ISSN 2522-9818 (print)
ISSN 2524-2296 (online) Innovative technologies and scientific solutions for industries. 2023. No. 2 (24)

UDC 004.023; 311.21 DOI: https://doi.org/10.30837/ITSSI.2023.24.104

YA. LEIBA, M. SHIROKOPETLEVA, I. GRUZDO

RESEARCH ON METHODS OF DETERMINING CUSTOMER LOYALTY AND ASSESSING THEIR LEVEL OF SATISFACTION

The subject of research in the article is methods of data collection and processing to assess the level of customer satisfaction and loyalty to the company, as well as the possibility of evaluating the collected data. **The purpose** of the work is the analysis of methods for determining customer loyalty and assessing their level of satisfaction, the development of a unified assessment algorithm based on various types of data. The article deals with the following **tasks**: analysis of information acquisition methods – questionnaires and reviews, evaluation methods definition and comparison questionnaires with closed answers, reviews and open answers' text tonality evaluation methods analysis using an artificial intelligence, development of an algorithm for determining a unified evaluation and conducting an experiment. The following **methods** are used: theoretical research methods for determining existing data collection methods, as well as methods for assessing the level of customer loyalty and satisfaction using CSI, CSAT indexes, NLP methods for determining the text tonality, bringing the calculated values to one scale, determining the method of a unified assessment; empirical research methods for conducting an experiment, determining and proving the feasibility of applying the method. The following **results** were obtained: a method of assessing customer loyalty and their level of satisfaction based on the analysis of various types of information with further results unification was proposed. Various types of date are responses to questionnaires and user reviews. The questionnaires are analyzed using KPI, and reviews – using artificial intelligence methods. After normalizing the results (bringing them to one scale), the additive convolution method is used to unify the overall result. A prototype of the software system has been developed, which allows you to carry out a full cycle from collecting information to calculating both KPI-metrics and a unified assessment. **Conclusions**: Experimentally, it was determined that the method of assessing customer loyalty and their level of satisfaction based on the unification of a comprehensive assessment of various types of data is efficient and can be used to optimize business processes by reducing time and efforts spent on analyzing the gathered data. The use of this method is fully justified, since the measurement error is low, and the margin of error is acceptable.

Keywords: unified assessment; customer satisfaction level; customer loyalty; reviews; questionnaires.

Introduction

At a time of rapid development in the service sector, customer focus is gaining importance [1, 2]. Satisfied customers are considered the most important factor in any business, as their satisfaction is one of the key elements that contribute to business development and growth.

A secondary goal of a business is not only the provision of services, but also the customer's satisfaction with both the quality of these services and the appropriate level of service. These factors have a direct impact on the likelihood of a customer's repeat business, the popularity of a particular product or service, and increase the company's competitiveness in the market [3, 4].

To track the satisfaction factor, many methods are used, including surveys (both electronic and in-person), receiving feedback in the form of reviews, and offering discounts to attract customers to participate in surveys. All of these methods are effective, but they require a lot of time and the involvement of specialists. The process of tracking the satisfaction factor involves collecting information, processing and analyzing it, drawing conclusions and making the necessary further decisions. However, despite the high cost and considerable time spent, companies continue to conduct such activities.

In addition to the high time costs of organizing and conducting surveys, companies also need to have the appropriate software resources to generate, receive and process the results. The most common methods include [5]: questionnaires, interviews, sociometry, expertise, tests, free-form feedback, and surveys. Usually, such types of surveys as questionnaires and tests are automated, so they require less effort to collect and analyze data, while other types, such as feedback and interviews, are usually partially automated in the form of web forms or specialized applications.

Thus, customer focus for companies is increasingly about product quality, and automating the collection, processing, and analysis of results will significantly simplify the company's tasks, reduce the cost of such activities, and increase the company's analytical capacity. That is why this topic is gaining relevance.

Analysis of recent problems and publications

A significant number of studies by both foreign and domestic scholars have been devoted to the problem of determining customer loyalty and assessing the level of customer satisfaction. Among the Western classics, we highlight the works of F. Kotler, D. Aaker, A. Eisen,

ISSN 2522-9818 (print)
Сучасний стан наукових досліджень та технологій в промисловості. 2023. № 2 (24) ISSN 2524-2296 (online)

A. Verbel, T. Jones, R. Cunningham, T. Levesque, G.H.G. McDougall, D. McConnell, J. Newman, B. Rice, F. Reicheld, M. Stone, S. Sutton, W. Tucker, G. Tellis, J. Hofmeyer, D. Hoyer, P. Schwartz, M. Fishbein, etc. [2–4, 6–8]. Applied aspects of consumer satisfaction in Ukrainian realities are highlighted in the works of I. Holovachov, O. Litovkina, O. Naumova, I. Ponomarenko, V. Sinkovska, S. Smerichevska, A. Fedorchenko, T. Chunikhin, etc. [9–12]. However, it is important to emphasize that most of them are only theoretical approaches to customer loyalty; the practical component depends on the specific field of application of the existing models, methods and algorithms. Accordingly, modern approaches, models, methods and algorithms require constant study and updating due to rapid changes and development of market relations, as well as adaptation to a specific industry.

Enterprise performance management involves the use of various approaches to ensuring the collection, analysis and use of information on its economic activities, and Ukraine’s integration into the global economic space requires the use of modern controlling methodologies in management practice, including the latest systems and concepts of performance management [13].

For a business to be successful, it is necessary to support its operations, constantly monitor the company’s performance and improve them. To evaluate the company’s performance and customer satisfaction, analysts and marketers often use special metrics called key performance indicators, or KPIs.

KPIs are measurable performance indicators that reflect all the information about a particular area of a company’s activities [14]. These are primarily customer relations, company operations, conversions and sales, employee productivity, the level of incentives, etc. The main task of key performance indicators is to optimize the company’s processes to increase its productivity.

A considerable number of works by foreign and domestic scholars are devoted to the study of the problems of measuring company performance indicators. Among Western scholars, it is worth mentioning the works of M. Bourne, S. Globerson, R. Kaplan, J. Mills, M. Meyer, D. Norton, E. Neely, K. Plats, H. Rampersad [4, 6, 10, 13, 15]. Among Ukrainian researchers, these are primarily I. Gordienko, O. Martynov, V. Samuliak, I. Seredyna, V. Seredyna, R. Fedorovych, R. Feshchur, etc. [16–18]. It should be noted that solving the same task by different authors can lead to significant variations in the choice of the necessary KPIs, so sometimes it is important to use several KPI assessments for their further comparison. Because sometimes some KPIs complement each other and answer different questions in the project evaluation process. This should be taken into account when determining the list of required project or company performance indicators. In addition, the choice of KPIs depends on the specific goal, strategic decision-making, different types of activities, time, specific goals, the work of individual departments, the team, the way of communicating with customers, the amount of resources, etc.

In ISO 9001:2015, the word "performance" has two definitions [19]:

– productivity – the degree of achievement of the planned results, the ability of the company to be result-oriented;

– effectiveness – the ratio between the results achieved and the resources spent the company’s ability to realize its goals and plans with a given quality level expressed by certain requirements – time, costs, and degree of goal achievement.

The use of KPIs allows an organization to assess its performance and formulate a strategy based on the data obtained.

