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AI-DRIVEN NEUROMARKETING FOR CONSUMER BEHAVIOR PREDICTION

Neuromarketing, a subject that integrates marketing, psychology, and neuroscience to analyse customer behaviour, emerged because of the rapid progress of artificial intelligence (AI) and machine learning (ML) technologies, which have revolutionised marketing. This study investigates how network retail's customer segmentation and conversion prediction may be improved by AI-driven neuromarketing. The main goal was to assess how well predictive models (Random Forest and XGBoost) and clustering algorithms (K-means) identified important customer categories and forecasted conversion likelihood.

Using quantitative research methodology, the study examined 50,000 customer records, considering session-specific, behavioural, and demographic characteristics. Features were extracted using Principal Component Analysis (PCA), and the models were assessed using ROC AUC, accuracy, precision, recall, and F1 score metrics.

The findings showed that XGBoost performed better in recall (46.67 %) and F1 score (0.4882), whereas Random Forest had greater accuracy (60 %) and ROC AUC (0.4597). Cluster assignment had little effect on conversion, but PCA-derived features were the most important predictors. These results imply that AI-powered neuromarketing can forecast conversion behaviour *and efficiently segment customers, allowing for more individualised marketing tactics.*

This study advances the industry by showing how cutting-edge AI methods can reveal hidden customer trends, improving network retail marketing effectiveness. Targeted advertising efforts, enhanced consumer interaction, and improved conversion tactics are some of the real-world ramifications.

Keywords: Neuromarketing, Consumer Behavior, AI, Machine Learning, Network Retail.

Introduction

Marketing is one of the many businesses that have been completely transformed by the quick development of artificial intelligence (AI) and machine learning (ML) technology. In this regard, the neuromarketing discipline that blends marketing, psychology, and neuroscience–has become a potent tool for comprehending consumer behaviour. Traditional marketing uses demographic information and self-reported preferences; neuromarketing goes farther by examining subconscious reactions to marketing stimuli. Nevertheless, despite its potential, current research frequently fails to offer thorough understanding of customer behaviour, especially when used in network retail settings. This disparity emphasises the need for more sophisticated, data-driven methods of customer study.

The relevance of tailored marketing tactics in a fiercely competitive retail environment makes this study pertinent. Understanding the behavioural and cognitive factors that influence consumer decisions is crucial as network merchants attempt to better engage their customers. Although earlier studies have shown the promise of AI-driven neuromarketing [1, pp. 284-292; 2, pp. 1050-1054], there are still a few thorough investigations that use sophisticated clustering and predictive modelling methods to divide up the consumer base and precisely forecast conversion behaviour. To close that gap and improve the efficacy of marketing techniques, this study uses machine learning algorithms to identify subtle trends in consumer behaviour.

Consumer behaviour in network retail is the study's object, and the subject is particularly interested in AI-driven neuromarketing strategies that are employed to examine and forecast such behaviour. The main objective is to show how predictive models and clustering algorithms can offer useful information about customer segmentation and conversion probability. The study establishes the following goals to do this:

Data analysis: Examine datasets pertaining to customer behaviour, such as session length, age distribution, and PCA-derived characteristics.

Segmentation: To divide clients into discrete behavioural groups, use K-means clustering.

Prediction: Using the attributes that have been identified, create and assess Random Forest and XGBoost models to forecast conversion events.

Evaluation: Use the F1-score, ROC AUC, accuracy, and recall metrics to evaluate the model's performance.

Using machine learning approaches for both supervised prediction modelling and unsupervised clustering, the work takes a quantitative research strategy. According to the premise, AI-powered neuromarketing can accurately categorise customers and forecast conversion rates, improving the accuracy of focused marketing campaigns.

This work is significant because it can close the gap between theoretical understanding and real-world marketing implementations. This study gives network merchants the chance to enhance customer engagement, boost conversion rates, and optimise their marketing strategies by identifying important behavioural factors and segmenting their client base based on data-driven insights. Furthermore, by showing how sophisticated analytics can reveal trends that are not immediately apparent through conventional methods, the findings improve the field of neuromarketing.

