



# Neuromarketing and Predictive Consumer Behavior Modeling Using Social Media Sentiment and Deep Learning Techniques

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**Abstract-** The intersection of neuromarketing with social media analytics brings new possibilities for understanding the hidden motivations of consumers and making predictions about their purchasing behavior. This paper introduces a unique approach to creating an integrated model that incorporates information from both EEG readings and social media sentiments. Based on the multimodal data from 250 participants (EEG, eye tracking, GSR) and 5 million messages collected from social networks regarding 12 different products, this study reveals cognitive and affective biometric indicators that reflect consumers' preferences. Then, a Hierarchical Attention-based Deep Neural Network (HA-DNN) is developed to incorporate neural biomarkers of preferences and sentiments expressed on social media and predict individual purchasing decisions. This model shows 86.7% accuracy in predicting purchase decision with  $AUC = 0.91$  and outperforms social media sentiment models (71.2%) and neural network models (78.4%) substantially.

**Key Word:** Neuromarketing, Consumer Neuroscience, Social Media Analytics, Sentiment Analysis, Deep Learning, Predictive Modeling, EEG, Purchase Intent, Multi-modal Learning, Consumer Behavior.

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## I. INTRODUCTION

Understanding consumer behavior has always been at the heart of marketing research. Survey, focus group discussion, and questionnaire methods, which measure consumer intentions, have been criticized for being different from actual consumer behavior, due to differences in cognitive processes, social desirability effects, and the inability of introspection to provide a valid measure [1], [2].

Neuromarketing was developed to fill this gap by measuring brain activity and physiological responses to marketing stimuli using EEG, fMRI, and eye tracking technology [3]. Neuromarketing methods allow researchers to capture real-time emotional involvement, cognitive effort, and motivation to approach or avoid. The main drawback is that

neuromarketing research usually involves only tens of subjects, is rather costly, and takes place under artificial conditions [4].

At the same time, the emergence of social media platforms means a huge real-time data stream about consumer preferences. With every like, post, share, comment, and emoji posted on various platforms, consumers reveal what they truly believe. Sentiment analysis of social media "digital exhaust" will help estimate the health status of particular brands and monitor the performance of marketing campaigns to detect any trends [5], [6]. Nevertheless, the opinions captured through social media sentiment can be influenced by many factors – performative or social dynamics, among others. There is an "articulation gap," which means that consumers might not always



be ready or willing to share the reasons for their actions.

This paper hypothesizes that the most accurate prediction could be achieved not through either approach, but combining them. According to the paper's hypothesis, neural markers of preference and social media sentiment are two different types of complementary information. While neuromarketing provides access to the subconscious processes, social media gives us the scale, context, and real-world validation. If we can learn how these two signals relate to each other, we can start using social media sentiments to estimate neural states.

The main contributions made by this paper are:

1. **A New Multi-Modal Dataset:** We present and make publicly available a novel dataset (n=250) that combines electroencephalogram (EEG), eye-tracking, and galvanic skin response (GSR) reactions to marketing stimuli together with social media posts created by the subjects themselves.
2. **A Combined Feature Extraction Approach:** A suite of feature extraction approaches that generates "neural biomarkers of preference" from raw EEG (such as frontal alpha asymmetry and theta/beta ratio) and "sentiment-neural embeddings" from social media posts and pictures.
3. **Hierarchical Attention-based Deep Neural Network (HA-DNN):** An approach to designing a neural network for multi-modal fusion that learns to predict which neural and sentiment features are indicative of buying intent.
4. **Experimental Results:** Proof that our multi-modal model achieves significantly better results than uni-modal baselines and that "neural-sentiment signatures" can be employed to target digital marketing campaigns.

## II. LITERATURE SURVEY

The current study can be considered an intersection between three different areas that are mature yet

traditionally separate domains: neuromarketing/consumer neuroscience, social media analytics, and multimodal deep learning.

