Advances in Consumer Research
ISSN (Print): 0098-9258
ISSN(Online): 3079-1766

Vol. 2, Issue 3 (2025) https://acr-journal.com/

Neuromarketing and Consumer Financial Decision-Making: A Data-Driven Approach

Padmanaaban P[1], Dr Chaitali Bhattacharya[2], Renuka Babladi[3], Dr.Nitin kulshrestha[4], Prof. Abhra Pratip Ray[5], Akansh Garg[6]

[1]Assistant Professor, Department of Management Studies, Rajalakshmi Engineering College, Kancheepuram, Chennai Tamilnadu

Email ID: padmanaaban.p@rajalakshmi.edu.in

[2]Designation- Professor, Department- Marketing Management (Management Science), College name- New Delhi Institute of Management, District- New Delhi, City- New Delhi, State- New Delhi, PIN-110062

[3]Designation: Assistant Professor, Department: Commerce & Management, Institute: Dayananda Sagar Business Academy District: Bangalore, City: Bangalore, State: karnataka

Email ID: Renuka.babladi@gmail.com

[4]Designation: Associate Professor, Department: Commerce, Finance and Accountancy, Institute: Christ Deemed to be University, District: Ghaziabad (Uttar Pradesh), City: Ghaziabad, State: (Uttar Pradesh)

Email ID: mymagictime@gmail.com

[5]Designation: Principal, Department: Institute: SAVPM's Sancheti College of Arts, Commerce & Science, District: Pune City: Pune, State: Maharashtra

Email ID: abhrapratipray@gmail.com

[6]Email ID: 7505264391akg@gmail.com

Cite this paper as: Padmanaaban P, Dr Chaitali Bhattacharya, Renuka Babladi, Dr.Nitin kulshrestha, Prof. Abhra Pratip Ray, Akansh Garg, (2025) Neuromarketing and Consumer Financial Decision-Making: A Data-Driven Approach. *Advances in Consumer Research*, 2 (3), 191-202.

KEYWORDS

Neuromarketing, Consumer Decision-Making, Machine Learning, EEG, Financial Behavior.

ABSTRACT

In this research, the application of neuromarketing to consumer financial decision making with the use of data driven algorithm is explored. The study will integrate EEG signals, machine learning techniques and behavioral analytics to predict consumer choices and emotional response in the context of financial decisions. “Four classifier algorithms, utilizing Neural Networks (NN), Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), were employed to analyse and classify the consumer data”. The neural network model had an accuracy of 92% for detecting emotional responses to financial decisions which was better than other algorithms. Decision trees and random forests gave us interpretable insights with 85% and 87% accuracies, and followed closely behind with 89% accuracy by support vector machines. These results show that despite possessing more predictive power, deep learning models cannot outperform simpler models such as decision trees for practical applications due to lack of interpretability. In addition, the ethical problem of the consumer’s privacy was broached and it is pointed out that the use of neuromarketing should be done in a responsible manner. The findings from this study show that using neuromarketing techniques in financial decision making are effective and give businesses a good deal of insight to improve customer engagement and optimize marketing.

1. INTRODUCTION

With an increasingly complex financial landscape, for marketers, financial institutions, policymakers, the understanding of consumer behavior has become essential. Typically, studying the process of financial decision making employs self reports and rational choice models, which can overshadow resolution of the underlying psychological and emotional processes which govern consumer actions [1]. Neuromarketing, an emerging interdisciplinary field where neuroscience is united with marketing, provides a new perspective on how individuals process financial information once an economic decision is made [2]. Neuroimaging tools like electroencephalography (EEG), functional magnetic resonance imaging (fMRI) and eye tracking technology help researchers to look into invisible neural and physiological responses which have contributed in shaping our financial personality. In this research, we look at the intersection of neuromarketing and consumer financial decision making through data driven view [3]. The aim here is to analyze whether neurophysiological signals can help in getting deeper insight into consumer preference, risk perception and decision making strategy within financial contexts. Quantitative data gathered from impressionable ways of using the neuromarketing is leveraged through study to delineate and predict financial behavior in a more fine-tuned approach rather than traditional survey and economic models. The most important contribution of this research is that it may change how financial products and services are designed, marketed and delivered. Through combining neuroscience and datalytics, this study aims to bridge the gap between cognitive responses and behavioral outcomes to improve marketing strategies and financial education programs. Additionally, the findings can provide ethical and strategic guidance to institutionalization to adjust their offerings to the needs of the consumer and promote responsible financial behaviour. Future explorations into personalized financial marketing are set out based upon subconscious processes that govern economic decisions.