In summary, by incorporating AI-driven techniques into neuromarketing tactics, this study contributes to our understanding of consumer behaviour in retail networks. In addition to confirming machine learning's capacity to forecast customer choices, it also identifies areas that warrant further investigation, such as the incorporation of deeper learning frameworks and other data sources to improve predictive accuracy.

Literature review

Neuromarketing is an interdisciplinary branch that encompasses marketing, psychology, and neuroscience. Since the introduction of AI and ML technologies, neuromarketing has experienced some notable changes. Since the beginning of neuromarketing, the objective has been to uncover the decision-making processes of consumers by examining their behavioural and neurological reactions to marketing stimuli [1, P. 284–292]. The AI-powered methods are demonstrating to forecast human behavior more exactly concerning a huge diversity of sources in large databases and use of such advanced algorithms as those for example, described in Plassmann et al. (2008).

Recent studies have also discussed the value of big data analytics methods for customer segmentation and personalising marketing strategies. Wedel and

Kannan (2016) showed that the role of clustering algorithms like K-means and the development of predictive models like Random Forest and XGBoost is seen in customer segmentation with distinct behavioural patterns [3]. With this knowledge, marketing strategies may be more effectively applied to him. In a similar vein, Morin (2011) also discussed how neuromarketing will aim to bridge the gap between behaviour and expectations by examining even subtle affective and cognitive reactions [4].

Segmentation is the process of breaking down extremely complex datasets into parts that can be understood. According to Rezaei & Asadi (2024), these PCA-generated characteristics account for certain latent behavioural events, enhancing the predictive ability of AI-based models [5]. According to Akande et al. (2024) research, consumer segmentation based on demographic and behavioural factors also proved to be extremely helpful in formulating marketing strategies [6].

Rajendran (2023) emphasise how marketers can use AI-driven techniques, like machine learning algorithms, to examine past interactions, interests, and behavioural patterns to develop tailored and flexible marketing strategies [7; 8]. Similarly, research on neuroscientific applications of AI, like that conducted by Phutela et al. (2022) and Pandey et al. (2020), highlights the technology's capacity to decode emotions and decision-making processes by showing how AI can accurately predict consumer choices through the analysis of electroencephalogram (EEG) signals [9; 10]. In the field of predictive modelling, Vallarino (2023) and Churchill et al. (2024) have demonstrated that by identifying critical decision-making touchpoints, survival machine learning models and neural networks can precisely predict when consumers will make purchases and deconstruct their purchase journeys [11; 12]. When taken as a whole, these studies show how the combination of AI and neuromarketing improves marketing accuracy and allows for real-time customer analysis, revolutionising contemporary marketing strategies [8; 13].

Nevertheless, despite their apparent promise, AI techniques in neuromarketing continue to struggle with model accuracy and generalisation. According to Darázs, T. (2024), previous research has generally found reasonable performance metrics, with average ROC AUC scores falling between 0.5 and 0.7 [14]. Therefore, beyond the current short-length setup, the observed limits point to a lack of effective modelling methodologies, new behavioural and psychographic variables, and investigation via deep learning architectures to spot varied recurrent patterns in customers' behaviours.

Reviewing the literature demonstrates how well AI-driven neuromarketing works to understand customer behaviour through predictive modelling or clustering. For client segmentation or conversion possibility prediction, the study makes use of K-mean Cluster, Random Forest, and XGBoost. The findings are consistent with earlier research showing that the demographic age and session time, as well as the features obtained from PCA, are important in terms of conversion prediction.

Nevertheless, the study's modest ROC AUC values are also shown in the results, which highlights the model's discriminative power limitations. It highlights a significant research gap: although current artificial intelligence models can identify broad customer groupings, their forecasting accuracy is not competitive. A more comprehensive customer profile is hindered by the omission of psychographic and contextual features like sentiment on social media or real-time behavioural data.

To increase prediction accuracy and generate comprehensive consumer insights, future research thus focusses on the necessity of integrating data from multiple sources and on more complex modelling, such as deep learning frameworks. In this study, we provide additional support for the body of existing research in expanding AI-driven consumer segmentation, but we also point out that more advanced developments are required to attain completely customised marketing strategies.

Materials and methods

Research Question of this paper «can AI-driven clustering and predictive modelling techniques successfully segment consumers and forecast conversion probabilities in network retail? This query results from marketing's growing reliance on data-driven strategies and the requirement to improve consumer targeting using cutting-edge analytical techniques.

