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Intelligent Information System for Product Promotion in Internet Market

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Abstract: The influence of Internet marketing has grown so much that producers must now reconfigure their businesses from offline operation to online presence simply to meet user expectations. Thus, the development of an intelligent information system for product promotion online is quite relevant. It may lead to automatized selection of competing products and advertising content, a subsequent increase in the effectiveness of advertisements, and a decrease in costs for Internet ad placements. The paper presents the approach for creating an intelligent information system for product promotion in online spaces that makes it possible to reduce advertising costs. A methodology is based on outcomes of own previous studies as well as the flow nature and semantics of data streams. The framework of the proposed intelligent system includes the four key procedures and functions: intelligent formation of keywords for advertising content based on feedback, intelligent formation of product catalogs of online stores, generation of advertising content, and generation of improved advertising content and its targeting generation of text based on keywords. An experimental study confirmed that the effectiveness of posts on social media increased by at least 125%, while the price decreased by 87%.

Keywords: Internet marketing; intelligent data processing; information system; data flow

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1. Introduction

Today, the most used e-commerce system is the B2C (Business-to-Consumer)–a system characterized by the sale of goods or services at retail directly to the consumer. This includes any retail agreement between legal entities and individuals, e.g., transactions between an online store and a customer, purchase of training courses from registered experts, and software rental [1,2].

The development of information and communication technologies (ICT) and the digitization of business processes lead to the transformation of all aspects of enterprise activity: production, finance, management, marketing, and communication. At the same time, the marketing research environment is becoming simpler and more evolved thanks to the rapid spread of the Internet, the consumer is growing closer to the manufacturer and the seller, and effective feedback is easier to achieve in new conditions. Accordingly, marketing tools in today's environment must fully meet the requirements of the times, and technologies and strategies must be ahead of them. Research in the field of varieties, methods of application, combination, and formation of Internet marketing and digital marketing tools gain heightened relevance in today's turbulent environment.

The operation of any system is related to receiving, processing, and organizing large amounts of information. In turn, information and information support cover all aspects of economic activity and are integral elements of the existence and development of economic systems. Information systems ensure dynamic interaction between the company's personnel in the process of corporate planning and accounting, planning of advertising and sales promotion, management of products, sales channels, and direct sales. In addition, the marketing information system becomes one of the main elements of the process of development, adoption, and implementation of innovative marketing solutions and significantly affects its efficiency and quality.

Currently, scientists and marketers define digital marketing as the use of all possible forms of digital channels to promote a product or enterprise. The Internet, television, radio, and social media are all digital marketing tools. Like any other type of marketing, digital marketing helps to achieve the maximum result in an optimal way; that is, it enables saving money and avoiding unnecessary ineffective expenses.

Marketing analysis tools also do not remain stagnant because in the era of the fourth industrial revolution, that is, the era of the development and use of artificial intelligence, it is necessary to test new methods of influencing the consumer and new ways of selling an innovative product with a modified product life cycle model. Taking into account the fact that marketing research always results in a large amount of information and abstracting from discussions about the conflict of a person as a carrier of emotional intelligence and artificial intelligence incapable of the generation and accumulation of feelings and emotions, we conclude that any business entity today operates Big Data that are quite diverse in its structure. Its use in marketing analysis provides the management of business entities with objective and up-to-date information necessary for making management decisions and maintaining a favorable positioning on the market. However, due to the large number, lack of structure, and variety of data flows, it is quite difficult to manage such information.

Existing studies [3,4] on intelligent information systems for product promotion on the Internet have focused solely on the development of the systems themselves without considering the specifics of online advertising. That limitation restricts their practical use. This paper aims to fill this gap by exploring the utilization of an intelligent information system for automating the selection of competitive products and advertising content, as well as assessing its impact on the effectiveness of online advertising.

Thus, the development of an Intelligent information system for product promotion online is quite relevant. It may lead to automatized selection of competing products and advertising content, the subsequent increase in the effectiveness of advertisements, and a decrease in costs for Internet ad placements.

The rest of the paper is structured as follows. The section Related Work presents the analysis of recent related references, while the section Materials and Methods describes a methodology including the framework of the Intelligent Information System. Next, the section Case Study outlines the implementation example for the developed framework of the Intelligent Information System and the results of experimental research. Finally, the section Conclusion summarizes the entire study.

2. Related Work

Intelligent methods in information systems are used at various stages of development, e.g., data collection [5], detection of intrusions [6–9], semantic networks and intelligent agents [10,11], and decision-making [12].

Chen et al. [13] examined the effects of social media marketing on the intention to continue, participate, and purchase through social identification, perceived value, and satisfaction. Ivanov [14] presented the concept of building a digital marketing system based on the theory and practice of market segmentation, which takes into account many factors: geography, costs, time, and others. The proposed concept and method of assessing consumer demand in the target market is aimed at the prospective management of trading platforms using cloud technologies. Behera et al. [1] described a model for providing real-time personalized marketing information on recommended products to online and offline shoppers using a combination of sales strategies: up-selling, cross-selling, best-in-class up-selling, and meeting needs. Authors [1,13,14] analyzed Internet marketing strategies that make it possible to increase the profit from sales. However, to process them, we need to have high marketing skills, and these processes also take a lot of time.

Dharmaputra et al. [15] investigated the influence of artificial intelligence (AI) on consumers' perception of the effectiveness of digital marketing outcomes. IBM SPSS and Partial Least Squares Structural Equation Modeling (PLS-SEM) methods were used to analyze the data collected through the online questionnaire. Perceived ease of use of AI has been shown to positively influence consumer convenience (CC) and cost minimization (CM) as an e-marketing outcome. In addition, the use of AI enables to improve the effectiveness of advertisements. However, there is no description in [15] of how the above advantages can be used by a marketer who does not have the skills of intelligent data analysis. Lo et al. [16] focused attention on empirical targeting models. Peruta et al. [17] employed content analysis to study the themes and formats of 5932 Facebook posts from leading US colleges and universities. The results show that there are content topics, such as athletics, that significantly increase engagement, while others tend to lower it. In addition, format, like user-generated content, is another factor that promotes engagement. Evert et al. [18] concluded that Facebook is perceived as an effective means of advertising by users of social networks, and it is strongly associated with the benefits of "customer relationship management" and "new product promotion". Kamboj et al. [19] have shown that Facebook advertising had a significant impact on the brand image and its value; both of these factors contribute to the increase in brand sales. Ertugan [20] examined whether customer participation in brand communities on social networks affects brand trust, brand loyalty, and brand creation. The obtained results confirmed that the motivation to participate in SNSs significantly affects customer participation, which, in turn, positively affects brand trust and brand loyalty. Both users and ads are represented using vectors created using natural language processing techniques that harvest ontological entities from textual content.

Determining the emotional state is important when analyzing user reviews. The most accurate models for determining the emotional connotations of a review are based on machine learning [21], deep learning [22,23], and recursive and convolutional neural networks [24,25]. For example, Basiri and Habibi [26] considered a deep model for using features of reviews based on content, semantics, sentiment, and metadata to predict the usefulness of a review. Kauffmann et al. [27] presented a general framework that uses natural language processing (NLP) techniques, including sentiment analysis, textual data analysis, and clustering techniques, to obtain new ratings based on consumer sentiment for various product characteristics. Wehrmann et al. [28] proposed an approach for the sentiment and language classification of tweets, whose framework includes a convolutional neural network with two different outputs, each designed to minimize either classification error or allocation assignment, or language identification. Hartmann et al. [29] developed the SentiCR, a sentiment analysis tool specifically designed for customer comments, based on seven different approaches to text analysis. El Alaoui et al. [30] considered a number of methods for the automatic classification of unstructured text based on a dataset from social networks, covering the main social media platforms, different sample sizes, and languages. Xu et al. [31] proposed a semantics-enhanced and context-enhanced hybrid joint filtering for event recommendations, and it combines semantic content analysis and the influence of a contextual event on the user's neighbourhood selection.

Hou et al. [32] proposed a video representation for advertising video classification, which aims to capture the hidden semantics of an unsupervised advertising video. Experiments on real advertising videos demonstrate that the proposed method can effectively differentiate advertising videos. Smetanin and Komarov [24] proposed an approach based on trust and semantic social recommendation to eliminate the problems of starting advertisements. Shokeen and Rana [33] employed the Latent Dirichlet allocation (LDA) method to determine the feedback for the analysis of Internet shopping sentiments. The LDA approach is designed to solve the issues of Latent semantic analysis (LSA) and Probabilistic

Latent Semantic Analysis (PLSA). So, the authors of the works above [21–33] presented the results of the study of semantic text analysis for Internet advertising. However, none of them highlighted keywords based on the advertising text of the ad.

Nakata [34] proposed the generation of advertising texts based on keywords that take into account product information. Wei et al. [35] considered the automatic creation of an ad text to interest users in achieving a higher click-through rate (CTR). Here, the authors used an approach based on click-through rates to generate advertising text and create ad texts with high-quality user feedback. In general, the results of the research [34,35] have interesting implications. However, they are written in Japanese, which limits their distribution.

