EEG-Based Price Sensitivity Analysis Using Machine Learning: A Neuromarketing Approach

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***Abstract*—This paper presents a novel approach to analyzing consumer price sensitivity using electroencephalography (EEG) signals. By leveraging EEG data recorded during exposure to product pricing stimuli, band power features are extracted from multiple brain regions. These features are then used to train machine learning models capable of classifying purchase intent. Our findings demonstrate the relevance of EEG in capturing cognitive patterns associated with pricing decisions and offer a foundation for enhanced consumer analytics through brain-computer interfaces.**

***Index Terms*—EEG, price sensitivity, machine learning, neuroeconomics, XGBoost, band power, brain-computer interface (BCI)**

I. Introduction

Consumer purchase decisions are influenced by a complex interplay of cognitive and emotional factors, many of which are not observable through traditional surveys or behavioral analysis. The emerging field of neuromarketing integrates neuroscience tools into consumer research to understand underlying cognitive processes. Electroencephalography (EEG), a non-invasive technique to record brain signals, offers real-time insight into neural activity associated with valuation, attention, and decision-making.

In this study, we introduce a model for price sensitivity analysis using EEG data. Participants were exposed to product-price combinations while their EEG signals were recorded. Purchase decisions were labeled based on user interaction within a defined time window. We explore how specific brain regions and frequency bands relate to economic choices.

II. Related Work

Prior work in neuromarketing has applied EEG to evaluate consumer attention, brand preference, and emotional response. However, few studies have directly targeted price sensitivity. Our approach builds upon foundational research such as NeuMa – a neuromarketing dataset designed to understand consumer behavior through physiological data. We extend these concepts by focusing on pricing decisions using EEG band power classification.

III. Methodology

A. Data Collection

EEG recordings were collected from 44 participants using a 24-channel EEG system. During each trial, participants viewed product images and associated prices. Simultaneously, EEG signals and behavioral click responses were captured in XDF format.

Fig. 1. Filtered EEG signal from participant S01 across all 24 channels. (Bandpass: 1–40 Hz, 10-second window)

B. Preprocessing

The EEG data was processed using a bandpass filter (1–40 Hz) and a 50 Hz notch filter to eliminate line noise. From each stimulus event, a 15-second window was extracted. The signal was then decomposed into standard frequency bands:

- **Alpha (8–12 Hz)** – associated with relaxed wakefulness and internal processing
- **Beta (13–30 Hz)** – linked to active thinking, decision-making, and motor responses
- **Gamma (30–45 Hz)** – often involved in higher cognitive functions and sensory integration

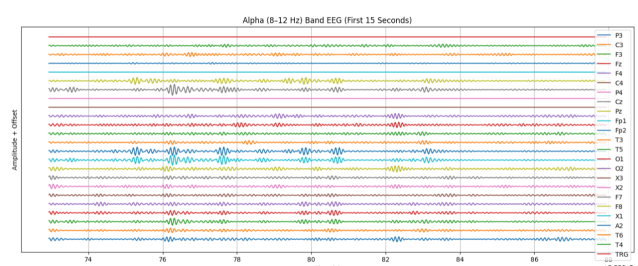

Fig. 2. Alpha Band EEG (8–12 Hz) from participant S01 for first 15 seconds.

C. Input and Output Labeling

For every trial, the input to the machine learning model was the set of features derived from EEG data — specifically, the mean band power of Alpha, Beta, and Gamma frequencies across a selected set of EEG channels. These features represent neural activity correlated with cognitive and emotional engagement with the pricing stimulus.

The output label (i.e., the ground truth) was defined based on behavioral interaction. If the participant clicked the mouse button within 15 seconds of viewing a product-price combination, it was labeled as a "Buy" decision (label = 1). If no click was recorded during the 15-second window, it was labeled as "No Buy" (label = 0). This binary classification allows the model to learn associations between brain activity and the decision to purchase.