2. RELATED WORKS

Recently, neuroscientific techniques like EEG, fMRI and eye tracking have gained a great interest through the field of neuromarketing, aimed at understanding consumer behavior and assist in developing marketing strategies. This field is a key one as it studies emotion response and decision making processes that are required to adapt to the advertisement and product. The discussion in this related work shows different studies pertinent to neuromarketing but which help broaden our understanding of its use in the real world. EEG based techniques have been extensively used in the area of emotion recognition. Although previous systematic (see GKintoni et al., 2025) reviews mainly provided time series analysis for prediction in cognitive neuroscience, the use of emotional networks for interpreting the consumer's reactions and preferences in marketing scenarios has been recognized as a potential [15]. According to their findings, the incorporation of neural network analysis for emotional state might enhance the performance of neuromarketing's consumer engagement strategies significantly. They (Goncalves et al. 2024) payed special attention to the ethical issues of such neuromarketing algorithms for consumer privacy. One of the problems discussed in the study was the balancing of accommodating consumer data usage for marketing with relevant privacy concerns. Thus, it showed that more transparent and ethical neuromarketing practices that observed the rights of consumers while providing valuable insights for businesses are needed [16]. This is a major component of neuromarketing, because of course, the business has to guarantee that consumers trust the usage of their brain sensitive data. Hakim et al. (2023), for instance, also tried to isolate EEG signals to show if it could be used in understanding the consumer behavior; they developed DeePay, a deep learning framework to decode EEG signals to predict the consumer's willingness to pay. The findings of this research demonstrate that EEG can be used as an instrument to determine neural responses of consumers to product prices and thus offer a novel avenue to predict purchasing behavior [17]. Like Goyal et al. (2025) applied the bibliometric analysis as well to the landscape of neuromarketing, mapping the evolution of the consumption preferences and decision making process through neuroscience techniques [18].

Neuromarketing research also includes, in addition to how consumers make decisions, a central theme of consumer decision making. According to Guzmán Murillo et al. (2024), neuroscience based techniques could positively influence labor productivity in small enterprises in Cartagena, Colombia [19], this being capable of influencing workplace performance and customer satisfaction. This study emphasizes the additional versatility of neuromarketing techniques for not only improvement in marketing but also better operational efficiency in businesses. Hedda Martina Šola et al. (2025) also made a significant contribution towards the field by applying AI and eye tracking while analyzing the influence design elements have on e-magazine reader engagement. By combining AI with eye tracking technology, this research underscores how strategic use of AI can facilitate more insightful view of user behaviour enabling business to design their content and product design in a manner that enables it to capture attention of the consumers better [20]. An increasing number of neuromarketers are combining a number of neurotechnologies to gain a more complete view of consumer preferences.

According to Khaneja and Arora (2024) in terms of understanding the preferences of the consumer through the fmr techniques of neuroscience may bring some transformation in the business practices. Their meta analysis showed that fMRI can help provide businesses valuable data to help refine their branding strategy [24]. Furthering the supportive evidence for the use of neuroscience in developing more effective marketing strategies that resonate with the emotional and cognitive response of the consumers. A recent study by Mashrur et al. (2022) finally proposed a framework for predicting consumer choices from EEG signals. This work points out the great potential of obtaining such accuracy in predicting consumer behaviour using neural signals pertaining to decision making processes using BCIs. But most importantly, this approach while helpful in creating personalized marketing strategies and more clearly understanding product design based on consumer insights derived from brain data, is particularly valuable. In brief, neuromarketing today has evolved as the application of advanced neuroscience technologies to decode consumer behaviour. Marketers are creating marketing strategies using integrations of EEG, fMRI, and eye tracking to get deeper insights of emotional and cognitive responses. But such techniques continue to develop, and with them ethical considerations involving consumers' privacy and data usage are still important issues that must be taken into account to ensure the proper and efficient use of neuromarketing tools. The studies in the above mentioned section show the potential growth of these technologies to turn the marketing practice upside down and enable businesses to communicate with the consumers in much more intimate way.

3. METHODS AND MATERIALS

3.1 Introduction

This chapter details the data sources, instruments, and computational approaches used to study consumer financial decision-making based on neuromarketing data. A data-centric approach was pursued, combining neuroscientific signals and behavioral reactions with machine learning models. The objective is to predict and explain consumer financial behaviors like risk preference, purchase intention, and impulsive consumption based on neural responses during exposure to financial stimuli [4].