Wang et al. [4,36–38] focus on the problem of link prediction in heterogeneous social networks, where the types of relationships can be diverse and novel. The authors propose various approaches to address this issue: adaptive meta-learning methods for knowledge transfer across different types of relationships [4], Transferable Domain Adversarial Networks utilizing transferable knowledge to predict new types of relationships [36], and adversarial learning methods for knowledge transfer [37]. Furthermore, in [38], the evolution in networks is examined, highlighting the significance of diverse node evolution mechanisms and their impact on relationship prediction. Collectively, these studies provide a set of methods and approaches that enhance link prediction in complex social networks, considering their diversity and evolutionary aspects.

Cui et al. [39] presented an intelligent framework of an online marketing system to better facilitate online marketing. This system can help advertisers to reduce operating costs, improve operational efficiency, optimize ROI, and increase customer engagement. The disadvantage is that the system does not enable to attract new customers.

Kotsyuba et al. [40] analysed the principles of operation of existing software analogues, considered the methods of choosing a marketing strategy in the field of Internet business, and developed and tested algorithms based on user preferences. However, there is a lack of a systematic approach that facilitates methods of permanent work with customers.

Aguilar and Garcia [41] presented an intelligent system to manage advertising in social networks based on data analysis methods. Its drawbacks are a limited possibility of adding potential customers and a lack of intelligent advertising content.

In general, it can be noted that the works mentioned above mostly analyse the influence of users on Internet advertising. On the other hand, a number of works are considering the developed information systems for Internet marketing (analogues) that have limited functions, displaying only statistical indicators of Internet advertising and paying insufficient attention to customers' attraction.

Thus, the goal of this paper is to fill this gap and develop the framework of an intelligent information system that provides an automatic selection of keywords for creating content and producing a set of effective Internet marketing ads.

3. Materials and Methods

3.1. Methodology

To reach the goal above, the authors have analyzed the outcomes of own previous studies [42–46] and stream data's flow nature and semantics [47,48]. As a result, we are proposing the four key procedures and functions of an intelligent information system:

1. Intelligent formation of keywords for advertising content based on reviews;
2. Intelligent formation of product catalogs of online stores;
3. Generation of advertising content;
4. Generation of improved advertising content and its targeting generation of text based on keywords.

A framework of the intelligent information system for product promotion on the Internet has been developed through the synthesis of these functions (Figure 1).

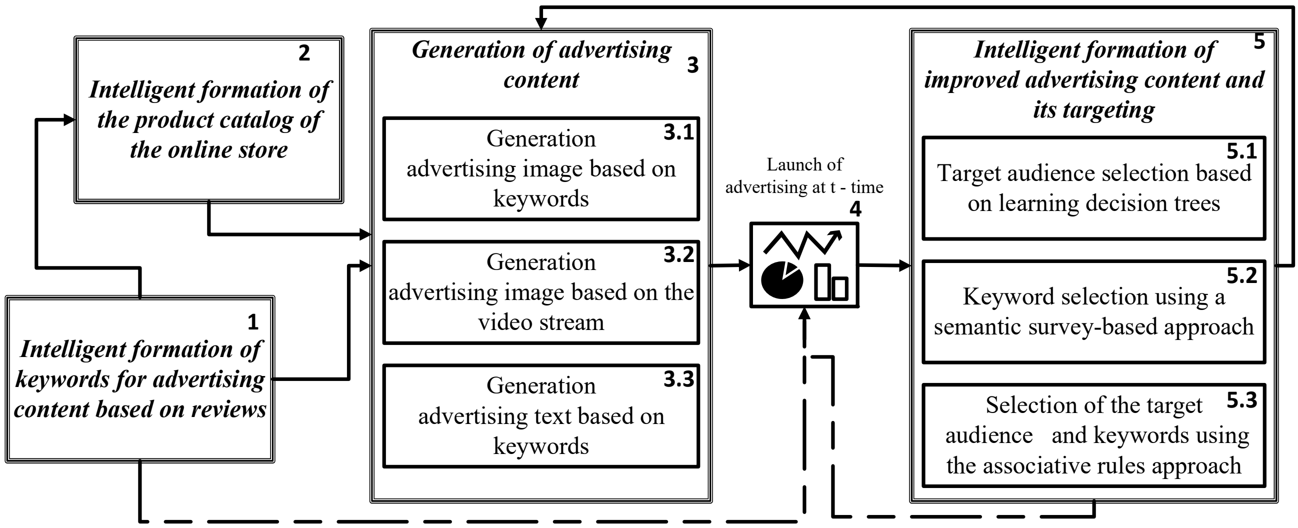


Figure 1. Framework of intelligent information system for promoting products on Internet markets.

First, to form keywords, the authors developed an intelligent method of selecting a competitive product based on the emotional content of reviews, which makes it possible to distinguish positive and negative reviews [42]. The resulting data is useful for marketers when managing customers' websites and will help them make investment decisions. In addition, the analysis of the emotional connotations of feedback is of significant importance in determining the most popular product in the segment, giving the seller the opportunity to choose the most profitable product/service for sale. One of the most important functions of procedure 1 is the selection of the classifier model based on machine learning algorithms. For this purpose, we use eight classic classification methods: Support Vector Classifier, Stochastic Gradient Decent Classifier, Random Forest Classifier, Decision Tree Classifier, Gaussian Naive Bayes, K-Neighbors Classifier, Ada Boost Classifier, and Logistic Regression [44]. After that, the marketer can launch a test ad based on the generated keywords (Block 4).

Upon procedure 1, the marketer can immediately include the product in the formation of the product catalog of the online store based on the intelligent method (Block 2) or transfer the keywords to the content generation (Block 3). An online store is one of the most popular business models of B2C e-commerce. Online stores are distinguished by their ability to offer a much larger number of products and services than physical stores and to provide consumers with a much larger amount of information needed to make a purchase decision. In addition, thanks to the use of Internet technologies, it is possible to set previous visits to the store and purchases made in it as factors for marketing research (surveys, customer conferences, etc.). The main requirements of consumers for the website of an online store are the following: convenient navigation, a system of links to products and the store itself, a clear interface for choosing products or services, as well as a small number of operations for making a future purchase. If these requirements are met, pages will be indexed correctly and quickly in Google, simplifying the purchase process for potential customers.

Machine learning models can classify images with high accuracy. This enables the automatic formation of catalogs, thanks to accurate and meaningful tags related to products, and improves catalog management processes. Moreover, these models improve the filtering functions of the online store, ensure uninterrupted product search for customers and contribute to saving time and costs.

Content can be generated in the form of advertising images based on keywords (Block 3.1), advertising images based on video streams (Block 3.2), and advertising text based on keywords (Block 3.3). When designing a video for advertising on social networks, one must take into account many nuances and follow various rules; for example, keep the Thumbnail preview image format (a reduced representation of the file in the form of a graphic shell with convenient viewing). Therefore, visual search engines usually use them when searching for relevant content. Generating an image from video content will reduce the time spent on developing a preview image that will be displayed before the video starts. When generating, it is advisable to enter the main parameters of the output image: size in pixels, millimeters, and bytes. Generated content creates an opportunity to launch advertising (Block 4).

Based on the obtained advertising results, the marketer can conduct intelligent formation of improved advertising content and its targeting (Block 5). This is performed in order to improve advertising for regular customers and potential customers. The advertising content is improved in the following ways: the target audience is selected based on learning decision trees (Block 5.1), the keywords are selected based on the semantic survey-based approach (Block 5.2), and the target audience and keywords are selected based on associative rules (Block 5.3).

Contextual advertising is currently one of the most effective methods of Internet advertising. Its main advantage is the active use of targeting technologies. Targeting is an advertising mechanism that enables one to select only the target audience from the entire existing audience and show advertising specifically to it [49]. Users are shown advertisements for goods and services relevant to their query in the search engine. The user perceives this type of advertisement as advice or a hint and not as an annoying search engine add-on.

The main advantages of advertising in social networks are multi-targeting, in particular (i) geo-targeting (classification by countries, regions, cities, districts, and even individual streets); (ii) demographic targeting (segmentation by age, gender, preferences, marital status, language, etc.); (iii) by interests and hobbies (travel, sports, studies, business, etc.); (iv) by education (schools, institutes, universities, etc., as well as working population, housewives, etc.); (v) other types of targeting [49].

Let us analyze in more detail the features per each block of the developed system.

3.2. Intelligent Formation of Keywords for Advertising Content Based on Reviews

Let us take a closer look at the data flow when generating keywords for advertising content based on reviews (Figure 2). First, the user selects the desired site for further work (Block 1.1) and enters the necessary links (Block 1.2).

