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ANALYSIS OF THE PROJECT OF A MARKETING CAMPAIGN TO PROMOTE ROBOTIC SOLUTIONS USING RANDOM FOREST CLASSIFICATION

The object of research is marketing strategies for promotion in social networks, which are the basis for achieving the basic requirements of brands: audience commitment, brand loyalty, awareness, positioning, conversion and reputation. Because of this, a significant number of modern companies that manufacture robotic complexes are considering the possibility of implementing such strategies using a project approach.

The work is aimed at analyzing data and evaluating marketing campaigns for the promotion of robotic solutions, carried out using Random Forest classification, in order to identify patterns and increase the effectiveness of such campaigns. The analysis was conducted on the example of three advertising campaigns. The analysis showed how the criteria taken into account when displaying advertisements on social networks, namely the age category of a person, gender, interest group of a person (according to the public profile of the social network), the number of ad impressions affect the number of clicks on the corresponding advertisement. As well as the total number of people who became interested in the product after seeing the advertisement, the total number of people who bought the product after watching the advertisement. The essence of the results obtained is that the study showed the possibility of assessing the effectiveness of marketing campaigns at the early stages, the measurability of performance indicators in terms of audience reach, level of interaction and conversion into reverse actions. The results of the study reflect the complex relationship between the conversion indicators of advertising campaigns and the main criteria for their implementation, emphasizing the importance of a project approach and the use of machine learning for building marketing campaigns. The study focuses on practical aspects. From a practical point of view, mastering the basic metrics of data mining, segmentation, the ability to use A/B testing and the use of machine learning methods, in particular the Random Forest classification algorithm, allows to increase the effectiveness of campaigns. And also reduce the risks of losing money due to incorrect conclusions regarding the segmentation of target audiences. The results of the study can become the basis for the formation of new strategies for conducting marketing campaigns when promoting robotic systems, adjusting existing ones, capable of effectively and flexibly adapting depending on the target audience and the dynamics of working with it.

Keywords: *project management, digital marketing, machine learning, robotics complex, competitiveness.*

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1. Introduction

With the increasing complexity of modern machine-building industries, which require increased productivity while maintaining stability in conditions of significant variations in the market for highly skilled workers, the use of robotic systems is increasingly widely used. At the same time, the development of artificial intelligence significantly affects the transformation of modern enterprises and in many cases becomes the basis that ensures their competitive advantage for the coming decades. According to the results of the World Economic Forum [1], approximately 75 % of the surveyed companies plan to integrate AI technologies over the next five years. At the same time, according to the International Federation of Robotics, the density of use of industrial robots in the world has reached a record level – 151 robots per 10 thousand employees, which is more than twice the indicator of six years ago [2, 3]. As the assessment of clusters of recent publications (2022–2025) shows, the range of research in this area is constantly transforming (Fig. 1).

To promote robotic equipment for the marketing and communications sectors, integration with artificial intelligence technologies allows to optimize advertising strategies, improve interaction with customers and their experience of interaction with the company, as well as collect data on their behavior [4, 5]. The use of social networks allows to effectively support marketing campaigns, and given the significant increase in costs for their development [6], makes it one of the main channels of communication with customers and brand promotion.

According to Fig. 1, there are 4 main clusters of research in this topic. On the one hand, the traditional marketing approach (red color) which has at its disposal developed tools for predicting consumer behavior. The second cluster (green) is social media marketing, which is closely interconnected with specific social networks, the behavior of opinion leaders, and the implementation of virtual and augmented reality. Given that the flow of data from social networks is constantly growing and there are difficulties in interpreting them, machine learning methods are becoming increasingly widespread for processing Big Data – the yellow cluster. It is presented in more detail in Fig. 2, where newer, highly cited studies are presented in yellow.