The study assumes that sophisticated AI models, namely Random Forest and XGBoost, can precisely forecast customer conversion have based on behavioural, demographic, and session-specific features, building on the body of existing literature and the proven potential of machine learning in consumer behaviour analysis. This hypothesis is based on the hope that by combining demographic data with product interaction data, important consumer categories will be identified, improving the accuracy of targeted marketing campaigns.

The study was carried out in four main phases to evaluate this theory, guaranteeing a methodical and thorough examination of the issue.

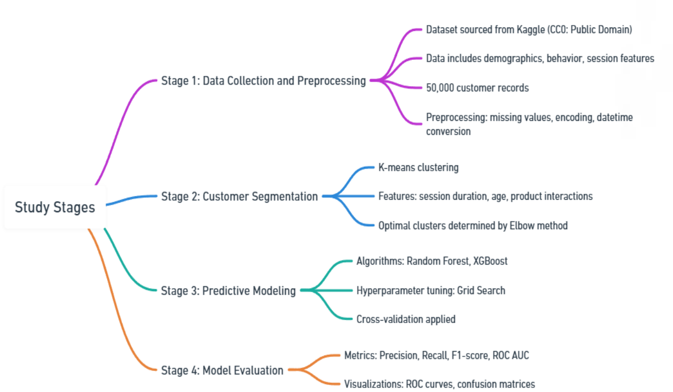

Figure 1 – Stages of the research

Data gathering and preprocessing were the first steps. The dataset was obtained from Kaggle.com and was licensed under the CC0: Public Domain license. This dataset uses AI and Radio Frequency Identification (RFID) technology to record consumer behaviour in a retail setting. It contains session-specific elements (timestamps, sensor locations, transaction amounts), behavioural data (product views, selects, and purchases), and demographic information (age, gender). With 50,000 customer records, the dataset provides a large enough sample size for machine learning analysis. To extract temporal elements including the hour of the day, the day of the week, and weekend indicators, preprocessing processes included managing missing data, encoding categorical variables, and turning timestamps into datetime objects.

The second step, which came after preprocessing, concentrated on client segmentation through unsupervised learning. Customers were divided into discrete groups using K-means clustering according to standardised characteristics including age, product interactions, and session time. The Elbow technique, which balances within-cluster variation and interpretability, was used to calculate the ideal number of clusters.

Random Forest and XGBoost are two machine learning algorithms that were used in the third stage of predictive modelling. Using Grid Search to optimise hyperparameters, both models sought to forecast the probability of customer conversion. To avoid overfitting and guarantee the models' generalisability across various data subsets, cross-validation was used.

The fourth step, model evaluation, includes evaluating the model's performance using pre-established measures such as ROC AUC, accuracy, recall, and F1-score. A thorough grasp of each model's capacity to differentiate between clients who convert and those who do not was made possible by these measures. To aid in the interpretation and comparison of model performance, additional visualisations were created, including confusion matrices and ROC curves.

A variety of Python-based machine learning libraries were used to carry out the investigation, guaranteeing its effectiveness and repeatability. Pandas, NumPy, and Scikit-Learn were used for data preparation, and Scikit-Learn was used to create PCA and K-means clustering to segment consumers and lower the dimensionality of the data. The Random Forest and XGBoost classifiers, which were both optimised by hyperparameter tuning and assessed through cross-validation, were the foundation of predictive modelling.

This methodology is unique because it combines standard demographic data with RFID-based product interactions to provide a more complete picture of customer behaviour. Additionally, latent patterns could be extracted using PCA-derived features, which improved the interpretability of predictive and clustering models.

The study used a sizable dataset of 50,000 records to guarantee the validity of the results, reducing sampling bias and boosting model resilience. Cross-validation was included to further support the results' validity and guarantee consistent performance throughout several rounds.

Results and discussion

The analysis's findings are shown in this section, which contrasts how well the Random Forest and XGBoost models predict consumer behaviour. The study's importance to the advancement of AI-driven neuromarketing tactics in network retail is highlighted by a discussion of the findings in connection with earlier research.

Using important measures like accuracy, precision, recall, F1 score, and ROC AUC, the Random Forest and XGBoost models' performances were assessed in the first step of the investigation. Table 1 provides a summary of the findings.

