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Using Machine Learning to Predict the Effectiveness of Email Campaigns in Marketing

Volodymyr Boyko,

State University of Intellectual Technologies and and Communication,

Odesa, Ukraine,

https://orcid.org/0009-0002-1395-9221

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Abstract. The topic's relevance is because in the context of the rapid development of digital marketing, email communications are one of the most important ways for businesses to interact with their audience. High competition and information overload of subscribers encourage marketers to search for new approaches to accurately predict user reactions to received emails. Given this, the use of modern analytical tools, particularly machine learning technologies, is of particular importance, as they contribute to the effective prediction of the effectiveness of marketing campaigns.

The article aims to study the potential of using machine learning technologies to predict the effectiveness of email campaigns in digital marketing and to substantiate their practical feasibility for enterprises in the context of increased market competition.

The study uses an analysis of scientific sources, systematisation of approaches to applying machine learning technologies, modelling user response to emails using the gradient boosting algorithm, and a comparative analysis of existing models.

The study has revealed that a personalised approach, determination of the optimal time of sending, and analysing the target audience's behavioural models are important factors for accurate forecasting. The main difficulties that hinder the active use of such models are highlighted, including problems with the availability and quality of data, the complexity of interpreting the results of algorithms, the shortage of qualified specialists and the issue of personal data protection. In addition, a predictive model has been developed and practically tested to accurately predict user behaviour regarding opening emails, clicking on links, conversions, and unsubscribes.

The conclusions confirm that the proposed model, developed based on the gradient boosting algorithm (XGBoost), has demonstrated high accuracy in predicting the opening of emails and link clicks, which indicates its practical effectiveness. Prospects for further research are related to improving the transparency of predictive models and expanding their application in integrated solutions for automating enterprises' marketing processes.

Keywords: digital marketing, predictive models, user behaviour, content personalisation, email communication.

Використання машинного навчання для прогнозування ефективності емейл-кампаній у маркетингу

Бойко Володимир Мурадович,
Державний університет інтелектуальних технологій і зв'язку,
м. Одеса, Україна
https://orcid.org/0009-0002-1395-9221

Анотація. Актуальність теми зумовлена тим, що в умовах стрімкого розвитку цифрового маркетингу емейл-комунікації є одним із найважливіших способів взаємодії бізнесу з аудиторією. Висока конкуренція та інформаційне

перевантаження підписників спонукають маркетологів до пошуку нових підходів для точного передбачення реакцій користувачів на отримані листи. З огляду на це, використання сучасних аналітичних інструментів, зокрема технологій машинного навчання, набуває особливого значення, оскільки вони сприяють ефективному прогнозуванню результативності маркетингових кампаній.

Метою статті є дослідження потенціалу застосування технологій машинного навчання для прогнозування ефективності емейл-кампаній у цифровому маркетингу та обґрунтування їхньої практичної доцільності для підприємств в умовах посиленої ринкової конкуренції.

У дослідженні використано аналіз наукових джерел, систематизацію підходів до застосування технологій машинного навчання, моделювання реакції користувачів на електронні листи із застосуванням алгоритму градієнтного бустингу, а також порівняльний аналіз наявних моделей.

У результаті дослідження виявлено, що важливими чинниками точного прогнозування є персоналізований підхід, визначення оптимального часу надсилання та аналіз поведінкових моделей цільової аудиторії. Виокремлено основні труднощі, що стримують активне використання таких моделей, зокрема проблеми з доступністю та якістю даних, складність інтерпретації результатів роботи алгоритмів, дефіцит кваліфікованих фахівців і питання захисту персональних даних. Крім того, розроблено й практично перевірено прогностичну модель, яка точно передбачає поведінку користувачів щодо відкриття листів, переходів за посиланнями, конверсій та відписок.

Висновки підтверджують, що запропонована модель, розроблена на основі алгоритму градієнтного бустингу (XGBoost), продемонструвала високу точність прогнозування відкриття листів та переходів за посиланнями, що свідчить про її практичну ефективність. Перспективи подальших досліджень пов’язані з удосконаленням прозорості прогнозних моделей і розширенням

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їхнього застосування в комплексних рішеннях для автоматизації маркетингових процесів підприємств.

