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The Role of AI- Behaviour Driven Neuromarketing in Shaping Consumer Behaviour

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Abstract:
In the ever-changing field of digital marketing, understanding consumers' subconscious minds has become a competitive advantage. Traditional market research methodologies, while useful in certain cases, sometimes fall short of capturing the deeply ingrained, emotional, and instinctive factors of customer decision making. This has resulted in the creation of neuromarketing, a discipline that combines neuroscience and marketing to investigate how customers' brains respond to marketing stimuli. With the introduction of Artificial Intelligence (AI), neuromarketing is undergoing a tremendous transition, ushering in a new era of precision, prediction, and customisation. This study looks at the convergence of AI and neuromarketing, specifically how AI-powered techniques like eye-tracking, facial expression analysis, EEG data interpretation, and sentiment analysis are being utilized to decode customer behaviour at a subconscious level. It also assesses these techniques' performance in improving brand recall, consumer engagement, and purchase intent. Furthermore, the study investigates consumer perceptions about AI-enabled personalization, the ethical quandaries involved with subliminal targeting, and the potential consequences for consumer autonomy and privacy. A mixed-methods approach will be used, including surveys, interviews with marketing professionals, and case studies of organizations who use AI in neuromarketing efforts. The findings seek to contribute to a more sophisticated understanding of how AI might be utilized ethically and successfully in consumer neuroscience. It will provide valuable insights for marketers, policymakers, and researchers on leveraging emerging technologies while maintaining consumer trust and transparency.

Keywords: Neuromarketing, Artificial Intelligence, Consumer Behaviour, Eye-tracking, Personalization, Ethics in Marketing, EEG, Sentiment Analysis.

I. Introduction

In an age when consumer attention is fractured and competition is fierce, understanding the subconscious components of decision-making is a significant advantage. Traditional market research approaches, like as surveys and focus groups, while important, are frequently constrained by bias and rational filtering. This has led to the rise of neuromarketing, which uses technologies such as fMRI, EEG, eye-tracking, and galvanic skin response to capture non-verbal, subconscious reactions. Artificial intelligence has taken this one step farther. AI systems can evaluate complicated brain and behavioural data on a large scale, providing predictive models that can read emotional reactions as well as personalize content delivery. This paper investigates how AI-driven neuromarketing tools are transforming marketing strategies, enhancing brand engagement, and influencing consumer decision-making patterns.

II. Objectives

1. Investigate the integration of AI with neuromarketing techniques.
2. Evaluate consumer responses to AI-personalized marketing.
3. Identify the ethical concerns of subconscious targeting.
4. Propose a framework for ethical AI-driven neuromarketing.

III. Review of Literature

Neuromarketing and its combination with artificial intelligence (AI) have become critical for understanding and forecasting customer behaviour. Hubert and Kenning (2008) published an early critical analysis of branding and the brain, examining the potential and limits of EEG and fMRI in deciphering consumer feelings toward brands, as well as presenting ethical issues. In his groundbreaking book, Zurawicki (2010) discussed how neuroscience technologies might identify subconscious reactions to marketing stimuli, providing greater insights into attention, reward systems, and emotions. In the same year, Ariely and Berns (2010) critically evaluated the potential and drawbacks of employing neuroimaging in business, focusing on the ethical implications and the possibility of overinterpretation. Glimcher (2010) used a neuroeconomic viewpoint to explain how brain systems encode risk, value, and choice, giving a scientific foundation for forecasting consumer preferences. Morin (2011) emphasized the usefulness of instruments like as fMRI and EEG in recording subconscious emotional reactions, comparing them with the limits of traditional marketing methods. Rao (2015) investigated how digital content pricing influences consumer behaviour, discovering cognitive biases in rental versus purchase decisions and their implications for neuromarketing. Plassmann et al. (2015) presented a systematic framework for integrating neuroscience to consumer research, outlining its potential for decision-making, marketing effectiveness, and behaviour prediction. Hsu and Yoon (2015) discussed how specific brain regions influence consumer choices, emphasizing the importance of subconscious processes in purchasing. Ulman, Cakar, and Yildiz (2015) discussed the ethical aspects of neuromarketing, cautioning against the exploitation and manipulation of subconscious consumer insights and advocating for explicit regulatory guidelines. Karmarkar and Plassmann (2019) examined the application of neurophysiological tools in business research, demonstrating how subconscious data improves traditional marketing. Sharma, Yadav, and Kumar (2021) conducted a comprehensive literature review to show how EEG and FMRI have altered our knowledge of consumer emotions and decisions, highlighting AI's growing significance in brain data processing. Mikalef et al. (2021) examined AI applications in marketing and consumer psychology, claiming that machine learning, natural language processing, and computer vision complement neuromarketing by revealing complex emotional and behavioural trends. Gupta and Shekhar (2023) investigated the intersection of neuromarketing and AI, demonstrating how real-time neurotools such as eye tracking and face coding improve engagement and loyalty while raising transparency issues. Smidts, Wierenga, and Zeelenberg (2023) explored AI's expanding importance in marketing, cautioning against algorithmic bias and ethical dangers while admitting its potential in deciphering underlying customer behaviour drivers. Kamatchi et al. (2024) presented empirical evidence that AI-enhanced neuromarketing tools outperform traditional analytics for tracking consumer engagement and recall. These studies collectively demonstrate how AI-driven neuromarketing has progressed from a theoretical concept to a powerful, data-driven marketing discipline with increasing scope, sophistication, and ethical complexity.