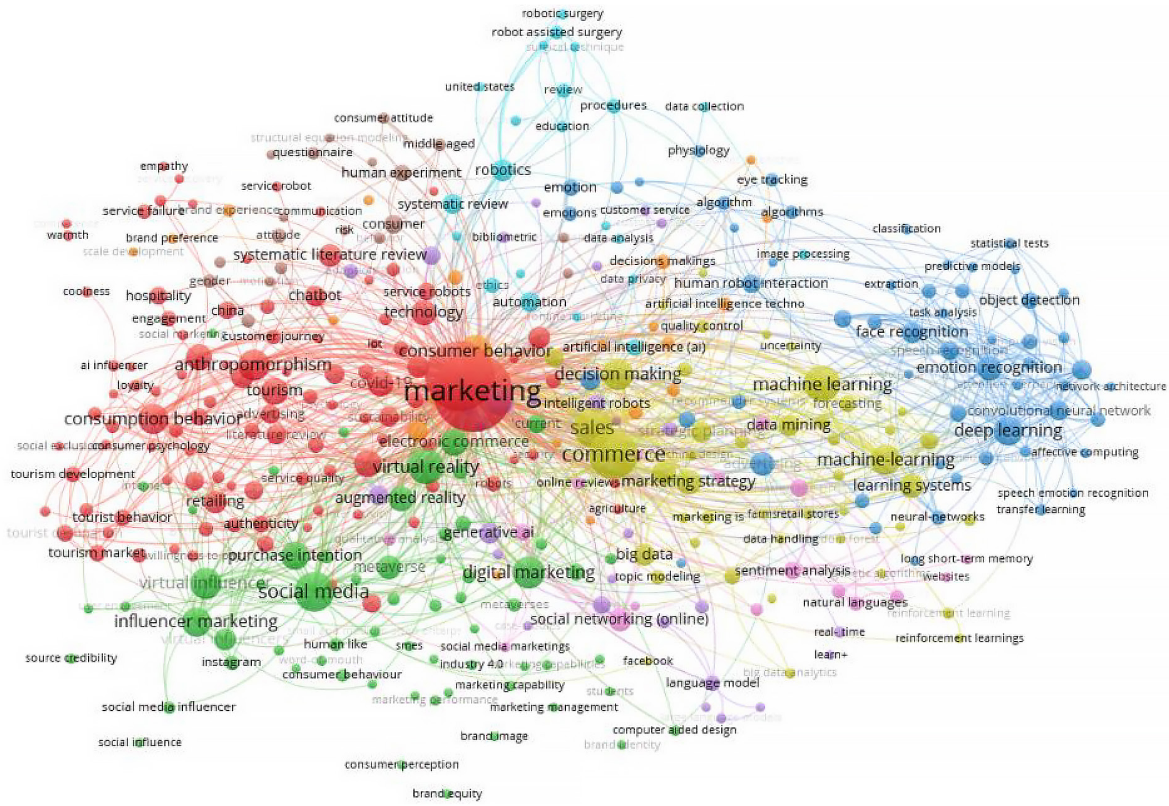

Fig. 1. Clusters of research areas in the use of marketing communications to promote robotic systems (data – Scopus database from 09.12.2024)

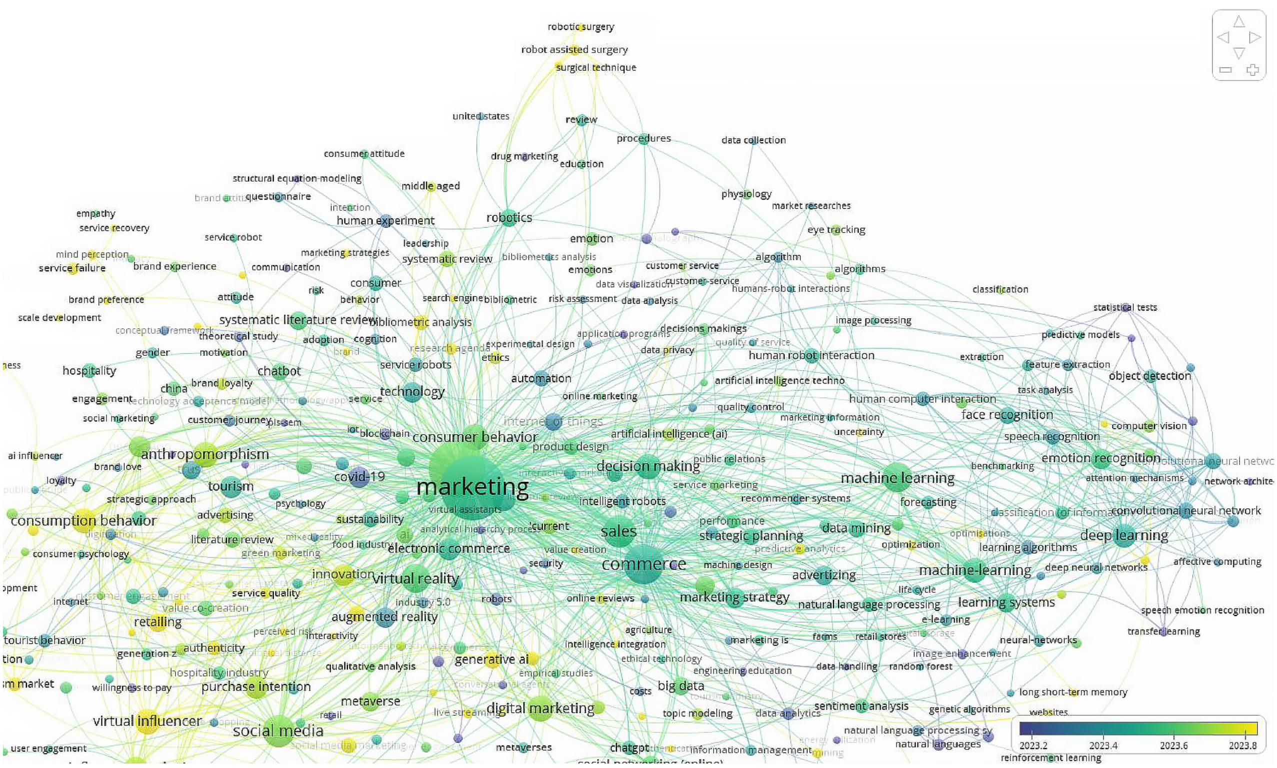

Fig. 2. Dynamics of publications for 2020–2025 in the areas of research in the use of machine learning and marketing communications to promote robotic systems (data – Scopus database from 09.12.2024)

