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## SEMANTIC AND SENTIMENT ANALYSIS OF BRAND REPUTATION

*The formation of a modern marketing strategy in the digital environment involves the use of various data that make it possible to assess the current situation and identify development prospects. The hypothesis is formulated that sentiment and semantic analysis using machine learning algorithms allows businesses to objectively assess the attitude of the target audience to the activities of brands on the Internet and identify popular thematic content. Conducting the research, general scientific methods of analysis and synthesis were used to characterize the basic principles of using sentiment and semantic analysis in the process of assessing brand reputation; empirical methods, graphic representation, and system-structural analysis. The feasibility of using text information and emoticons as a valuable source of data for developing effective management decisions in the field of marketing is proven. The implementation of sentiment and semantic analysis based on text and emoji is justified. A structural and logical scheme of the differences between sentiment and semantic analysis is presented. The features of building information support when implementing the two*

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## СЕМАНТИЧНИЙ ТА СЕНТИМЕНТНИЙ АНАЛІЗ РЕПУТАЦІЇ БРЕНДУ

*Формування сучасної маркетингової стратегії в цифровому середовищі передбачає використання різноманітних даних, що дають можливість оцінювати поточну ситуацію та ідентифікувати перспективи розвитку. Сформульовано гіпотезу, що сентиментний та семантичний аналіз із застосуванням алгоритмів машинного навчання дозволяє об'єктивно оцінювати відношення цільової аудиторії до активностей брендів в Інтернеті та ідентифікувати популярний тематичний контент. При проведенні дослідження використано загальнонаукові методи аналізу та синтезу для характеристики основних принципів застосування сентиментного та семантичного аналізу у процесі оцінювання репутації бренду; емпіричні методи, графічне зображення та системно-структурний аналіз. Доведено доцільність використання текстової інформації та емотіконів як цінного джерела даних для розробки ефективних управлінських рішень у сфері маркетингу. Обґрунтовано реалізацію сентиментного та семантичного аналізу на основі тексту та емодзі. Представлено структурно-логічну схему відмінностей між сентиментним та семантичним аналізом.*



*approaches under study are investigated. The necessity of using social media for assembling text content and emoticons is proven, which is associated with the significant activity of generations Y, Z, and Alpha on such platforms as YouTube, Instagram, TikTok, etc. The feasibility of using sentiment and semantic analysis for retail chains that sell consumer electronics on the Internet is proven. Machine learning algorithms are used to assess user sentiment and interests, which allows for effective processing of text content.*

**Keywords:** brand, content, emoticon, marketing, machine learning, semantic and sentiment analysis, social media, text.

*Досліджено особливості побудови інформаційного забезпечення при реалізації двох досліджуваних підходів. Доведено необхідність використання соціальних медіа для збору текстового контенту та емотіконів, що пов'язано зі значною активністю поколінь Y, Z та Альфа на таких платформах, як YouTube, Instagram, TikTok тощо. Обґрунтовано доцільність використання сентиментного та семантичного аналізу для торговельних мереж, які реалізують споживчу електроніку в Інтернеті. Для оцінювання настроїв та інтересів користувачів використано алгоритми машинного навчання, які дозволяють ефективно обробляти текстовий контент.*

**Ключові слова:** бренд, контент, емотікон, маркетинг, машинне навчання, семантичний та сентиментний аналіз, соціальні мережі, текст.

**JEL Classification:** C55, C81, D83, M31, M37.

## Introduction

The Internet acts as a global information environment that allows a large number of users to interact on a continuous basis. The purpose of interaction can be business interests, education, leisure, social communications, etc. For modern companies, the Internet is an important environment that allows companies to maximize the reach of the target audience and accelerate the process of promoting goods and services. Optimization of marketing strategy in the global network involves the use of effective digital tools. Information support is the basis for making effective management decisions in the marketing field. The digital environment is characterized by a high level of data collection efficiency, since, thanks to the use of modern approaches, it is possible to accumulate relevant information continuously in real time. The main methods of data collection on the Internet include web analytics, parsing, API queries, collection from open data, etc.

For brands in conditions of high competition, it is important to identify the interests of the target audience and assess the level of loyalty to their products. The digital environment is structured in such a way that a large number of users publicly post information about their attitudes towards certain companies, goods, and services. The presented public information can be used by all market participants to assess their competitive positions, identify the advantages and weaknesses of other companies, as well as determine areas for strengthening interaction with the target audience. Many companies in Ukraine do not pay due attention to assessing the mood of the target audience based on comments on the Internet and processing the relevant information using machine learning algorithms, which prompted this study to solve the outlined scientific problem.

First of all, social media should be used to assess user judgments, since the overwhelming majority of modern generations Y, Z, and Alpha show interest in social interaction on specialized online platforms (Instagram, TikTok, YouTube, Facebook, etc.). Expression of one's attitude towards

relevant brands can be carried out by posting comments, emoticons, photos, and video content etc. To assess heterogeneous information about users' attitudes towards relevant brands and their products, it is advisable to use semantic and sentiment analysis, which are implemented thanks to high-performance machine learning algorithms. The advantages of using the presented approaches based on mathematical models are the processing of big data in a digital environment characterized by dynamic changes in user behavior.

Scientific works indicate the relevance of using semantic and sentiment analysis in marketing. An important area of research is the adaptation of machine learning algorithms to process heterogeneous information containing information about users' attitudes, brands, and their products. The issue of using semantic and sentiment analysis to identify the context and emotional coloring of statements on the Internet is addressed in the works of many scientists. Scientists are investigating areas of comprehensive analysis of text content, emoticons, and visualized materials used by the audience to demonstrate their attitude toward certain issues.