There are the following types of KPIs:
– target
– process;
– project.

Target indicators include those that reflect the degree of approach to the goal. Process indicators are indicators of economic efficiency. Project indicators are those that reflect the effectiveness of the project. Today, there are a very large number of key performance indicators.

To be effective, a KPI system must have the following characteristics
– correct orientation
– achievability;
– limited tasks;
– ease of perception;
– balance.

Choosing the right KPIs depends on understanding what is important to the company, what processes need to be monitored, and how. The importance directly depends on the area of activity of the department that measures performance. For example, key performance indicators will be different for marketing, finance, and development departments.

An important part of assessing the efficiency and quality of services provided by a company is the level of customer satisfaction. Companies usually receive this information from end users. For this purpose, sociological research methods are used.

ISSN 2522-9818 (print)
ISSN 2524-2296 (online) Innovative technologies and scientific solutions for industries. 2023. No. 2 (24)

Sociological research is a system of consistent methodological, methodological, organizational and technical procedures aimed at obtaining accurate objective information about the social phenomenon or process under study [20].

The stages of empirical sociological research include the following:

– preparatory: defining the goal, developing a program, research work plan and tools;

– collecting primary sociological information: conducting surveys, observations, experiments and/or document analysis;

– processing of the collected information;

– analyzing the collected information, interpreting the results, formulating conclusions and recommendations, and preparing final documents.

To conduct a research, one method of collecting information or a combination of them is used. The most common methods include the following:

– surveys
– interviews
– sociometric survey;
– expert survey;
– document analysis;
– observation;
– experiment.

It is worth noting that none of the methods is universal, and each of them has clear limits of cognitive capabilities. Thus, an incorrectly selected method can lead to a loss of quality of sociological information, which in turn leads to a loss of value and relevance of the conclusions from the collected information.

The study determined that a survey is the best option for determining customer loyalty and assessing the level of customer satisfaction in the system. Therefore, let us consider this method in more detail.

A survey is a method of obtaining primary sociological information based on a set of questions offered to the respondent, and the answers to which form the necessary research information [5]. Information is collected with the help of special tools, namely questionnaires, forms or forms. This method makes it possible to collect sociological data from a large group of people in a short time.

The most commonly used types of surveys are:

– questionnaires
– interview
– sociometric survey;
– expert surveys.

Questionnaire survey is the process of filling out a paper or electronic questionnaire. The most common variant is the distribution of printed questionnaires by a sociologist and consultation on the available questions to obtain more accurate results. Now this method is rapidly becoming electronic.

A questionnaire is a replicated document that contains a system of questions connected by a common logic, formulated and linked to each other according to established rules [5].

Since the questionnaire is filled out directly by the respondent, it is necessary that it has a clear structure and interrelated questions, clearly formulated and understandable for a specific target audience.

The questionnaire consists of the following blocks:

– introductory part;
– contact questions;
– main questions;
– closing questions.

The introductory part contains the purpose of the survey, the rules for completing it, and information about the person or company conducting the survey.

The contact questions section contains socio-demographic information about the respondent.

The main questions block contains questions that help determine the purpose and objectives of the survey.

The questions are divided into open and closed.

Closed-ended questions allow you to express your opinion on a proposed scale, by choosing one or more of the following options.

Open-ended questions allow the survey participant to express his or her opinion in an arbitrary form. In this format, the information is more individualized. Provided that the respondent is familiar with the problem area, such information will be more complete and accurate. If a person is poorly or not at all familiar with the problem area, his or her answers become more stereotypical and uninformative, which can distort the results of the study.

Semi-closed questions are a combination of open and closed questions that allow you to choose from a list of possible options or offer your own if the required option is not listed above.

Closing questions are those that are designed to relieve the respondent's psychological stress, to give the respondent a sense that his or her participation in the survey was necessary.

There are also substantive and functional questions.

Сучасний стан наукових досліджень та технологій в промисловості. 2023. № 2 (24) *ISSN 2522-9818 (print)* *ISSN 2524-2296 (online)*

Content questions are used to determine the essence of the problem under study, to obtain specific results on the problem raised.

Functional questions are used to eliminate unnecessary information, to make sure that the respondents' answers are accurate, etc.

To get more reliable information, you need to give people the opportunity to express their opinions openly. But usually, the number of questions and the limited time for answering affect the level of encouragement and willingness of the client to participate in the survey. Therefore, a more flexible option is to divide the questionnaire into two parts:

– closed questions in the form of a questionnaire;

– open-ended questions in the form of feedback.

This combination will allow the user to answer a short questionnaire with clearly formulated questions and, if desired, leave feedback. Filling out the questionnaire will save the respondent's time, as they will spend less effort expressing their opinion, and companies will receive concise and clear answers.

Unlike classical questionnaires, processing feedback is a more complex and time-consuming process. Thanks to the development of the information technology industry, in particular artificial intelligence, this process can also be automated using methods of analyzing the tone of the test. For this purpose, Natural Language Processing (NLP) tools are most often used.

Natural language processing is a method of computer analysis and synthesis of natural language based on the methods of artificial intelligence and mathematical linguistics. It involves the development of methods and algorithms that interpret, generate, and recognize human speech. There are the following approaches to natural language processing [21–23]:

– controlled natural language processing – training a model on a sample with labeled data;

– uncontrolled natural language processing – using a statistical language model to predict a pattern;

– natural language understanding (NLU) – recognition and understanding of input information in the form of text; detection of similar meanings in different sentences;

– natural language generation (NLG) – the generation of textual or spoken information based on specified keywords or topics.

Since understanding natural language requires a significant amount of knowledge about the subject area and interaction methods, this method is considered an AI complete task.

An AI complete task is highly complex, as it requires artificial intelligence to be able to solve a complex task at the level of human intelligence. Such tasks include:

– natural language analysis;

– computer vision;

– systems for generating works of art (literary, visual, musical, etc.);

– decision-making systems.

An AI complete task in the context of binary classification has to process the input information and determine which category it belongs to. For artificial intelligence, this is a difficult task due to a combination of various factors that complicate the processing of the results.

The use of natural language processing methods simplifies the process of determining the tone of user feedback and does not require the mandatory participation of analysts when processing survey results.

The use of computer technology to determine customer loyalty and assess customer satisfaction significantly increases the efficiency of collecting, processing, and analyzing results.

Therefore, **the purpose** is to study methods for comprehensively assessing the level of customer loyalty and satisfaction.

Identification of previously unresolved parts of the overall problem

During the market analysis, the following systems were identified among the available solutions:

– *Zonka;*https://www.zonkafeedback.com/

– *SurveyLegend;*

– *Hively.*

Advantages of these systems:

– ease of use;

– user-friendly interface.

Disadvantages of the systems:

– lack of ability to work with feedback or automate its processing;

– simultaneous analysis by only one metric;

– high cost;

– lack of text analysis for mood.

It can be concluded that the above-mentioned software systems do not fully meet the needs of businesses in determining the level of customer loyalty and satisfaction with the company's work.

ISSN 2522-9818 (print)
ISSN 2524-2296 (online) Innovative technologies and scientific solutions for industries. 2023. No. 2 (24)

The main problem of these systems is the lack of assessment of the level of customer loyalty and satisfaction, as well as the lack of the ability to automate the analysis of the tone of feedback using artificial intelligence and unify the assessment of the results obtained. This is necessary to improve analytical capabilities and unify different types of information based on survey results and feedback.