The authors of the work conducted a series of studies on data processing and interpretation using machine learning methods [7] and computer vision [8], demonstrating the high efficiency of using such methods compared to classical statistical ones. And finally, the cluster on the use of robotic complexes and, accordingly, related new technologies of deep learning, advanced machine vision, machine learning methods without reinforcement, and emotion recognition is highlighted in blue.

Today, digital marketing has gained significant importance. Thus, most company leaders believe that the effective activities of their organizations are associated with the effective promotion of brands through social networks [9], and more than 75 % plan to significantly increase advertising budgets and consider them a necessary investment. Marketing strategies for promotion in social networks are the basis for achieving the basic requirements of brands: audience commitment, brand loyalty, awareness, positioning, conversion and reputation [10]. Therefore, a significant number of modern companies are considering the possibility of implementing such strategies using a project approach. This approach provides a clear structure, effective allocation of resources and optimal implementation of the tasks set. However, the main problem today is assessing the effectiveness of such campaigns, the measurability of performance indicators in terms of audience coverage, the level of interaction and conversion into reverse actions.

The aim of research is to evaluate a marketing company for the promotion of robotic products using a project approach to establish new patterns, identify impacts on the performance indicators of marketing companies. From a practical point of view, this will make it possible to assess the effectiveness of advertising campaigns and provide recommendations on the use of metrics at an early stage of their implementation.

2. Materials and Methods

The research used a project approach for advertising campaigns aimed at familiarizing the audience and selling robotics. This approach allowed to clearly define the goals, which allowed not only to familiarize the audience with the direction, increase conversions through social networks, but also to use machine learning to identify insights into user behavior. After cleaning and preparing the data, it is possible to perform a conversion assessment, segmentation, and assessed the cost-effectiveness and effectiveness of the campaign. Using A/B testing, it is possible to check the effectiveness of advertising campaigns and determined which of the options is the most effective, reducing the risks of spending on ineffective ads. The RandomForestClassifier regressor was used for machine learning.

3. Results and Discussion

The data for the research were obtained as a result of three advertising campaigns to promote robotic complexes.

Before using the dataset, let's conduct an exploratory data analysis (Exploratory Data Analysis). Conducting EDA allowed to evaluate the data structure, identify possible deviations, and formulate working hypotheses for the study. The EDA process involved the use of statistical methods, visualization and data aggregation for further modeling and decision-making.

The following were investigated as the main parameters: a unique identifier for each ad; an identifier associated with each advertising campaign (3 campaigns were conducted). The analysis used the criteria that are taken into account when displaying advertisements on social networks:

– a person's age category;
– gender;
– a code indicating the category to which the person's interest belongs (according to the public profile of the social network);
– the number of ad impressions;
– the number of clicks on the corresponding advertisement;
– payment for displaying advertisements to social network users; the total number of people who became interested in the product after seeing the advertisement;
– the total number of people who bought the product after viewing the advertisement.

According to the age group and gender, the display of advertisements was made according to the division presented in Fig. 3. The coverage of the campaigns included almost all age groups relevant to the content of the advertisements. The age group 30–34 years old showed the greatest activity – 47.53 %, which corresponds to the end consumers of this product. A close spread of 16.97–18.33 % was intended for the age groups 35–49 years old, which correspond mainly to middle managers – structural units responsible for the introduction of new technologies into production. If to compare the number of impressions by gender, the sample contains somewhat unequal ratios of the male group 72.36 % to the female group 27.64 %. This is due to the fact that even at enterprises that introduce such products, the groups are not equal.

The impact of gender on the main indicators of the marketing campaign was assessed (Fig. 4). It was found that for each of the categories, the impact of gender on the main indicators was not clearly identified. This indicates the balance of this set of marketing data and the possibility of using it both for assessments and for forecasting using machine learning models, in particular the RandomForestClassifier regressor.

The distribution within the advertising campaigns (Fig. 5) indicates a decrease in the number of female individuals compared to male individuals. However, considering that the product is mainly oriented towards the male gender, such a distribution is acceptable for this study.

