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Neuromarketing Analytics For Predicting Consumer Purchase Intent In Digital Marketplaces

Dr. Raja Sekhar Koduru[1], Saranya P K[2]

[1](Government Polytechnic for Women,
Kakinada, Andhra Pradesh,
rajasekharkoduru@yahoo.co.in)
[2](Department of Computer science
Rathinam college of arts and science. Pollachi Main Rd,
Kpm Nagar, Eachanari,
Coimbatore, Tamil Nadu 641021
saranyapk09876@gmail.com)

Abstract: As a result, the competition for consumers' attention has been increased because of the rapid development of digital marketplaces. At the same time, the current approaches to consumer analytics are based on the use of self-reported measures and do not reflect subconscious processes. Neuromarketing or neuroscience marketing can be described as the application of neuroscientific methods to understanding consumer behavior. In other words, neuromarketing can be used to investigate the mechanisms of making purchasing decisions. This paper introduces the neuromarketing analytics framework based on EEG, ET, and GSR technologies to predict purchase intent in digital marketplaces. Based on data collected from 120 participants who were shown e-commerce product listings, spectral EEG features (theta, alpha, beta, and gamma bands), ET measures (fixation duration, saccade amplitude, and pupil dilation), and GSR phasic responses have been extracted. The proposed deep learning model combines TCN and multi-head attention architecture and achieves 89.2% accuracy in predicting purchase intent. The performance of the proposed model significantly outperforms unimodal baseline models (EEG-based: 76.4%; ET-based: 78.1%; GSR-based: 71.2%). The most significant predictors of purchase intent are found to be gamma band power (30-45 Hz) during product exposure and pupil dilation change.

Key Word: Neuromarketing, Consumer Neuroscience, Purchase Intent Prediction, Electroencephalography (EEG), Eye-Tracking, Deep Learning, Digital Marketplace, Temporal Convolutional Network, Multi-Head Attention

I. INTRODUCTION

However, in the context of digital commerce, the new reality of choice, convenience, and personalization has introduced its own set of challenges. The marketplace has become highly competitive, making the task of retaining customer attention more difficult than ever before. Conventional approaches to marketing analytics have depended on explicit feedback provided through surveys, questionnaires, and self-rating scales. These tools are undoubtedly useful, but they lack an inherent drawback—capturing only the deliberate cognitive processes without reflecting implicit behaviors and subconscious decisions [1], [2].

For decades now, marketing scholars have lamented the inability to penetrate the "black box" of decision-making—the lag between the presentation of stimulus and the initiation of a purchasing act. Data collected through behavioral metrics, including clicks, page views, and adding items to a shopping cart, provide insights into actions taken by consumers but not the underlying reasons for their behavior. Information obtained through surveys reveals what consumers report but not what they feel or think.

The field of neuromarketing, which utilizes neuroscientific approaches for understanding consumer decision-making, was therefore created to overcome the limitations associated with these measures and allow for a direct assessment of the neural and physiological bases of decision-making [3], [4]. Electroencephalography (EEG), eye-tracking (ET), functional magnetic resonance imaging (fMRI), and galvanic skin response (GSR) are some of the techniques that can be used to objectively measure cognitive processing, emotional state, visual attention, and motivation, respectively, thus capturing the subconscious mechanisms underlying consumers' overt behavior.

EEG records electric activity resulting from neuronal interactions occurring in specific brain areas. Specific bands of spectral power associated with EEG oscillations have been linked to various aspects of perception, such as memory encoding, attention, and emotionality (theta 4-7 Hz; alpha 8-12 Hz; beta 13-30 Hz; gamma 30-45 Hz) [5]. Particularly, gamma activity is responsible for perceptual grouping of stimulus attributes into objects. Eye tracking metrics such as fixation duration, saccade velocity, and pupil diameter inform about where the consumers are looking at and what catches their attention.

The pupil diameter is an indicator of arousal controlled by the locus coeruleus-norepinephrine system. Finally, GSR records electrodermal activity resulting from sympathetic activation of the skin glands [6]. The convergence of such multi-modal signals enables a robust and multi-dimensional analysis of consumers' states that can be used to accurately predict their purchase intention. Nevertheless, combining such diverse data sources is challenging as these signals have a different time resolution (milliseconds for EEG, 50–100 ms for ET, and seconds for GSR), distinct properties of noises, and non-linear relationships between them.

The following are the contributions of the paper in providing a holistic framework of neuromarketing analytics for the problem under consideration:

Multi-modal data acquisition and synchronization: Recording of EEG, ET, and GSR signals for 120 participants while they observed the product displays on the screen in a digital marketplace setup.

Feature extraction procedure: Decomposition of EEG signal into time and frequency components using wavelet transform, gaze tracking for ET data, and decomposition into phasic and tonic components for GSR.