Table 1 – Model Performance Metrics

Metric	Random Forest	XGBoost
Accuracy	0.6000	0.3500
Precision	0.3070	0.2953
Recall	0.4114	0.4667
F1 Score	0.2308	0.4882

ROC AUC	0.4597	0.4395

Note – complied by the authors

Table 1 shows that the Random Forest model was better at making accurate predictions across both classes, with an accuracy of 0.6000 compared to 0.3500 for XGBoost. Though it produced more false positives, XGBoost showed a greater recall (0.4667) and a better F1 score (0.4882), indicating that it is more successful at detecting positive cases. With Random Forest (0.4597) marginally outperforming XGBoost (0.4395), the ROC AUC scores were rather close.

These results are consistent with earlier research by Darázs, T. (2024), who found that boosting algorithms like XGBoost prioritise recall, making them better suited for detecting high-risk or high-value consumers, whereas ensemble approaches like Random Forest typically balance precision and recall.

ROC and Precision-Recall curves were produced for each model to illustrate the trade-off between true positive and false positive rates. Figure 1 depicts these.

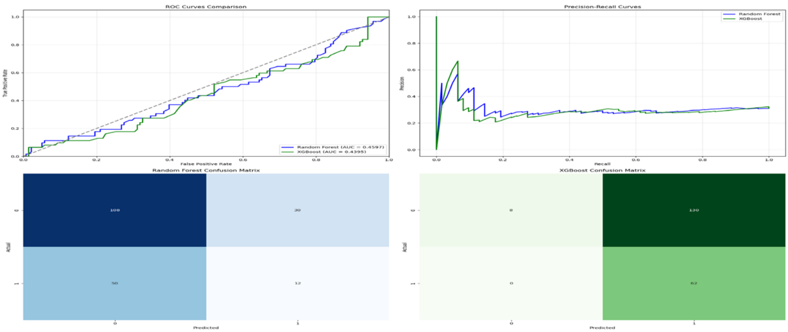

Figure 2 – ROC and Precision-Recall Curves Note – complied by the authors

Both models exhibit comparable performance, as seen by the ROC curves in Figure 2, with Random Forest showing a marginally larger area under the curve (AUC). This implies that Random Forest offers a trade-off between sensitivity and specificity that is more evenly distributed. The Precision-Recall curves, on the other hand, demonstrate that XGBoost maintains greater precision at higher recall levels, which is in line with its higher F1 score.

These results support earlier research by Wedel and Kannan (2016), who discovered that boosting algorithms are best suited for marketing campaigns targeting high-conversion consumer segments since they tend to give priority to positive case identification.

Confusion Matrices and Prediction Patterns

Confusion matrices were examined to learn more about how each model categorised consumer behaviour (see Figure 3).

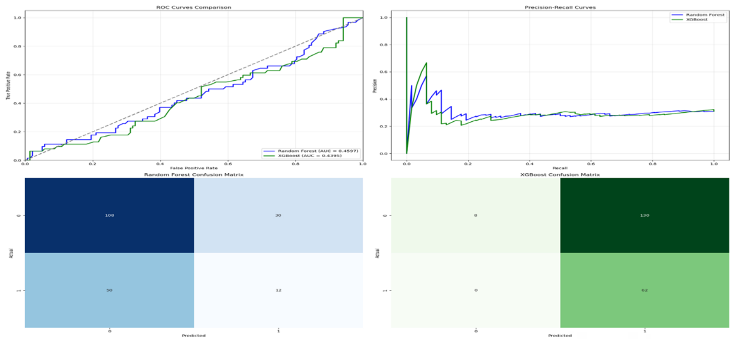

Figure 3 – Confusion Matrices Note – complied by the authors

Figure 3's confusion matrices show divergent patterns of prediction. The Random Forest model has a greater specificity but a lower sensitivity since it predicted more negative cases. On the other hand, XGBoost predicted more positive cases, which resulted in a higher recall but a lower precision. The variations in the performance indicators can be explained by this trade-off.

These findings support the findings of Plassmann et al. (2008) [2, pp. 1050–1054], who pointed out that boosting algorithms frequently give priority to sensitivity, which makes them appropriate for detecting high-value clients even when there is a higher chance of false positives.