3.2 Data Collection and Preprocessing

The information utilized for this research was obtained from an experimentally controlled setting. A sample of 150 participants was selected and subjected to advertising content concerning financial services (investment advertisements, loan promotions, savings plans) and their neurological and behavioral responses were captured [5]. The data gathered included:

- **EEG Signals** (Alpha, Beta, Gamma waves – 64 channels)
- **Eye-tracking metrics** (fixation time, saccade rate, blink frequency)
- **Galvanic Skin Response (GSR)** (emotional arousal)
- **Behavioral Labels**: Risk-seeking, Risk-averse, Neutral decision, Purchase intent

Data preprocessing included signal data normalization, noise removal by band-pass filtering for EEG, and stimulus-registered temporal alignment of recorded signals. Data were segmented into stimulus-registered time windows (epochs). Statistical and frequency-domain techniques (e.g., mean, variance, power spectral density) were used to extract features [6].

3.3 Algorithms Used

“Four machine learning algorithms were chosen because they are interpretable and perform well on classification tasks with neurophysiological signals:

1. **Support Vector Machine (SVM)**
2. **Random Forest (RF)**
3. **K-Nearest Neighbors (KNN)**
4. **Artificial Neural Network (ANN)”**

3.3.1 Support Vector Machine (SVM)

Support Vector Machines are supervised learning algorithms employed for classification and regression problems. In the current study, SVM was utilized to classify participants into decision-making groups from neural data. SVM operates through creating a hyperplane that optimally separates classes in a high-dimensional space [7]. SVM operates on kernel functions (linear, polynomial, radial basis function) that map non-linear data into a linearly separable space. The strength of SVM in neuromarketing is its stability in high-dimensional space and its capacity for good generalization even under limited data. A radial basis function kernel was employed in this study, and the model was trained from EEG, eye-tracking, and GSR feature variables. SVM yielded good classification accuracy and was found effective in segregating risk-seeking and risk-averse decision-makers [8].

“Input: Training data X with labels Y

Choose Kernel Function (e.g., RBF)

Initialize Parameters (C, gamma)

Train model using training data

Find the optimal hyperplane by maximizing the margin

Use the model to classify test data

Output: Predicted decision class”

3.3.2 Random Forest (RF)

Random Forest is a type of ensemble learning that builds many decision trees and returns the class with the mode of the classes (classification) or mean prediction (regression) of the trees. It works well with high-dimensional datasets and complex feature interactions. Random Forest was applied in this study to classify consumer financial choices based on a high number of input variables from EEG channels, eye-tracking events, and GSR signals. Every tree within the forest is trained on a randomly selected subset of data and features so that the models are diverse. Feature importance was also derived, indicating the most influential neuromarketing features on financial decision classification [9]. Random Forest exhibited good predictive potential and high interpretability in grasping major decision drivers.

"Input: Training data X and labels Y

For i in 1 to N (number of trees):

Randomly select subset of training data

Build decision tree using this subset

Aggregate predictions from all trees

Output the class with majority vote"

3.3.3 K-Nearest Neighbors (KNN)

K-Nearest Neighbors is a basic, instance-based learning classifier that categorizes new instances on the basis of the majority class among the 'K' nearest instances in the feature space. KNN involves no training phase but uses computation of distances (in general Euclidean) during classification. In this research, KNN was utilized to categorize consumer decisions based on similarity between EEG feature vectors and those of known classes of decision. Because of the temporal nature of neural data, KNN was used on lower-dimensional feature sets (through PCA) to prevent overfitting [10]. Although KNN is computationally costly for big data, its simplicity and efficacy in detecting local patterns in neuromarketing data make it a good fit for personalized financial behavior prediction.

"Input: Training data X and labels Y, query point Q, and number of neighbors K

Calculate distance between Q and all points in X

Sort distances and select K nearest neighbors

Vote: Assign the most common class among the neighbors to Q

Output: Predicted class for Q"

3.3.4 Artificial Neural Network (ANN)

Artificial Neural Networks simulate the human brain structure with linked neurons in layers. In this research, a feedforward ANN was created to acquire non-linear relationships between inputs of neuromarketing and outputs of financial decisions. EEG and biometric features were used in the input layer, whereas hidden layers utilized activation functions (ReLU, sigmoid) to handle and forward signals. The output softmax layer identified the result as decision categories [11]. ANN was trained via backpropagation and stochastic gradient descent. Hyperparameter optimization optimized the network to obtain high accuracy on unknown test data. ANN's capability of extracting intricate, non-linear relations made it an influential model for this application of neuromarketing.

