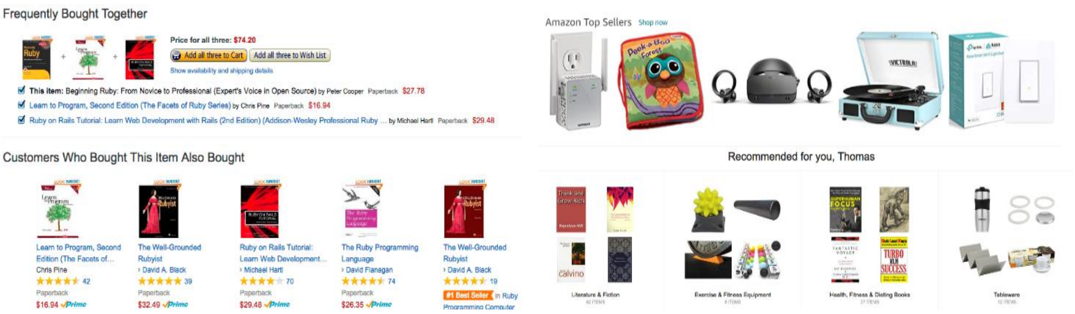

Figure 2. Examples of Amazon recommendation categories

Source: Amazon (https://www.amazon.com/)

Recommendations in the On-Site Recommendations category include Recommender for You, Frequently Bought Together, Your Recently Viewed Items, and Featured Recommendations, among other categories. The following categories are included in the Off-Site Recommendations with Email: Frequently Bought Together is the best-selling book this week (in three formats).

Another example of using multiple types of recommendations on one site is eBay. The most popular given categories of recommendations are Explore Popular Categories, Daily Deals-Carousel, Explore popular categories, Recommended for you. In addition, eBay conducts a survey of users to personalize the recommendations, on the following questions: How many items would you like to sell one Bay per month, What do you need most from a tool, What would also be useful, Select a recommended tool package (Figure 3).

The considered examples confirm the effectiveness of using several directions of providing recommendations to users. The key advantage is to expand the user's choice, as he is able to choose which recommendation he wants to receive at a particular time.

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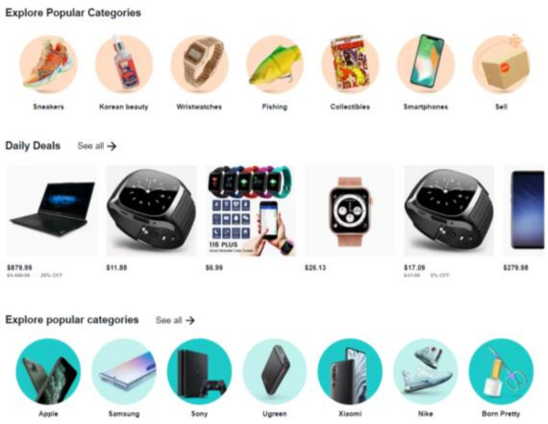

Figure 3. Examples of eBay recommendation categories

Source: eBay (https://www.ebay.com/)

Key characteristics of the developed hybrid set of RSs by classification:

• Subject of recommendation: goods from the list;

• Units of recommendation: point recommendation of products (excluding additional purchases);

• Subject of recommendation: registered users;

• Type of recommendations: new products (not purchased by this user);

• Used grades: score on a 5-point scale, product characteristics; product category; comments.

Personalized recommendation. The demographic technique of the content method of the system and the matrix of factorization of the collaboration method are provided in a HRS of the type "addition of features." The mechanism for determining the similarity coefficients of user profile vectors and object profile vectors has been improved, allowing forecasting predictions to be more accurate. The first step is to analyze the user's monthly spending for the previous six months on this platform (the number of months the user is registered, if less than six). Other users with monthly spending in the same interval are filtered based on this information (intervals are set by the author). The next step is to create a user similarity function. The work employs the following strategies of similarity formation: Pearson correlation coefficient, Jacquard coefficient, inverse Euclidean distance, and cosine measure of similarity are all terms used to describe how similar two things are. The similarity feature looks for people who have made similar purchases in the past. As a result, the current user's suggestions from similar users are crossed. Recommendations and the order in which they are provided are produced based on the computation of the rating of items using their own system of scoring. The benefit of the recommendation system approach is that it provides recommendations that are tailored to the preferences of customers as well as their financial resources. The "Personalized Recommendation" has the drawback of requiring frequent recalculation with each purchase of new or similar consumers.