Ключові слова: цифровий маркетинг, прогнозні моделі, поведінка користувачів, персоналізація контенту, емейл-комунікація.

Problem statement. In modern marketing, considerable attention is paid to an individual approach to communication with customers, which stimulates the need to find effective tools for analysing the effectiveness of interaction. Email marketing is one of the main digital marketing channels today, but its effectiveness depends on predicting the audience's reaction to specific messages. Given this, there is a need to introduce new tools that can analyse large amounts of information, identify non-obvious relationships and predict the success of email campaigns. Of particular scientific interest is the use of modern analytical methods that help to improve the marketing decision-making process, enhance audience segmentation, optimise content and maximise the personalisation of emails for each recipient. In terms of practical application, creating such predictive models can significantly reduce the cost of unsuccessful mailings, attract a wider audience, and increase the efficiency of marketing activities in a competitive environment. Thus, the importance of the study is determined by the real need for scientifically sound and effective solutions for predicting the results of email communication using modern data analysis technologies.

Analysis of the latest research and publications. A review of research papers on predicting the effectiveness of email campaigns based on machine learning technologies allows us to identify four main areas of digital marketing. The first area of research concerns the general principles of implementing modern technologies, including artificial intelligence and machine learning, in digital marketing. For example, V. Bondarenko and O. Omelianenko [1] analyse the impact of artificial intelligence on the development of online marketing, emphasising that these technologies help companies better understand the behaviour of their customers. Also, T. Dronova, V. Khurdei, D. Mishchenko, and I. Pavlovska [2] consider the possibilities of digital tools, particularly email marketing, in advertising and prove that modern approaches significantly improves the efficiency of customer interaction. Researchers T. Yanchuk and T. Furman [3] emphasise the role of information technology in improving the effectiveness of marketing campaigns, noting that automation contributes to the growth of efficiency in working with the audience.

The second area covers research on specialised algorithms for predicting the results of email campaigns. Researchers R. Abakouy, E. En-Naimi, and A. Haddadi [4] use classification methods to predict user reactions, proving that this approach allows for the successful planning of marketing campaigns. Scientists C. Araújo, C. Soares, I. Duarte, M. Coelho, and A. Madureira [5] proposed an approach that determines the best time to send email messages, thereby significantly increasing the frequency of their opening. In addition, K. Bayoude, S. Ardchir, and M. Azzouazi [6] developed a methodology for selecting key features to better predict the success of email campaigns.

The third area combines studies that consider using neural network models and predictive analytics to assess the potential of email campaigns. Y. Gorodetskyi [7] emphasises the importance of analytics for strategic decision-making in marketing, noting that it allows us to accurately predict consumer reactions. Researchers E. Wenger and V. Nikulcha [8] explain the peculiarities of using artificial neural networks to analyse customer behaviour, demonstrating that it allows us to more accurately determine how successful email campaigns will be. Researcher A. Strungar [9] also notes that neural networks significantly improve the automation of processes in digital marketing strategies.

The fourth area includes works related to the use of NLP (natural language processing) technologies for the personalisation of marketing emails. The authors R. Nair, N. Singh, M. Reddy, and A. Chopra [10] analyse in detail how NLP and predictive algorithms allow the creation of highly personalised email messages.

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Researchers A. Sharma, N. Patel, and R. Gupta [11] prove that the use of reinforcement learning and NLP algorithms significantly increases user engagement through the accurate personalisation of messages. Scientists D. Yadav, J. Singh, P. Verma, V. Rajpoot, and G. Chhabra [12] demonstrated the effectiveness of machine learning technologies in predicting customer reactions and increasing customer loyalty through personalised content. Researcher T. Sangsawang [13] proves the effectiveness of the SVM algorithm in predicting clicks on links to advertising, which confirms the possibility of using this method in email marketing. Authors V. Paliy and Y. Paliy [14] also note that the personalisation of email campaigns is especially effective for small and medium-sized businesses in times of crisis.