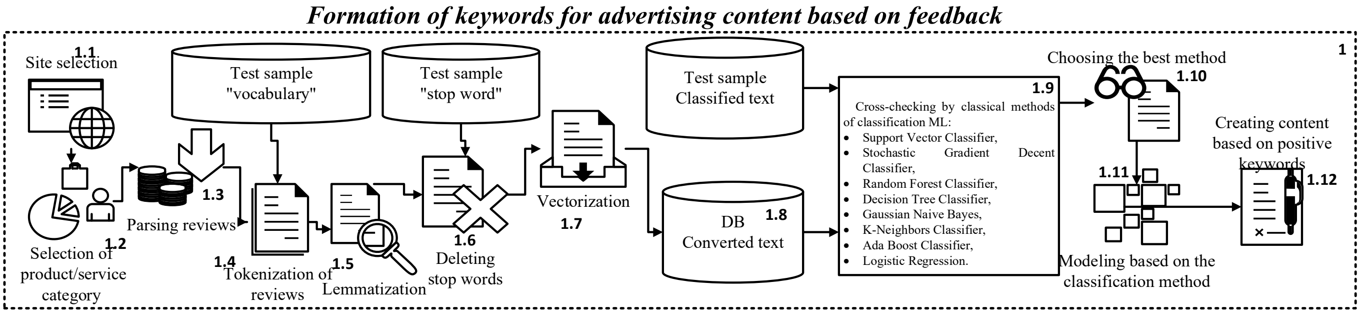


Figure 2. Block of intelligent forming keywords for advertising content based on reviews.

Next, the automated collection of user feedback on products is performed (Block 1.3) [50]. Since the unprocessed text is raw, it is cleaned up during the tokenization algorithm (Block 1.4). Here, the confidential elements of data are replaced by non-confidential equivalents called tokens, which have no independent meaning/value for external or internal use. Next, the document is lemmatized (Block 1.5)–the process of transforming a word into its basic form, i.e., truncation of its endings. In Block 1.6, single characters (which create noise in the text) are eliminated by using a ready-made set of "stop words". Stop words are very common words such as if, but, we, he, she, and they. In Block 1.7, vectorization is carried out–the process of converting text into numbers. This will enable us to obtain the value of each word in a numerical format for sentences and text; that is, a weight is assigned to each word, which will show the power of influence. Possible approaches to vectorization include Bag of words (BOW), CountVectorizer, Word2vec, TF-IDF, and BERT. It is advisable to choose BERT because of its higher accuracy in predicting the semantics of words [51,52].

The transformed text database for choosing the classifier model is formed in Block 1.8. The test sample is cross-checked to select the optimal classifier in Block 1.9 using eight classification methods [39]. Based on the obtained results, the best classification method with the highest training evaluation parameters is selected (Block 1.10), and a text classification model is formed (Block 1.11), configured to classify the text according to certain categories. Finally, in Block 1.12, the first test advert content for positive keywords is formed.

3.3. Intelligent Formation of a Product Catalog of an Online Store

In order to reduce the time spent on forming the product catalog (see Figure 1, Block 2) of the online store, we have developed an improved method of forming the online store product catalog on the basis of [45], applicable to the data flow (Figure 3).

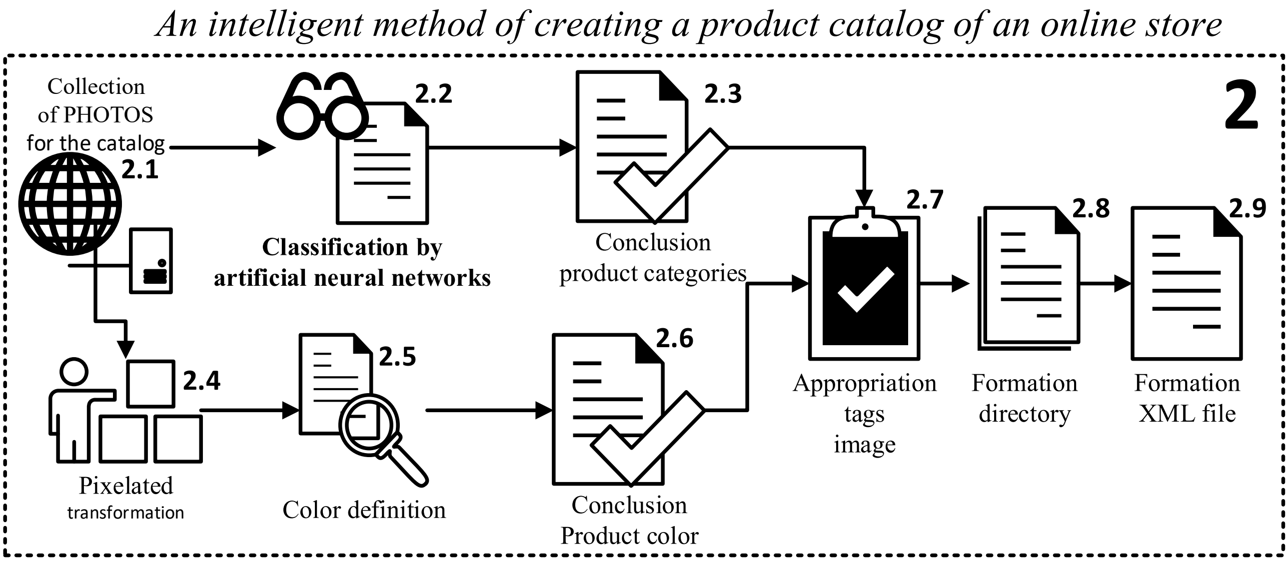


Figure 3. Block of intelligent forming the product catalog for online store.

First, Block 2.1 accumulates all the photos (images) that should form the product catalog. Next, on the basis of artificial neural networks, images are classified (Block 2.2), and goods are assigned appropriate categories (Block 2.3). In parallel, the images are pixelated and transformed (Block 2.4), and the main color in the picture is determined (Block 2.5); this makes it possible to assign the appropriate product colors to the image (Block 2.6).

In Block 2.7, tags are assigned to the product, and the pictures are described based on the obtained results (Blocks 2.3 and 2.6). Next, the catalog of goods for the online store is formed with respect to tags (Block 2.8), and finally, the product catalog is formed in XML format (Block 2.9). The structure of such a file and its parameters are prescribed using tags, attributes, and preprocessors.

3.4. Generation of Advertising Content

Taking into account the flow nature of the data, we have developed a detailed structure of Block 3.2 (see Figure 1), which is presented in Figure 4.

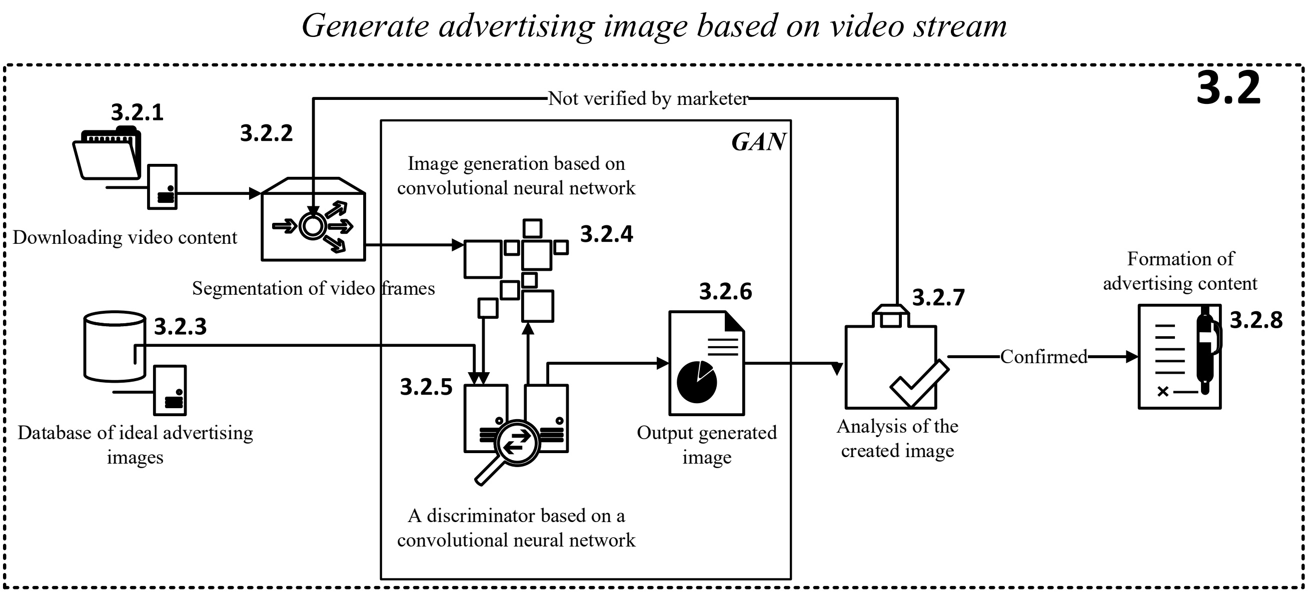


Figure 4. Block generating advertising images based on video streams.