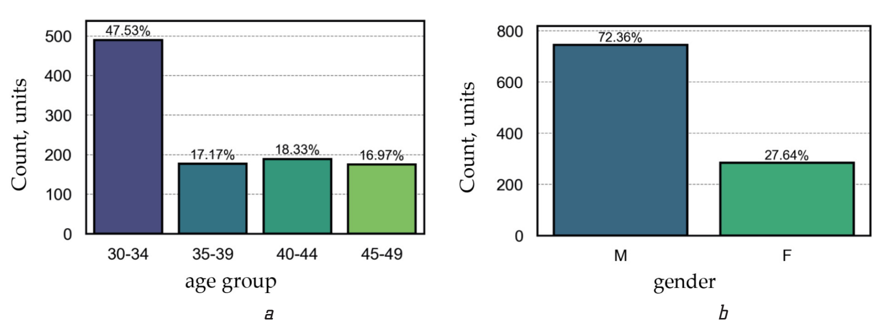

Fig. 3. Generalized distribution of data by characteristics: *a* – age; *b* – gender

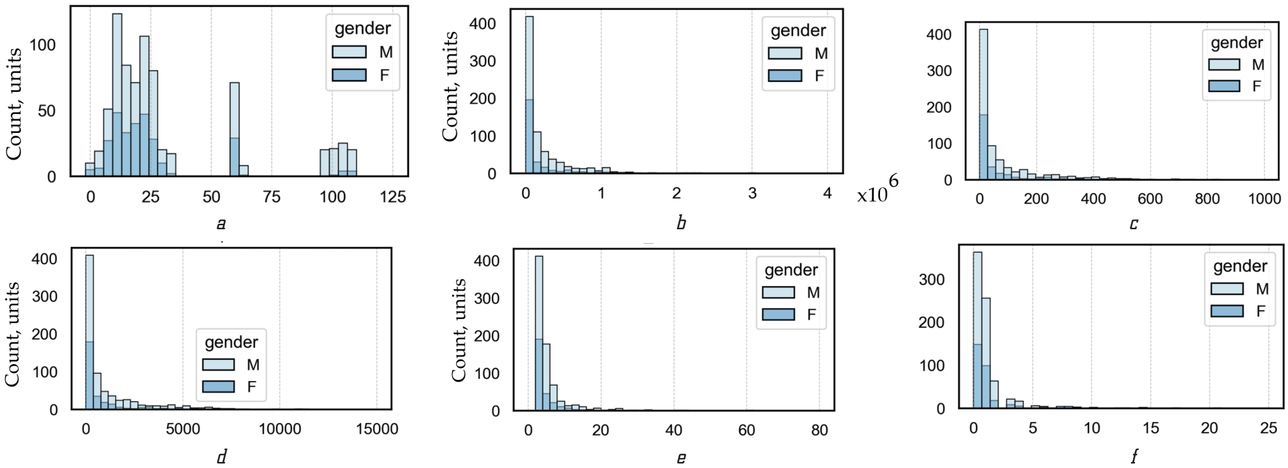

Fig. 4. Gender distribution when determining the main indicators of a marketing campaign: *a* – code indicating the category to which the person's interest belongs (according to the public profile of the social network); *b* – number of ad impressions; *c* – number of clicks on the corresponding advertisement; *d* – payment for displaying advertising to social network users; *e* – total number of people who became interested in the product after seeing the advertisement; *f* – total number of people who bought the product after viewing the advertisement

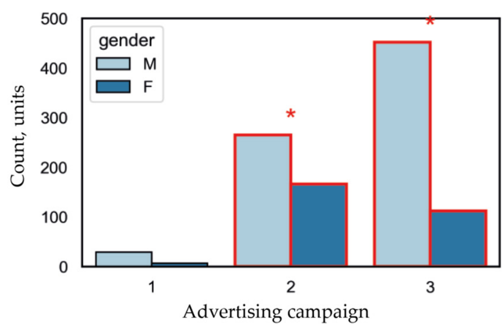

Fig. 5. Distribution histogram within the advertising campaigns

3.1. Conversion analysis

Among the main conversion characteristics studied, the following should be noted (Fig. 6). Click Through Rate (CTR), % – corresponds to the share of users who clicked on the ad out of the total number of impressions. A high indicator indicates that the ad successfully makes people click on it. Allows to assess the effectiveness of the ad in attracting attention. The average CTR is 0.033 %. This means that on average 1 click is generated for every 3030 impressions. (since 0.033 out of 100 impressions lead to a click, and therefore, 1/0.00033≈3030 how many impressions are needed for 1 click). More than 175 ads have a CTR of 0 %, which means that no clicks were made. That is, most people do not buy from the ad after seeing it.

Total Conversion Rate (TCR), % – shows the share of conversions (Total Conversion) from the total number of clicks. Allows to analyze the effectiveness of converting clicks into targeted actions. For the advertising companies under study, there is a significant share (over 350) where not a single click led to a conversion. Accordingly, the average value for TCR has not been determined. There are some ads with a TCR above 150, which means that the total number of people who were interested in the product after viewing the ad exceeds the number of people who clicked on this ad. The maximum TCR is about 200. This means that at least 2 times more people asked about the ad than clicked on it.