Abbasi-Moud et al. (2021) investigate the specifics of collecting data from social media and its use in the process of forming relevant recommendations for consumers using the example of the tourism sector. The feasibility of using semantic clustering of comments and a comprehensive analysis of their sentiments to identify preferences is proven.

Song et al. (2021) prove the feasibility of conducting a tonality analysis of texts that can be collected in a digital environment. The feasibility of using the semantics perception and refinement network (SPRN), which allows analyzing tonality based on aspects, is justified. The advantages of the presented approach are the possibility of using multichannel convolution, which significantly improves the quality of assessing the content load in the text.

Lu et al. (2022) proposed a novel graph convolutional network with sentiment interaction and multi-graph perception for aspect-based sentiment analysis. The advantage of implementing the presented approach is the ability to simultaneously take into account semantic relationships and tonality of text content.

Chandra and Kulkarni (2022) focus on the study of text translation problems that can lead to distortion of tone and content. They substantiate the feasibility of using bidirectional encoder representations from transformers (BERT) for building modern language models.

Khan et al. (2023) investigate the features of semantic analysis of unstructured data, which constitutes a significant portion of information on the Internet and can serve as a valuable source for forming effective management decisions. They propose to use a hybrid DNN model that allows taking into account tone and context based on the attention mechanism.

Iswari et al. (2024) investigate methods to improve sentiment analysis based on online travel product reviews through semantic similarity search. The implementation of the presented approach involves the use of a keyword library that is collected according to the frequency of mentions in customer comments.

Mercha et al. (2024) presented multilingual sentiment analysis (MSA–GCN), which involves the use of a graph convolutional network to identify short- and long-range semantics in complex text messages. It is assumed that a unified heterogeneous text graph will be used, which allows achieving effective results in the analysis of multilingual text content in a digital environment.

Cao et al. (2025) investigate the problems of the polarity of individual terms' tonality in sentences. The authors propose to use Aspect-Level Sentiment Analysis with Semantic and Emotional Modeling (ALSEM) in text processing. They manage to establish a structure that identifies the relationship between semantic information and evaluative words.

Deng and Liu (2025) assessed the emotions of society groups and their requirements using high-performance mathematical algorithms. Data from microblogs and social media comments were comprehensively processed using Python. The feasibility of using the RoBERTa–BiLSTM–Attention model for evaluating the semantics of text content was established.

Machine learning algorithms have proven effective in the process of analyzing heterogeneous data, but the possibilities of improving the quality of sentiment identification are being studied. The configuration of complex mathematical models is focused on identifying real user judgments, since in many cases human behavior involves the use of indirect manifestations of emotions (sarcasm, jokes, irony). In the process of selecting and configuring machine learning algorithms, the specifics of the brand's activities and the characteristics of its target audience are taken into account, since certain groups of consumers may be characterized by a certain slang, especially for representatives of generations Z and Alpha. An important area of scientific research in the field of semantic and sentiment analysis is the adaptation of models to a multilingual environment, since, in the conditions of globalization, a large number of users may use various languages or constructs specific to their culture, despite the use of another language.

The aim of the research is to substantiate the areas of integration of semantic and sentiment analysis based on machine learning algorithms into the process of assessing brand reputation in the digital environment.

Following the presented aim, the hypothesis is formulated that the use of sentiment and semantic analysis based on machine learning algorithms makes it possible to reliably assess consumer perception of brands on the Internet and determine relevant content according to the interests of the target audience.

Creating an effective information system in a digital environment based on server technologies allows for the continuous accumulation of information from various sources regarding the discussion and evaluation of the brand and its products by users. Along with this, cloud computing is adapted for the implementation of high-performance machine learning algorithms that are used to process big data in structured, semi-structured, and unstructured formats.

The research involves the use of the following scientific research methods: analysis and synthesis to characterize the main approaches to the application of sentiment and semantic analysis in assessing brand reputation; empirical methods, graphical representation, and system-structural analysis.

In the context of active digitalization, semantic and sentiment analysis approaches are important for companies, as they allow using text and visualized information to assess the mood of the target audience in real time. The risks of using the approaches presented by brands include the formation of ineffective marketing strategies based on the misinterpretation of the mood of the target audience.

The three sections of the main part of the article present key approaches to sentiment and semantic analysis for processing text content. The feasibility of using emoticons to assess user sentiment is proven, and the main approaches to transforming emojis into mathematical form are characterized by the possibility of implementing machine learning algorithms. A diagram of the characteristic differences between semantic and sentiment analysis in the process of analyzing text content and emoticons is presented. A system for providing information for sentiment and semantic analysis in the digital environment is presented. The research used data from the Comfy YouTube channel: comments under videos for January–July 2025. The results of assessing the content topic and target audience sentiment based on machine learning algorithms are presented, which allows optimizing the brand's marketing strategy in the digital environment, including thanks to a modern content plan.

### **1. Semantic and sentiment analysis: concepts, goals, and role in digital marketing**

The functioning of companies in a highly competitive digital environment involves using opportunities to gain advantages over other participants in the relevant market. On the Internet, a large number of users discuss different topics on various resources every day. Posted reactions in the form of text messages and visualized content (emoticons, GIFs, pictures, etc.) can serve as a valuable resource for analyzing the popularity and current attitude of the target audience to the corresponding company, as well as identifying changes in user behavior. It is advisable to complete the set tasks through the use of semantic and sentiment analysis, which have gained considerable popularity in the field of marketing.

Semantic analysis is used in the study of text content presented in the form of natural language (words, phrases, and full-fledged texts) to identify the essence and context laid down by the target audience. The implementation of specialized algorithms allows software to understand the real content of texts posted by users on the Internet. When implementing semantic analysis, two main approaches are used:

*Text classification.* This direction involves dividing users into certain groups (by emotions, interests), attributing text content to a specific category (goods for young people, financial sector, online education), etc.