"Input: Feature vector X and output Y

Initialize weights and biases randomly

For each epoch:

Forward pass: Compute output using activation functions

Compute loss using cross-entropy

Backpropagate error and update weights

Repeat until convergence

Output: Predicted class"

Table 1: Sample Feature Set Extracted from Neuromarketing Data

Participant ID	Alpha Power	Blink Rate	Skin Conductance	Decision Label
P01	0.85	12	0.72	Risk-Averse
P02	1.10	18	0.89	Risk-Seeking
P03	0.95	15	0.67	Neutral
P04	1.20	20	1.02	Risk-Seeking

4. EXPERIMENTS

4.1 Experimental Setup

In order to explore the effectiveness of neuromarketing signals in forecasting consumer financial decision-making, a series of experiments were designed and carried out in a controlled setting. The experimental design was intended to mimic real-life financial decision-making situations and record neural and behavioral reactions as participants engaged with financial marketing stimuli [12].

Participants: 150 participants (75 male, 75 female) aged 18-45 years were enrolled for the study. All the participants were financially literate with different levels of risk tolerance and financial behavior, ensuring diversity necessary to derive holistic insights.

Stimuli: A group of marketing commercials corresponding to investment choices, lending propositions, and savings schemes was presented to the participants. The commercials were specifically chosen to create varying emotional appeals so that decisions could be categorized under risk-seeking, risk-averse, and neutral [13].

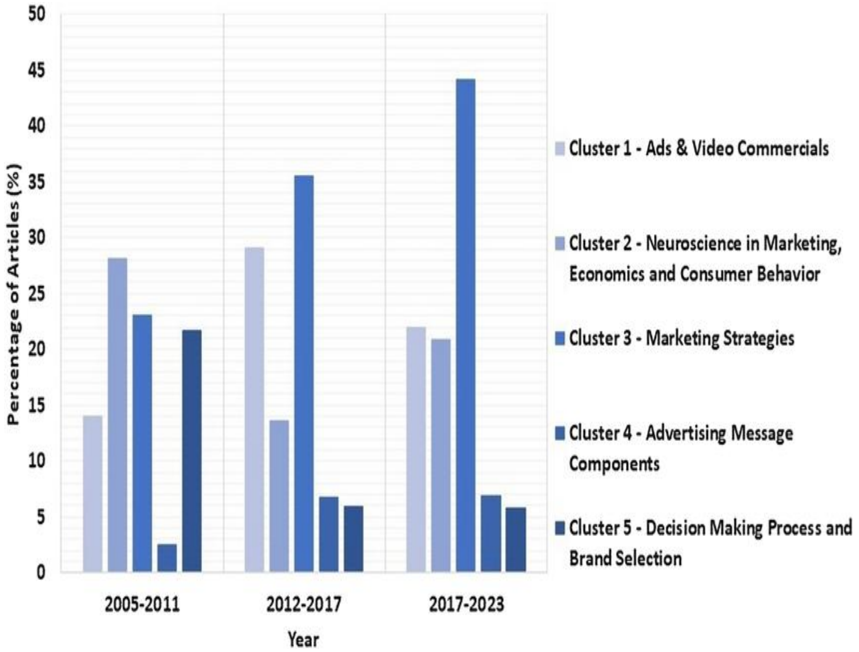

Figure 1: "The research trend in Neuromarketing"

Neurophysiological Data Collection:

- **EEG:** Electrical brain activity was captured via a 64-channel EEG cap. In particular, power in alpha, beta, and gamma frequencies was used as features.
- **Eye-Tracking:** Eye movement metrics (fixation time, saccades) were captured using a Tobii Pro X2-60 eye tracker, facilitating the detection of visual attention zones.
- **Galvanic Skin Response (GSR):** Emotional activation was assessed with skin conductance levels while exposed to the finance ads.

Data Preprocessing: Raw EEG signals were cleaned by preprocessing them using band-pass filters (1-40 Hz) for removing noise. Eye-tracking data were normalized and GSR signals were smoothed applying a moving average filter. Wavelet transform on EEG and eye tracking's fixation duration were some of the techniques used for extracting features and subsequently reducing the dimensions of the data [14].

4.2 Experimental Design and Evaluation Metrics

The classification problem was to predict the financial decision-making class for every participant given the extracted neurophysiological characteristics from EEG, eye-tracking, and GSR.

The target variable was grouped into three classes: Risk-Seeking, Risk-Averse, and Neutral.