First, the advertising video content is loaded (Block 3.2.1), and the video is divided into frames that are segmented (Block 3.2.2). Then, based on the Generative Adversarial Network algorithm [53], the generator (Block 3.2.4) and discriminator (Block 3.2.5) models were implemented. The generator creates fake images and tries to trick the discriminator into believing they are real. At the same time, the discriminator studies the main characteristics of the images (Block 3.2.3) to distinguish real examples from fake ones. Both models work on the basis of convolutional neural networks. Output-generated images (Block 3.2.6) are analyzed (Block 3.2.7) by a marketer to confirm the quality of the created image. These results are recorded in the test database for further improvement of learning (Block 3.2.2). If the image does not correspond to the format, it should be generated again. In the next step (Block 3.2.8), the marketer can proceed to create advertising content. The generated content is launched for a test advertising campaign at t-time (see Figure 1, Block 4).

3.5. Intelligent Improvement of Advertising Content and Its Targeting

After adverts are placed, the data received from them is exported back to the system. This data allows intelligent formation of advertising content and its targeting (see Figure 1, Blocks 5.1–5.3).

Let us consider each of these methods.

- Selection of the target audience based on learning decision trees

First (Figure 5), it is necessary to prepare data, which are exported from social networks (Block 5.1.1), for analysis (Block 5.1.2) [54]. Next, the user selects the type of targeting they are interested in (Block 5.1.3), and a new database is formed (Block 5.1.4) according to the selected type. During the next step, control samples are created (Blocks 5.1.5 and 5.1.6). Block 5.1.7 coordinates the construction of the model based on the recursive partitioning and regression tree. Next, graphs of the decision tree [3] are built with the selection of the best target audience (Block 5.1.8) based on the modeling assessment (Block 5.1.9) and model error graphs. Finally, the target audience is formed (Block 5.1.10).

- Selection of keywords using the semantic survey-based method

To identify the interest of the target audience, one must conduct a sociological survey of listeners, which takes a lot of time. The use of semantic text analysis can accelerate the selection of keywords and, accordingly, the creation of advertising content. Reference [39] shows that the development of an intelligent method of forming advertising content based on semantic analysis makes it possible to increase the effectiveness of advertisements and, accordingly, to reduce the costs of Internet advertising.

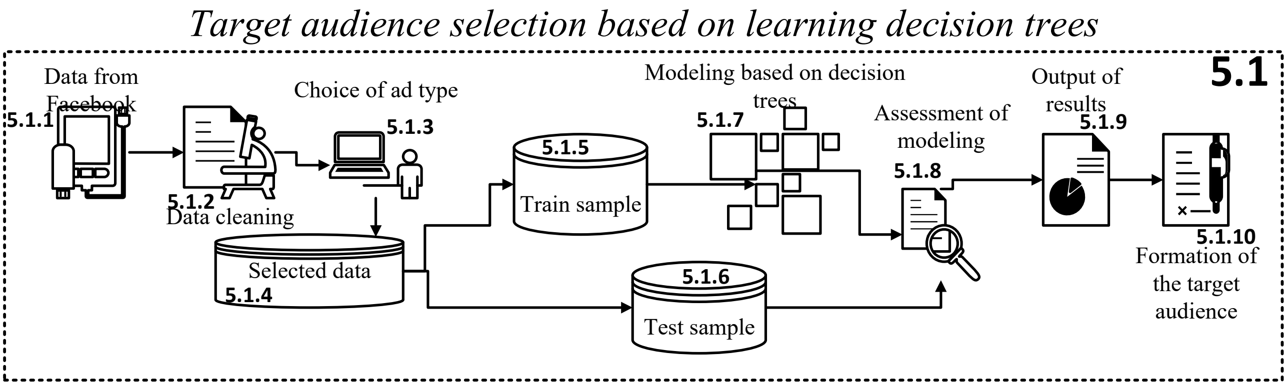


Figure 5. Block of selecting the target audience based on learning decision trees.

Based on the advertising campaign and product sales, we can conduct a customer survey, which will allow us to more accurately form the target audience and select new advertising content.

Semantic analysis is based on a customer survey (Figure 6, Block 5.2.1), which makes it possible to create advertising content. At the same time, as mentioned above, it is necessary to prepare each survey text document for analysis. In particular, the operations include tokenization (Block 5.2.2), lemmatization (Block 5.2.3), ignoring single characters («.», «;», «:», «!», «‘», «?», «,», «“», «()», «[]») (Block 5.2.4) and vectorization (Block 5.2.5). Next, LSA and LDA semantic analysis is performed (Block 5.2.6), and keyword output (Block 5.2.7) for documents is based on the LSA and LDA methods and advertising context formation (Block 5.2.8).

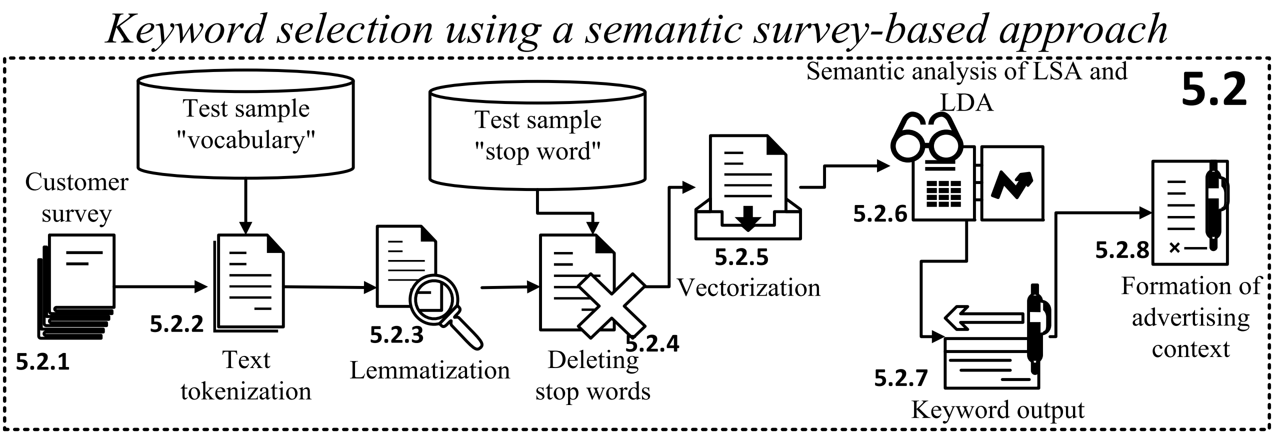


Figure 6. Block of selecting keywords using a semantic survey-based approach.

- Selection of the target audience and keywords based on associative rules

Based on the conducted customer survey, content can be created using the approach of associative rules (see Figure 1, Block 5.3). We have developed the approach to the formation of the advertising context and the target audience based on the study of associative rules. This approach enables the creation of ties between respondents' answers, the formation of advertising content, and the target group's selection (Figure 7).

On the basis of the survey (Block 5.3.1), it is possible to identify the gender characteristics of the respondents and, subsequently, to determine the target audience. At the same time, the data is transformed into a list (Block 5.3.2). After the associative rules are learned (Block 5.3.3), the rule results are derived based on the Apriori method [43] (Block 5.3.4). On their basis, the marketer can once again proceed to set the context of advertising and the target audience (Block 5.3.5).

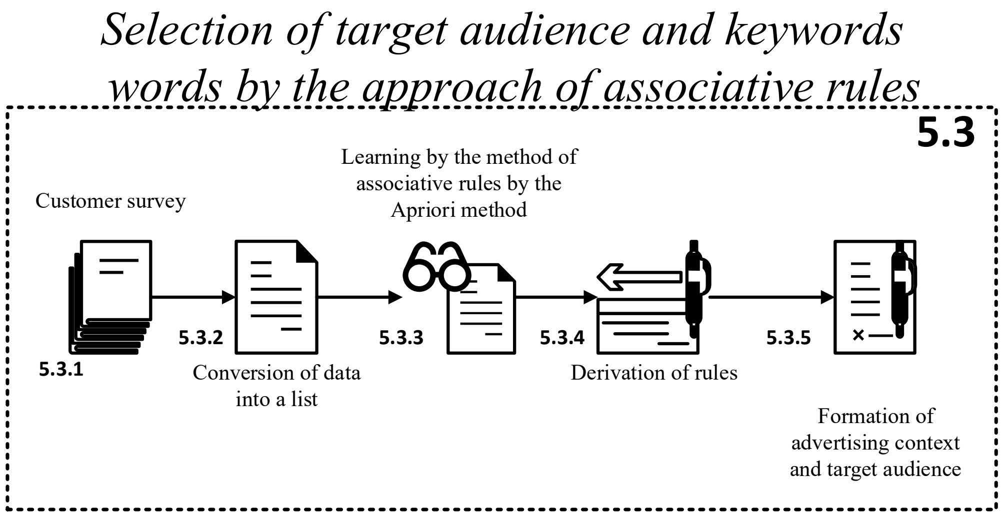


Figure 7. Block of selecting the target audience and keywords based on associative rules.