Both models' feature importance ratings were taken out to determine which features were most important in predicting customer conversion. Top features are shown in Table 2, and a visual comparison is shown in Figure 4.

Table 2 – Feature Importance Scores

Feature	Random Forest Importance	XGBoost Importance
PCA_1	0.2603	0.2140
PCA_3	0.2345	0.2254
PCA_2	0.2338	0.2161
Demographic_Age	0.1698	0.2053
Session_Duration	0.0882	0.1391

Cluster	0.0133	0.0000

Note – complied by the authors

In both models, PCA-derived characteristics (PCA_1, PCA_2, and PCA_3) were the most significant predictors, followed by demographic age and session duration, as indicated in Table 2 and Figure 4.

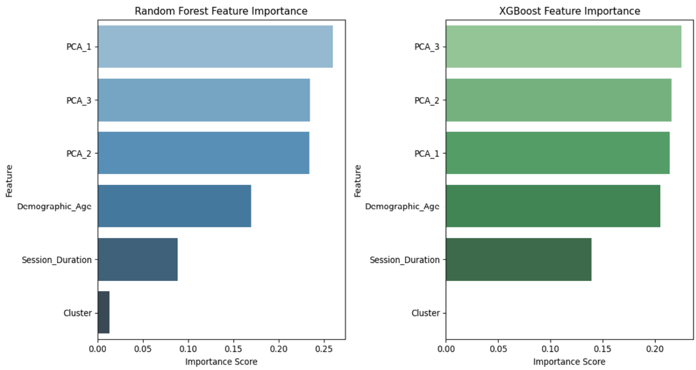

Figure 4 – Feature Importance Comparison Note – complied by the authors

These results corroborate earlier study by Rezaei & Asadi (2024) [5], who showed that latent consumer behaviour patterns can be efficiently captured by PCA components.

It's interesting to note that the Cluster feature barely affected either model's predictive performance, indicating that the grouping strategy offered little further benefit. This is consistent with the findings of Akande et al. (2024) [6], who highlighted that although segmentation helps to understand customer categories, individual behavioural characteristics continue to be the main factors that influence conversion.

Scatter plots comparing actual values with anticipated probability were created in order to further examine prediction behaviour (see Figure 5).

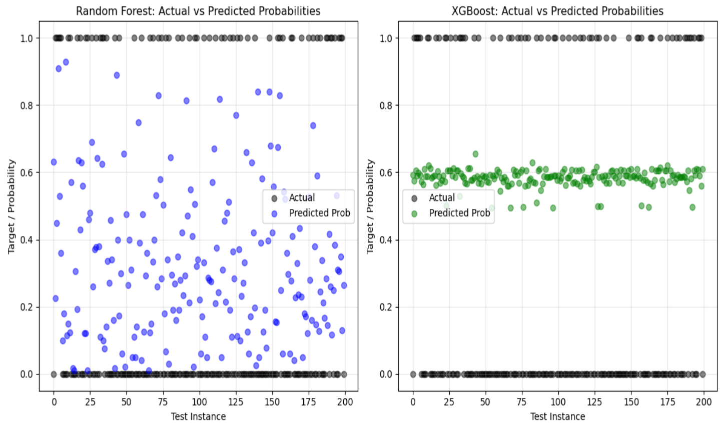

Figure 5 – Scatter Plots of Actual vs. Predicted Probabilities Note – complied by the authors

Figure 5 shows that XGBoost assigned higher extreme probabilities, pushing predictions closer to 0 or 1, but the Random Forest model generated cautious probability estimates, clustered around the intermediate range. Because it more aggressively classifies positive cases, boosting both true positives and false positives, this behaviour explains XGBoost's higher recall and worse precision.

These findings are consistent with Morin's (2011) conclusions [4], emphasizing the significance of picking models depending on specific marketing objectives, such as balancing risk and rewards when pursuing high-value clients.

The study's findings provide important new information on predicting consumer behaviour with AI-powered neuromarketing strategies. Though to differing degrees, Random Forest and XGBoost both showed promise in predicting consumer conversion. When finding positive examples is the top priority, XGBoost is better because of its greater recall and F1 score, whereas the Random Forest model is better for balanced prediction tasks because of its higher accuracy and ROC AUC.