The paper should investigate methods of assessing respondent satisfaction based on the results of questionnaires and feedback, as well as experimentally prove the possibility of forming an overall assessment of customer satisfaction based on the information and feedback received.

To conduct the experiment, the following issues need to be worked out:

a) analysis of methods of obtaining information:

1) methods of forming questionnaires;

2) determining the type of questions (questionnaires are a closed type of question, feedback is an open type of question);

3) formulation of questions in accordance with the peculiarities of information perception by a particular target audience;

4) drawing up several types of questionnaires according to the type of target audience;

b) analysis of questionnaires:

1) identification and comparison of evaluation methods;

2) defining criteria and scales for evaluating questionnaires;

3) normalization, reduction to one scale;

c) analysis of feedback:

1) selection of AI methods for determining the tone of texts;

2) comparison of AI methods;

3) selection and justification of the method;

4) application of the selected method;

d) combining results, unification of evaluation:

1) normalization, reduction to one scale;

2) applying the convolution method to generate statistical data;

3) development of methods for formulating recommendations.

Once these issues have been worked out, it is necessary to develop a prototype application that will automate surveys, analyze questionnaires for the most popular KPIs, and find out the tone of feedback to determine and unify the assessment of customer satisfaction and loyalty.

Materials and methods

Usually, analysts have to use different services to determine the level of customer loyalty, which complicates the overall process and cost of such measures. This negatively affects the accuracy of the results, increases data processing time, and requires additional study of the results in order to summarize them and use them further.

Customer satisfaction is defined as the level of customer loyalty to the company, which is formed and determined during the customer’s interaction with the company’s staff, products and services. A sufficiently high level of loyalty is explained by the proper quality of goods and good service. Thus, this level affects whether the customer will use the company’s services again.

To maintain the level of loyalty, it is necessary to constantly improve the company’s already established activities and consider new areas of work with clients and ways to maintain constant communication and increase background satisfaction. Another important task is to track the quality of the company, team, and products. An equally important component is tracking the trend and level of customer satisfaction against the background of these changes. It should also be remembered that *the Retention Rate* will be different at different stages of the project and the software will need to analyze different metrics.

Common indicators are as follows [24–25]:

– CSAT (*Customer Satisfaction Score*) index;

– CSI (*Customer Satisfaction Index*) index;

– NPS (*Net Promoter Score*) index;

– CRR (*Customer Retention Rate*) index;

– *North Star Metric*.

The CSAT index is a metric that helps determine the level of satisfaction with a customer’s experience of interacting with a company based on customer surveys.

A scale from 1 to 5 is used to determine the answers, which reflects the level of customer satisfaction from "very dissatisfied" to "very satisfied" respectively. Having collected all the answers, the CSAT index is calculated using the formula:

$$CSAT = \frac{A_5 + A_4}{A_a} \times 100\%, \tag{1}$$

where A_a – total number of ratings;

A_5 – number of "very satisfied" ratings;

A_4 – number of "satisfied" ratings.

ISSN 2522-9818 (print)
Сучасний стан наукових досліджень та технологій в промисловості. 2023. № 2 (24) ISSN 2524-2296 (online)

According to the CSAT metric, a sufficient level of customer satisfaction is considered to be a value of 76.5% or more.

The Customer Satisfaction Index (CSI) is a metric used to measure the overall satisfaction of a person with a product, service, or experience.

This metric can be used to find out how a customer feels about a company, as well as to gain insight into various aspects of a business and how a customer feels about it. The following formula is used to calculate the indicator:

$$CSI = \frac{1}{n}\sum_{i=0}^{n} a_i, \quad (2)$$

where a – measured attribute;

n – number of attributes.

The Net Promoter Score (NPS) is a metric that measures the level of customer loyalty to a company. It is used on the basis of a questionnaire. Usually, the scale is considered to be from 1 to 10, where:

– 0 to 6 – critics;

– 7 to 8 – neutral consumers;

– 9 to 10 – supporters.

The variability of the value of this metric ranges from –100 to 100, and the value is calculated using the following formula:

$$NPS = C_p - C_d, \quad (3)$$

where C_p – percentage of supporters;

C_d – percentage of critics.

It is important to remember the axiom that it is cheaper for a business to sell to a regular customer than to attract a new one. There is no need to talk in detail about the benefits of the product, introduce the brand – after all, a person is already familiar with the company's range of goods and services and delivery terms. He already has a positive purchase experience and can make another one. The *Customer Retention Rate* (CRR), or *Retention Rate*, is a measure of how well a business retains customers. To determine it, you need to choose the period of time for which you want to calculate the CRR – month, quarter, half a year, year. A good sample is 1 month, because this is enough time to analyze the advertising campaign and analyze customer behavior. However, it is necessary to remember that everything depends on the business sector. Mobile game manufacturers can track CRR on a daily basis.

$$CRR = \frac{\text{number of customers at the end of the period} - \text{number of customers who came during the entire period}}{\text{number of customers at the beginning of the period}} \times 100\%.$$

The customer retention rate shows how the company works with the base. If you only look for new customers, you can miss out on some of the profit from repeat sales. Even minor changes in the retention strategy will pay off. A 5% increase in the *Retention Rate* can increase profits by 75–95%.

North Star Metric – is a leading metric that shows the core value of a product for users. This metric helps to take into account variable features and change the focus from one metric to another in order not to miss new opportunities and understand the reasons for the deterioration of the user experience. It is this metric that allows you to observe the experience of regular customers and analyze the increase in their background satisfaction, as well as better understand user preferences and bring them closer to the aha moment

Different BI systems are used to calculate them.

Using the described metrics, the company understands the end user better and is able to adjust its actions to improve services, product quality, etc.

One of the challenges is to reduce the values to a single scale, given that the metrics have different scales.

The CSAT and CSI indices are measured on a scale from 1 to 5, and the NPS index is measured from 1 to 10. We can equate it to a scale from 1 to 5, where 1–3 are critics, 4 are neutral consumers, and 5 are supporters. In order to use these indices simultaneously, it is necessary to reduce them to a common form for further use and increase the accuracy of the assessment.

Thus, all indicators will be calculated on the same scale, which will provide a more accurate overall assessment and increase analytical value. For the effective work of analysts, KPI results should also be additionally displayed in the original version, while maintaining the original value scales.

In addition to questionnaires, feedback is a common form of communication. Usually, it takes not only a lot of time but also a lot of specialists to process them. Feedback usually reflects the client's general attitude towards the company in the form of emotionally colored words.

The combination of feedback and questionnaires more accurately assesses the user. With the help of questionnaires, the respondent answers direct questions about the company and evaluates it within the framework of the questions asked. Unlike a questionnaire, feedback

ISSN 2522-9818 (print)
ISSN 2524-2296 (online) Innovative technologies and scientific solutions for industries. 2023. No. 2 (24)

allows the user to express an opinion and draw attention to relevant aspects outside the scope of the questions and express their attitude to them. Unlike questionnaires, this type of information is more analytically complex and requires the use of artificial intelligence.