From the results of the operation of Blocks 5.1.10, 5.2.8, and 5.3.4 (see Figures 5–7, respectively), the marketer can choose one of the options: (i) manually create a better advertisement or (ii) perform it automatically using the generation of advertising content (see Figure 1, Block 3).

4. Case Study

4.1. Implementation of Intelligent System

The implementation of the proposed framework for the Intelligent Information System is considered an example of a web-oriented system. This will make it possible to develop it as an add-on for CRM systems and provide management in the future. In addition, the web-based system simplifies work with the user and does not require installation.

In the initial phase, the system enables the marketer to choose a competitive product (Figure 8) using the intelligent method of generating keywords for advertising content based on reviews [42]. This phase is implemented on the array of reviews (477 reviews) [54]. Next, a JSON file is generated, and unnecessary characters and stop words are removed.

After vectorization and lemmatization, the most optimal methods of text classification based on machine learning are selected [42] (see Figure 2. block 1.9). All these methods showed an average evaluation result (Figure 8), and the reviews include both Ukrainian and Russian versions. The RandomForestClassifier is the best among them, with a prediction score of 0.78. The reviews were then sorted into positive and negative based on the RandomForestClassifier classification. Among the feedback words with the largest n-gram index, several stand out: "Cool" (0.71), "Best" (0.56)—for positive sentiments, and ("Not convenient" (−0.77), "Not high-quality" (−0.63)—for negative connotations. Advertising content is formed on the basis of positive words; that is, they are key elements for generating advertising content.

In addition, the system can automatically download the corresponding product to the online store, which works on the basis of the intelligent method of forming the product catalog [40]. Figure 9 shows how this method works with the addition of the selected product. All product photos receive tags with the name of the category and color and some others. The photos of the goods are uploaded to the catalog for the online store according to the assigned tags. Next, an XML file can be created from the received product catalog. After that, the description and characteristics of each product can be edited.

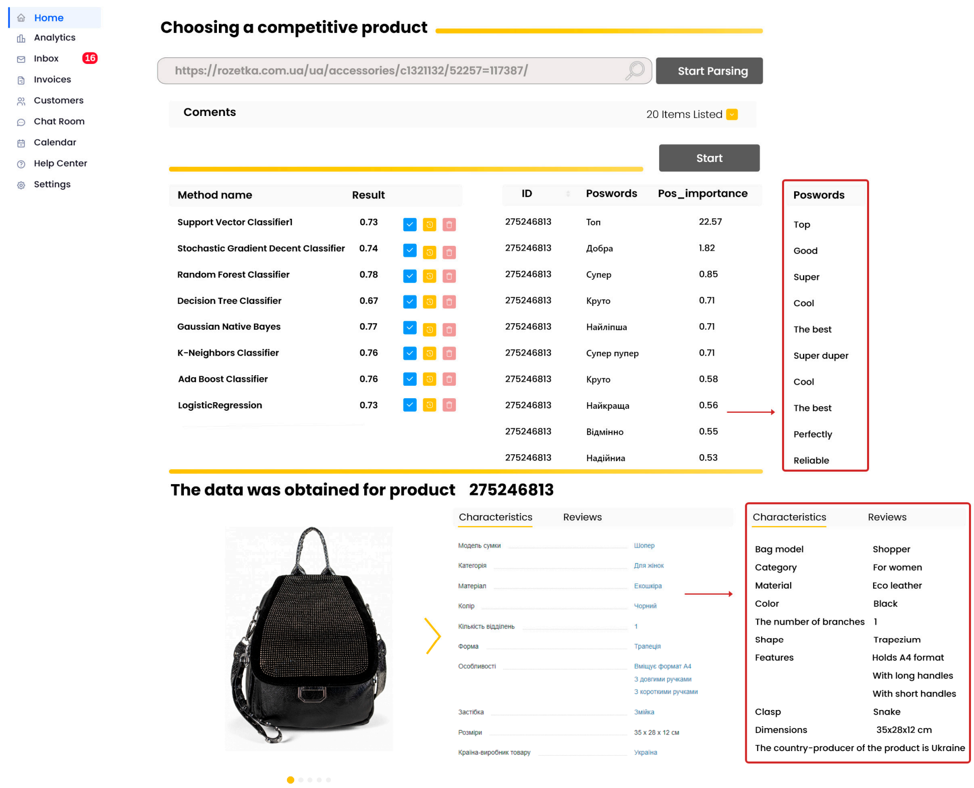


Figure 8. Parsing and classification of comments.

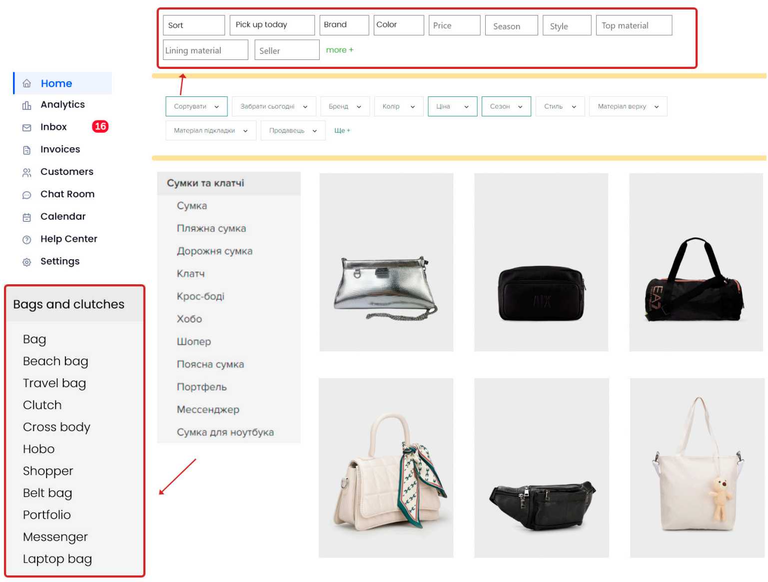
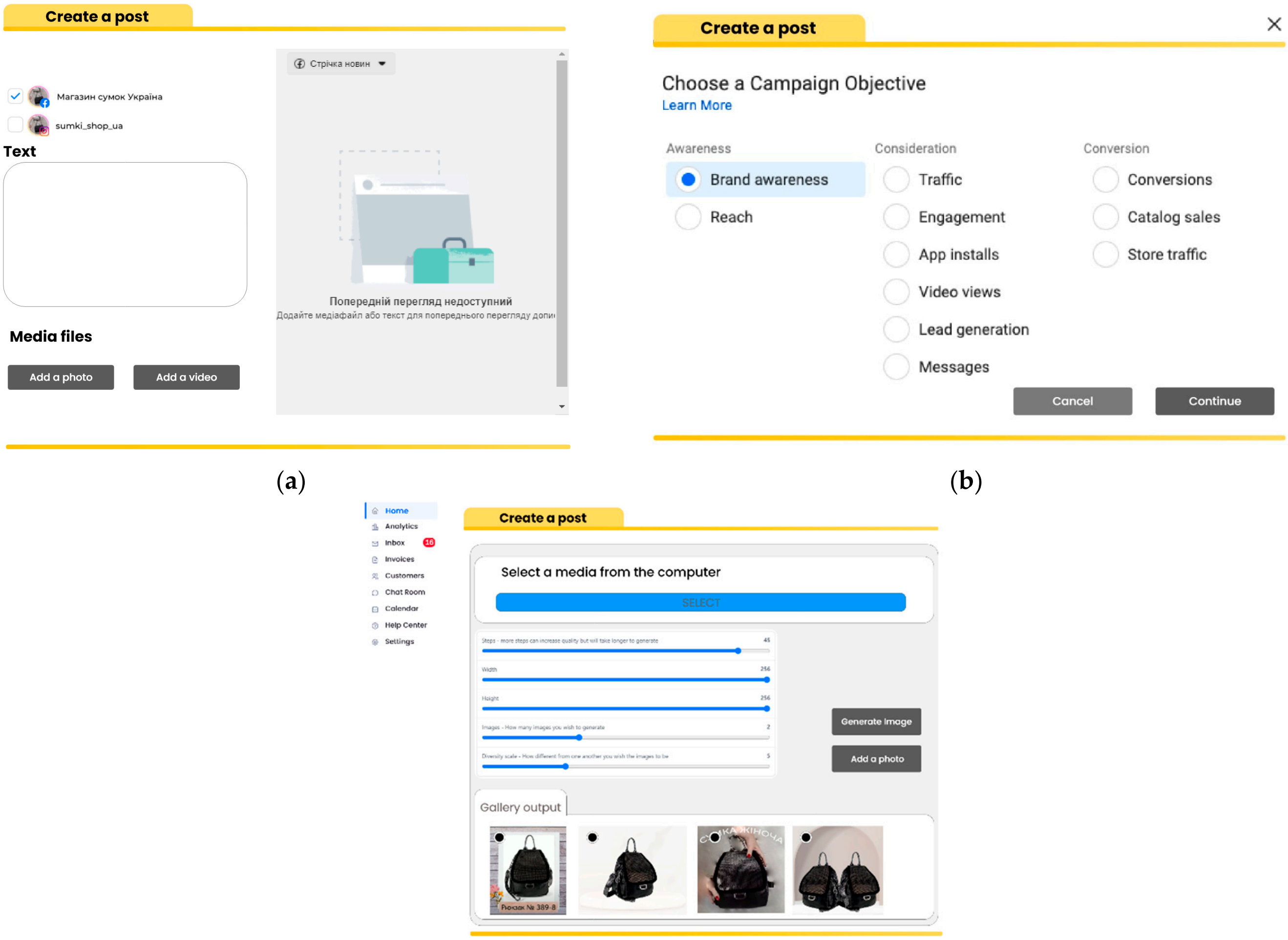


Figure 9. Product catalog window.