*Text extraction.* A comprehensive audit is used to determine the hidden value of the corresponding text content and use the identified features as a basis for optimizing marketing strategies in the digital environment (Thieshen, 2024, November 5).

The process of processing text data is possible through the use of traditional analysis; however, the significant growth of verbal information on the Internet leads to the need to use various artificial intelligence algorithms, including Natural Language Processing (NLP). High-performance mathematical models based on server technologies allow companies to quickly process big data presented in a structured, semi-structured, and unstructured form. To implement machine learning algorithms, it is necessary to transform the text data array in a certain way, which includes the following stages:

- first: *lexical analysis*. The purpose of this stage is to bring text content into a structured form suitable for processing by a computer. The collected text information is divided into individual words or tokens, that is, individual lexical elements are isolated;
- second: *grammatical analysis*. Identification of speech parts (nouns, verbs, adjectives) and the grammatical structure of a sentence allows algorithms to be provided with information about the syntactic connections between words. This stage allows building a structured model for the text that was collected on the Internet;
- third: *syntactical analysis*. A comprehensive analysis of the syntax of text content is carried out to identify the principles of combining words into sentences. The transformation of sentence construction logic into a mathematical form significantly simplifies text processing by machine learning algorithms. Converting text into a form acceptable to artificial intelligence involves breaking each sentence into components by the grammatical rules' characteristic of a particular language;
- fourth: *semantic analysis*. The presented stage acts as a generalizing one, since it involves combining the results obtained in the three previous stages. The qualitative implementation of lexical, grammatical, and syntactical analysis allows for the determination of the essence and meaningful relationships in the studied text as accurately as possible. The key goal of this stage is to provide conditions for the interpretation of text content by mathematical algorithms in accordance with human understanding and meaningful subtext.

Sentiment analysis is used as a separate approach, but in many cases is part of semantic analysis. The presented approach is used to determine the tone of text generated by users on the Internet. Lexical analysis is implemented according to the selected set of words and involves determining the mood of users on certain web resources (social media, sites, forums, etc.).

Along with text content, emojis (emoticons) are often used in the implementation of semantic analysis. For the most active in the digital environment, generations Y, Z, and Alpha, it is natural to use thematic emoticons in the process of discussing various issues and expressing certain

emotions. Visualized content in combination with text is used mainly in the implementation of AI sentiment analysis.

To ensure high-quality sentiment analysis based on the emoticons used, they are grouped according to the identified emotional reactions. The process of preparing emojis for the implementation of certain approaches involves manual marking in accordance with a specific emotional state.

To use artificial intelligence algorithms, it is necessary to transform emoticons into digital form. The most popular transformation methods include:

*One-Hot Encoding.* Emoticons receive certain indices containing a binary vector (0 and 1). For example:

😊 – [1, 0, 0]

😏 – [0, 1, 0]

😎 – [0, 0, 1]

*Count-Based Features.* Statistical analysis of emoticons in text content is used: total number of emoticons in a message or comment; density of emoticons in the text; distribution of emojis by emotion. *Figure 1* presents three groups of emoticons according to the main emotions.

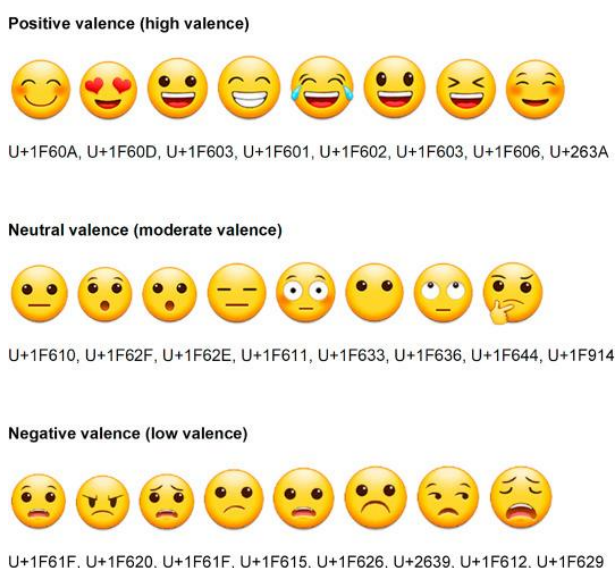


Figure 1. Emoticon groups according to basic emotions

Source: (Kaye et al., 2022).

*Embeddings.* This approach is very effective because it allows companies to qualitatively prepare data for processing by machine learning algorithms. Emoticons are converted into high-dimensional numerical vectors, the distance between which serves as a characteristic of specific reactions. The main methods include Pre-trained Models, Custom Embeddings; Contextual Embeddings.

*Hybrid Approaches.* In the practice of machine learning, ensemble models have become widespread, which allow companies to combine several approaches at the same time to obtain the optimal result. The use of hybrid

models for processing emoticons is based on the multiplicative effect, which allows analytics to use the strengths of each of the algorithms in a common mathematical model.

For a comprehensive assessment of brand reputation in the digital environment, semantic and sentiment analysis are often used together. However, the development and implementation of an effective marketing strategy involve understanding the main differences between the presented approaches (*Figure 2*).