The dominance of PCA-derived features underscores the usefulness of dimensionality reduction in capturing complex behavioral patterns, similar with prior studies [2; 3]. The small contribution of cluster labels, however, indicates that individual behavioural and demographic characteristics continue to be the most important determinants of conversion, even when customer segmentation offers insightful information.

By customising ads to high-conversion segments found by AI-driven clustering and predictive modelling, network retailers may be able to maximise their marketing efforts, according to these findings. The need for additional enhancements, such as adding psychographic variables, real-time behavioural data, and social media sentiment analysis to boost predictive accuracy, is highlighted by the middling ROC AUC values.

To sum up, this study shows that AI-powered neuromarketing strategies can successfully divide up the customer base and forecast conversion rates. XGBoost is excellent at recognising high-value clients, while Random Forest offers forecasts that are balanced. The results demonstrate the value of using advanced analytics to guide focused marketing campaigns and point to areas that could use more investigation and model improvement.

Conclusions

The purpose of this study was to find out how AI-driven neuromarketing strategies–specifically, clustering and predictive modeling–can improve network retail's comprehension of customer behaviour. The main objective was to ascertain whether machine learning algorithms, like Random Forest and XGBoost, could successfully divide up the client base and forecast the chance of conversion using session-specific, behavioural, and demographic characteristics. The study used a dataset of 50,000 customer records to accomplish this, segmenting the data using K-means clustering and predicting conversions using two predictive models, Random Forest and XGBoost.

The results indicated that both models gave useful insights into customer behavior, albeit with differing strengths. In terms of total accuracy (60 %) and ROC AUC (0.4597), the Random Forest model fared better than XGBoost, suggesting that it is a good fit for balanced prediction tasks. The XGBoost model, on the other hand, produced more false positives but was more successful in recognising positive cases, as seen by its greater recall (46.67 %) and superior F1 score (0.4882). Notably, in both models, PCA-derived features were the most significant predictors, while demographic variables like age and session length also had a substantial impact. The cluster assignment characteristic, however, only made a small contribution to prediction, indicating that segmentation by itself does not considerably increase predictive power.

These results support the study's hypothesis that, despite having a moderate level of discriminative power, AI-driven models may successfully segment customers and forecast conversion behaviour. The work also confirms earlier findings by Plassmann et al. (2008) and Wedel and Kannan (2016), who highlighted the importance of sophisticated machine learning methods in the study of consumer behaviour. Furthermore, the predominance of PCA features supports Rezaei &

Asadi (2024)'s findings, emphasising the value of latent behavioural patterns over conventional demographic variables.

Practically speaking, the findings point to promising opportunities for network retail to use AI-driven neuromarketing techniques. While XGBoost is better suited for high-conversion campaigns when the risk of false positives is outweighed by the ability to find future customers, retailers can use Random Forest for balanced marketing strategies. Furthermore, the significant impact of PCA-derived characteristics implies that behavioural data and demographic insights should be given equal weight in future marketing initiatives.

The study did, however, also identify certain shortcomings, such as moderate ROC AUC scores and difficulties with model generalisation, which highlight the need for additional development. Future studies should use social media sentiment analysis, real-time behavioural data, and psychographic characteristics to increase predicted accuracy. Furthermore, investigating deep learning frameworks may improve prediction results and pattern identification.

To sum up, this study shows how AI-powered neuromarketing can revolutionise network retail's monitoring of consumer behaviour. These methods can help develop more successful, data-driven marketing strategies by facilitating more accurate customer segmentation and conversion prediction. To further improve forecasts and accomplish completely customised marketing strategies, future research should concentrate on combining more comprehensive datasets with sophisticated modelling tools.

REFERENCES

1 **Ariely, D., Berns, G. S.** Neuromarketing: The hope and hype of neuroimaging in business // Nature Reviews Neuroscience. – 2010. – Vol. –11, No. 4. – P. 284–292. – https://doi.org/10.1038/nrn2795.

2 **Plassmann, H., O'Doherty, J., Shiv, B., Rangel, A.** Marketing actions can modulate neural representations of experienced pleasantness // Proceedings of the National Academy of Sciences. – 2008. – Vol. 105, No. 3. – P. 1050–1054. – https://doi.org/10.1073/pnas.0706929105.