Taking into account the above, a marketer (Figure 10a) can create a simple advertising post based on positive words and immediately post it on Facebook and Instagram social networks. In the process, the user first encounters a window with two options: (i) to choose the type of Internet advertisement (Figure 10b), or (ii) to use the function of generating content (Figure 10a, the "Create photo" button). After that, a window will open where the user can upload video content (Figure 10c) and add a new content if necessary.



(**a**) (**b**)

(**c**)

Figure 10. Menu for creating the advertising post where: (**a**) creating an advertising post, (**b**) setting the advert parameters, (**c**) attaching the generated image.

4.2. Experimental Results

The results of a test advertisement conducted from 15 April to 30 April 2022 are presented in Table 1. After running the advert for a *t* period of time (chosen individually by the marketer), the marketer analyzes the obtained results and, if necessary, forms better advertising content for a more effective target group.

Table 1. Results of test advertisement (15 April 2022–30 April 2022).

Advert Version	Content	Target Audience	Results	Reach	Views	Cost per Result
Version 0 (initial)	"Women's handbags for everyone"	All of Ukraine, all age groups and genders	85	1236	2365	0.75

In the designed system, we considered a type of video content (Figure 11) where the generated image is used for the initial thumbnail before the video advert starts. The system includes a previously developed targeting model based on decision trees and distribution of the target group [3], which allows using tree branches to make changes to the advertising campaign based on attributes that depend on the target function. Moreover, this model makes it possible to quickly clean and filter the data. To verify the results of modeling based on decision trees, repeated modeling of targeted advertising was carried out, where the following target group for advertising was selected: women of the age groups 18–25, 35–40, 35–45, 40–45, and 45–50 (see Figure 11).

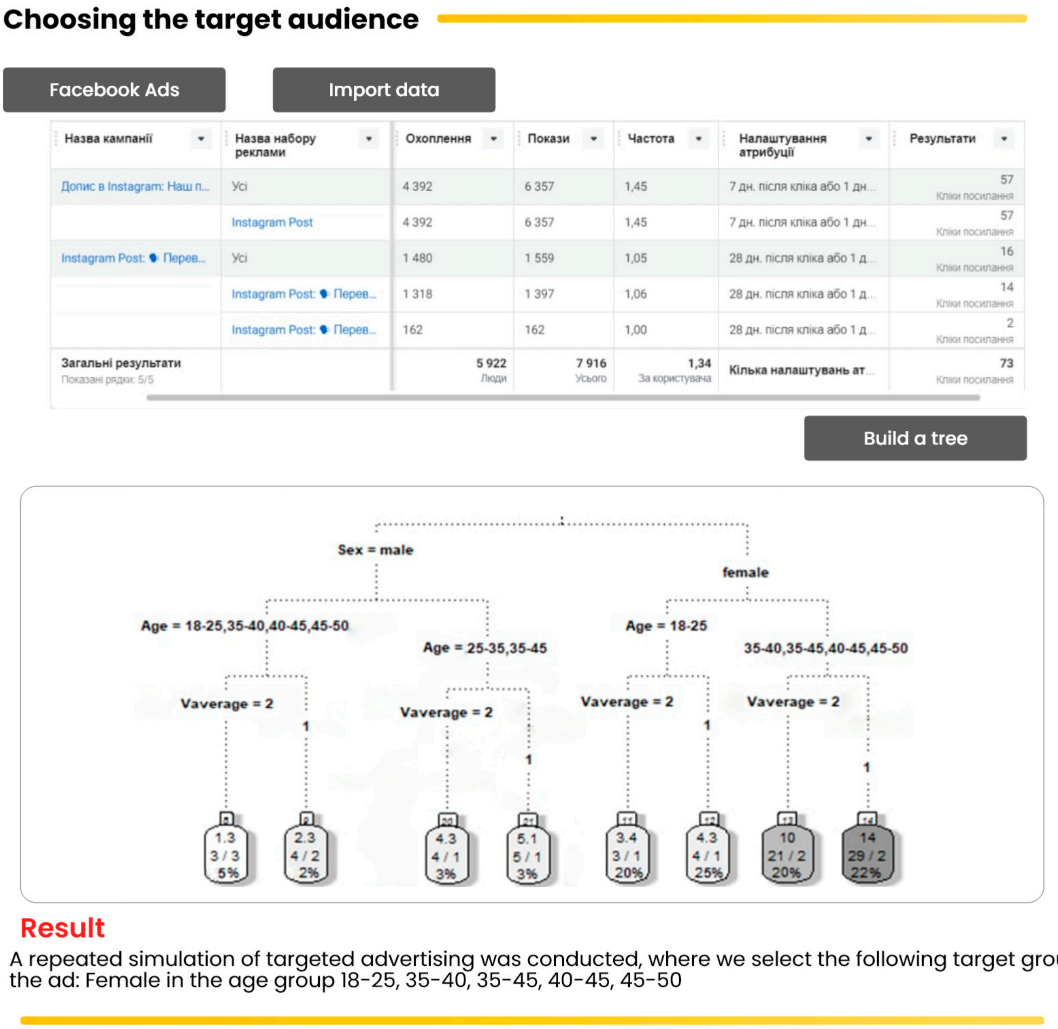


Figure 11. Selection of target audience based on decision trees.

Note that the marketer can, after receiving the results, conduct a repeat advertising campaign and check their quality. In rerun ads, the cost per conversion for video ads dropped from USD 0.75 to USD 0.15 for the period 1–15 May 2022, which is about 20% better than the original test ad. The average value of advertising effectiveness (click rate) CTR increased from 3.6 to 6.6, i.e., 83% better.

Moreover, the target audience is chosen, and the content is created using two more methods: (i) the method of setting the advertising context and the target audience based on learning associative rules [43] and (ii) the intelligent method of creating advertising content based on semantic analysis. To implement the methods, surveys were conducted for 56 buyers of the product selected at the stage of intelligent selection of a competitive product.

A set of rules was formed based on the developed method of setting the advertising context and the target audience, as well as the learning of associative rules (Figure 12). This made it possible to obtain advertising content (Table 2), which compares the effectiveness of the advertising content created on the basis of learning associative rules in the period from 1 May 2022 to 15 May 2022, with all variants of content with rules (see Figure 12). Based on the latter, the marketer creates an ad including the old initial Version 0.