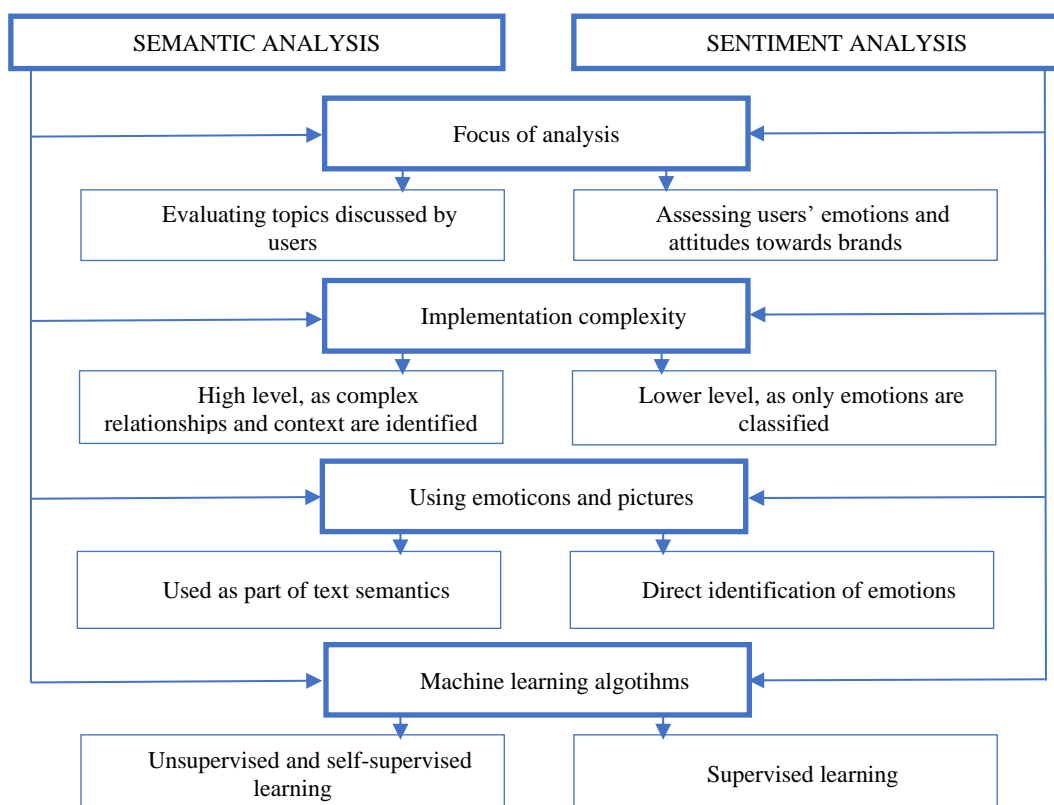


Figure 2. Differences between semantic and sentiment analysis

Source: compiled and supplemented by the authors from (Williams, 2025, January 7).

Despite the simpler procedure for implementing sentiment analysis, the presented approach is widely used in the practice of marketing analytics in the digital environment. The availability of limited resources and the need to obtain quick results in a highly competitive environment make the presented approach effective and allow companies to achieve optimal results in the process of establishing communications with a demanding target audience, which easily switches from one brand to another.

The ability to choose between semantic and sentiment analysis, or to combine the two presented approaches, allows companies to effectively process large amounts of text information, emoticons, and other visualized content in the process of identifying the mood of the target audience and key trends in the markets of operation.



## 2. Information support for sentiment and semantic analysis

The digital environment allows for the collection of large amounts of textual and visual information for sentiment and semantic analysis. At this stage of development, the assessment of topics and user sentiments on the Internet is carried out through the use of emoticons and images. However, the evolution of machine learning algorithms leads to the testing of approaches that involve the processing of audio and video content. The formation of effective information support for sentiment and semantic analysis involves the use of specific methods of data collection on various resources on the Internet (Figure 3).