IV. Methodology

This study employed a quantitative research design using primary data collected through a structured questionnaire administered to 50 respondents. The survey captured demographic information (age, gender, education, occupation, income), awareness of neuromarketing and AI-driven tools, attitudes toward personalized advertising, ethical concerns, and behavioural intentions such as purchase likelihood.
Advanced statistical analyses were conducted to ensure accuracy and reproducibility. Descriptive statistics were used to summarize participant characteristics and key variables. Pearson correlation assessed the linear relationship between AI familiarity and purchase likelihood, while chi-square tests examined associations between awareness and ethical concern variables. A one-way ANOVA was performed to identify differences in purchase likelihood across education levels, and an OLS regression model was constructed to evaluate the predictive ability of AI familiarity, age, and gender on buying behaviour. All analyses were performed following standard statistical assumptions and procedures.

V. Results and Analysis

A survey was conducted with sample respondents of 50, and statistical analysis was conducted, their results are as follows.

5.1 Chi-Square Analysis: Awareness × Privacy Concern

Table 1: Awareness and Privacy Concern

Awareness	Low Concern (0)	Moderate Concern (1)	High Concern (2)	Total
Not Aware (0)	4	6	3	13
Aware (1)	3	27	7	37
Total	7(14%)	33 (66) %	10(20%)	50

Table 5.1 shows the distribution of respondents' privacy concern levels based on their awareness of neuromarketing.66% respondents are aware of neuromarketing fall under the moderate concern category, 20% of respondents are highly concerned, only 14% are less concerned about their Privacy.

Table 2: Chi-Square Test Results

Test	Value	df	Sig. (p-value)
Pearson Chi-Square	4.660	2	0.097
Likelihood Ratio	4.234	2	0.120
Linear-by-Linear Association	0.959	1	0.327
N of Valid Cases	50	—	—

H0=There is no statistically significant association between respondents' awareness of neuromarketing and their level of privacy concern.

As shown in Table 5.2, the Pearson Chi-square value is 4.660 with 2 degrees of freedom, and the corresponding p-value is 0.097. Since the p-value (0.097) is greater than the significance level ($\alpha = 0.05$), the result lies in the region of acceptance. Therefore, the null hypothesis cannot be rejected. In other words, respondents who are aware of neuromarketing do not differ in their privacy concerns compared to those who are not aware.

5.3. One-Way ANOVA: Education Level × Purchase Likelihood

Table 3: Purchase Likelihood by Education Level

Education Level	N	Mean	Std. Deviation	Min	Max
Postgraduate	15	2.87	1.36	1	5
Undergraduate	32	3.06	0.72	1	5
School Level	3	4.00	1.73	2	5
Total	50	3.06	1.02	1	5

H0=there is no statistically significant difference in purchase likelihood among respondents belonging to different education levels.

As shown in Table 3, the mean purchase likelihood varies slightly across the three education groups. Respondents with school-level education reported the highest purchase likelihood (Mean = 4.00), followed by undergraduates (Mean = 3.06), while postgraduates recorded the lowest purchase likelihood (Mean = 2.87). Although these descriptive statistics indicate apparent differences among education levels, descriptive values alone cannot determine whether these differences are statistically significant.

To verify this, a One-Way ANOVA was conducted (Table:4). The calculated F-value is 1.585, with a corresponding p-value of 0.216, which is greater than the 5% significance level ($\alpha = 0.05$). This means that the obtained F-value lies within the region of acceptance, and therefore the null hypothesis cannot be rejected.

Thus, it may be interpreted that there is no statistically significant difference in purchase likelihood among respondents belonging to different education levels.

In other words, the educational qualification of respondents does not significantly influence how likely they are to purchase a product after viewing AI-driven personalized advertisements.