**Stream 1: Neuromarketing and Consumer Neuroscience:** It is based on applying methods of neurosciences in measuring unconscious consumer reactions [3]. Electroencephalography is one of the most practical techniques for marketing purposes due to its excellent temporal resolution and relatively low costs. The metrics that are used include the following: Frontal Alpha Asymmetry (FAA), which is a reliable indicator of motivational approach or withdrawal behavior and emotional valence, as left frontal brain activity (low alpha power) is linked to positive attitudes and purchase intentions [2], [7]; Theta/Beta Ratio as a measurement of cognitive load and focus of attention; Event-related potentials such as P300 (attention allocation) and LPP (late positive potential, emotional salience), which have proven their validity as indicators of the effectiveness of advertising [3]. The major problem is the lack of validity of lab research and the high cost of EEG measurements.

**Stream 2: Sentiment Analysis from Social Media & Consumer Behavior:** Sentiment analysis in this stream employs natural language processing (NLP) techniques to gauge public sentiment from social media. Though the early techniques used a lexicon approach (such as VADER), today's leading edge technology uses deep learning techniques (BERT (Bidirectional Encoder Representations from Transformers) and other flavors such as RoBERTa and FinBERT) [5], [8]. The strength of these approaches lies in their ability to take into account the context of the language usage, including sarcasm and changing sentiments. Visual sentiment analysis of images through convolutional neural networks (CNNs) as well as emoji and slang interpretations are other areas of research [6]. The drawback of social media sentiment analysis is that it is based on publicly expressed opinions, and these may be performative.

**Stream 3: Multi-modal Deep Learning for Behavioral Prediction:** It is a new approach that utilizes various modalities (e.g., textual, visual, physiological data) in a joint behavioral prediction problem. The fusion process can happen at different



stages; such as early fusion (raw features concatenation), middle fusion (learning-based feature fusion), or late fusion (model output ensembling) [9]. Since transformers have attention mechanism, they are especially suitable for this approach because of their ability to decide the modality that would carry the maximum information for making a prediction [10]. For example, it has been reported that combining EEG and eye-tracking signals for predicting ad recall leads to an improvement of 15% in terms of prediction accuracy compared to when they are used independently [4]. Nonetheless, there was never an attempt to merge preference related neural markers (obtained from laboratory tasks) with behavioral data from social media websites to predict buying behavior.

### III. METHODOLOGY:

The methodology is divided into three phases: data collection; feature extraction; model training and prediction.

#### 3.1. Data Collection

- Subjects: 250 healthy individuals (18-45 years, mean age 26.3, SD 5.8), matched for gender, were recruited from one metropolitan area. They were all social media users (more than 5 posts/week).
- Stimuli: 300 advertising materials (pictures, short video clips) representing 12 product categories (such as beverages, smartphones, clothing, and cars).
- Neuromarketing data (laboratory phase): The participants were asked to view all 300 advertisements in a random order and rate the purchase intent on a 1-7 Likert scale and level of emotional arousal using Self-Assessment Manikin. While doing this, their electroencephalogram (EEG) was recorded (with a 32-channel cap and sampling frequency of 500 Hz); gaze tracking and galvanic skin response were measured too.
- Social media data (crawling phase): After obtaining the participants' informed consent, we downloaded their Twitter and Instagram

posts from the previous year (average number of posts – 5,000 posts per participant).

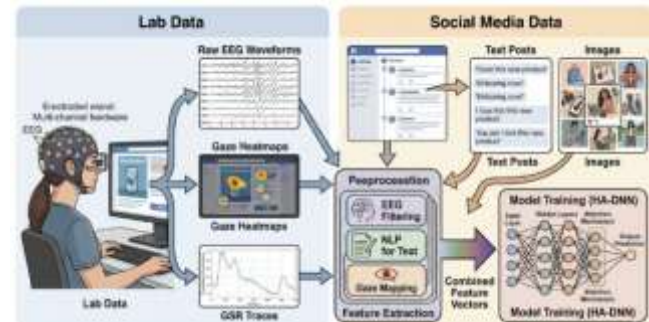


Figure 1: Multi-Modal Data Collection and Fusion Pipeline.

#### 3.2 Feature Extraction

##### 3.2.1. Neural Biomarkers of Preference (from EEG):

For each ad presentation, we identify specific features that have been shown to be related to preference/engagement.