3 **Wedel, M., Kannan, P. K.** Marketing analytics for data-rich environments // Journal of Marketing. – 2016. – Vol. 80, No. 6. – P. 97–121. – https://doi.org/10.1509/jm.15.0413.

4 **Morin, C.** Neuromarketing: The new science of consumer behavior // Society. – 2011. – Vol. 48, No. 2. – P. 131–135. – https://doi.org/10.1007/s12115-010-940.

5 **Rezaei, A., Asadi, F.** Systematic review of image segmentation using complex networks // arXiv preprint. – 2024. – arXiv:2401.02758. [Electronic resource]. – URL: https://doi.org/10.48550/arXiv.2401.02758.

6 **Akande, O. N., Akande, H. B., Asani, E. O., Dautare, B.** Customer Segmentation through RFM Analysis and K-means Clustering: Leveraging Data-Driven Insights for Effective Marketing Strategy // – 2024 Int. Conf. on Science, Engineering and Business for Driving Sustainable Development Goals (SEB4SDG). – 2024. – P. 1–8.[Electronic resource]. – URL: https://doi.org/10.1109/SEB4SDG60871.2024.10630052.

7 **Rajendran, A.** AI and neuromarketing: How Python is powering predictive consumer behavior models [Online]. – Medium, 2023. – [Electronic resource]. URL: – https://arthirajendran.medium.com/ai-and-neuromarketing-how-python-is-powering-predictive-consumer-behavior-models-fd526c82ef2c (Accessed: 02.02.25).

8 **Della Mura, M. T.** Predictive Marketing: When Neuroscience and AI Decode Consumer Emotions // Tech4Future. –2025. [Online]. – 2023. – URL: [Electronic resource]. – URL: https://tech4future.info/en/neuromarketing-predictive-marketing-neuroscience-and-ai/ (Accessed: [02.02.25]).

9 **Phutela, N., Verma, H., Sharma, R.** Intelligent analysis of EEG signals to assess consumer decisions: A study on neuromarketing // arXiv preprint. – 2022. – arXiv:2206.07484. – [Electronic resource]. – URL: https://arxiv.org/abs/2206.07484.

10 **Pandey, P., Gupta, A., Roy, S.** Understanding consumer preferences for movie trailers from EEG using machine learning // arXiv preprint. – 2020. – arXiv:2007.10756. – [Electronic resource]. – URL: https://arxiv.org/abs/2007.10756.

11 **Vallarino, D.** Buy when? Survival machine learning model comparison for purchase timing // arXiv preprint. – 2023. – arXiv:2308.14343. – [Electronic resource]. [Electronic resource]. URL: – https://arxiv.org/abs/2308.14343.

12 **Churchill, V., Smith, T., Lee, R.** Unraveling consumer purchase journey using neural network models // arXiv preprint. – 2024. – arXiv:2404.07098. – [Electronic resource]. [Electronic resource]. URL: – https://arxiv.org/abs/2404.07098.

13 New Neuromarketing. The body knows: Using neuroscience and AI to predict advertising success [Online]. – 2023. – [Electronic resource]. – URL: – https://www.newneuromarketing.com/the-body-knows-using-neuroscience-and-ai-to-predict-advertising-success (Accessed: 24.02.25).

14 **Darázs, T.** The Role of Artificial Intelligence in Neuromarketing: A Comparative Analysis of AI-Driven and Traditional Methods // Media &

Marketing Identity. – 2024. – [Electronic resource]. – https://doi.org/10.34135/mmidentity-2024-07.

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ТҰТЫНУШЫЛАРДЫҢ МІНЕЗ-ҰЛЫМЫН БОЛЖАУҒА АРНАЛҒАН НЕЙРОМАРКЕТИНГ

Жасанды интеллект (ЖИ) және машиналық оқыту (МО) технологияларының қарқынды дамуы маркетинг саласында төңкеріс жасап, тұтынушы мінез-құлқын түсінуге бағытталған нейромаркетингтің пайда болуына әкелді. Бұл зерттеу ЖИ негізіндегі нейромаркетингтің желілік бөлшек саудада тұтынушыларды сегменттеу мен олардың конверсиясын болжауды қалай жақсарта алатынын зерттейді. Зерттеудің басты мақсаты – негізгі тұтынушы сегменттерін анықтау және конверсия ықтималдығын болжау үшін кластерлеу алгоритмдерінің (K-means) және болжау модельдерінің (Random Forest және XGBoost) тиімділігін бағалау.