Thus, this review demonstrates that machine learning technologies open up new opportunities for accurately predicting the effectiveness of email marketing campaigns and contribute to a significant improvement in customer engagement.

Identification of previously unsolved parts of the overall problem. Despite the significant progress in the study of predictive models for email marketing, there are still issues that need further clarification and deeper study. In particular, insufficient attention has been paid to a comprehensive analysis of the interaction between user characteristics and behavioural patterns, as only individual factors have usually been analysed. At the same time, the forecasting methods currently used do not always effectively adapt to the conditions and rapid changes in audience behaviour. In addition, there is often a lack of empirical research using real marketing cases, which makes it difficult to transfer the results of existing models to the practical realm.

This article provides an in-depth analysis of the interaction of the main behavioural factors and proposes an adaptive model that takes into account the specifics of email communications and is tested on real data. Additionally, highlights practical difficulties that may arise when integrating predictive systems into marketing activities and provides clear recommendations for the effective application of such models in practice. This will not only deepen the scientific understanding of these issues but will also significantly increase the effectiveness of the practical application of intelligent technologies in marketing.

Formulation of the article's objectives (definition of tasks). The purpose of the article is to study machine learning models for predicting the effectiveness of email campaigns in digital marketing and to justify their practical application in a highly competitive market.

Objectives of the work:

1. Identify the main factors of email campaign effectiveness, taking into account the behavioural characteristics of the target audience, and analyse existing machine learning models used to predict the effectiveness of email campaigns.

2. Develop and experimentally test a predictive model based on machine learning that can estimate the likelihood of opening emails, clicking on links, converting or unsubscribing;

3. To highlight the current problems of implementing intelligent systems in modern marketing practice and formulate recommendations for the optimal use of predictive models in the planning and implementation of email campaigns.

Summary of the main research material. In digital marketing, email campaigns are one of the most effective ways to communicate directly with customers. They help companies not only keep in touch with existing customers but also attract new ones. To achieve the desired result, such email campaigns should take into account the peculiarities of audience behaviour and a number of factors that influence the recipient's interaction with the message content. It is important to understand which factors are crucial, as they shape the effectiveness of the campaign and allow you to predict the reaction of the target group. In this regard, their systematic study is important in the context of the actual behaviour of email recipients, taking into account the results in practical marketing activities (Table 1).

Table 1

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Key factors influencing the effectiveness of email campaigns based on the behavioural characteristics of the target audience

Main factors of influence	Brief description	Related aspects of audience behaviour
Time of sending the email	The best time is determined by the recipients' individual email viewing habits	Periods of online activity, convenience of checking mail
Subject line.	An attractive, short, and informative subject line increases the chance of an email being opened	Brand trust, propensity to engage
Frequency of newsletters	Excessive frequency can lead to a negative reaction, and insufficient frequency can lead to a loss of interest	Tolerance to communication frequency, audience habits
Personalisation	Use of individual data and previous user interactions	Need for a personal approach, expectation of attention from the brand
Content type	The choice of format (text, graphic, interactive) depends on the preferences of the audience	How you perceive information, interests and preferences
Previous interaction	Taking into account previous activity: openings, transitions, purchases	Degree of engagement, level of loyalty, communication history

Source: compiled by the author on the basis of [1, p. 321; 2, p. 71-72; 12, p. 3-4].

In today's marketing environment, the factors presented in the table are increasingly being used not as abstract guidelines but as real-world parameters for building precise, adaptive email strategies. In particular, platforms such as Salesforce Marketing Cloud [15], Iterable [16], Klaviyo [17], and Mailchimp [18] allow you to automatically collect and process detailed information about each subscriber's behaviour: when they open emails, what topics attract their attention, how often they interact with content, and what links they click. This data is not only accumulated but also becomes the basis for personalised scenarios: the system independently determines the optimal time to send emails, selects the appropriate type of content, and even formulates email topics according to the recipient's interests. For example, if the activity history shows that a certain user most often opens emails after 19:00, the next messages are automatically scheduled for this time. This approach significantly increases the likelihood of engagement and improves open rates.