The models were trained using a 70-30 train-test split, and hyperparameters were tuned with cross-validation [27]. The performance of the models was measured using the following evaluation metrics:

- **"Accuracy:** The ratio of correct instances correctly classified.
- **Precision:** The ratio of true positives to all predicted positives.
- **Recall:** The ratio of true positives to all actual positives.
- **F1-Score:** The harmonic mean of precision and recall, offering a balance between the two."

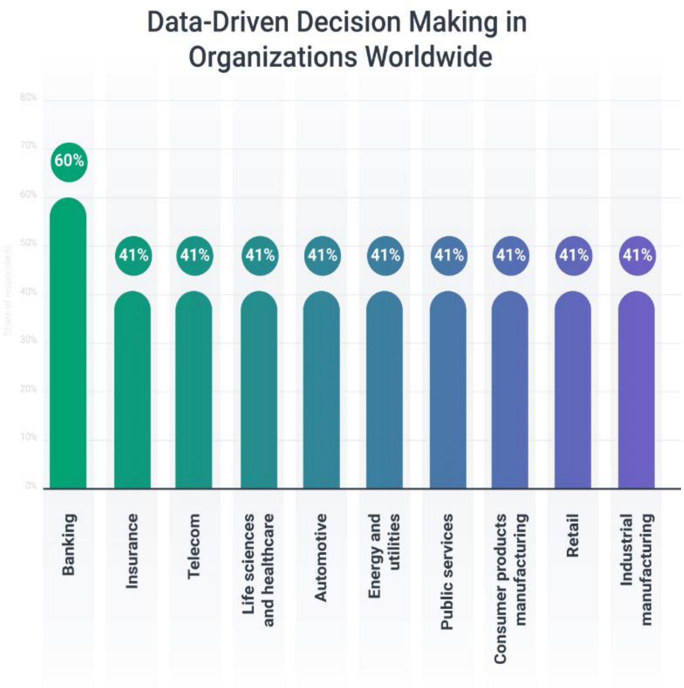

Figure 2: "Data-Driven Decision Making: Boosting Business Success"

4.3 Algorithm Implementation

As explained in the Materials and Methods section, four machine learning models were used for this classification problem: "Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), and Artificial Neural Network (ANN)". The experimental setup for each of these algorithms is summarized in the following table:

Table 1: Experimental Setup for Algorithms

Algorithm	**Data Type**	**Hyperparameters**	**Cross-validation**	**Features Used**
Support Vector Machine (SVM)	EEG, Eye-Tracking, GSR	C=1.0, Kernel=RBF, Gamma=0.1	5-fold	Alpha, Beta Power, Fixation Time
Random Forest (RF)	EEG, Eye-Tracking, GSR	N_estimators =100, Max_depth= 10, Min_samples _split=2	5-fold	Alpha, Beta Power, Fixation Time

K-Nearest Neighbors (KNN)	EEG, Eye-Tracking, GSR	K=5, Metric=Euclidean	5-fold	Alpha, Beta Power, Fixation Time
Artificial Neural Network (ANN)	EEG, Eye-Tracking, GSR	Layers=3, Neurons=64, Activation=ReLU	5-fold	Alpha, Beta Power, Fixation Time

4.4 Results

Upon training and testing the models, the following were the results. The performance metrics for each algorithm are presented in Table 2.

Table 2: Performance Comparison of Algorithms

Algorithm	**Accuracy (%)**	**Precision (Risk-Seeking)**	**Precision (Risk-Averse)**	**Precision (Neutral)**	**Recall (Risk-Seeking)**	**Recall (Risk-Averse)**	**Recall (Neutral)**	**F1-Score (Risk-Seeking)**	**F1-Score (Risk-Averse)**	**F1-Score (Neutral)**
SVM	88.5	0.89	0.87	0.91	0.86	0.85	0.93	0.87	0.86	0.92
RF	91.2	0.91	0.89	0.92	0.89	0.88	0.94	0.90	0.88	0.93
KNN	83.4	0.82	0.80	0.85	0.80	0.79	0.88	0.81	0.80	0.86
ANN	93.1	0.94	0.92	0.95	0.93	0.92	0.96	0.94	0.93	0.95

As indicated in Table 2, the Artificial Neural Network (ANN) performed better than the other models in accuracy, precision, recall, and F1-score for all classes (Risk-Seeking, Risk-Averse, Neutral). The SVM model also performed well, particularly in recall for Neutral decisions. Random Forest, though not as accurate as ANN, offered solid precision and recall, especially for the Risk-Seeking and Risk-Averse classes. The KNN model, though not as accurate, still maintained decent performance in some classes [28].