Determining the tone of a text is quite a difficult task. There are a number of factors that make it difficult to correctly determine this aspect or lead to an erroneous result [26, 27].

These include

– subjectivity: tone can be variable and perceived differently by different people, for example, the same expression can be seen as positive by one person and negative by another;

– context: the meaning and tone of a text can be strongly influenced by its context;

– development and evolution of language: language is constantly evolving and improving; the emergence of new words and the use of foreign language borrowings complicates the work of AI, which is explained by the low probability of correct interpretation of such vocabulary;

– ambiguity: the use of sarcasm, irony, etc. complicates the possibility of accurate interpretation of the result, as such texts usually have the opposite meaning and can be misinterpreted by AI;

– cultural diversity: complications in the tone of the text may be caused by cultural factors, namely the use of regional dialects and idioms.

To solve the above problems, companies are constantly updating the dictionaries used by AI and improving the algorithm.

There are several artificial intelligence methods that can be used to analyze text tone.

– Rule-based systems. They use a set of rules to analyze text and determine tone. The rules are based on keywords, phrases, or language patterns associated with positive or negative content.

– Machine learning algorithms. The algorithms are trained on a dataset that has pre-marked examples (positive or negative feedback) to learn how to classify new texts. Popular machine learning algorithms for sentiment analysis include the naive Bayesian algorithm, support vector machines (SVMs), and artificial neural networks (ANNs).

– Deep learning. Deep learning methods can also be used to analyze sentiment. Examples of such methods are Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN).

– Natural language processing (NLP). Such methods are used to extract characteristics from the text, such as the presence of certain words or phrases, sentence structure, or context.

– The choice of an AI method to solve the text tone analysis task depends on various factors, such as the size and complexity of the data, accuracy requirements, available computing resources, etc. The most suitable method is selected based on the results obtained.

Determine the scope of the methods to choose the best one to use.

Rule-based systems can be used to quickly categorize text into positive, negative, or neutral categories. However, they are limited by the quality of the rules and may not be as accurate as machine learning or deep learning methods.

Machine learning algorithms are more accurate than rule-based systems and can handle more complex data patterns. However, they require a significant amount of labeled training data to be effective, and they may not be as efficient if the data is noisy or the features are not clearly defined.

Deep learning methods are the most accurate method of sentiment analysis and can handle very complex data patterns. They can also be used to obtain more detailed information about feelings, such as emotions or relationships. However, these methods require a significant amount of labeled training data and a large amount of computing resources.

NLP methods can be used to extract characteristics from text that are relevant to tone analysis, such as the presence of specific words or phrases, sentence structure, or the context in which the text appears.

Based on the comparison, it can be concluded that NLP is the best method to use for the task of analyzing the tone of feedback, as it provides more detailed information about the context among all these methods.

The main tasks of NLP include [28]:

– data mining;
– speech synthesis;
– speech recognition;
– natural language generation;
– machine translation;
– question and answer systems;
– topic recognition/determination;
– information retrieval;
– data mining;
– linking;
– text simplification;
– dealing with lexical diversity;

ISSN 2522-9818 (print)
Сучасний стан наукових досліджень та технологій в промисловості. 2023. № 2 (24) ISSN 2524-2296 (online)

– recognizing abbreviations and titles;
– detecting individual linguistic units;
– morphological decomposition.

Let’s consider the feedback processing process more thoroughly.

The processing stages include [29, 30]:
– sentence tokenization;
– extraction of stop words;
– word normalization;
– converting words into a numerical representation for classification.

Tokenization is the process of breaking down text fragments into more atomic units. Such units can be sentences or words. During tokenization, AI also adds punctuation marks, so there is a need for additional processing of such values.

The next step is the extraction of "stop words". At this stage, the information is cleared of emotionally neutral and meaningless words during classification. Punctuation marks are also removed. The result of this stage is the selection of significant lexemes that emphasize the emotional context, as well as a reduction in the number of words for further processing.

At the normalization stage, all forms of words are reduced to one type by lemmatization. This method uses a special data structure that links all derived forms of a word to its simplest form, called a lemma. Lemma checking is applied for each token.

At the vectorization stage, tokens are converted into a numerical array – various token characteristics. The vectors are used to search for similarities between words and their further classification.

Machine learning classifiers are used to generate a summary that contains information about the objects of the statement and their corresponding tonal vocabulary.

There are four main stages to analyze the emotional coloring of a test:
– data loading;
– data pre-processing;
– classifier training;
– data classification.

These stages include:
– dividing the data into training and evaluation sets;
– selecting an architecture model;
– using data to train the model;
– using test data to evaluate the model’s performance;
– using the trained model to generate new data to make predictions, which in a particular case will be a number between –1.0 and 1.0.

To train the model, it is advisable to use batch data processing, which will reduce memory usage.

For the classifier to work correctly and to be more accurate in determining the tone of the text, it is necessary to train the model on prepared examples taken from open sources.

To evaluate the progress of training, the following values should be calculated:
– true positive results;
– false positives;
– true negatives;
– false negatives.

True positives include documents that were correctly predicted by the model as positive.

False positives include documents that were mistakenly predicted as positive, when in fact they are negative.

True negatives are documents that were correctly predicted by the model as negative.

False negatives include documents that were mistakenly predicted as negative, when in fact they are positive.

The model returns a score from 0 to 1, which indicates the accuracy and completeness of the text tone determination. The general performance indicators of the model include the following [31]:

– accuracy – the ratio of true positive labels to true and false positives;

– recall – the ratio of true positive responses to all true positive responses;

– *F*-measure – a measure of text accuracy, defined as the accuracy and completeness of the text. Precision is the number of correctly identified positive outcomes divided by the number of all positive outcomes, including incorrectly identified ones. Completeness is the number of correctly identified positive results divided by the number of all samples that need to be identified as positive.

If the model is successfully trained, it is possible to use it to work with real data. For the convenience of using the results of the response analysis, we will reduce the result scale of 0–1 to a scale of 1–5. The scale is divided in increments of 0.2.

Feedback that has a score of less than 3 (equivalent to an accuracy of less than 60–40%) is recommended to be provided to employees to identify problematic aspects and further processing.

Once the results of the two parts of the survey (feedback and survey) are obtained, the score will be determined using additive convolution. Since questionnaires have more information directly about the

ISSN 2522-9818 (print)
ISSN 2524-2296 (online) Innovative technologies and scientific solutions for industries. 2023. No. 2 (24)

subject area and more specific answers, this method of evaluation is more significant than feedback, so in total, a coefficient value of 0.6 is proposed for certain indicators, and the impact of CSAT, NPS, CSI will be considered equivalent. Feedback has a coefficient value of 0.4 because there is a possibility of irrelevant feedback or an error in determining its tone.

The calculation formula is as follows:

$$R\_\text{gen} = CSAT \times 0.2 + NPS \times 0.2 + CSI \times 0.2 + Fb \times 0.4. \quad (4)$$

If only one part of the survey is available, the corresponding value will be taken as the absolute value of the customer satisfaction level. If another part of the survey is received, the score will be recalculated taking into account the results obtained.