Another practical area is the automatic adjustment of the frequency of newsletters - adaptive frequency [6, p. 944]. If the system detects signs of information fatigue (reduced open rates, lack of link clicks), the frequency of messages is automatically reduced to maintain interest and avoid unsubscribes. At the same time, personalisation is not limited to the name or greeting: dynamic blocks are used, which are formed depending on the user's previous behaviour. For example, it can be recommendations of goods or services related to the user's recent browsing. This helps to achieve higher engagement rates, reduce the cost of ineffective campaigns, and, at the same time, create a sense of attention and individual approach to each subscriber.

Predicting the effectiveness of email communications based on machine learning has become a key trend in modern marketing, as it allows not only the assessment of the expected response of subscribers but also the active adaptation of content and strategy to changing behavioural patterns. Machine learning algorithms effectively analyse large amounts of historical data on email opens, clicks, unsubscribes, spam complaints, etc., revealing patterns that are not always obvious to marketers [9]. Today, both classical and deep machine learning methods are used, differing in complexity of implementation, resource requirements, and accuracy of predictions. The most common ones include classification models, regression analysis, decision trees, neural networks, and ensemble methods. Their use allows not only to predict the likelihood of opening an email or clicking on a link but also to form dynamic communication strategies that change depending on the context of the subscriber's behaviour (Table 2).

Table 2

The main machine learning models used to predict the effectiveness of email campaigns in marketing

Machine learning model	How it works	Typical tasks in email marketing	Examples of use
Logistic regression	Estimates the probability of an event occurring based on independent variables	Prediction of email opening, classification of reactions	Determine the likelihood of a link being clicked on depending on the topic and time
Decision Trees	Building a decision hierarchy by criteria	Identifying influential factors, audience segmentation	Analysis of combinations of factors leading to discovery
Random Forest	Combines multiple decision trees to improve accuracy	Stable multi-factor forecasting	Predicting the effectiveness of a new campaign based on the data of previous ones
Gradient boosting (XGBoost, LightGBM)	Consistent improvement of weak models	Prediction of link clicks and conversions with high accuracy	Use platforms like Iterable and Klaviyo
Artificial neural networks	Identify complex non-linear dependencies in large data sets	Deep behavioural prediction, content adaptation	Email personalisation in large e-commerce companies
K-nearest neighbours (KNN)	Classifies based on similarity to other observations	Recommendations for segments, behavioural analysis	Determine the best time to send out emails to similar users

Source: compiled by the author on the basis of [4, p. 3-4; 5; 6, p. 942; 12, p. 4; 13, p. 227-229].

Logistic regression is used to estimate the probability of an email being opened based on factors such as subject line, time of sending, type of content, etc. It's a good choice when you need to perform a quick analysis based on a limited number of variables. Decision trees allow you to identify critical combinations of features that increase the likelihood of opening an email or clicking a link and serve as a convenient tool for visualising the decision-making process.

More sophisticated models, such as gradient boosting, are especially effective when working with large contact databases. They help build multidimensional forecasts, taking into account numerous parameters, from the user's device to their history of interaction with emails. Large online retailers use such models to fine-tune their campaigns. For example, Nova Poshta uses an analytics platform with machine learning elements to adapt email communications to regional peculiarities, delivery times, or order types, which helps to increase the relevance of messages and customer satisfaction [3].

Neural networks provide a high level of personalisation by generating email content in real-time according to the user's last activity on the website [12, p. 5]. For example, if a customer browses certain products, the system automatically generates a selection based on their interests. These models are effective in dynamic campaigns where you need to respond quickly to changes in behaviour. The Ukrainian company Rozetka LLC has implemented an automated CRM system with machine learning algorithms, which allows not only the segmenting of customers by behavioural patterns but also the generating personalised mailings. As a result, the company increased its revenue by 10% and reduced advertising costs [3].