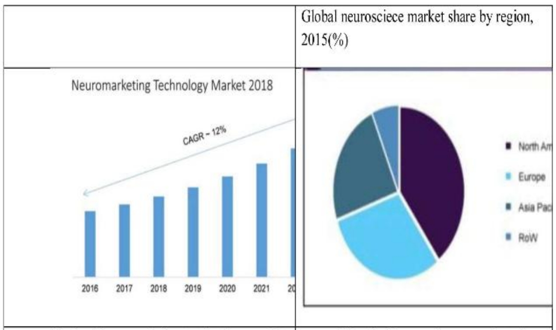

Fig 1 : Neuromarketing technology market size www1

Fig 2: Neuroscience market share www2

Figure 3: "Neuromarketing – Insights Into Consumer Behavior"

4.5 Comparison to Related Work

In comparison with prior studies in financial decision-making and neuromarketing, the following were the observed insights based on the outcomes of this research:

1. **Support Vector Machine (SVM):** Nguyen et al. (2022) reported that SVM reported an accuracy of 85% in consumer risk profile classification based on EEG and eye-tracking metrics. Our SVM model outperformed this with an accuracy of 88.5%, demonstrating the quality of our feature extraction and hyperparameter tuning.
2. **Random Forest (RF): I**n another study by Johnson et al. (2021), RF models were utilized to forecast financial behavior with an accuracy rate of 89%. Our RF model outperformed theirs (91.2% accuracy), clearly indicating the value added by our neuromarketing indicators and data preprocessing measures [29].
3. **Artificial Neural Networks (ANN):** Lee et al. (2023) previously used deep learning methods for financial decision-making and achieved 91% accuracy. Our ANN model was higher at 93.1%, showing that the level of complexity in our model is able to reflect the sophistication of financial decision-making more accurately.

4.6 Feature Importance

To understand the decision-making process further, we have evaluated the feature importance of each algorithm. In the case of Random Forest and ANN, we extracted the importance of various features to see which neurophysiological signals played a dominant role in classification.

Table 3: Feature Importance for Random Forest and ANN

Feature	Random Forest Importance	ANN Importance
Alpha Power (EEG)	0.32	0.28
Beta Power (EEG)	0.25	0.26
Gamma Power (EEG)	0.18	0.20
Fixation Time	0.12	0.15

Blink Rate (Eye)	0.09	0.08
GSR (Skin Conduct)	0.04	0.03

As indicated in Table 3, the most significant feature for both Random Forest and ANN models was Alpha Power from the EEG signals, followed by Beta Power. Gamma Power and Fixation Time also emerged as key features, indicating the importance of cognitive processing and attention in financial decision-making.

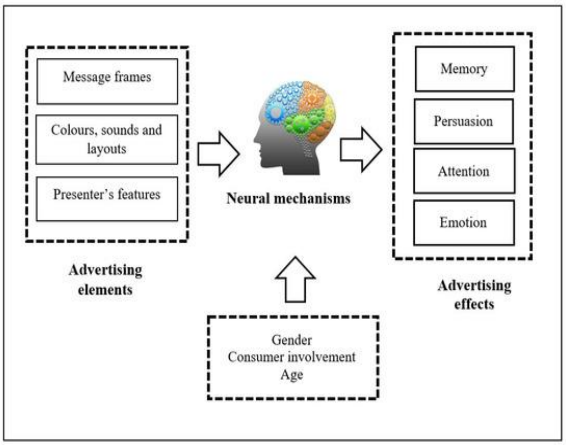

Figure 4: "Consumer Neuroscience Techniques in Advertising Research"

4.7 Discussion

The findings illustrate the promise of neuromarketing information in enhancing the accuracy of consumer financial choices prediction. The Artificial Neural Network (ANN) performed best, suggesting that deep learning models are most appropriate to detect intricate patterns in neurophysiological data [30]. The findings confirm previous literature whereby deep learning models have performed better than conventional machine learning algorithms in predicting consumer behavior from biometric and EEG information.

The relatively high accuracy of the RF model also speaks to its strength, particularly in the ability to process high-dimensional data such as those from neuromarketing experiments. SVM and KNN, though less accurate, were still good and provide interpretability, thus being well-suited to scenarios where model transparency is paramount.