D. Channel Grouping and Subsets

EEG channels were grouped by brain lobes:

- **Frontal**: Fp1, Fp2, F3, F4, Fz, F7, F8 – associated with reasoning, attention, and planning
- **Temporal**: T3, T4, T5, T6 – involved in memory and emotional processing
- **Parietal**: P3, P4, Pz – spatial awareness and sensory integration
- **Occipital**: O1, O2 – visual processing
- **Central**: C3, C4, Cz – motor control and sensorimotor integration

Based on these lobes, we defined subsets:

- Subset 1: Frontal Only (7 channels)
- Subset 2: Frontal + Parietal (8 channels)
- Subset 3: Frontal + Central + Parietal (10 channels)
- Subset 4: Frontal + Temporal + Parietal (12 channels)
- Subset 5: Parietal + Occipital (5 channels)
- Subset 6: All Lobes (21 channels)
- Full: All 24 channels (including additional electrodes such as A2, TRG)

E. Feature Engineering

Band power was computed for Alpha, Beta, and Gamma bands across each selected channel. For example, Subset 4 produced 36 features (12 channels × 3 bands), capturing neural oscillatory energy that correlates with cognitive states relevant to decision-making.

F. Model Training

The supervised learning task was framed as a binary classification problem. The input matrix $\mathbf{X}$ consisted of engineered EEG features — specifically, mean band power values (Alpha, Beta, Gamma) for each selected EEG channel. For example, Subset 4 resulted in 36 features (12 channels $\times$ 3 frequency bands). The output vector $\mathbf{y}$ consisted of binary labels: `1` for "Buy" and `0` for "No Buy", derived from the user's mouse-click behavior.

Among many possible classifiers (e.g., logistic regression, SVM, decision trees), we selected XGBoost due to its:

- Proven performance on tabular data with mixed feature importance
- Built-in regularization to prevent overfitting in high-dimensional spaces
- Ability to handle imbalanced classes and nonlinear interactions efficiently
- Support for parallel training and hyperparameter tuning

We used GridSearchCV for hyperparameter optimization with 3-fold cross-validation. The final tuned parameters were:

- `n_estimators = 150` (number of trees)
- `max_depth = 5` (controls complexity)
- `learning_rate = 0.1`
- `subsample = 0.8` and `colsample_bytree = 0.8` for feature and data sampling

The data was split into 70% training and 30% testing using a stratified approach to preserve the class distribution.

G. Evaluation

The model was evaluated on Accuracy, Precision, Recall, and F1 Score to ensure performance balance.

IV. Results and Discussion

TABLE I
PERFORMANCE COMPARISON ACROSS EEG CHANNEL SUBSETS

ID	Subset	Ch	Acc	Prec	Rec	F1
1	Frontal Only	7	0.6200	0.6119	0.5694	0.5899
2	Frontal + Parietal	8	0.6200	0.6119	0.5694	0.5899
3	Frontal + Central + Parietal	10	0.6333	0.6232	0.5972	0.6099
4	Frontal + Temporal + Parietal	12	**0.6733**	**0.6769**	0.6111	**0.6423**
5	Parietal + Occipital	5	0.6667	0.6486	**0.6667**	0.6575
6	All Lobes	21	0.6467	0.6338	0.6250	0.6294
F	Full 24 Channels	24	0.5800	0.5672	0.5278	0.5468