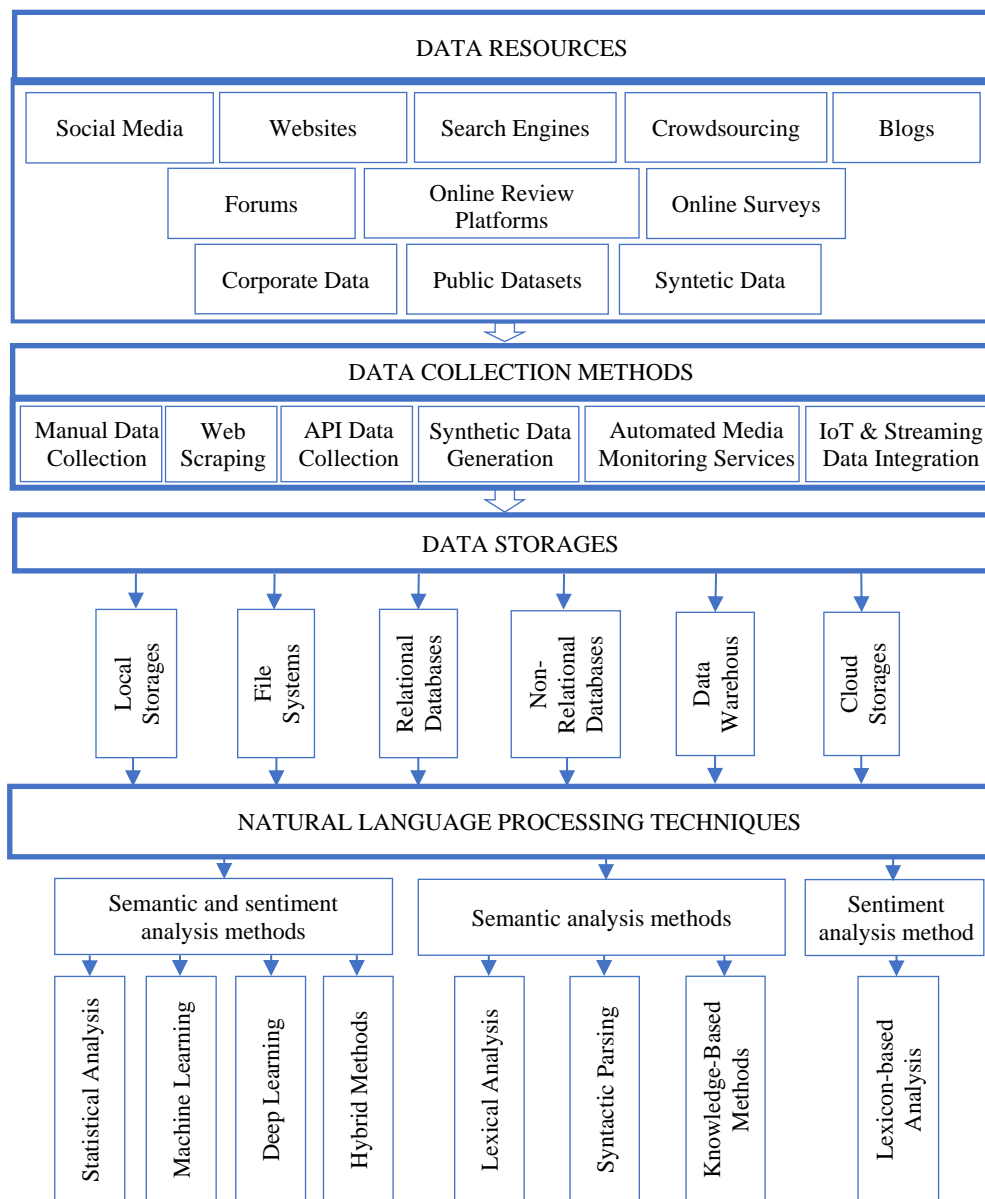


Figure 3. Information system of semantic and sentiment analysis

Source: compiled and supplemented by the authors from (Watchers, 2025, March 6).

The consumer electronics market was chosen to conduct sentimental and semantic analysis, as users consistently generate high demand for innovative products. Interest in modern electronics among representatives of generations Y, Z and Alpha implies active use of digital communication channels by companies to promote products and establish close communications. On the Internet, the leaders in consumer electronics sales in Ukraine in 2025 are Rozetka, Allo, Comfy, Foxtrot, and Moyo (Vtop-Shop, 2025, August 10; Similarweb, 2025, August 10). The activity of the presented brands in the digital environment and interaction on various web resources, primarily in social media, allows the collection of large amounts of text information in combination with emoticons. According to the presented information support scheme on the Internet, data was collected on the consumer electronics market for the Comfy retail chain. The sources of information for conducting sentimental and semantic analysis of the brand were popular on social media (*Table 1*).

Table 1

Characteristics of Comfy social media accounts, July 2025

Social Media	Posts/Videos	Readers/followers
X	632	1779
Instagram	3401	275k
YouTube	557	11.3k
TikTok	42	15.3k
Facebook	≈ 500	490k

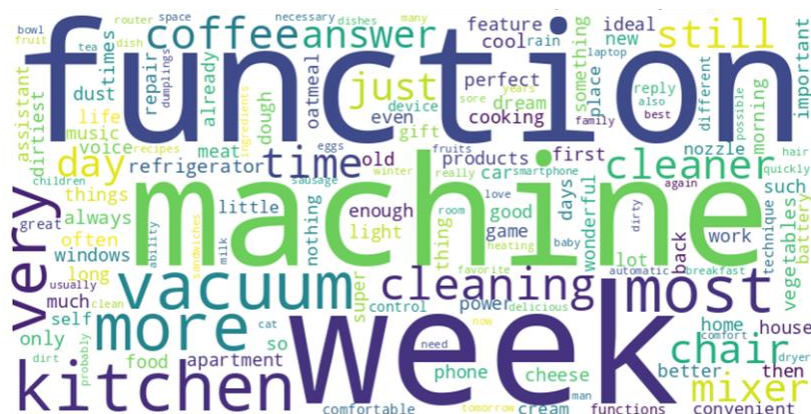
Source: (Comfy X, n. d.; Comfy\_ua, n. d.; COMFYchannel, n. d.; comfy\_media, n. d.; COMFY, n. d.).

The intensive activity of the Comfy retail chain in interacting with the target audience on social media allows it to attract a large number of potential users. Along with this, the target audience is stimulated to leave feedback and wishes regarding certain activities of the company. A detailed analysis of posts and videos made it possible to establish that modern users do not have a particular desire to leave comments for most of the posted content in all the above media. Along with this, the target audience actively participates in various promotions that involve active communication in text format. On Instagram, the company constantly holds various draws that attract the attention of thousands of users and stimulate posting comments according to the specifics of the posted content. During the UKRAINEPRIDE events, Comfy posted a post on its own social media accounts with the text: "Be yourself. Speak out loud. Stand up for equality". A large number of users in the comments joined the discussion of this issue, expressing their position.

Social media in Ukraine, popular among generations Y, Z, and Alpha, are characterized by a larger number of comments that can be collected for sentimental and semantic analysis. Along with this, the X network, which is characterized by significant popularity in the world and is considered a valuable resource for collecting text content and reactions in the form of emoticons, does not allow collecting large amounts of information about the company under study in Ukraine.

The process of processing text content and emoticons in the formed database was carried out in the following stages:

- When implementing sentiment and semantic analysis, a word cloud is widely used, which allows companies to visually assess the presence of the most common words in the studied text array. The formation of text popularity was carried out on the basis of nouns, adverbs, and adjectives (*Figure 4*). The most popular thematic words for the Comfy brand include machine (315 words or 1.03%), kitchen (296 words or 0.97%), vacuum (288 words or 0.94%).