To conduct the experiment, we structure the sequence of steps for processing the results to determine a unified assessment of customer satisfaction based on different types of data:

– obtain user data from questionnaires and feedback;

– measure the KPI values based on the obtained questionnaire results (CSI, CSAT, NPS determination by formulas (1–3));

– normalize the results of performance indicators to one measurement scale (see the description of normalization of indicators);

– determine the tone of the feedback, get the probability of the accuracy of the result (see the stages of feedback processing);

– based on the probability, determine the score for the feedback (see normalization of indicators);

– normalize the response score to bring it to the same measurement scale as the questionnaire results;

– using additive convolution, determine the value of the unified score (see formula (4));

– as a result, we return a unified assessment of customer satisfaction based on different types of data.

Depending on the availability of results, the unified assessment may contain one or another data component. That is, if we have only the results of questionnaires, we calculate a unified score, despite the results of the feedback, and vice versa. If we have the results of both the feedback and the questionnaire, the unified score is calculated based on both of these components. The flowchart of the algorithm is shown in Fig. 1.

To implement the algorithm and conduct the experiment, a prototype system was created. For this purpose, an N-layer architecture was used, using *Nest.js* as the *Rest API* server, *React* to develop the web interface, *PostgreSQL* as the database, and *Python* to develop the NLP module [32, 33].

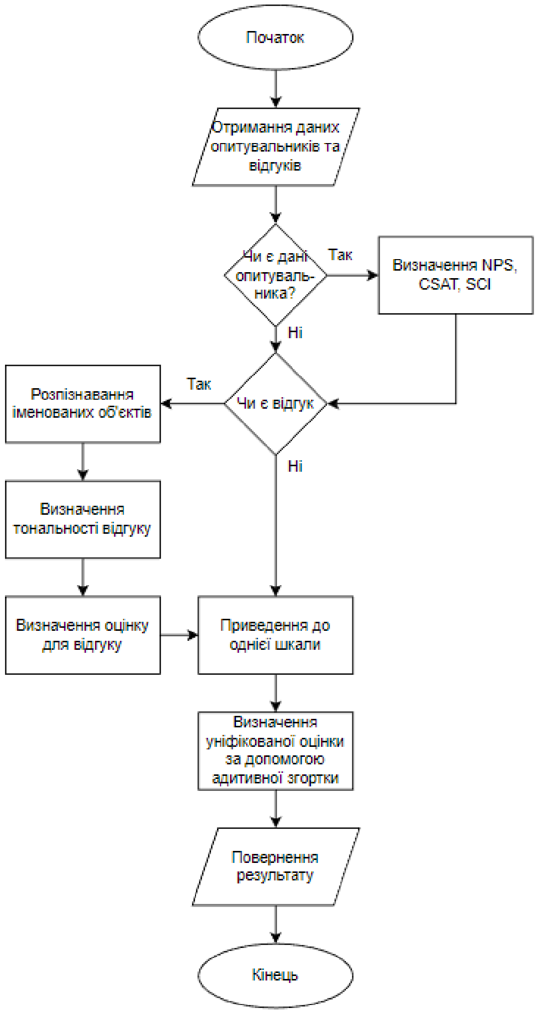

Fig. 1. Flowchart of the algorithm

To determine a sufficient sample size to train a model, you can use the following formula (sample power calculation):

$$n = \frac{t^2 pN\left(100 - p\right)}{\Delta^2 N + t^2 pN\left(100 - p\right)}, \quad (5)$$

where t is the confidence level, a statistical value whose value for social research is 1.96 (assuming 95% accuracy of the statistical conclusion). The confidence level is set by the researcher in accordance with their requirements for the reliability of the results obtained. The most commonly used confidence levels are 0.95 or 0.99,

p – % of objects that are likely to have a trait important for the study;

ISSN 2522-9818 (print)
Сучасний стан наукових досліджень та технологій в промисловості. 2023. № 2 (24) ISSN 2524-2296 (online)

N – the size of the general sample;

Δ is the margin of error in %, set arbitrarily in the process of planning the study.

For our analysis, we chose $p = 80\%$ because not all of the customers provided candid feedback.

Let's calculate the sample size to make sure how much data is needed to train the model.

For our analysis, we chose $p = 80\%$ because not all customers provided honest feedback.

Calculate the sample size to see how much data is needed to train the model.

$$n = \frac{1.96^2 \times 80\% \times 21436 \times (100-80)}{5\%^2 \times 21436 + 1.96^2 \times 80\% \times 21436 \times (100-80)}. \quad (6)$$

After performing the calculations, we determined that the dataset should have at least 20 thousand responses and be pre-prepared specifically for training and testing models. The grouping was performed with a relatively equal interval. To train the model, we will use a dataset with reviews taken from a popular online store. This dataset was prepared to train a neural network for natural language processing. It contains 21.436 reviews, 10.718 of which are labeled as positive and negative, and 10.718 reviews without text tone markers to conduct an experiment on the trained model.

During the study, 20 training iterations were conducted.

The next step of the experiment is to conduct a survey and obtain an evaluation for the questionnaire. For this purpose, 24.165 questionnaires were analyzed. It was determined that user responses can be divided into 7 groups. The questionnaire contains 5 questions. Most users left their feedback. Analyzing the feedback with the help of AI, we will get their scores and determine the average value for each group.

To make data analysis easier, let's summarize the answers to the questionnaires and feedback scores in one table. Table 1 shows an example of the survey results.

Table 1. *An example of a summary table with questionnaire responses and feedback assessment*

Groups	Question 1	Question 2	Question 3	Question 4	Question 5	Feedback
1	5	4	5	4	3	4
2	4	5	4	4	4	4
3	3	4	5	4	5	4
4	5	4	4	3	2	3
5	4	4	5	4	5	4
6	5	5	5	5	5	5
7	4	5	4	5	5	4

Using additive convolution, we determine a unified score for each user.

Next, we calculate the average KPI value based on the answers to the questionnaire for each group. Since each group has a different number of users, we will calculate the percentage of people in each group to establish the correct final score.

To get a unified score for all users for the entire period of time, it is necessary to calculate the average of the previously defined unified scores for each user.

Research results and discussion

Based on the results of the experiment, we have the following graphs of metrics:

– dynamics of changes in metrics indicators over the past five years;

– dynamics of changes in the unified score over the past five years;

– dynamics of changes in the average value of the unified score over the past five years.

For the sake of ease of display, data for some graphs were calculated on a quarterly basis.

Fig. 2 shows the dynamics of changes in metrics over five years for all groups. For greater detail, the metrics are defined for each quarter.

According to Fig. 2, we can conclude that such fluctuations in the indicators are caused by changes in the level of customer loyalty and satisfaction. It can be assumed that the reason for the sharp increase in the indicators is the identification of customer dissatisfaction problems and their solution.

Using the data presented in Fig. 2 and analyzing the feedback, we determined the dynamics of the unified assessment values for each quarter (see Fig. 3).

As can be seen from Fig. 3, the level of customer satisfaction varies greatly from quarter to quarter. Most of the time, there is an increase in the indicators, which may indicate that the company has processed the results of recent surveys and solved certain problems.

Next, we determined the dynamics of the average values of the indicators, taking into account all previous unified assessments, which are shown in Fig. 4. The data are for the last five years.