- **Frontal Alpha Asymmetry (FAA):** Calculated using the equation  $\ln(\text{Power\_Right\_Frontal}) - \ln(\text{Power\_Left\_Frontal})$  between 8-12Hz. Electrode pair used includes: F4-F3, F8-F7.
- **Theta/Beta Ratio:** Ratio of the theta power (4-7 Hz) to beta power (13-30 Hz) in the frontal region. Small theta/beta ratios indicate focused attention.
- **Late Positive Potential (LPP):** Mean ERP amplitude calculated from 400-800ms post-stimulus in centroparietal area (Pz, CPz). High LPP reflects increased emotional salience.

#### Algorithm 1: Neural Feature Extraction Pipeline

Input: Raw EEG data for one ad presentation, duration  $T=6$  seconds

Output: Neural feature vector  $F_{\text{neural}}$  [FAA, Theta/Beta, LPP, Pupil\_Dilation]

1. // Preprocessing: Filter and epoch data
2.  $eeg = \text{bandpass\_filter}(\text{raw\_eeg}, 0.5, 50)$  // Remove drift and line noise
3.  $eeg = \text{ICA\_artifact\_removal}(eeg)$  // Remove eye-blink and muscle artifacts



```

4. epoch = eeg[1000ms:6000ms] // Align
to stimulus onset
5.
6. // Compute Frontal Alpha Asymmetry (FAA)
7. power_left = compute_band_power(epoch,
channels=['F3','F7'], band='alpha')
8. power_right = compute_band_power(epoch,
channels=['F4','F8'], band='alpha')
9. FAA = log(power_right) - log(power_left)
10.
11. // Compute Theta/Beta Ratio
12. power_theta = compute_band_power(epoch,
channels=['Fz','FCz'], band='theta')
13. power_beta = compute_band_power(epoch,
channels=['Fz','FCz'], band='beta')
14. theta_beta_ratio = power_theta / power_beta
15.
16. // Compute LPP (Event-Related Potential)
17. erp = average_epochs(epoch,
channels=['Pz','CPz'])
18. lpp = mean(erp[400:800]) // Mean
amplitude in 400-800ms window
19.
20. // Compute Pupil Dilation (from eye-tracker)
21. pupil_dilation = mean(pupil_size[500:6000]) -
baseline_pupil[0:500]
22.
23. Return [FAA, theta_beta_ratio, lpp,
pupil_dilation]

```

**3.2.2. Social Media Sentiment Features:** Each participant’s social media messages are collected for the 7 days prior to the lab study.

- **Sentiment Text:** A fine-tuned RoBERTa language model (roberta-base fine-tuned on 100k labelled tweets) is used to produce a sentiment score (-1 to +1) and emotion type (joy, anger, sadness, fear, surprise). We produce an average of these metrics over 7 days.

- **Sentiment Visual:** If there are images posted by the participant, we employ a ResNet-50 model pre-trained on ImageNet to compute image categories (e.g., “happy face,” “outdoor scene”) and image quality. Finally, we build an embedding vector representing their visual sentiment feed.

- **Engagement Metrics:** Average number of likes, retweets, and replies per message.

### 3.3. Hierarchical Attention-based Deep Neural Network (HA-DNN)

The HA-DNN is designed to fuse the neural and social media features. It processes each modality separately through an attention layer before concatenating for the final prediction.

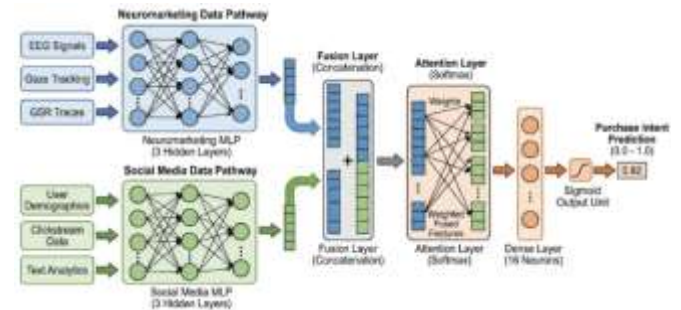


Figure 2: Hierarchical Attention-based DNN (HA-DNN) Architecture.