Approved Conversion Rate (ACR), % – the share of approved conversions (Approved Conversion) from the total number of clicks, which may be more important depending on the goals of the campaign. Allows to estimate the percentage of quality conversions. This rate has a significant bias and indicates that a small number of conversions are quality.

Cost Per Click (CPC), UAH (USD)/click – the average cost of each click on an ad. The distribution is close to the shape of a normal distribution. The average cost per click is 13.44 UAH (0.32 USD). The cost per click does not fluctuate significantly around the average value. The minimum cost per click is below 1.5 UAH (0.04 USD).

Cost Per Conversion (CPConv), UAH (USD)/conversion – the average cost of one conversion (UAH/conversion). The lower the values, the better, as this indicates the effectiveness of click and conversion costs. The distribution is strongly skewed to the left. At least one ad costs more than 1000 UAH (23.74 USD).

The analysis of the conversion of the conducted advertising campaigns showed the following. To make 1 click, it is necessary to generate an average of 3030 impressions. For the conducted companies, on average, not a single click led to a conversion, and its cost is 13.44 UAH (0.32 USD). Among the conducted advertising campaigns, at least one ad has a cost of more than 1000 UAH (23.74 USD).

Audience segmentation by age categories, gender and interests. A study was conducted on the segmentation of audience age (Fig. 7). Considering that the age group 30–34 years in the data set has the largest number of respondents – 339 men and 151 women, it accounts for the largest part of the money spent on advertising campaigns – 49.6 %. Other age groups vary from 12.8–19.6 %.

The Click Through Rate (CTR) indicator practically does not change depending on the age categories and ranges from 21.9 % to 28.9 %, increasing to the age category 45–49 years. This increase means that in this age category, people who view ads are more likely to click on it, but the decrease in ACR for this group indicates the practical absence of influence of this group on the conducted campaign. TCR, CPC and CPConv practically do not depend on age categories. ACR percentage – the share of approved conversions from the total number of clicks increases for the main group of 30–34 years. Segmentation by gender and interest group showed (Fig. 8, 9) that they do not have a significant impact on the main indicators of advertising campaigns. At the same time, it is of interest to assess the effectiveness of the conducted campaigns among themselves (Fig. 10).

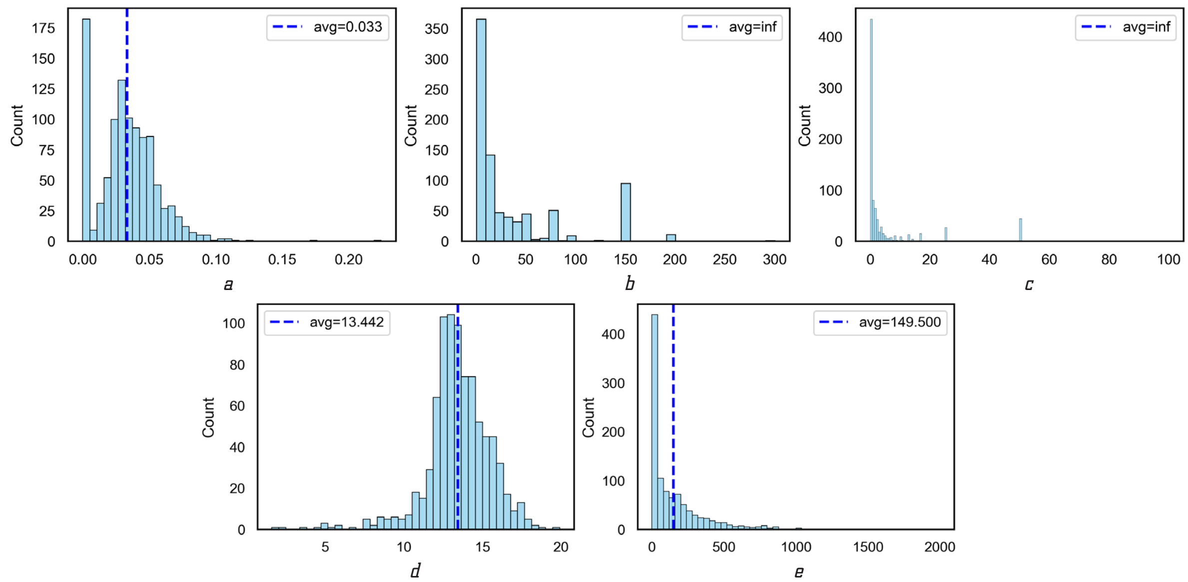

Fig. 6. Analysis of conversion rates for advertising campaigns: *a* – Click Through Rate (CTR), %; *b* – Total Conversion Rate (TCR), %; *c* – Approved Conversion Rate (ACR), %; *d* – Cost Per Click (CPC), UAH/click; *e* – Cost Per Conversion (CPConv), UAH/conversion