*Source:* calculated by the authors based on (COMFYchannel, n. d.).

The next step is to use the t-SNE Visualization of Comments graph, which displays the results of sentiment analysis of comments in a two-dimensional space (*Figure 5*). The presented graph contains three mood categories (positive, neutral, and negative), as well as intensity zones for each state. The analysis of mood dynamics indicates the prevalence of positive reviews at the beginning of 2025, the peak of which is noted in March-April of the studied period. Subsequently, a partial shift in user moods is noted due to an increase in the share of negative comments.

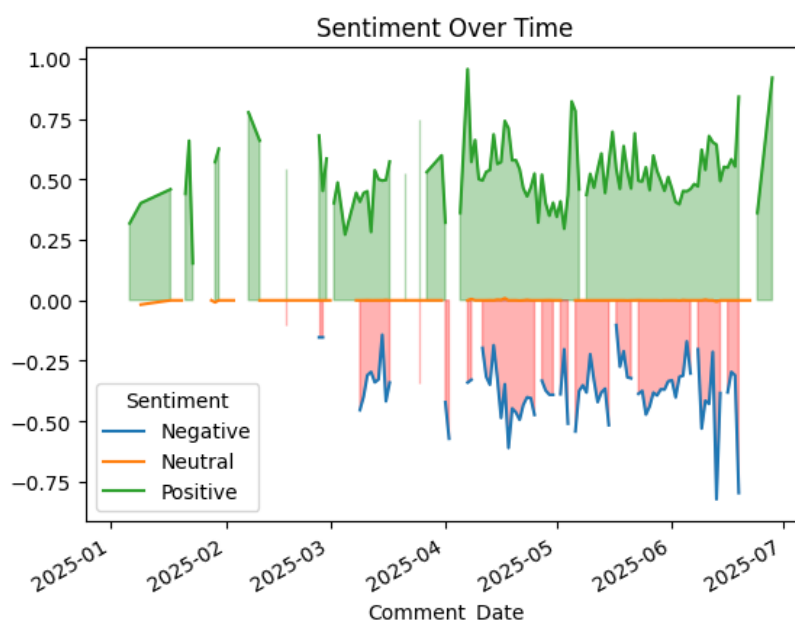


Figure 5. Sentiment analysis of Comfy's YouTube channel from January to July 2025

Source: calculated by the authors based on (COMFY channel, n. d.).

In the next step, we will use the t-SNE Visualization of Comments graph, which demonstrates the results of sentiment analysis of comments in a two-dimensional space (*Figure 6*). The study of semantics shows that local structures are identified for reviews of the Comfy brand on YouTube, and the density of the cluster of points in the center of the graph is noted. Accordingly, there are key topics that stimulate users to actively participate in the discussion, leaving emotionally similar comments in the content. Negative reviews in this segment are mainly associated with user dissatisfaction with the quality of Comfy services, and neutral reviews are associated with the discussion of products in the corresponding video reviews.

The concentration of neutral and negative reviews mainly in the center requires the brand to isolate this segment and conduct additional surveys to identify relative amorphousness and dissatisfaction. Identifying problems will allow Comfy to minimize negativity and ensure increased loyalty of the target audience.

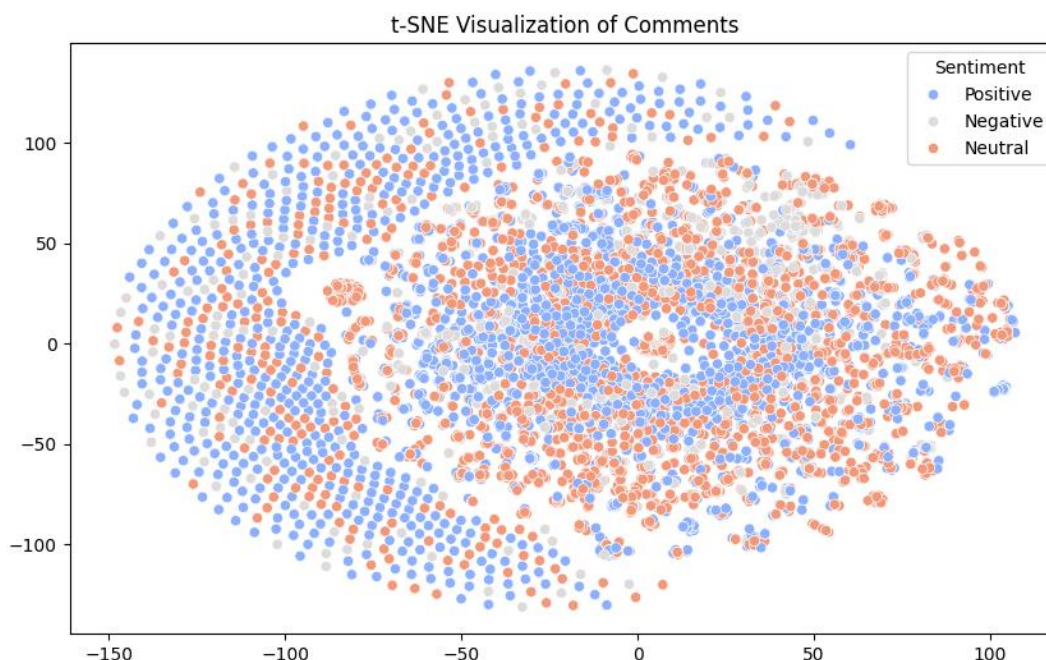


Figure 6. t-SNE Visualization of comments on Comfy's YouTube channel from January to July 2025

*Source:* calculated by the authors based on (COMFY channel, n. d.).