ISSN 2522-9818 (print)
ISSN 2524-2296 (online) Innovative technologies and scientific solutions for industries. 2023. No. 2 (24)

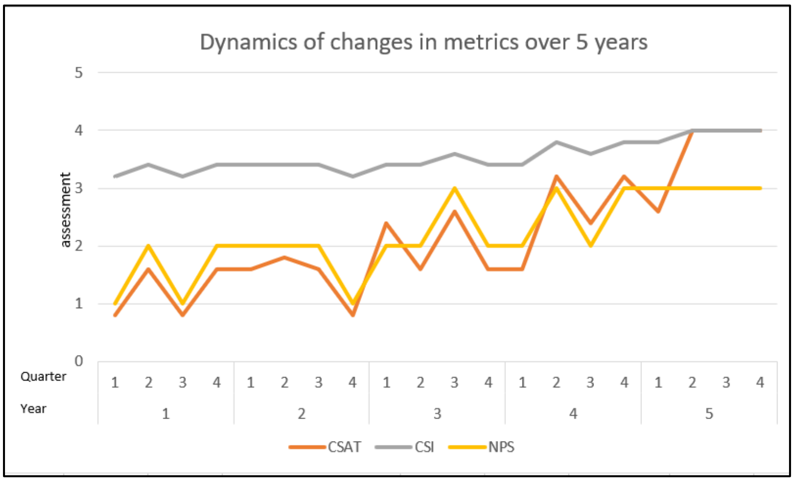

Fig. 2. Dynamics of changes in metrics over five years for all groups

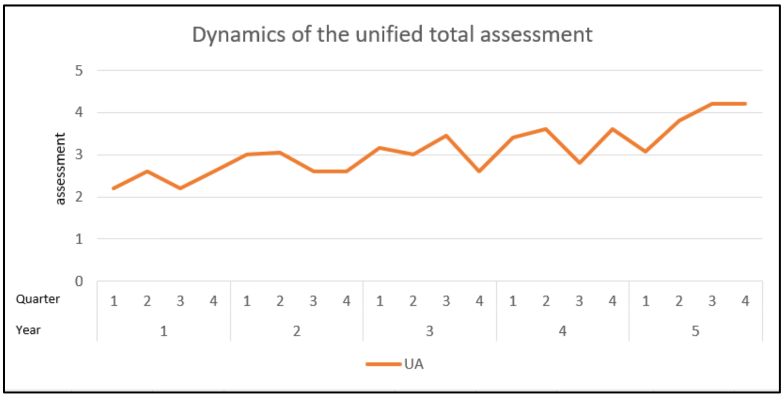

Fig. 3. Dynamics of the unified total assesment for each quarter

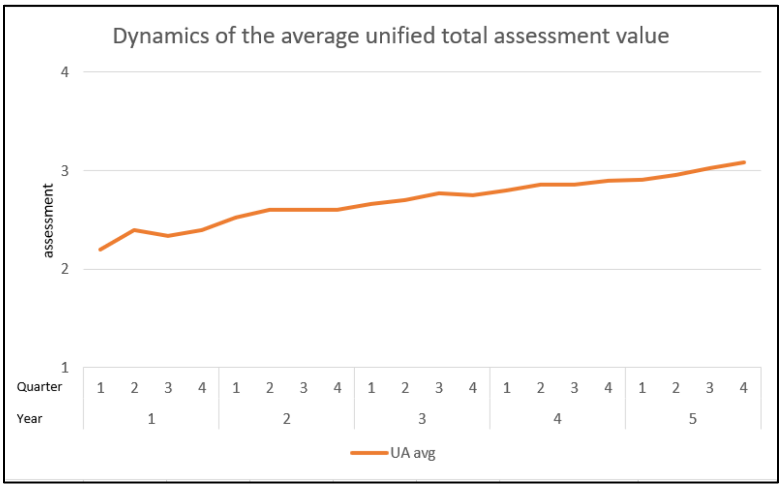

Fig. 4. Dynamics of average values of unified assessment indicators for each quarter

As can be seen from Fig. 4, despite the sharp ups and downs in the metrics, the overall score is growing steadily. Given this, we can conclude that the level of customer loyalty and satisfaction is growing every year. This may be due to the identification of business problems by collecting information from customers and solving these problems, i.e., regaining

ISSN 2522-9818 (print)
Сучасний стан наукових досліджень та технологій в промисловості. 2023. № 2 (24) ISSN 2524-2296 (online)

customer trust and, at the same time, the level of customer loyalty and satisfaction.

The results of the study showed that the proposed method of unifying the assessment to determine the level of customer loyalty and satisfaction can be applied in real systems. It allows not only to track popular KPIs but also to analyze customer feedback, while spending significantly less resources and time.

Conclusions and prospects for further development

In the course of the work, the subject area was analyzed and the main methods of obtaining information from end users about the quality of service and the company's work were identified. The methods of processing and analyzing the data obtained, methods of determining the results for forming an assessment are characterized.

The study analyzes popular key performance indicators and natural language processing methods. It is determined that the NPS, CSI and CSAT indicators have the greatest analytical value, so it is proposed to use them as the basic ones for use in the algorithm for determining the level of customer satisfaction. In analyzing the methods of natural language processing, the use of *Natural Language Processing* to determine the tone of the text is proposed.

The article proposes a universal method of unifying the assessment to determine the level of customer satisfaction and loyalty based on the results of questionnaires and feedback. This method consists in using the NPS, CSI, CSAT metrics and natural language processing by means of artificial intelligence to reduce these values to one measurement scale for further determining a unified assessment of customer satisfaction. It is calculated using additive convolution and is a general criterion for assessing satisfaction.

The study analyzed and verified the correctness of the results of the developed method. Determining the tone of the response may have an acceptable error that arises from unreliable input data. As a result, it was determined that the algorithm works in accordance with the requirements. Taking into account all these factors, we can conclude that the use of the method is appropriate. Based on the analysis of the method's shortcomings, ways to improve it are proposed.

In the process of designing a software system prototype, the main requirements and technologies for implementation are identified. The advantages of using these technologies to solve the task are described.

Thus, it has been determined that the method of assessing customer loyalty and satisfaction is based on the unification of a comprehensive assessment of various types of results, and is also effective and can be used to optimize business processes. The described method is not universal, as each business has its own needs. This reason is part of the potential development of the method to expand its scope.

Another disadvantage of the assessment method is the lack of candid customer feedback, as the system takes into account and processes all information. In addition, there is a possibility that the system may incorrectly determine the tone of the feedback, which will also affect the final result.

But, given all the above factors, the use of the method under consideration is quite justified, since the probability of obtaining a false value is low, and the level of permissible error is satisfactory.

In order to improve the method, a study can be conducted using a combined method of feedback analysis with the use of artificial intelligence. This will increase the accuracy of determining the emotional tone of reviews and develop a recommendation model based on them. In addition, to expand the scope of the survey method to cover a larger market segment, it is important to explore the possibility of using additional KPIs in the system.