News. The authors describe a HRS that integrates a number of content recommendation algorithms. It is proposed that suggestions be made based on the similarity of prior user evaluations and item features within the context of the method. Modifications of Pearson coefficient approaches and the Hacker ranking algorithm are used combined as a method. As a result, a new product's absence of a sufficient number of answers (cold start of production) is countered by its high time priority. At the same time, this component of the analysis' suggestions ignores new items, which have more evaluations but a lower priority in terms of time. As a consequence, the strategy balances new and older items for the consumer based on their preferences. This strategy has the benefit of solving the problem of cold start items and personalizing suggestions for things that have not yet been purchased but have been changed. The downside is that the interest in the improved product was not taken into consideration. This problem can be rectified in the future by enhancing the capacity to track multiple e-commerce sites' active browsing times. Despite the fact that this feature might be included, most firms do not include it in their user database.

Best buy. The technology is presented as a direct collaborative guiding system with a direct connection. The first step is to create a database with lower dimensions than the first in terms of the number of items purchased in the previous week. The next step is to provide recommendations based on the Wilson confidence interval for the Bernoulli parameter that has been calculated. Consequently, customers will get product suggestions in descending order of adjusted product rating among those who have purchased the most in the previous seven days. The benefit of having a "Best Buy" category is that it eliminates the problem of a user's cold start. The downside of this technique is that recommendations are not personalized.

Recommendation for the survey. The technique of content direct approach of the recommendation system with later situational application of the recommendation systems of existing species is provided as a HRS with a cascade approach. Within the technique, it is suggested that the user be asked questions in order to have a thorough understanding of their wants and desires. This type of survey should be done once a month when enrolling a user, and if feasible, use the functionality to update the responses. The existence of direct user replies, rather than simulated by a computer of likely user choices, is a benefit of utilizing the approach of recommendations for surveys. The disadvantage is that not all users know exactly what they want to buy; the survey recommendation narrows the options. This is related to a narrowing of consumer preferences in specific sectors. In the developed HRS, a number of the following questions are formed:

• Planned monthly cost budget on the platform. By default, the average monthly budget of users.

• Planned number of purchased units. By default, the average number of units purchased by users in one month. Taking into account the previous paragraph, the user chooses the pricing policy of the product.

• Product categories a person is interested in (unlimited quantity).

• Product features that interest a person (unlimited quantity).

• Method by which a person wants to receive recommendations: Personalized recommendation (for active users), News, Best buy.

Directions for improving the developed set of HRSs for the possibility of their implementation on various e-commerce sites:

▫ internal characteristics of the recommendation system;

▫ providing recommendations "Optionally purchased", "Customers who buy this product also buy";

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▫ taking into account the tone of comments in a collaborative approach. This involves the formation of a general tone of comments on specific products;

▫ taking into account the user's psychotype: pessimist, optimist. The current item means the analysis of estimates, the tone of the feedback of the individual user to meet the needs of the user. For example, user A rates 5 on almost all of their purchases; user B can give a top score of 4, because I'm waiting for 5 to be something special that can impress him;

▫ analysis of images of users in the reviews when making a purchase when forming a product score;

▫ expand the provision of recommendations based on visual similarity;

▫ tracking user data:

• time of active product review. The function expands the qualitative side of the product score. For example, user A accidentally clicked and went to product page X and left after 5 seconds; User B purposefully went to product page X and 10 minutes viewing the product but did not buy the product for some reason. The average system will take into account the transition of both user A and user B to page X;

• ability to find visual similarities and translate the state of products from quality to photo to quantitative dimension.