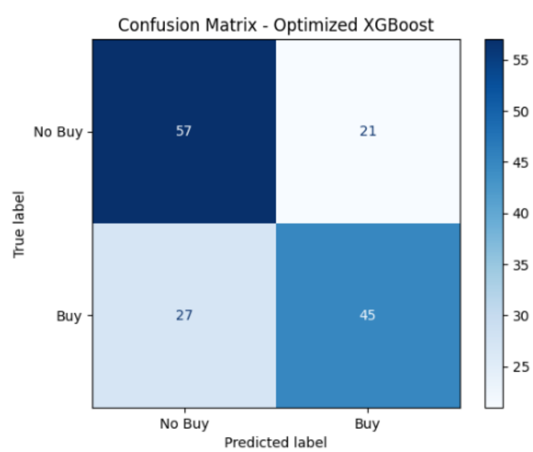

Fig. 3. Confusion matrix of the optimized XGBoost model using Subset 4. Channels used: Fp1, Fp2, F3, F4, Fz, T3, T4, T5, T6, P3, P4, Pz. These regions are responsible for logical reasoning (frontal), emotional and memory integration (temporal), and evaluative processing (parietal), making this subset ideal for modeling purchase decisions.

The **ROC (Receiver Operating Characteristic) curve** above visualizes the trade-off between the true positive rate and false positive rate for different decision thresholds. The AUC (Area Under Curve) value of 0.75 suggests that the model has a strong ability to distinguish between buying

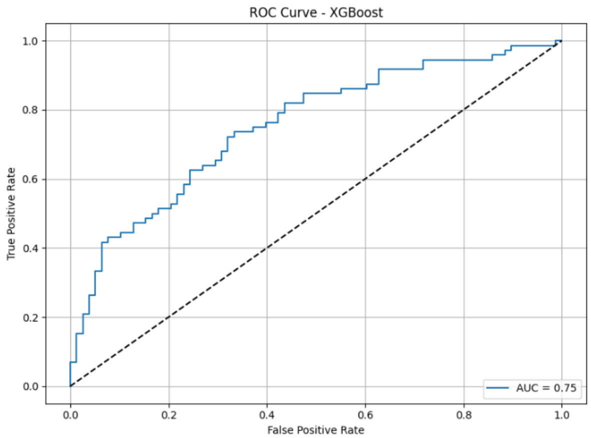

Fig. 4. ROC Curve of the XGBoost model trained on Subset 4. The area under the curve (AUC) is 0.75, indicating a good balance between sensitivity and specificity in classifying buy versus no-buy decisions.

and non-buying behavior. Future improvements in model performance could be achieved by incorporating more subject-specific data, increasing sample diversity, or using hybrid deep learning approaches.

V. Future Work

Two promising directions for future research emerge from this study:

1. Regression-Based Scoring Model: Instead of binary classification, future models could predict a continuous "purchase intent score" (e.g., 1 to 10) based on EEG responses and response time. A quick click with high EEG engagement could correspond to a higher score, while delayed or no clicks with low engagement may indicate low appeal. Such scores would help brands distinguish between products that are inherently appealing and those that need refinement.

2. Brand Familiarity and Price Diagnostics: A second approach involves using EEG responses to well-known popular brands at different price points to build a neural benchmark. When a new product elicits EEG patterns similar to popular products but results in no purchase, it can be inferred that price — rather than product appeal — is the limiting factor. This enables a more targeted adjustment of pricing strategy without altering the core offering.

VI. Conclusion

This research illustrates how EEG signals can be used to predict consumer price sensitivity using machine learning. By analyzing band-specific neural responses from targeted brain regions, we identified a subset of electrodes that optimally reflect decision-related activity. Subset 4, encompassing frontal, temporal, and parietal lobes, demonstrated superior performance among various channel configurations.

Beyond simple classification, this approach can assist in assessing product-market fit. By testing new products on participants and analyzing their EEG responses, companies can determine whether the product evokes engagement and buying intent. If a product fails to trigger the neural patterns associated with purchase decisions—even without a click—it may lack appeal. Conversely, strong EEG activity but no purchase could point to pricing as the issue, guiding more precise product or pricing strategy revisions. This EEG-driven framework offers a powerful tool for data-informed product development in neuromarketing.

References

[1] NeuMa Dataset: "NeuMa - the absolute Neuromarketing dataset en route to an holistic understanding of consumer behaviour," 2023.