The Nearest Neighbours method is useful when working with new subscribers. It allows you to predict customer reactions based on the behaviour of similar users. This approach is especially effective in campaigns with limited information about the recipient, for example, at the stage of the first contact after subscribing.

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Together, all these models form the core of modern email marketing systems. They automate the processes of segmentation, forecasting, personalisation, timing, and even content editing before sending. Thus, machine learning not only improves the accuracy of forecasts but also actively influences user behaviour, transforming the approach to customer communications and providing strategic flexibility in marketing decisions.

In modern email marketing, there is a need not only to record campaign results but also to predict recipients' reactions to messages in advance. This task requires building adaptive predictive models that can estimate the likelihood of an email being opened, clicked on a link, converted or unsubscribed. The difference between such models and classical statistical approaches is their ability to take into account complex and interdependent aspects of influence, including user behavioural patterns, dynamics of changes in consumer activity, content characteristics of messages, and external factors (e.g. seasonality or time zones). In practice, this helps to generate email campaign scenarios not intuitively but based on predicting future actions of subscribers, which reduces the risk of losses and increases the profitability of email campaigns.

To create such a model, we used an open dataset based on the results of previous email campaigns, which contains information about email parameters (subject line length, content type, images), time characteristics (day of the week, time of sending), and results (opens, clicks, conversions, unsubscribes). The gradient boosting algorithm was chosen as one of the most effective for solving classification tasks with multiple interrelated factors (Fig. 1).

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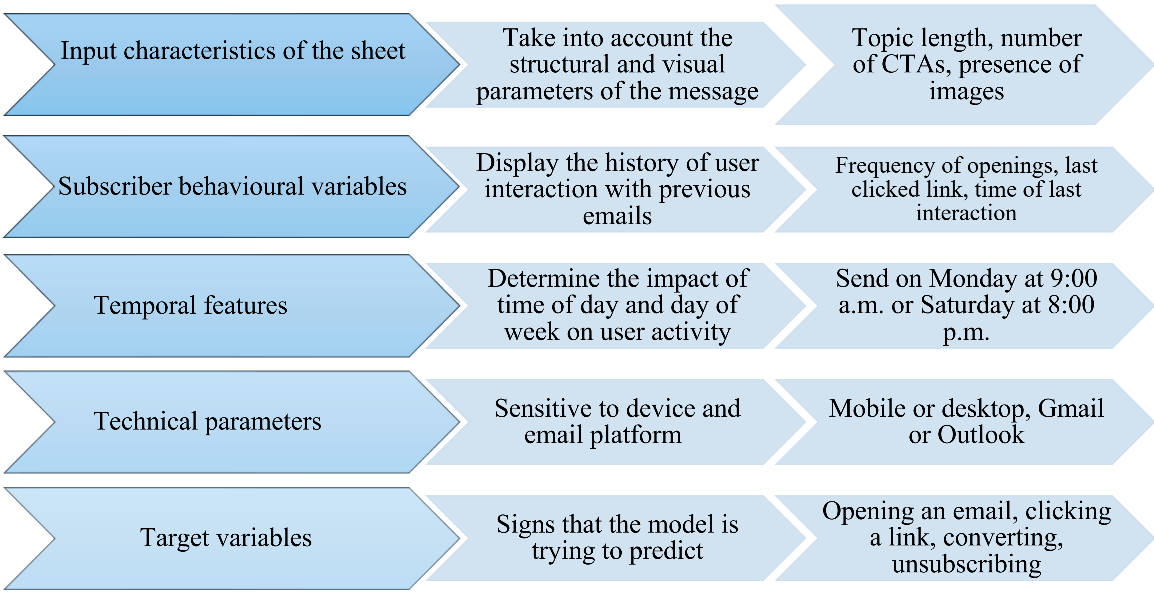