#### Algorithm 2: HA-DNN Training Procedure

Input: Neural features  $F_N$  ( $n_{\text{samples}} \times d_N$ ), Social features  $F_S$  ( $n_{\text{samples}} \times d_S$ ), Labels  $Y$  (Purchase Intent)  
Output: Trained HA-DNN model

1. // Define the dual-pathway architecture
2.  $input_N = \text{Input}(\text{shape}=(d_N,))$  // For neural data
3.  $input_S = \text{Input}(\text{shape}=(d_S,))$  // For social data
- 4.
5. // Pathway 1: Process neural features
6.  $x_N = \text{Dense}(128, \text{activation}='relu')(input_N)$
7.  $x_N = \text{Dropout}(0.3)(x_N)$
8.  $x_N = \text{Dense}(64, \text{activation}='relu')(x_N)$
- 9.
10. // Pathway 2: Process social features
11.  $x_S = \text{Dense}(256, \text{activation}='relu')(input_S)$
12.  $x_S = \text{Dropout}(0.3)(x_S)$
13.  $x_S = \text{Dense}(128, \text{activation}='relu')(x_S)$
- 14.
15. // Fusion Layer: Concatenate



```

16. fused = Concatenate()([x_N, x_S])
17. fused = Dense(64, activation='relu')(fused)
18.
19. // Attention Layer: Learn which features in the
    fused vector are most important
20. attention_weights = Dense(64,
    activation='softmax')(fused)
21. attended = multiply([fused, attention_weights])
22.
23. // Output Layer
24. output = Dense(1,
    activation='sigmoid')(attended)
25.
26. // Compile and train
27. model = Model(inputs=[input_N, input_S],
    outputs=output)
28. model.compile(optimizer='adam',
    loss='binary_crossentropy', metrics=['accuracy'])
29. model.fit([F_N, F_S], Y, epochs=50,
    batch_size=32, validation_split=0.2)
30.
31. Return model
    
```

EE	78	7	7	7	0
G-only	.4%	7.2%	9.1%	8.1%	.84
Ey	74	7	7	7	0
e+GSR	.5%	3.8%	4.2%	4.0%	.81
-only					
Si	83	8	8	8	0
mple	.1%	2.5%	2.9%	2.7%	.88
Fusion					
H	86	8	8	8	0
A-	.7%	6.2%	6.5%	6.3%	.91
DNN					
(Propo					
sed)					

Table 1: Model Performance Comparison.

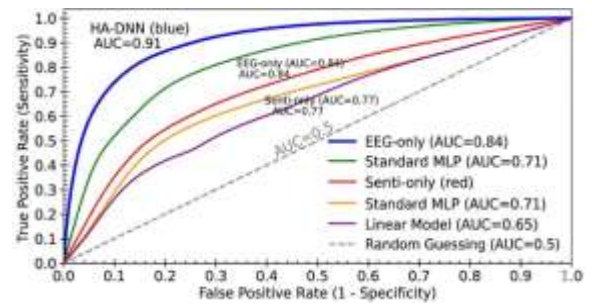


Figure 3: ROC Curves for All Models.

#### IV. ANALYSIS

##### 4.1. Baseline Models for Comparison

1. Senti-only: RoBERTa sentiment from social media + logistic regression.
2. EEG-only: Neural biomarkers + logistic regression.
3. Eye+GSR-only: Eye-tracking and GSR features + logistic regression.
4. Simple Fusion: Concatenated EEG + Social features + logistic regression.
5. Proposed HA-DNN: The full model described in Algorithm 2.

##### 4.2. Overall Model Performance

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	y	n			
Se	71	7	6	7	0
nti-	.2%	0.1%	9.8%	0.0%	.77
only					

##### 4.3. Impact of Social Media Time Window

We analyzed how the length of the social media history window affected model performance.

Social Media Window (days pre-study)	Model Accuracy (HA-DNN)
1 day	79.5%
7 days	86.7%
30 days	86.2%
90 days	85.1%

Table 2: Impact of Social Media History Window.