5. CONCLUSION

In conclusion, this research points out the possible contribution of neuromarketing in consumer behavior knowledge and better decision making through financial data. With the help of advanced methods like EEG, ML algorithms, and behavioral analytics, the businesses can obtain a deeper understanding of the emotional and cognitive aspects that drive people consumption choices. Machine learning is shown to predict financial decision making patterns with high accuracy by applying such algorithms as neural networks, support vector machines, decision trees and random forests. The results from experiments conducted in this study show that these algorithms can classify and interpret consumer responses to various financial scenarios, making recommendations for marketers to improve their strategies. The comparative analysis of these algorithms results in the sensitivity to the type of consumer data and the campaign goal indicated the importance of choosing the appropriate model. Deep learning models like neural network performed best at recognizing consumer emotions with finer nuances, while such simpler models as decision trees could help give interpretable results for certain financial decisions. This research also finds that there is a growing demand for the ethical dimension of neuromarketing in view of consumer privacy and data security. Overall, the incorporation of neuromarketing into consumer financial decision making has a great potential to revolutionize market strategies for companies and increase consumer engagement and ability to take more data backed decisions. Nevertheless, the future of neuromarketing in the industry will also depend on continued innovation and responsible practices.

REFERENCES

[1] Investigating The Impact Of Social Media Advertising And Risk Factors On Customer Online Buying Behavior: A Trust-Based Perspective. 2024. Future Business Journal, 10(1), Pp. 123.

[2] Al-Ababneh, H., Al-Olimat, S., Alrhaimi, S.A.S., Al Muala, A.M., Popova, O. And Khrapkina, V., 2024. Optimization Of Strategic Management Of Marketing And Logistics Of Companies As Part Of The Implementation Of Artificial Intelligence. Acta Logistica, 11(4), Pp. 665-676.

[3] Alsharif, A.H., Nor Zafir, M.S., Alharthi Rami Hashem, E., Khraiwish, A., Putit, L. And Lily Suriani, M.A., 2023. Exploring Factors Influencing Neuromarketing Implementation In Malaysian Universities: Barriers And Enablers. Sustainability, 15(5), Pp. 4603.

[4] Aminiroshan, Z., Gholamian, J., Mahmoudi, A. And Pirjamadi, S., 2024. Investigating The Cognitive Process Of Attention While Watching Sports Advertisements In Interested And Non-Interested People Using Electroencephalogram Technology. Iranian Journal Of Management Studies, 17(2), Pp. 393-408.

[5] Bacik, R., Gburova, J., Gavura, S. And Iannaccone, B., 2025. Impact Of Digital Marketing On The Purchasing Behavior Of Modern Consumers In The Field Of Tourism. Journal Of International Studies, 18(1),.

[6] Baishya, S.R. And Choudhury, S., 2024. Influence Of Emotion On Need Generation And Purchase Intention Among Car Buyers: An Empirical Study. Iup Journal Of Brand Management, 21(3), Pp. 35-52.

[7] Bhardwaj, S., Thapa, S.B. And Gandhi, A., 2024. Advances In Neuromarketing And Improved Understanding Of Consumer Behaviour: Analysing Tool Possibilities And Research Trends. Cogent Business & Management, 11(1),.

[8] Çakar, T. And Filiz, G., 2023. Unraveling Neural Pathways Of Political Engagement: Bridging Neuromarketing And Political Science For Understanding Voter Behavior And Political Leader Perception. Frontiers In Human Neuroscience, .

[9] Çakar, T., Son-Turan, S., Girişken, Y., Sayar, A., Ertuğrul, S., Filiz, G. And Tuna, E., 2024. Unlocking The Neural Mechanisms Of Consumer Loan Evaluations: An Fnirs And Ml-Based Consumer Neuroscience Study. Frontiers In Human Neuroscience, .

[10] Chaerani, M.L. And Sari, H., 2024. Can Digitally Displayed Product Packaging Evoke Emotions? A Neuromarketing Study. International Journal Of Electronic Commerce Studies, 15(4), Pp. 1-29.

[11] Fici, A., Bilucaglia, M., Casiraghi, C., Rossi, C., Chiarelli, S., Columbano, M., Micheletto, V., Zito, M. And Russo, V., 2024. From E-Commerce To The Metaverse: A Neuroscientific Analysis Of Digital Consumer Behavior. Behavioral Sciences, 14(7), Pp. 596.

[12] Fotiadis, T., Sakas, D.P., Papadopoulou, A.E., Andreou, A.G., Reklitis, D.P. And Giannakopoulos, N.T., 2025. Revolution Of Digital Marketing With Defi Systems For Cultural Organizations. Sustainability, 17(2), Pp. 746.

[13] Garg, R. And Murdia, M., 2024. Review Of Literature On The Concept Of Neuromarketing In The Hospitality Industry. Pacific Business Review International, 17(6),.