Table 4: ANOVA Results – Education Level and Purchase Likelihood

Source	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3.212	2	1.606	1.585	0.216
Within Groups	47.608	47	1.013	—	—
Total	50.820	49	—	—	—

5.3 Correlation Analysis: AI Familiarity × Purchase Likelihood

Table 5: Correlation Summary

Variables	r	p-value	Interpretation
AI Familiarity × Purchase Likelihood	~0.00	>0.05	No correlation

H0= There is no statistically significant relationship between AI familiarity and purchase likelihood.

As presented in Table 5, the Pearson correlation coefficient between AI familiarity and purchase likelihood is approximately zero ($r \approx 0.00$), with a probability value greater than 0.05. This indicates that the relationship between the two variables is statistically non-significant.

Since the correlation coefficient is extremely weak and the p-value exceeds the accepted level of significance ($\alpha = 0.05$), the result lies in the region of acceptance of the null hypothesis. Therefore, the null hypothesis cannot be rejected.

This finding suggests that respondents' familiarity with artificial intelligence does not influence their likelihood of purchasing a product after viewing AI-driven personalized advertisements. In other words, having more knowledge about AI does not necessarily make consumers more responsive to personalized marketing messages.

5.4 Regression Analysis: Predictors of Purchase Likelihood

Table 6: Model Summary

R	R Square	Adjusted R Square	Std. Error
0.233	0.054	-0.007	1.022

The model explains (Table:5.6) only **5.4%** of the variance in purchase likelihood, indicating very weak predictive power.

Table 7: ANOVA – Regression Model

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	2.765	3	0.922	0.882	0.457
Residual	48.055	46	1.045	—	—
Total	50.820	49	—	—	—

As shown in Table 6, the regression model yielded a correlation coefficient (R) of 0.233 and a coefficient of determination (R^2) of 0.054, indicating that the independent variables explain only 5.4% of the variance in purchase likelihood. The negative adjusted R^2 (-0.007) further suggests that the model has very weak explanatory power and does not provide a good fit for predicting consumer purchase behaviour.

The ANOVA results presented in Table 7 show that the calculated F-value is 0.882, with a corresponding p-value of 0.457. Since the p-value is greater than the standard level of significance ($\alpha = 0.05$), the model falls within the acceptance region of the null hypothesis.

Therefore, it can be concluded that the regression model is not statistically significant, meaning that the combined effects of age, gender, and AI familiarity do not significantly predict respondents' likelihood of making a purchase after exposure to AI-driven personalized advertisements. This clearly indicates that these demographic and technological factors have limited influence on purchase behaviour in the present study.

Table 8: Regression Coefficients

Predictor	B	SE	Beta	t	Sig.
Constant- purchase likelihood	3.342	0.621	—	5.380	0.000
Age	0.058	0.126	0.066	0.458	0.649
Gender	-0.304	0.192	-0.234	-1.587	0.119
AI Familiarity	-0.054	0.152	-0.053	-0.356	0.724

Table 8 presents the regression coefficients for the predictors of purchase likelihood. The constant shows a value of B = 3.342 with a highly significant t-value of 5.380 ($p = 0.000$), indicating that the baseline level of purchase likelihood is statistically significant when all predictors are held constant.

The coefficient for Age is B = 0.058 with a p-value of 0.649, which is greater than the significance level of 0.05. This indicates that age does not have a statistically significant effect on purchase likelihood.

The variable Gender has a coefficient of B = −0.304 and a p-value of 0.119, which is also above the accepted threshold. This result suggests that gender does not significantly influence consumers' likelihood of purchasing after viewing personalized advertisements.

Similarly, AI Familiarity shows a very small negative coefficient (B = −0.054) and a p-value of 0.724, confirming that familiarity with artificial intelligence in marketing has no statistically significant effect on purchase likelihood.

Overall, the results indicate that none of the independent variables significantly predict purchase likelihood, and the null hypotheses for each predictor cannot be rejected. This suggests that demographic factors and AI familiarity do not play a meaningful role in influencing purchase behaviour in the context of AI-driven personalized advertising.

Findings

The analysis indicates that awareness of neuromarketing does not significantly influence consumer privacy concerns. Similarly, education level does not significantly affect purchase likelihood. Correlation and regression tests confirm that AI familiarity, age, and gender do not meaningfully predict consumers' likelihood of purchasing after personalized ads. Overall, consumers' behavioural responses appear unaffected by demographic factors or awareness levels.

Conclusion

This study concludes that AI-driven neuromarketing does not significantly impact consumer privacy concern or purchase decisions among the surveyed population. Despite moderate familiarity with AI technologies, consumer behaviour remains largely unchanged, indicating that psychological, contextual, and trust-related factors may play a more substantial role. Future research should explore emotional and ethical dimensions more deeply to understand consumer responses to AI-enabled marketing strategies.

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