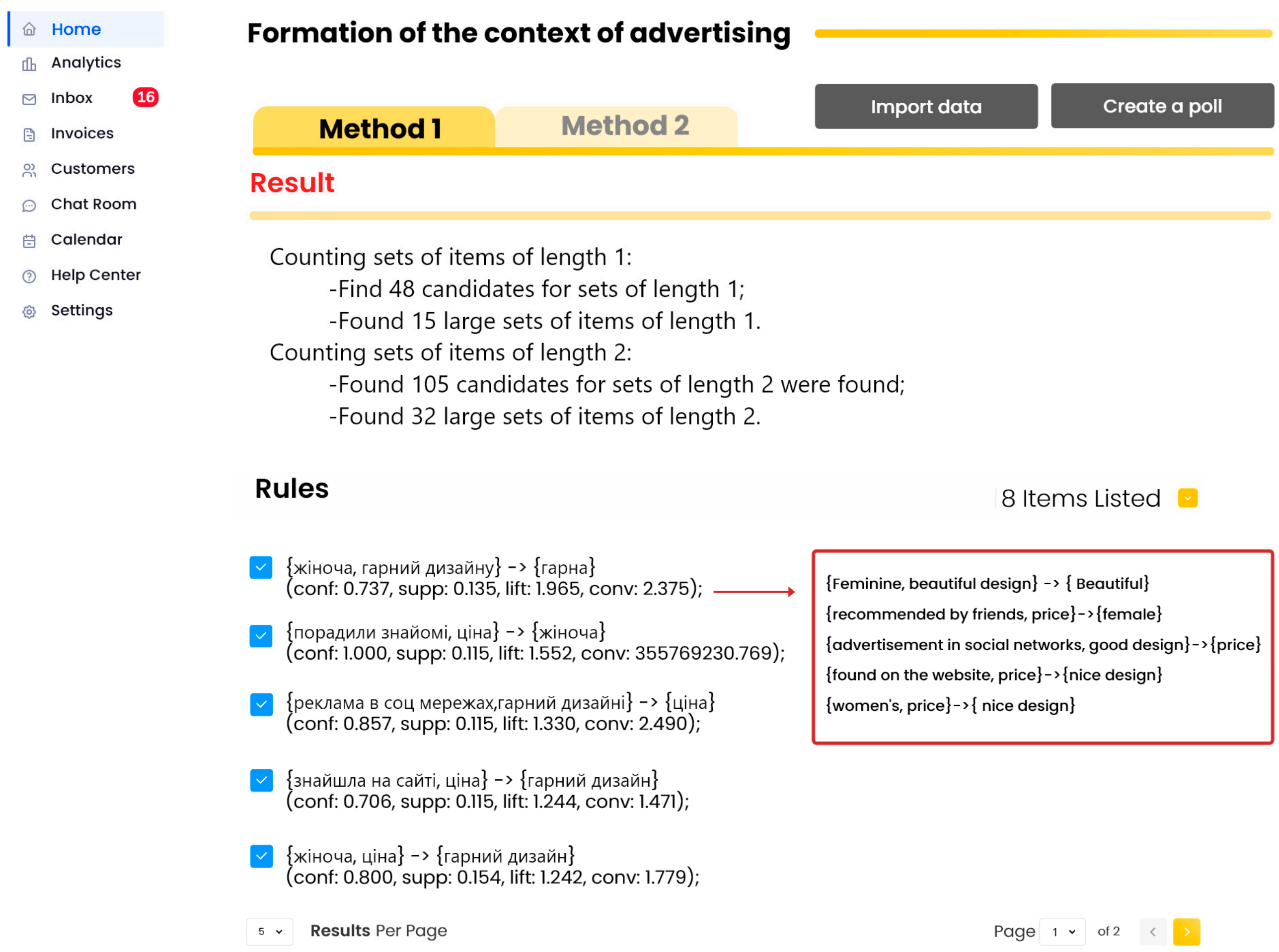


Figure 12. Derivation of associative rules.

Table 2. Comparison of effectiveness for the generated advertising content based on learning associative rules.

Advert Version	Content	Results		Reach, Thou		Views, Thou		Cost per Result	
		Value	Change	Value	Change	Value	Change	Value	Change
Version 0 (initial)	"Women's handbags for everyone"	85	100%	1236	100%	2365	100%	0.75	100%
Version 1 (rule usage)	"Women's handbag of good design"	90	6%	1896	53%	3698	56%	0.33	−56%
Version 2 (rule usage)	"Handbag for good price with high review score"	120	41%	4251	244%	5698	141%	0.12	−84%
Version 3 (rule usage)	"Great price nice design. Details in Messenger"	136	60%	5548	349%	9683	309%	0.08	−89%
Version 4 (rule usage)	"Great price nice design"	115	35%	3442	178%	4771	102%	0.16	−79%
Version 5 (rule usage)	"Women's handbag for great price and with nice design"	86	1%	1453	18%	1867	−21%	0.63	−16%

Table 2 shows that all versions of the new advertisement have improved results. In addition, the result indicator shows how many times customers interacted with the ad. As it's evidenced, the advert v.3 is performed best (60% better than version 0) (see Table 2). In particular, the Reach indicator is 4.5 times better than that of version 0, and the Views indicator is 4.1 times better. It also made it possible to reduce the cost per result by 89%. So, the effectiveness of advertising in social networks increased by at least 60%, and the cost decreased by 89%.

The intelligent method of creating advertising content based on semantic analysis can be used to create the content too. To determine the accuracy of this method, a semantic analysis of customer surveys (similar to the previous approach) was conducted based on the LSA and LDA methods (Figure 13). Figure 13 shows that based on the LSA method, the vast majority of keywords are present in documents 0–81%. Based on the LDA method, the majority of keywords are represented as well in the document 0–78%. The following advertising text was formed on the basis of these words:

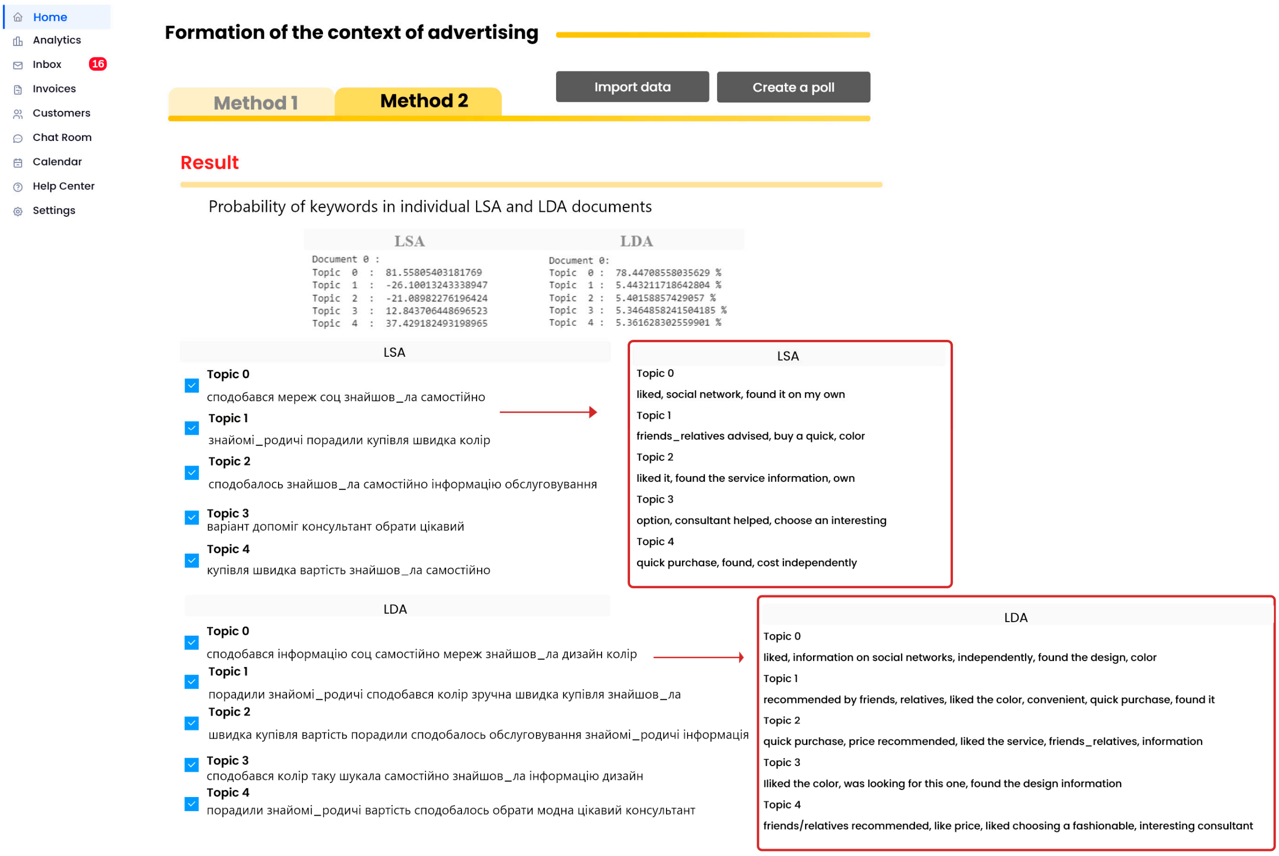


Figure 13. Probability of including keywords in individual phrases of LSA and LDA methods.

"You'll love the design and the color. More details in Messenger"

Table 3 presents a comparison of the effectiveness for the generated advertising content based on LSA and LDA methods. The results of an advertising campaign with text content, conducted from 1 May to 15 May 2022, were used as initial data. Table 3 shows that the Reach indicator increased by 80 people and the Results indicator—by 94%, the cost per result is decreased by USD 0.70 accordingly. The comparison results show that the effectiveness of the advertisement based on the LSA and LDA methods is increased approximately thrice, and the cost per result is decreased by 31%.

Table 3. Comparison of effectiveness for the advertising content generated by LSA and LDA methods.

Advert Version	Content	Results		Reach, Thou		Views, Thou		Cost per Result	
		Value	**Change**	**Value**	**Change**	**Value**	**Change**	**Value**	**Change**
Version 0 (initial)	"Women's handbags for everyone"	85	100%	1236	100%	2365	100%	0.75	100%
Version 6 (LSA and LDA)	"You'll love the design and the color. More details in Messenger"	165	94%	3698	199%	7635	223%	0.05	−93%

As can be seen from the above, all approaches showed a better result compared to the initial option (see Table 1, Version 0,). In order to optimize them, an additional experiment was conducted: a new advertisement was run based on the best-obtained results (Figure 14).