Continuous interaction with users on social media will allow Comfy to meet the expectations of generations Y, Z, and Alpha in Ukraine. The digital marketing strategy of this brand involves the formation of a positive consumer experience based on identified trends, which will contribute to the expansion of the segment of positive comments. Along with this, it is necessary to use other effective digital marketing tools to obtain a multiplicative effect (Iankovets, 2025).

### Conclusions

Ensuring the effectiveness of marketing strategies of companies is important, as it is a key element of a high level of competitiveness. In the conditions of digitalization, brands get the opportunity to receive diverse information and use it to make effective management decisions in the process of ensuring long-term communications with the target audience. Comments contain text responses and visualized reactions in the form of emoticons that users leave on the Internet. The best sources for assessing the reaction of modern generations (Y, Z, and Alpha) include social media, which allow brands to constantly post thematic content and collect comments from users. The most effective approaches to text and emoji processing include sentiment and semantic analysis, which allow assessing the thematic areas of the issues discussed in the comments and assessing the attitude of users to brands and their activity in implementing marketing strategies.



The development of e-commerce and high demand for consumer electronics in Ukraine in modern conditions necessitated conducting research in this area. Comfy was chosen as the brand under research, as one of the market leaders that actively uses various digital marketing tools to interact with the target audience. Comments and emojis for sentiment and semantic analysis were collected on the company's YouTube channel for January-July 2025. The specified social media was chosen due to the ability to quickly collect a large number of text reactions from users regarding the assessment of the Comfy brand.

The results obtained in the research process confirm the effectiveness of using machine learning algorithms for sentiment and semantic analysis. Studying user sentiment and assessing user interests allows companies to quickly adapt to existing demand and form a positive brand image in the digital environment. The practical significance of the presented study lies in the fact that, using the example of the Comfy retail chain, users' attitudes towards its activity on YouTube were assessed and popular video content topics in Ukraine were identified in the context of digitalization and military operations. The effectiveness of using videos describing the characteristics of various consumer electronics to attract the attention of representatives of modern generations and encourage them to express themselves in comments was proven. Video content in the field of gaming and entertainment is mainly interesting for representatives of generations Z and Alpha. Also, stimulation of interest and active posting of comments is observed for videos related to Comfy contests and the drawing of valuable prizes. It should be noted that consumers are more active in posting comments to participate in contests on Instagram. The importance of the research conducted lies in substantiating the need for Ukrainian companies to use high-performance machine learning algorithms when conducting semantic and sentiment analysis to assess brand reputation based on text content and emoticons.

Further research will focus on expanding the sources of information from the digital environment to implement sentiment and semantic analysis. The use of modern and high-performance machine learning algorithms will allow optimizing the interaction process between brands and consumers, contributing to increasing the loyalty of the target audience.

#### REFERENCE/СПИСОК ВИКОРИСТАНИХ ДЖЕРЕЛ

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Abbasi-Moud, Z., Vahdat-Nejad, H., & Sadri, J. (2021). Tourism recommendation system based on semantic clustering and sentiment analysis. *Expert Systems with Applications*, (167), 114324. <https://doi.org/10.1016/j.eswa.2020.114324>

---

Cao, X., Bi, X., & Meng, T. (2025). *ALSEM: aspect-level sentiment analysis with semantic and emotional modeling*. *Int. J. Mach. Learn. & Cyber.* <https://doi.org/10.1007/s13042-025-02567-3>

---

Chandra, R., & Kulkarni, V. (2022). Semantic and sentiment analysis of selected Bhagavad Gita translations using BERT-based language framework. *IEEE Access*, (10), 21291–21315. <https://doi.org/10.1109/ACCESS.2022.3152266>