The study proposes an original product evaluation model based on such methods as Wilson's score, Bayesian approximation and Hacker ranking algorithm (Kumar, 2020; Salihefendic, 2015). The proposed evaluation model is calculated:

$$R = \frac{a}{(t+2)^g}\sqrt{r\_w^2 + b \times r\_b^2},$$

where *r_w* – Wilson's score; *r_b* – Bayesian approximation; *g* – degree of relevance; *t* – number of days of product publication; *a, b* – independent variables.

The Wilson (*r_w*) and Bayes (*r_b*) metrics are merged as the root mean square value of their values by normalizing to calculate the rate *R*. The variable b is used to normalize the values of these estimations. The user can choose a preferred estimating technique or fix the variable such that the estimations' maximum values are all within the same range. The Hacker approach (a numerator before the root) is used to adjust the score to the number of days a product is available for purchase (*t*), the degree of relevance (*g*). The variable *a* is used just to broaden the scope of the evaluation and has no bearing on the calculation's core.

2.2. Product evaluation models

The system of developed recommendation systems includes 4 different HRSs: 3 independents of each other (Personalized recommendation, Novelties, Best buy) and 1 (Survey recommendation), which includes one of the three previous recommendation systems of the user's choice. The following key features of the developed RSs can be identified:

• specificity of the combination of different methods of recommendations;

• uniqueness of the developed assessments to each recommendation system.

This part of the paper describes the causality of the use of such adjusted estimates within each system separately and demonstrates their effectiveness in comparison. The environment for the implementation of the developed RSs is the programming language R.

Hacker evaluation is a method of adjusting an existing assessment to take into consideration the moment of release of the product, rather than the series as a whole. The Hacker score grows steeper and more time-sensitive as the necessity of publication time rises.

In order to give suggestions to the user on the most recent items, the recommendation system "News" must take into consideration the moment of product release on the site. The degree of sensitivity to the duration of articles in the recommendation system is 1.8, allowing to person alter the evaluation in the right direction. For example, a product with a standard rating of 4 and a publishing duration of 2 days has the same Hacker rating as a product with a standard rating of 5 and a publication time of 3 days. The Hacker score drops in lockstep with the score (there is a direct relationship).

Based on Wilson's score, Bayesian approximation, and the Hacker ranking algorithm, the personalized recommendation system has built its own way of adjusted estimation (mathematical description in section 2.1). The root mean square value is equivalently taken as the Wilson method (r_w) and Bayes (r_b) values, adjusted for the degree of relevance (g) of days (t) according to Hacker method. R code is built to implement the developed assessment for a certain selected product from the database in the environment. The examination of each approach was done independently depending on the input parameters in comparison to assess the efficacy of the overall adjusted estimate.

The value of Wilson's score is determined by two key indicators: the percentage of favorable assessments and the total number of evaluations. Wilson's score will be greater if there are more favorable ratings, and the product is of higher quality. The ranges go from 0 (in the case of no grades or positive scores) to 1 (in the case of no grades or positive scores) (in the case of a large number of grades and they are all positive).

The investigation revealed that as the number of evaluations goes from 0 to 100, there is a substantial increase in the assessment (the steeper the growth, the higher the share of positive feedback). The severity of Wilson's score development decreases as the number of grades surpassed increases. Figure 4 depicts the general scenario but based on the activity of a specific e-commerce site, the limit on the number of estimations from which the adjusted score does not climb as steeply should be changed. Another notable tendency in Wilson's evaluation is its unmistakable rise in tandem with the rise in the percentage of favorable evaluations. This is especially true when there are a lot of assessments.

The K-dimensional evaluation method is suited to Bayesian estimation. The research provides a 5-point grading system, which is the most common and widely utilized in the database under study. In contrast to Wilson's estimate, the current measure is based on the amount of points each species has, rather than on positive and negative values. The highest Bayes score possible is 5. The higher the number of scores and the higher the highest score, the faster the score approaches 5. Bayes' score, on the other hand, is always larger than 0.