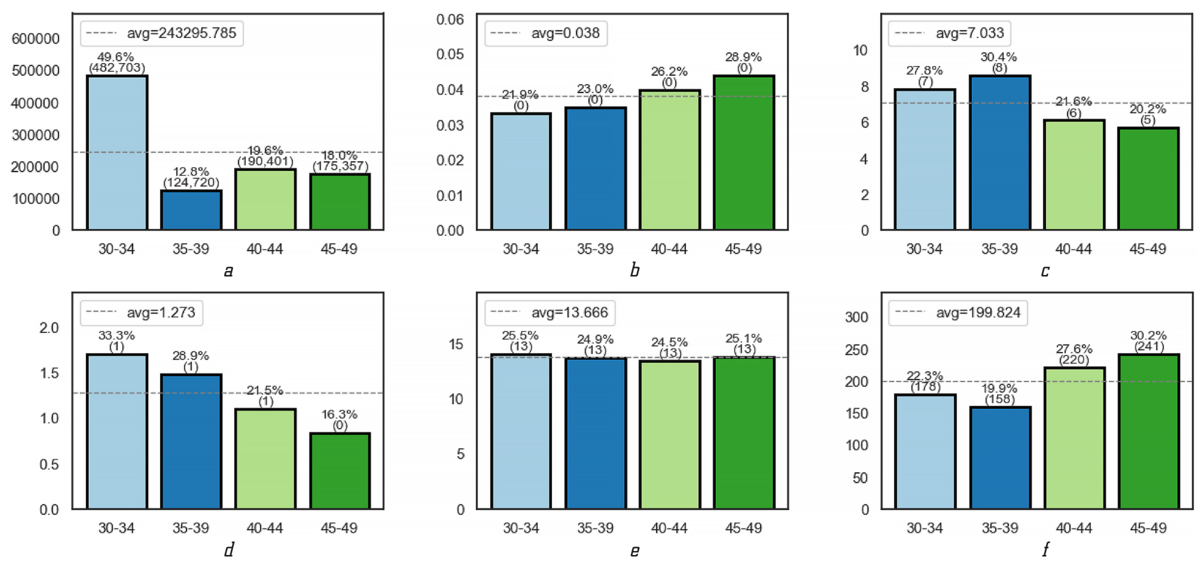

Fig. 7. Analysis of conversion rates for advertising campaigns by age groups: *a* – Total Amount of Money Spent, UAH (USD); *b* – Click Through Rate (CTR), %; *c* – Total Conversion Rate (TCR), %; *d* – Approved Conversion Rate (ACR), %; *e* – Cost Per Click (CPC), UAH (USD)/click; *f* – Cost Per Conversion (CPConv), UAH (USD)/conversion

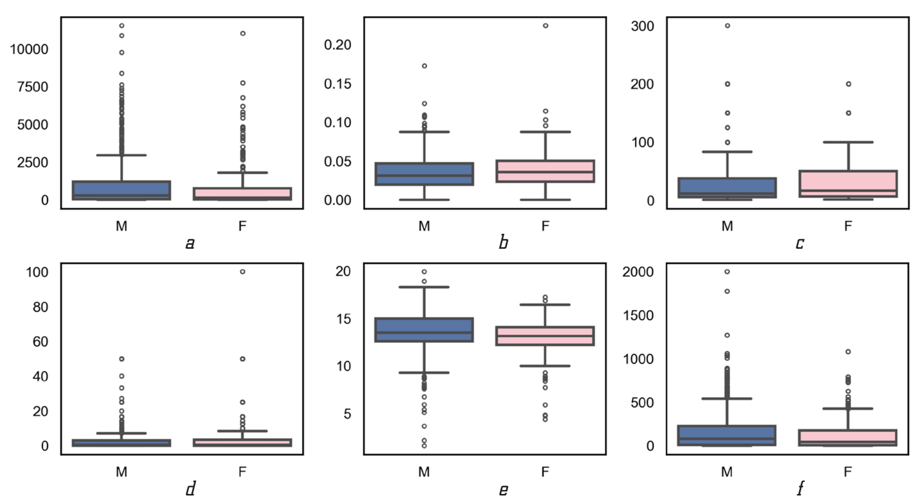

Fig. 8. The spread of values within each gender group regarding the main characteristics of marketing campaigns: *a* – Total Amount of Money Spent, UAH (USD); *b* – Click Through Rate (CTR), %; *c* – Total Conversion Rate (TCR), %; *d* – Approved Conversion Rate (ACR), %; *e* – Cost Per Click (CPC), UAH (USD)/click; *f* – Cost Per Conversion (CPConv), UAH (USD)/conversion