---

Chiny, M., Chihab, M., Bencharef, O., & Chihab, Y. (2021). LSTM, VADER and TF-IDF based hybrid sentiment analysis model. <i>International Journal of Advanced Computer Science and Applications (IJACSA)</i> , 12(7). <a href="https://doi.org/10.14569/IJACSA.2021.0120730">https://doi.org/10.14569/IJACSA.2021.0120730</a>	
COMFY X. (n. d.). COMFY channel (X). <a href="https://x.com/comfy_official">https://x.com/comfy_official</a>	COMFY X. (б. д.). Канал COMFY (X). <a href="https://x.com/comfy_official">https://x.com/comfy_official</a>
COMFY. (n. d.). COMFY channel (Facebook). <a href="https://www.facebook.com/comfy.ua/?locale=uk_UA">https://www.facebook.com/comfy.ua/?locale=uk_UA</a>	COMFY. (б. д.). Канал COMFY (Facebook). <a href="https://www.facebook.com/comfy.ua/?locale=uk_UA">https://www.facebook.com/comfy.ua/?locale=uk_UA</a>
Comfy_media. (n. d.). COMFY channel (TikTok). <a href="https://www.tiktok.com/@comfy_media">https://www.tiktok.com/@comfy_media</a>	Comfy_media. (б. д.). Канал COMFY (TikTok). <a href="https://www.tiktok.com/@comfy_media">https://www.tiktok.com/@comfy_media</a>
Comfy_ua. (2025, July 5). COMFY channel (Instagram). <a href="https://www.instagram.com/comfy_ua/">https://www.instagram.com/comfy_ua/</a>	Comfy_ua. (б. д.). Канал COMFY (Instagram). <a href="https://www.instagram.com/comfy_ua/">https://www.instagram.com/comfy_ua/</a>
COMFY channel. (n. d.). COMFY channel (YouTube). <a href="https://www.youtube.com/@COMFYchannel">https://www.youtube.com/@COMFYchannel</a>	COMFY channel. (б. д.). Канал COMFY (YouTube). <a href="https://www.youtube.com/@COMFYchannel">https://www.youtube.com/@COMFYchannel</a>
Deng, J., & Liu, Y. (2025). Research on sentiment analysis of online public opinion based on RoBERTa-BiLSTM-attention model. <i>Applied Sciences</i> , 15(4), 2148. <a href="https://doi.org/10.3390/app15042148">https://doi.org/10.3390/app15042148</a>	
Iankovets, T. (2025). Digital Marketing and Experience Design. <i>State University of Trade and Economics</i> . 392 p. <a href="https://doi.org/10.31617/m.knute.2025-51">https://doi.org/10.31617/m.knute.2025-51</a>	Янковець, Т. (2025). Цифровий маркетинг та дизайн вражень. <i>Держ. торг.-екон. ун-т</i> . 392 с. <a href="https://doi.org/10.31617/m.knute.2025-51">https://doi.org/10.31617/m.knute.2025-51</a>
Iswari, N. M. S., Afriliana, N., Dharma, E. M., & Yuniari, N. P. W. (2024). Enhancing aspect-based sentiment analysis in visitor review using semantic similarity. <i>Journal of Applied Data Sciences</i> , 5(2), 724–735. <a href="https://doi.org/10.47738/jads.v5i2.249">https://doi.org/10.47738/jads.v5i2.249</a>	
Kaye, L. K., Darker, G. M., Rodriguez-Cuadrado, S., Wall, H. J., & Malone, S. A. (2022). The Emoji Spatial Stroop Task: Exploring the impact of vertical positioning of emoji on emotional processing. <i>Computers in Human Behavior</i> , (132), 107267. <a href="https://doi.org/10.1016/j.chb.2022.107267">https://doi.org/10.1016/j.chb.2022.107267</a>	
Khan, J., Ahmad, N., Khalid, S., Ali, F., & Lee, Y. (2023). Sentiment and Context-Aware Hybrid DNN With Attention for Text Sentiment Classification. <i>IEEE Access</i> , (11), 28162–28179. <a href="https://doi.org/10.1109/ACCESS.2023.3259107">https://doi.org/10.1109/ACCESS.2023.3259107</a>	
Lu, Q., Sun, X., Sutcliffe, R., Xing, Y., & Zhang, H. (2022). Sentiment interaction and multi-graph perception with graph convolutional networks for aspect-based sentiment analysis. <i>Knowledge-Based Systems</i> , (256), 109840. <a href="https://doi.org/10.1016/j.knosys.2022.109840">https://doi.org/10.1016/j.knosys.2022.109840</a>	
Mercha, E. M., Benbrahim, H., & Erradi, M. (2024). Heterogeneous text graph for comprehensive multilingual sentiment analysis: capturing short-and long-distance semantics. <i>PeerJ Computer Science</i> , (10), e1876. <a href="https://doi.org/10.7717/peerj-cs.1876">https://doi.org/10.7717/peerj-cs.1876</a>	
Similarweb. (n. d.). <i>Similarweb website</i> . <a href="https://pro.similarweb.com/#/digitalsuite/home">https://pro.similarweb.com/#/digitalsuite/home</a>	
Song, W., Wen, Z., Xiao, Z., & Park, S. C. (2021). Semantics perception and refinement network for aspect-based sentiment analysis. <i>Knowledge-Based Systems</i> , (214), 106755. <a href="https://doi.org/10.1016/j.knosys.2021.106755">https://doi.org/10.1016/j.knosys.2021.106755</a>	
Thieshen, L. (2024, November 5). <i>Gain New Insights Into Data with Semantic Analysis</i> . <a href="https://www.progress.com/blogs/semantic-analysis">https://www.progress.com/blogs/semantic-analysis</a>	
Vtop-Shop. (n. d.). <i>The best online stores of household appliances in Ukraine, ranking 2025</i> . <a href="https://vtop-shop.com.ua/catalog/category/pobutova-tehnika">https://vtop-shop.com.ua/catalog/category/pobutova-tehnika</a>	Vtop-Shop. (n. d.). <i>Найкращі інтернет-магазини побутової техніки в Україні, рейтинг 2025 року</i> . <a href="https://vtop-shop.com.ua/catalog/category/pobutova-tehnika">https://vtop-shop.com.ua/catalog/category/pobutova-tehnika</a>

---

Watchers. (2025, March 6). Semantic and Sentiment Analysis: *What Are the Best Sources of Consumers' Thoughts?* <https://watchers.io/post/semantic-and-sentiment-analysis-what-are-the-best-sources-of-consumers-thoughts>

---

Williams, B. (2025, January 7). Semantic Analysis vs. Sentiment Analysis: *Key Differences*. <https://insight7.io/semantic-analysis-vs-sentiment-analysis-key-differences/>

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**Conflict of interest.** The authors certify that they don't have financial or non-financial interest in the subject matter or materials discussed in this manuscript; the authors have no association with state bodies, any organizations or commercial entities having a financial interest in or financial conflict with the subject matter or research presented in the manuscript. Given that one of the authors are affiliated with the institution that publishes this journal, which may cause potential conflict or suspicion of bias and therefore the final decision to publish this article (including the reviewers and editors) is made by the members of the Editorial Board who are not the employees of this institution.

The authors received no direct funding for this research. *The article was written within the scope of the research work "Digital Marketing Management" (state registration number is 0124U000158).*

Ponomarenko, I., & Ponomarenko, D. (2025). Semantic and sentiment analysis of brand reputation. *Scientia fructuosa*, 4(162), 134–149. [http://doi.org/10.31617/1.2025\(162\)08](http://doi.org/10.31617/1.2025(162)08)

*Received by the editorial office 06.07.2025.*

*Accepted for printing 16.08.2025.*

*Published online 16.09.2025.*