References

1. Hogreve, J., Iseke, A., Derfuss, K., (2021), "The service-profit chain: reflections, revisions, and reimaginations", *Journal of service research,* Vol. 25(3), P. 460–477. DOI: 10.1177/10946705211052410
2. Narayan, R., Gehlot, A., Singh, R., Akram, S. V., Priyadarshi, N., Twala, B., (2022), "Hospitality feedback system 4.0: digitalization of feedback system with integration of industry 4.0 enabling technologies", *Sustainabilit,* Vol. 14(19), 12158 p. DOI: 10.3390/su141912158
3. Capuano, N., Greco, L., Ritrovato, P., Vento, M., (2020), "Sentiment analysis for customer relationship management: an incremental learning approach", *Applied intelligence,* Vol. 51, P. 3339–3352. DOI: 10.1007/s10489-020-01984-x
4. Cherednichenko, O., Yanholenko, O., Vovk, M., Sharonova, N., (2020), "Towards structuring of electronic marketplaces contents: items normalization technology", *Proceedings of the 4th International Conference on Computational Linguistics and Intelligent Systems (COLINS 2020),* P. 44–55, available at: https://ceur-ws.org/Vol-2604/paper4.pdf
5. Nichols, P., (2000), *Social Survey Methods: A field guide for development workers,* Oxfam GB. Practical Action Publishing, 132 p.

6. McDougall G. H. G., Levesque, T., (2000), "Customer Satisfaction with Services: Putting Perceived Value into the Equation", *Journal of Services Marketing*, Vol. 14(5), P. 392–410. DOI:10.1108/08876040010340937

7. Gonchar, O., Polishchuk, I., (2019), "Integration factors of today as a prerequisite for forming a mechanism for managing the marketing potential of the enterprise", *Journal of European Economy*, Vol. 18(2), P. 213–225. DOI: https://doi.org/10.35774/jee2019.02.213

8. Saher, L., Kolesnyk, A. (2018), "Customer Loyalty: the Essence and Program Types", *Market Infrastructure*, Vol. 20, P. 176–186, available at: http://www.market-infr.od.ua/journals/2018/20_2018_ukr/32.pdf

9. Sinkovska, V., (2019), "Measuring consumer loyalty in competition", *Marketing and digital technologies*, Vol. 4, No. 3, P. 40–53. DOI: 10.15276/mdt.3.4.2019.4

10. Holovachov, I., (2023), "Digital marketing strategies of the enterprise", *International Scientific Journal* "*Internauka*". *Series:* "*Economic Sciences*", No. 2(70), P.95-100. DOI: https://doi.org/10.25313/2520-2294-2023-2-8658

11. Fedorchenko A., Ponomarenko I., (2019), "A/B-testing as an efficient tools for digital marketing", *The problems of innovation and investment-driven development*, No. 19, P. 36–42, available at: https://doi.org/10.33813/2224-1213.19.2019.4

12. Pavlyk, S., Chunikhina, T., (2023), "Marketing in electronnic kommerce", *Brand Management: Marketing Technologies*, P. 389-392, available at: https://knute.edu.ua/file/MzEyMQ==/dfa2684085a58809d90b630a0fe26059.pdf

13. Balan, V., (2023), "Fuzzy hybrid model for forming a system of indicators for assessing the efficiency of an enterprise", *Ekonomy and society*, No. 48. DOI: https://doi.org/10.32782/2524-0072/2023-48-70

14. Parmenter, D. (2020), *Key Performance Indicators: developing, implementing, and using winning KPIs*, Hoboken, New Jersey: John Wiley & Sons. 384 p., available at: https://digilibdprdsumselprov.id/index.php?p=fstream-pdf&fid=53&bid=44

15. Fritze, A., Schnup, C., Moller, K., (2017), "Strategy-based prioritisation of KPIs using the fuzzy analytic network process–An application in the context of shared services", *Magazine for success-oriented corporate management*, No. 29(2), P. 58–68. available at: https://www.alexandria.unisg.ch/entities/publication/d0787a67-8732-4e0d-ba51-08f6027eac9f/details

16. Hordiienko, I., (2010), "Modeling of the system of key performance indicators of the organization", *Collection of Scientific Papers "ECONOMY AND ENTREPRENEURSHIP"*, No. 25. P. 205–215, available at: https://ir.kneu.edu.ua/handle/2010/2044?locale-attribute=en

17. Martynova, O., (2018), "Basic principles and provisions of the company's evaluation modeling using a balanced scorecard", *Young Scientist*, No. 11(63). P. 1158–1165, available at: http://repository.hneu.edu.ua/bitstream/123456789/21361/1/4%20%d0%9c%d0%b0%d1%80%d1%82%d0%b8%d0%bd%d0%be%d0%b2%d0%b0_%d0%b6%d1%83%d1%80%d0%bd%d0%b0%d0%bb%20%d0%9c%d0%be%d0%bb%d0%be%d0%b4%d0%b8%d0%b9%20%d0%b2%d1%87%d0%b5%d0%bd%d0%b8%d0%b9.pdf

18. Feshchur, R., Samuliak, V., (2010), "The groups of indexes (indicators) of evaluation of level of enterprises development", *Bulletin of the National University "Lviv Polytechnic"*, No. 691. P. 231–239, available at: https://ena.lpnu.ua/bitstreams/970e4a3b-b052-494d-9be9-25c9d3c5ed4a/download

19. "Quality management systems–Requirements", (2015), ISO 9001:2015(en), available at: https://www.iso.org/obp/ui/#iso:std:iso:9001 (last accessed 11.04.2023)

20. Picha, V. (2018), Sociology: basic terms and concepts encyclopedic dictionary-reference, New World-2000. 658 p.

21. Panchenko, D., Maksymenko, D., Turuta, O., Yerokhin, A., Daniiel, Y., Turuta, O. (2022), "Evaluation and Analysis of the NLP Model Zoo for Ukrainian Text Classification", *Communications in Computer and Information Science*, available at: https://link.springer.com/chapter/10.1007/978-3-031-20834-8_6

22. Batiuk, T., Dosyn, D. (2023), "Implementation of the intellectual system of sentiment analysis and clusterization of publications in the Twitter social network", *Innovative Technologies and Scientific Solutions for Industries*, No. 1 (23), P. 25–44. DOI: https://doi.org/10.30837/ITSSI.2023.23.025

23. Yuvchenko, K., Yesilevskyi, V., Sereda, O. (2022), "Human emotion recognition system using deep learning algorithms", *Innovative Technologies and Scientific Solutions for Industries*, No. 3(21). P. 60–69. DOI: https://doi.org/10.30837/ITSSI.2022.21.060

24. Farris, P., Bendle, N., Pfeifer, P., Reibstein, D. (2010), *Marketing metrics: the definitive guide to measuring marketing performance*, Upper Saddle River, N.J: Wharton School Pub. 53 p., available at: https://ptgmedia.pearsoncmg.com/images/9780137058297/samplepages/9780137058297.pdf

25. Rachitsky, L. (2021), "Choosing your north star metric", *Future*, available at: https://future.com/north-star-metrics/ (last accessed 12.04.2023).