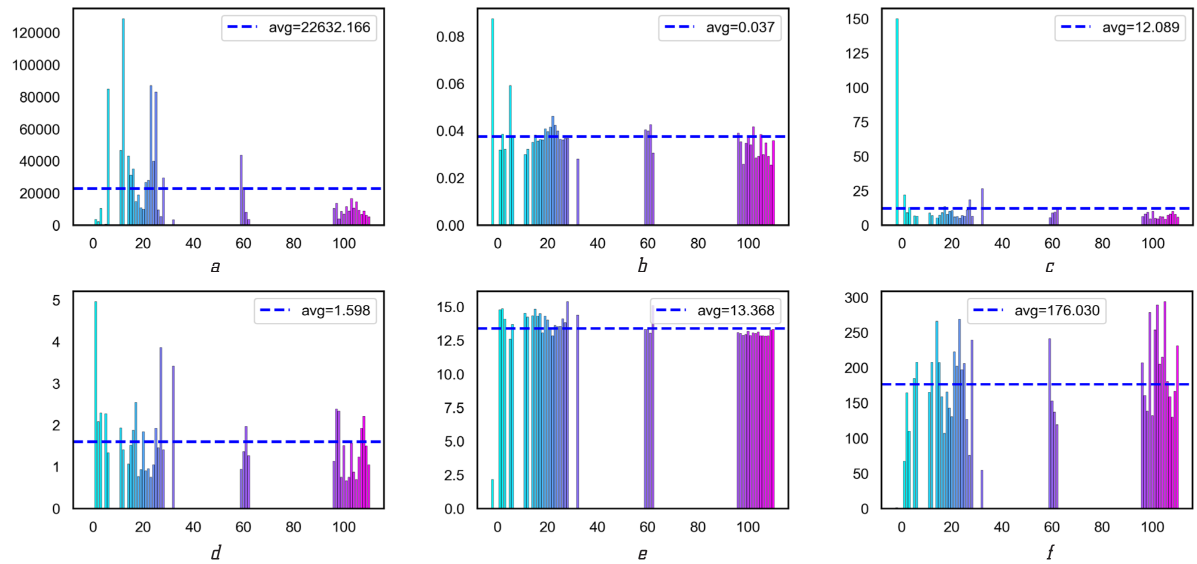

Fig. 9. Audience segmentation by code indicating the respondent's interest category (according to the public social network profile): *a* – Total Amount of Money Spent, UAH (USD); *b* – Click Through Rate (CTR), %; *c* – Total Conversion Rate (TCR), %; *d* – Approved Conversion Rate (ACR), %; *e* – Cost Per Click (CPC), UAH (USD)/click; *f* – Cost Per Conversion (CPConv), UAH (USD)/conversion

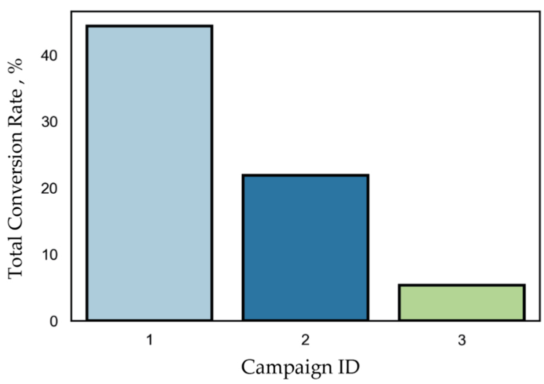

Fig. 10. Total conversion of conducted advertising campaigns

The Total Conversion Rate assessment for conducted campaigns showed that the first campaign is the most effective. Given its volume – reaching 78 people, such indicators indicate the effectiveness of small advertising campaigns.

3.2. A/B testing

Such testing usually involves comparing two or more versions of the same element (for example, different advertising creatives or messages) shown to similar audience segments. The data set does not show different versions of the same campaign, but rather different ads and three different campaigns.

Traditional testing should be comprehensive and meet the following prerequisites:

– the same audience (random division of the same audience into two or more groups);

– controlled variations (showing each group a different version of the ad (for example, different content, message), while all other variables remain unchanged);

– direct comparison (measuring which version works better in terms of conversions, clicks or another specific metric).

Additionally, because the dataset includes multiple campaigns with potentially different audience segments (e. g., age, gender, interests), impressions, and other variables, it is difficult to isolate the impact of one variable (e. g., campaign variation) without considering the impact of other factors.

To test the hypotheses, let's group ads by similar characteristics (same age range, gender, and interests) and then compared how different campaigns performed within these groups. The null hypothesis is that there is no significant difference in conversion rates between campaigns (Table 1).

Table 1

Summary of advertising campaigns

Campaign name	Number of clicks, pcs.	Total number of people who saw the ad	Conversion rate
1	176	111	0.630682
2	4184	1403	0.335325
3	66394	3564	0.053680

According to the results of the calculations ((p_value< <(ALPHA=0.05)), that is, the null hypothesis could not be rejected. The value of p_value=0.001. There is no significant difference in conversion rates between campaigns.

Using machine learning to predict conversion. A machine learning algorithm based on the Random Forest Classifier method was used. It uses a large number of decision trees to obtain more accurate predictions and avoid overtraining. The main input characteristics in this model are age, gender, code indicating the category to which the person's interest belongs (according to the public profile of the social network); the number of ad impressions; the number of clicks on the corresponding advertisement; payment for displaying advertising to users of the social network. Three conversion classes were selected as the initial feature for the prediction task: low, medium conversion and high conversion. The dataset was divided into training – 70 % of the total volume of 721 and verification – 30 %, i. e. 310 units.