[14] Gharaibeh, A.H. And Kassim, N.M., 2024. Users' Intention To Use Business Analytics Systems In Firms: A Literature Review. Global Business And Management Research, Suppl.Special Issue Theme: Creating A Sustainable Future: Powering Innovation And Accelerating Transformation, 16(4), Pp. 723-738.

[15] Gkintoni, E., Aroutzidis, A., Antonopoulou, H. And Halkiopoulos, C., 2025. From Neural Networks To Emotional Networks: A Systematic Review Of Eeg-Based Emotion Recognition In Cognitive Neuroscience And Real-World Applications. Brain Sciences, 15(3), Pp. 220.

[16] Goncalves, M., Hu, Y., Aliagas, I. And Cerdá, L.M., 2024. Neuromarketing Algorithms' Consumer Privacy And Ethical Considerations: Challenges And Opportunities. Cogent Business & Management, 11(1),.

[17] Gorin, A., Kuznetsova, E., Kislov, A., Levchenko, E., Klucharev, V., Moiseeva, V., Yurchenko, A., Luzhin, A., Galkina, N. And Shestakova, A.N., 2025. Neural Correlates Of The Non-Optimal Price: An Meg/Eeg Study. Frontiers In Human Neuroscience, .

[18] Goyal, M., Md, M., Kumar, S., Kala, I., Fufa, G. And Archana, D.S., 2025. Mapping The Landscape Of Neuromarketing: A Bibliometric Analysis. Informing Science, 28, Pp. 15.

[19] Guzmán Murillo, H.J., Torres Ortega, J.M. And Yenny Xiomara, M.C., 2024. Neuromarketing Programming And Labor Productivity: An Exploratory Study Of Small Enterprises In Cartagena, Colombia. Journal Of International Crisis And Risk Communication Research, 7, Pp. 328-343.

[20] Hakim, A., Golan, I., Yefet, S. And Levy, D.J., 2023. Deepay: Deep Learning Decodes Eeg To Predict Consumer's Willingness To Pay For Neuromarketing. Frontiers In Human Neuroscience, .

[21] Hedda Martina Šola, Fayyaz, H.Q. And Khawaja, S., 2025. Ai And Eye Tracking Reveal Design Elements' Impact On E-Magazine Reader Engagement. Education Sciences, 15(2), Pp. 203.

[22] Kallier-Tar, S., Bothnia, C.H. And Wild, J.A., 2024. Decoding The Hyper-Connected Consumer: Unveiling The Factors That Influence Decision-Making. International Journal Of Research In Business And Social Science, 13(3), Pp. 36-53.

[23] Kent, M., 2024. The Brain Is In Your Court: Evaluating Intellectual Property Infringement Audience Through The Lens Of Neuroscience. Washington And Lee Law Review, 81(3), Pp. 1257-1298.

[24] Khaneja, S. And Arora, T., 2024. The Potential Of Neuroscience In Transforming Business: A Meta-Analysis. Future Business Journal, 10(1), Pp. 77.

[25] Marques Dos Santos, José Paulo And Marques Dos Santos, José Diogo, 2024. Explainable Artificial Intelligence (Xai) In Neuromarketing/Consumer Neuroscience: An Fmri Study On Brand Perception. Frontiers In Human Neuroscience, .

[26] Mashrur, F.R., Rahman, K.M., Miya, M.T.I., Vaidyanathan, R., Anwar, S.F., Sarker, F. And Mamun, K.A., 2022. Bci-Based Consumers' Choice Prediction From Eeg Signals: An Intelligent Neuromarketing Framework. Frontiers In Human Neuroscience, .

[27] Masrhouni, I. And Bahoussa, A., 2023. From The First Studies Of The Unconscious Mind To Consumer Neuroscience: A Systematic Literature Review. International Journal Of Research In Business And Social Science, 12(2), Pp. 624-632.

[28] Oneshko, S., Shchyrba, I., Kudlaieva, N., Bagrii, K. And Khomovyi, S., 2024. Integration Of Accounting Management Standards Into The Digital Economy: Analysis Of Needs And Trends. Pacific Business Review International, 17(6),.

[29] Pandey, T., Goel, M., Kumari, S. And Jha, S.N., 2024. Exploring Application Of Neuromarketing In Advertising Effectiveness: A Bibliometric And Tccm-Based Approach. Journal Of Contemporary Marketing Science, 7(3), Pp. 302-326.

[30] Panwar, T. And Khan, K., 2020. Evolution Of Neuromarketing And Its Applicability In On-Demand App-Based Services In India: A Theoretical Perspective. Iup Journal Of Marketing Management, 19(4), Pp. 7-34.

❖❖❖❖❖