26. Erdem, E., Kuyu, M., Yagcioglu, S., Frank, A., Parcalabescu, L., Plank, B., Babii, A., Turuta, O., Erdem, A., Calixto, I., Lloret, E., Apostol, E.-S., Truică, C.-O., Šandrih, B., Martinčić-Ipšić, S., Berend, G., Gatt, A., Korvel, G. (2022), "Neural Natural Language Generation: A Survey on Multilinguality, Multimodality, Controllability and Learning", *Journal of Artificial Intelligence Research*, No. 73, P.1131–1207. DOI: https://doi.org/10.1613/jair.1.12918

27. Sharonova, N., Kyrychenko, N., Gruzdo, I., Tereshchenko, G. (2022), "Generalized Semantic Analysis Algorithm of Natural Language Texts for Various Functional Style Types", *Proceedings of the 6th International Conference on Computational Linguistics and Intelligent Systems (COLINS 2022)*, Gliwice, Poland, May 12-13, P. 16–26, available at: https://ceur-ws.org/Vol-3171/paper4.pdf

28. Kaur, G., Sharma, A. (2023), "A deep learning-based model using hybrid feature extraction approach for consumer sentiment analysis", *Journal of big data*. No. 10(5), 4227 p. DOI: https://doi.org/10.1186/s40537-022-00680-6

29. Haque, R., Islam, N., Tasneem, M., Das, A. K. (2023), "Multi-class sentiment classification on bengali social media comments using machine learning", *International journal of cognitive computing in engineering*, Vol. 4, P. 21–35. DOI: https://doi.org/10.1016/j.ijcce.2023.01.001

30. Smelyakov, K., Karachevtsev, D., Kulemza, D., Samoilenko, Y., Patlan, O., Chupryna, A. (2020), "Effectiveness of Preprocessing Algorithms for Natural Language Processing Applications", *2020 IEEE International Conference on Problems of Infocommunications. Science and Technology (PIC S&T)*, Kharkiv, Ukraine, P. 1–5. DOI: https://doi.org/10.1109/picst51311.2020.9467919

31. Xu, Y., Wu, G., Chen, Y. (2022), "Predicting patients’ satisfaction with doctors in online medical communities", *Of organizational and end user computing*, Vol. 34(6), P.1–17. DOI: https://doi.org/10.4018/joeuc.287571

32. Avrunin, O., Vlasov, O., Filatov, V. (2020), "Model of semantic integration of information systems properties in relay database reengineering problems", *Innovative Technologies and Scientific Solutions for Industries*, No. 4(14), P. 5–12. DOI: https://doi.org/10.30837/ITSSI.2020.14.005

ISSN 2522-9818 (print)
ISSN 2524-2296 (online)

33. Kosenko, V. (2017), "Principles and structure of the methodology of risk-adaptive management of parameters of information and telecommunication networks of critical application systems", *Innovative Technologies and Scientific Solutions for Industries,* No. 1(1), P. 46–52. DOI: https://doi.org/10.30837/2522-9818.2017.1.046

Received 16.06.2023

Відомості про авторів / About the Authors

Лейба Яна Алімівна – Харківський національний університет радіоелектроніки, студентка ІІ курсу, ІІ (магістерського) рівня вищої освіти; e-mail: yana.leiba.cpe@nure.ua; ORCID ID: https://orcid.org/0009-0009-6178-2193

Широкопетлєва Марія Сергіївна – Харківський національний університет радіоелектроніки, старший викладач кафедри програмної інженерії, заступник директора центру післядипломної освіти, Харків, Україна; e-mail: marija.shirokopetleva@nure.ua; ORCID ID: https://orcid.org/0000-0002-7472-6045

Груздо Ірина Володимирівна – кандидат технічних наук, Харківський національний університет радіоелектроніки, доцент кафедри програмної інженерії, Харків, Україна; e-mail: irina.gruzdo@nure.ua; ORCID ID: https://orcid.org/0000-0002-4399-2367

Leiba Yana – Kharkiv National University of Radio Electronics, second year graduated student (master's degree), Kharkiv, Ukraine.

Shirokopetleva Mariya – Kharkiv National University of Radio Electronics, Senior Lecturer at the Department of Software Engineering, Deputy Director of the Center for Postgraduate Education, Kharkiv, Ukraine.

Gruzdo Iryna – PhD (Engineering Sciences), Kharkiv National University of Radio Electronics, Associate Professor at the Department of Software Engineering, Kharkiv, Ukraine.

ДОСЛІДЖЕННЯ МЕТОДІВ ВИЗНАЧЕННЯ ЛОЯЛЬНОСТІ КЛІЄНТІВ ТА ОЦІНЮВАННЯ РІВНЯ ЇХНЬОЇ ЗАДОВОЛЕНОСТІ

Предметом дослідження є методи збирання й оброблення інформації для визначення рівня задоволеності та лояльності клієнтів щодо компанії, а також можливість оцінювання результатів. **Мета роботи** – аналіз методів визначення лояльності клієнтів та оцінювання рівня їхньої задоволеності, а також розроблення алгоритму визначення уніфікованої оцінки на підставі різнотипних даних. У статті вирішуються такі **завдання:** аналіз методів отримання інформації – опитувальників і відгуків; визначення та порівняння методів оцінювання опитувальників із закритими відповідями; аналіз методів оцінювання тональності тексту відгуків і відкритих відповідей із застосуванням методів штучного інтелекту; розроблення алгоритму визначення уніфікованої оцінки та проведення дослідження. У роботі використано такі **методи:** теоретичні – для визначення наявних методів збирання даних, а також методів оцінювання рівня лояльності та задоволеності клієнтів із використанням індексів CSI, CSAT; методи NLP для виявлення тональності тексту, зведення розрахованих значень до однієї шкали, визначення методу уніфікації оцінки; емпіричні – для проведення експерименту та доведення доцільності застосування методу. **Здобуті результати.** Запропоновано метод оцінювання лояльності клієнтів і рівня їхньої задоволеності на основі аналізу різнотипної інформації з подальшою уніфікацією результатів. Різнотипною інформацією є відповіді на опитувальники й відгуки користувачів. Опитувальники проаналізовано за допомогою KPI, відгуки – завдяки застосуванню методів штучного інтелекту. Після нормалізації результатів (зведення до однієї шкали), використано метод адитивного згортання для уніфікації загального результату. Розроблено прототип програмної системи, що дає змогу провести повний цикл робіт – від збирання інформації до розрахунку як KPI-метрик, так і уніфікованої оцінки. **Висновки.** Експериментально визначено, що метод оцінювання лояльності клієнтів та рівня їхньої задоволеності, оснований на уніфікації комплексної оцінки різнотипної інформації, є ефективним та може застосовуватися для оптимізації процесів бізнесу завдяки зменшенню витрат часу й зусиль на аналіз здобутих результатів. Використання запропонованого методу є цілком виправдане, оскільки вірогідність отримання хибного значення не висока, а рівень допустимої похибки задовільний.

Ключові слова: уніфікована оцінка; рівень задоволеності клієнтів; лояльність клієнтів; відгуки; опитувальники.

Бібліографічні описи / Bibliographic descriptions

Лейба Я. А., Широкопетлєва М. С., Груздо І. В. Дослідження методів визначення лояльності клієнтів та оцінювання рівня їхньої задоволеності. *Сучасний стан наукових досліджень та технологій в промисловості*. 2023. № 2 (24). С. 104–117. DOI: https://doi.org/10.30837/ITSSI.2023.24.104

Leiba, Y., Shirokopetleva, M., Gruzdo, I. (2023), "Research on methods of determining customer loyalty and assessing their level of satisfaction", *Innovative Technologies and Scientific Solutions for Industries*, No. 2 (24), P. 104–117. DOI: https://doi.org/10.30837/ITSSI.2023.24.104