Fig. 1. Structure of the built model for predicting email campaign results

Source: author's own development

For the experiment, we used a dataset of more than ten thousand email campaign records that captured both email parameters and user behaviour. The model was built using the XGBoost algorithm and trained on 80% of the cases, with the remaining used for validation. The model demonstrated the highest predictive power for the tasks of predicting opens and clicks on links, where the frequency of previous interaction, subject line length, and time of sending were the main factors. Predicting unsubscribes was more difficult due to their low frequency in the data set. Once trained, the model can be integrated into the email platform and, for example, warn the marketer when the probability of a negative response to an email exceeds a threshold. This allows you to adapt the message or not send it to a certain segment at all, reducing the risk of losing contact. In practice, this model can be used to plan

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dynamic campaigns on a daily basis, which adjusts to changes in the behaviour of each individual user.

Despite the growing popularity of intelligent technologies in marketing, their effective practical application is difficult due to a number of obstacles. One of the most important problems is the difficulty in obtaining complete and high-quality databases required for model training. Often, companies, especially small businesses, do not have enough organised and up-to-date data, and collecting this information requires significant time and resources. Another serious problem is related to the transparency of complex algorithms, such as neural networks [8, p. 317]. The results of their work are often difficult to explain, which is why marketers are cautious about forecasts and reluctant to integrate them into business processes [6, p. 945]. In addition, there is an acute shortage of highly qualified specialists capable of implementing and maintaining artificial intelligence in marketing activities [1, p. 324], which leads to the superficiality and inefficiency of systems. In addition, the high cost of implementing such systems makes them inaccessible to small and medium-sized businesses [7, p. 68]. ʼEthical issues related to the use of personal data for deep personalisation of marketing campaigns remain important. This raises legal and reputational risks, forcing companies to act more cautiously and with more restraint. Internal resistance to change in many organisations is a significant obstacle to the adoption of new technologies, which hinders their integration even when their effectiveness is proven in practice. All of these aspects together significantly slow down the full and effective use of intelligent systems in modern marketing. To effectively implement predictive models in the process of planning and implementing email campaigns, you need to follow a few key recommendations. First of all, you need to regularly update and expand your user behaviour databases by collecting information about email opens, clicks, purchases, and the characteristics that have produced the best results. This will help to continuously "train" the models on actual data and improve the accuracy of forecasts. In addition, it is worth using models with high transparency of results,

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such as decision trees or ensemble algorithms, which provide a clear interpretation of the factors that affect the effectiveness of campaigns. It's also important to combine predictive algorithms with A/B testing to test individual email parameters in real-time. This combination will allow you to quickly confirm the model's predictions and adapt communication to changes in audience reactions. Given the ethical and privacy aspects, it is advisable to introduce additional monitoring of compliance of data collection and processing with legal standards. In addition, regular training of the marketing team on the basics of working with predictive models is an important step which will allow them to integrate forecasting results into marketing strategies with more confidence and quality. Finally, to reduce the risk of resistance to change within the team, it is necessary to gradually introduce predictive systems by demonstrating their benefits in small, controlled campaigns, which will facilitate a quick and positive acceptance of innovations in marketing practice.

Conclusions. The article investigates the use of machine learning models to predict the effectiveness of email campaigns in digital marketing. The built model, based on the gradient boosting algorithm (XGBoost), has proven its practical effectiveness by demonstrating a high level of accuracy in predicting such indicators as email open rates and link clicks. Its main advantage is that it takes into account not only the characteristics of emails (subject line length, visual components) but also the behavioural and time parameters of users (activity history, time of sending messages). At the same time, a number of obstacles have been identified that hinder the widespread implementation of such models in marketing practice. These include insufficient quality of initial data, difficulty in interpreting model results, lack of qualified specialists, high cost of technology, and ethical and legal risks of using personal data. To ensure the most effective implementation of forecasting models, it is recommended to constantly update and expand existing databases, apply transparent algorithms, regularly conduct A/B testing, ensure ethical control over information processing, and gradually integrate innovations into the daily work of marketers.

Further research could be aimed at improving the clarity and transparency of the models and their full integration into marketing processes to increase the effectiveness of digital communications with customers.

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