According to the simulation results, a model with the following accuracy indicators was obtained (Table 2) and the resulting distribution density graph was constructed (Fig. 11).

The overall accuracy indicator for this model is 0.76. That is, the built machine learning model correctly predicted 76.77 % of the observations out of 310 considered.

The low conversion class (1–3) is characterized by good recognition by the model with high accuracy – 82 %

and sensitivity – 90 %. In addition, the F1-score is quite high 0.86, which indicates a high balance between the accuracy and sensitivity of the model.

Table 2

Metrics of classification accuracy of the machine learning model obtained using the Random Forest Classifier regressor

Campaign name	Precision	Recall	F1-score	Support, unit
1 – Low conversion	0.82	0.90	0.86	188
2 – Medium conversion	0.21	0.07	0.11	40
3 – High conversion	0.73	0.80	0.77	82

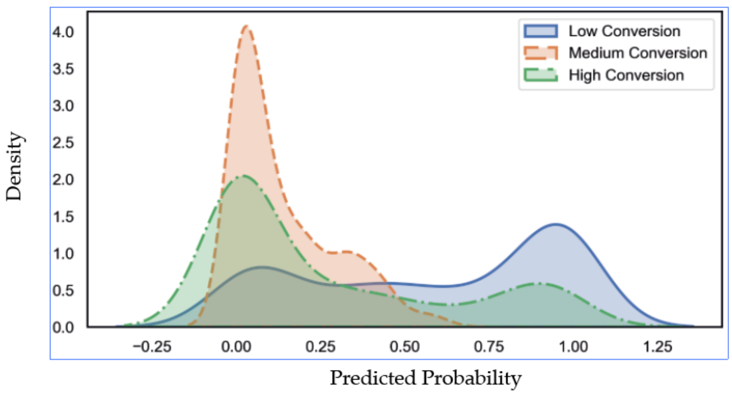

Fig. 11. Probability density graph for each group of conversions

The largest errors occurred in the model when classifying the average conversion. The F1-score demonstrated a strong imbalance between accuracy and sensitivity of 0.11. At the same time, the model for this class has many false positive predictions. The number of observations falling into this group is 40.

When predicting high conversion, the model demonstrates sufficiently high accuracy rates – 73 % and sensitivity of 80 %, and its F1-score is 0.77, which corresponds to a sufficiently high level of predictions for this class.

For further development of the research, it is necessary to conduct a more detailed segmentation of the audience, extensive A/B testing, and train the machine learning model on a larger data set.

4. Conclusions

The study solved the problem of assessing the effectiveness of a marketing company promoting robotic products based on the use of a project approach to establish new patterns, identify impacts on the effectiveness of marketing companies.

Conducting exploratory data analysis, which included the use of statistical methods, visualization and aggregation of data for further modeling and decision-making, made it possible to assess the data structure, identify possible deviations and formulate working hypotheses of the study. The coverage of the campaigns included almost all age groups relevant to the content of advertisements. The most active age group was 30–34 years old – 47.53 %, which corresponds to the end consumers of this product. The following should be noted for the main conversion characteristics that were studied. The Click Through Rate assessment showed that for the campaigns conducted, on average, 1 click is generated for every 3 thousand impressions. The Total Conversion Rate indicator allowed to record ads that have numerous repeated views, which indicates a significant opportunity to improve their quality. At the same time, Cost Per Click – the average cost of each click on an advertisement was 13.44 UAH (0.32 USD). The cost per click does not fluctuate significantly around the average value. The average cost of one conversion has a significant shift to the left, which indicates the inefficiency of costs for some campaigns. Segmentation by gender and interest group showed that they do not have a significant impact on the main indicators of advertising companies.

The conducted A/B testing confirmed the hypothesis that there is no significant difference in conversion rates for different companies.

Using the Random Forest Classifier algorithm, a machine learning model was built. The model takes into account the main factors of a marketing campaign and at the early stages allows predicting the correspondence of campaigns to one of three classes (low, medium and high conversion) – with an accuracy of 76.77 %. The accuracy of forecasts with low conversion is 82 %, with high – 73 %. Low sensitivity and accuracy of forecasts for medium conversion indicates the need to attract additional data sets, improve their quality and expand the class ranges.

From a practical point of view, the study makes it possible to assess the effectiveness of advertising campaigns for sales of robotic equipment using a project approach already at the early stages and provide recommendations on the use of metrics to improve the conversion of marketing campaigns.

Conflict of interest

The authors declares that they have no conflict of interest in relation to this study, including financial, personal, authorship or other, which could affect the study and its results presented in this article.

Financing

The study was conducted without financial support.

Data availability

The manuscript has no associated data.

Use of artificial intelligence

The authors confirms that they did not use artificial intelligence technologies when creating the presented work.

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