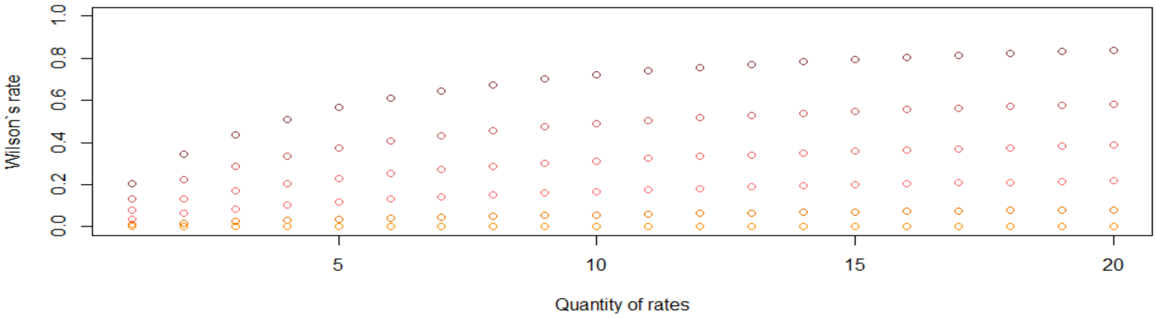

Figure 4. Change in Wilson's grade depending on the number of grades, a proportion of positive grades

Source: formed by authors

Table 1 illustrates that lowering the overall number of points not only lowers but also softens the Bayesian score, independent of internal distribution. For example, the Bayesian score for an unambiguous choice of a score of 5 with a total of 10,000, 100, 10 is 4.9997; 4.8046; 3.7222 - there is a trend to drop. Otherwise, the unambiguous choice of score 1 with a total of 10,000, 100, 10 is 0.9999; 0.9951; 1.0555 - the Bayesian score is greater with a small number of overall scores than with a large number of scores. In more real situations - the tendency to a certain score, rather than their unambiguous choice, the Bayesian score is directly proportional to the total number of grades and the attraction to a certain score.

Table 1. Bayes scores depending on the different number of scores for each type of score

Number of rates 1	Number of rates 2	Number of rates 3	Number of rates 4	Number of rates 5	Overall number of rates	Bayes rate
0	0	0	0	10000	10000	4.9979
0	0	0	10000	0	10000	3.9987
0	0	10000	0	0	10000	2.9994
0	10000	0	0	0	10000	1.9997
10000	0	0	0	0	10000	0.9999
0	0	0	0	100	100	4.8046
0	0	0	100	0	100	3.8810
0	0	100	0	0	100	2.9412
0	100	0	0	0	100	1.9762
100	0	0	0	0	100	0.9951
0	0	0	0	10	10	3.7222
0	0	0	10	0	10	3.2047
0	0	10	0	0	10	2.5999
0	10	0	0	0	10	1.8714
10	0	0	0	0	10	1.0555
1000	1000	1000	2000	3000	10000	2.8624
1000	2000	2000	4000	1000	10000	3.1770

1000	2000	4000	2000	1000	10000	2.9785
1000	4000	2000	2000	1000	10000	2.7772
3000	2000	1000	1000	1000	10000	1.8696
10	10	10	20	30	100	2.5431
10	20	20	40	10	100	2.9658
10	20	40	20	10	100	2.7882
10	40	20	20	10	100	2.5849
30	20	10	10	10	100	1.6501
1	1	1	2	3	10	2.0666
1	2	2	4	1	10	2.5170
1	2	4	2	1	10	2.4066
1	4	2	2	1	10	2.2503
3	2	1	1	1	10	1.4772

The score is adjusted to the Hacker denominator with a sensitivity to the time of operations of 0.5 in the "Personalized Recommendation" recommendation system. A person can alter the estimate using this number, although the reduction limitations are tiny (Figure 5). Because not just the length of time it takes to publish is a crucial aspect in the approach, the relevance of the length of time it takes to publish is only 0.5.