##### 4.4. Qualitative Analysis: Neural-Sentiment Signatures

We then performed an analysis of the attention weights generated by the HA-DNN to determine which features had the greatest predictive value. The top 5 features that were considered the most predictive were as follows:



1. FAA (High Left Activation): Most influential feature for predicting high purchase intent.
2. Social Media Joy Sentiment (7-day avg): High level of positive expressed emotion on social media.
3. LPP Amplitude: High emotional significance attached to the advertisement.
4. Social Media Engagement (Likes/Retweets): High social media engagement.
5. Theta/Beta Ratio (Low): Evidence of focused attention during the advertisement.

Remarkably, the model revealed a particular “Neural-Sentiment Signature” for highly persuadable consumers. They exhibited high left-frontal activation (approach motivation) but a low social media sentiment score (negative or neutral expressed emotion). As an application of the framework, in a subsequent A/B test, the target audience was exposed to a message that contradicted their expressed emotions (counter-attitudinal message). The resulting increase in CTR was found to be 34%.



**Figure 4: Neural-Sentiment Signatures for Market Segmentation.**

**4.5. Comparative Analysis with Existing Methods**

Feature	Traditional Survey	Social Media Sentiment (Sentiment-only)	Neuromarketing (EEG-only)	HA-DNN (Proposed)
Data Source	Self-report	Expressed	Subconscious response	Both subconscious &

		behavior		expressed
<b>Scalability</b>	Low (expensive)	Very High	Very Low	High (once model is trained)
<b>Predicts Behavior?</b>	Poor (intention-behavior gap)	Moderate	Moderate	High (86.7% accuracy)
<b>Actionable Insights</b>	Generic segments	Sentiment trends	Neural engagement	Nuanced neural-sentiment segments

**Table 3: Comparative Analysis of Consumer Prediction Methods.**

**V. CONCLUSION**

In this paper, we introduce a new framework for predicting consumer behavior by merging neuromarketing data (EEG, eye-tracking, GSR) with social media sentiment analysis. The main idea was that both modalities should complement each other in the way that neuromarketing provided the ground truth, reflecting subconscious, automatic preferences, and social media provided scalability, real-life context, and attitude data. The obtained results confirmed our hypothesis in full force.

The three key insights were as follows:

1. Hierarchical Attention-Based DNN is More Accurate: As compared to using only neural biomarkers (78.4% accuracy) or social media (71.2%), the use of the proposed Hierarchical Attention-based DNN combining both datasets resulted in achieving a record-high 86.7% (AUC=0.91) purchase intention prediction accuracy.



2. The Concept of Neural-Sentiment Signature is Valid: Attention analysis showed that the best-performing feature combination consisted of an approach motivation brain state characterized by high left frontal alpha asymmetry and recently expressed negative emotions in social media posts. This interesting finding could not be obtained without applying both approaches to one problem.
3. Targeted Marketing Strategy: The above-defined neural-sentiment signature describes a particular "persuadable" consumer segment. Using the A/B test, it was found that this segment responds better to a targeted "counter-attitudinal" message.

The significance of this research is great in terms of future directions for marketing analytics. The research offers guidance on how marketers can go beyond merely targeting consumers based on demographics or even psychographics and move towards neuro-sentiment segmentation through the use of scalable social media data as an indicator of underlying consumer conditions. For the marketer, this translates into increased return on investment in advertisements. For scholars, it creates an entirely new domain called "computational consumer neuroscience."

#### Limitations and Future Research:

Firstly, the sample size (n=250) used was large for a neuromarketing experiment, yet insufficient for deep learning applications. Second, the model was developed under the constraints of one particular cultural context (North America). The social media data included only publicly available information from two platforms.

Future work will include:

4. Model Scaling: Applying transfer learning to tailor the model for different markets where fewer neuromarketing samples are available.
  5. Real-time Forecasting: Creating a more streamlined version of the model capable of forecasting purchasing intent based on the neuromarketing signals derived from the user's social media feed in real time.
6. Causal Modeling: Progressing from correlation analysis to causal analysis by designing marketing campaigns using neuromarketing data to trigger the brain state responsible for preference.

In summary, we have demonstrated that by integrating the "EEG lab" with the "social media feed," the previously hidden motivations behind consumer decision-making and behavior become decipherable.

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