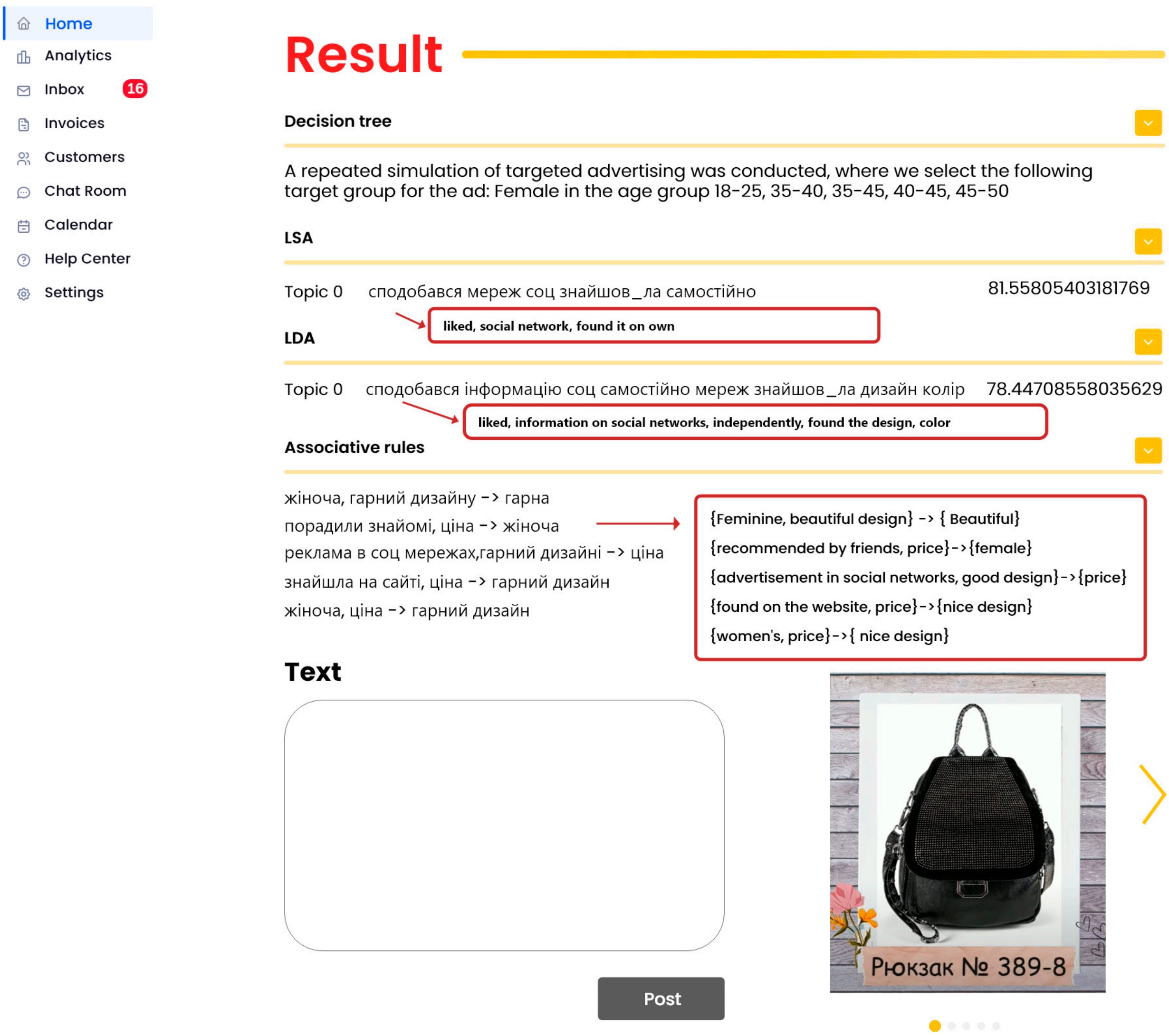


Figure 14. A window with the results of previous methods.

As a result, the following content for advertising can be created, targeting women of the age groups 18–25, 35–40, 35–45, 40–45, and 45–50:

"You'll love the beautiful design and color. More details in Messenger".

Table 4 presents a comparison of the effectiveness for the created advertising content based on the created new content for the relevant target group in the period 20 May 2022–4 June 2022.

Table 4. Comparison of effectiveness for the generated advertising content.

Advert Version	Content	Target Audience	Results		Reach, Thou		Views, Thou		Cost per Result	
			Value	Change	Value	Change	Value	Change	Value	Change
Version 0 (initial)	"Women's handbags for everyone"	All of Ukraine, all age groups and genders	85	100%	1236	100%	2365	100%	0.75	100%
Version 7 (final)	"You'll love the beautiful design and color. More details in Messenger."	All of Ukraine. Women. Age groups 18–25 and 35–50	191	125%	978	−21%	1036	−56%	0.1	−87%

Table 4 shows that the Results indicator is increased by 106 people, the Reach indicator is decreased by 21%, the Views indicator is decreased 2.3 times, and the cost per result indicator is decreased by USD 0.65

5. Discussion

A comparison of the proposed approach with existing ones-analogs [39–41] is illustrated in Table 5. In contrast to analogs, which enable only partial attraction of potential customers with their subsequent transition to regulars, the developed intelligent information system makes it possible to automate the selection of competitive products and the creation of advertising content. This increases the effectiveness of advertisements that work to attract potential buyers and regular customers and accordingly leads to a decrease in the cost of Internet advertising.

Table 5. Comparative evaluation of analogues.

Properties/Study	Work [39]	Work [40]	Work [41]	This Paper
Methods and techniques	Ensemble Learning, architectural design	Methods and algorithms for marketing strategy selection	Data mining techniques, automatic ad creation	Classic classification methods, machine learning
Characteristics of the information system framework	Intelligent online marketing system.	Intelligent ad management in social networks, including ERP module for database access and analytics model	Intelligent ad management system in social networks, considering their specificities, customer requirements, and online behavior	Intelligent formation of keywords for advertising content, intelligent creation of product catalogs for online stores, generation of improved advertising content
Numerical indicators	-	Model accuracy–76%	150% increase in advertising effectiveness, 56% cost reduction	125% increase in advertising effectiveness, 87% cost reduction

Regarding the numerical indicators (see Table 5), although [41] slightly lags behind in advertising effectiveness, we achieved significantly lower advertising costs.

The developed intelligent product promotion system is better suited for small B2C sellers than for large online stores. This is because small sellers typically have smaller budgets and fewer resources compared to large online stores. The intelligent product promotion system can help these small sellers improve the efficiency of their marketing efforts by automating tasks such as competitor research, keyword identification, and ad creation. Furthermore, the system can be used on various social media platforms and search engines, including Facebook, Twitter, LinkedIn, Google Ads, and Yahoo! Search.

The research evaluated the effectiveness of the intelligent information system based on only two parameters: the number of clicks and conversions it generated. This limitation may somewhat restrict the system's applicability. Therefore, in the future, the authors plan to investigate the impact of other factors on the system's effectiveness, such as brand recognition and customer satisfaction.

6. Conclusions

The developed framework of the intelligent information system for promoting goods on the Internet makes it possible to form advertising content and increase the efficiency of the advertisements.

Unlike analogues, the proposed framework allows the user to automate the choice of competitive product and advertising content, and increase the effectiveness of ad posts accordingly as well as reduce the costs of online advertising. The implementation of the proposed framework is considered in the example of a web-oriented system. Outcomes of experiments confirmed that the efficiency of ad posts on social networks is increased by at least 125%, and the cost is decreased by 87%.

In addition, the effectiveness of the advertisements is confirmed by the following. After the advert's re-launch based on the results of decision trees for the target group of women aged 18–25, 35–40, 35–45, 40–45, and 45–50, the cost of conversion for video advertising is decreased from USD 0.75 to USD 0.15, which is about 20% better than initial test ad results. The average performance of adverts is improved by 83%. Selection of the advertising context and the target audience based on the learning of associative rules enables to increase the effectiveness of ad posts on social networks by about 60% while the cost is decreased by 89%. According to the comparison results the advertising content based on the LSA and LDA methods showed an increase in efficiency by 199% and a decrease in cost by 31%.

In the future, we are going to investigate the methods of generating advertising both text and images, based on keywords and a technique of building an optimized array of the best ad items.

The generation of advertising text will enable the marketer to create many interesting ads that will have the correct lexical makeup and use the keywords that potential customers are most interested in. Generation of advertising images based on keywords can simplify the work of marketers, especially if they have no skills in developing and drawing such images.

Moreover, brand recognition and customer satisfaction can become the subject of future research.

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