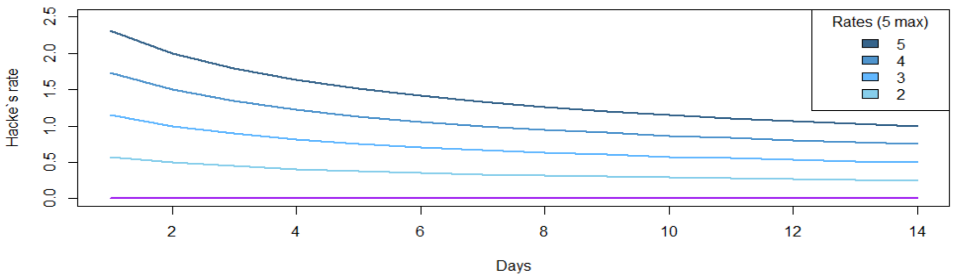

Figure 5. Change in Hacker score depending on the number of days of publication (importance 0.5)

Source: formed by authors

The developed assessment combines Wilson, Bayes, and Hacker methods based on the following principles:

• the Bayesian method score is divided by 5 for normalization with the Wilson score;

• the scores of the Bayes and Wilson methods are taken as the root mean square of the sum;

• degree of sensitivity to days of publication is 0.5;

• to reduce the adjusted score to a 5-point rating scale, the coefficient sets before the calculation formula.

For randomly selected products, the studied Amazon database (Jianmo, 2018) did a comparison characterization of estimations for differences by methodologies. Since the database was created in 2017-2018, the duration of publication is computed as the difference between the current product's publication date and the most recent publication date of a certain product. All estimations are normalized to have a maximum value of five (for ease of comparison). Due to its sensitivity to the examined criteria, a comparative examination of assessments revealed that the produced evaluation is more effective. If all of the conditions are satisfied to a high level, it is higher than others. At the same time, if at least one criterion is low, the score is lower than most other scores.

CONCLUSION

Key HRSs focus on overcoming cold start issues, focusing on long product tails, data tonality, telemetry, combined taxonomies and folklonomies, profile similarities and demographics, product description and user profile comparisons.

The Ukrainian e-commerce market has a limited number of the simplest algorithms for providing recommendations. They are limited to direct user information, such as history of purchases, viewed products and those added to the wish list. Other recommendations are based on information collected from all consumers of the company.

The concept of HRSs provides a recommendation in four categories: "Personalized Recommendation", "Best Buy", "News", "Recommendation for the survey". "Personalized recommendation" is a HRS of the type "addition of features": demographic methodology of the content method of the system and the matrix of factorization of the collaborative method. The method of calculating the similarity coefficients of user profile vectors and object profile vectors has been further developed, which allows to increase the accuracy of forecasting recommendations. The "News" recommendation system is a combination of content recommendation methods: it is proposed to provide recommendations based on the similarity of the characteristics of past user reviews of goods and the characteristics of items. "Best Buy" is a direct collaborative, direct-link referral system. The hybrid system "Recommendation for the survey" uses a cascading approach: the method of content direct approach to the recommendation system with subsequent situational application of the recommendation systems of existing species.

Developed own methods of product evaluation. In the "Personalized Recommendation" recommendation system, the assessment is based on a combination of Wilson, Bayes and Hacker methods in their normalization.

The research proposes a complex of hybrid recommendation systems in the markets with a low level of development of RSs in e-commerce that can be applied in Ukraine. Because of that, further research will aim to develop the concept of gradual implementation of HRSs by Ukrainian e-commerce sites further, including a wider practice of using internal characteristics of products and users of the complex of RSs; deeper analysis of the Ukrainian e-commerce market and RSs market, testing of systems on the data of domestic platforms and considering their features. Adhering to all that, we define the room for further research in terms of the practice of using RSs in Ukraine.

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Data Availability Statement:

The data presented in this study are available on request from the corresponding author.

Conflict of interests

The authors declare no conflict of interest.

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