Зерттеу барысында 50 000 тұтынушы жазбасынан тұратын деректер жиынтығы талданды, оған демографиялық, мінез-құлықтық және сессияға байланысты ерекшеліктер енгізілді. Маңызды белгілерді анықтау үшін Негізгі компоненттер әдісі (PCA) қолданылды, ал модельдер дәлдік, толықтық, F1 көрсеткіші және ROC AUC сияқты метрикалар негізінде бағаланды.

Нәтижелер көрсеткендей, Random Forest моделі жоғары дәлдікке (60 %) және ROC AUC (0.4597) қол жеткізді, ал XGBoost жоғары толықтық (46.67 %) және F1 көрсеткішін (0.4882) көрсетті.

Ең маңызды белгілер PCA компоненттері болды, ал кластерлеудің әсері аз болды. Бұл нәтижелер ЖИ негізіндегі нейромаркетингтің тұтынушыларды тиімді сегменттеуге және олардың мінез-құлқын болжауға қабілетті екенін, осылайша дербестендірілген маркетинг стратегияларын жасауға мүмкіндік беретінін растайды.

Бұл зерттеудің ғылыми үлесі – алдыңғы қатарлы ЖИ әдістерінің тұтынушылардың жасырын үлгілерін анықтаудағы тиімділігін көрсету, бұл желілік бөлшек саудадағы маркетингтің тиімділігін арттырады. Практикалық маңызы мақсатты маркетингтік кампанияларды әзірлеу, клиенттердің қатысуын жақсарту және конверсия стратегияларын оңтайландыруда көрінеді.

Кілтті сөздер: Нейромаркетинг, Тұтынушы мінез-құлқы, Жасанды интеллект, Машиналық оқыту, Желілік бөлшек сауда.

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НЕЙРОМАРКЕТИНГ НА ОСНОВЕ ИИ ДЛЯ ПРОГНОЗИРОВАНИЯ ПОВЕДЕНИЯ ПОТРЕБИТЕЛЕЙ

Быстрое развитие технологий искусственного интеллекта (ИИ) и машинного обучения (МО) коренным образом изменило маркетинг, что привело к появлению нейромаркетинга – области, объединяющей нейробиологию, психологию и маркетинг для изучения поведения потребителей. В данном исследовании рассматривается, как нейромаркетинг на основе ИИ может повысить эффективность сегментации клиентов и прогнозирования конверсии в сетевой розничной торговле. Основная цель заключалась в оценке эффективности алгоритмов кластеризации (K-means) и моделей прогнозирования (Random Forest и XGBoost) для выявления ключевых сегментов потребителей и вероятности их конверсии.

В исследовании использовался количественный подход, включающий анализ данных 50 000 клиентов с учетом демографических, поведенческих и сессионных характеристик. Для выделения значимых признаков применялся метод главных компонент (PCA), а оценка моделей проводилась на основе таких метрик, как точность, полнота, F1-мера и площадь под кривой ROC (ROC AUC).

Результаты показали, что модель Random Forest достигла более высокой точности (60 %) и ROC AUC (0.4597), в то время как XGBoost продемонстрировал лучший показатель полноты (46.67 %) и F1-меры (0.4882). Наиболее значимыми признаками оказались PCA-компоненты, тогда как кластеризация оказала минимальное влияние. Эти результаты подтверждают, что нейромаркетинг на основе ИИ может эффективно сегментировать потребителей и прогнозировать их поведение, способствуя созданию персонализированных маркетинговых стратегий.

Вклад данного исследования заключается в демонстрации того, как передовые технологии ИИ могут выявлять скрытые закономерности поведения потребителей, повышая эффективность маркетинга в сетевой розничной торговле. Практическая значимость включает разработку целевых маркетинговых кампаний, улучшение вовлеченности клиентов и оптимизацию стратегий конверсии.

Ключевые слова: Нейромаркетинг, Поведение потребителей, ИИ, Машинное обучение, Сетевая розничная торговля.

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