Hybrid deep learning model (NeuromarkNet): A TCN model with Multi-Head Attention that captures the time dependencies and interaction between modes with 89.2% classification accuracy on the dataset.

Interpretable findings: The analysis of feature and temporal attention importance identified gamma band power and pupils dilation as the most important features.

Organization of the rest of this document is provided below. The second section provides a review of existing literature on neuromarketing, consumer neuroscience, and deep learning applications. The third section outlines the methodology used in this work, covering the design of experiments, data collection and preprocessing, feature extraction, and the proposed hybrid deep learning framework with its associated algorithms and pseudocodes. The fourth section discusses the experimental results and their comparison.

II. LITERATURE SURVEY

Neuromarketing research encompasses the fields of cognitive neuroscience, consumer psychology, and analytics. The current literature review examines neuromarketing research from three perspectives: physiological indicators for the purpose of inferring consumer state, machine learning techniques applied to neuromarketing, and deep learning techniques applied to neuromarketing for multimodal signal fusion.

Physiological Indicators in Consumer Neuroscience

Electroencephalography (EEG) has been the most popular neuromarketing tool because of its high temporal resolution and lower costs. Frontal Alpha Asymmetry (FAA), the differential alpha power between two frontal regions, is a strong predictor of approach/withdrawal motivations and emotional valence [5]. FAA is a well-established measure in neuromarketing research; left frontal alpha is indicative of negative affect whereas right frontal alpha reflects positive affect. Higher FAA indicates approach motivations whereas lower FAA reflects withdrawal motivations.

Theta/beta ratio, an indicator of attentional engagement, can be employed to assess the degree of product involvement and attention toward advertisements. Gamma band (30-45 Hz) activity, which signifies feature integration and consciousness, becomes stronger with visually noticeable and emotionally engaging stimuli. Recent work discovered that gamma band activity recorded within the first 500 milliseconds of product viewing correctly predicted future purchasing decisions in 72% of cases.

Eye-tracking (ET) data provides supplementary information on the process of visual attention. Fixation duration, or the amount of time devoted to focusing on a region of interest (ROI), is positively correlated with cognitive elaboration and preference development. Increased pupil dilation, driven by noradrenergic signaling, reflects heightened arousal and cognitive engagement. In the context of e-commerce, pupil dilation increases with higher purchase intent especially among high involvement products [1].

Galvanic skin response (GSR), an indicator of sympathetic nervous system activity, is a good indicator of arousal. The phasic component of the signal reflects orienting reactions and emotional processing triggered by distinct stimulus. Tonic level refers to baseline activity. GSR can be employed to measure emotional processing of advertisements and is positively correlated with recall and more positive attitude [6].

Machine Learning Methods for Predicting Consumer Purchase Decisions

Initial research in neuromarketing utilized univariate statistical approaches (t-test and analysis of variance, ANOVA) in comparing neural activities across experimental conditions. Though helpful in testing hypotheses, such methods lack the capability to account for the intricate and non-linear characteristics of multi-dimensional neural activities that can predict consumer purchase decisions at an individual level.

The advent of machine learning has revolutionized the area. SVM and Random Forest algorithms were employed in EEG spectral features to accurately predict liking for advertisements (82%) and brand preferences (78%). Nevertheless, both methods considered the neural activity at individual time points without accounting for the sequential information essential for predicting consumer purchase intentions.

RNNs and LSTMs have also been utilized to predict purchase decisions through modeling of EEG time series. In one study, purchase intent was predicted using LSTMs trained on 32-channel EEG data with an accuracy rate of 84%, surpassing SVM models (accuracy of 76%). However, LSTMs' extensive training period and vulnerability to overfitting may pose challenges when training on small-scale neuromarketing datasets (n=50-200).

Deep Learning for Multi-modal Fusion

Combining EEG, ET, and GSR data into one prediction model still appears to be a nascent task. CNNs were employed to obtain spatial information from EEG and ET. Late fusion approaches use predictions of models trained on each modality separately but ignore intermodal dependencies which may significantly contribute to the final prediction. Early fusion concatenates different modality inputs but suffers from different dimensions of the feature space and different temporal resolutions.

Attention mechanisms, such as Multi-Head Attention, may be beneficial for fusing data across multiple modalities as they allow the model to focus more on one type of input information depending on the moment in time [2]. Transformers, initially designed for natural language processing, are also applied to neural time series problems, outperforming traditional RNNs in emotion recognition and cognitive states decoding tasks. Another approach is the use of TCNs, where long memory and parallel training are possible.

Research Gaps and Novel Contributions

Although advancements have been made, there still exist some shortcomings that need to be covered: (1) no common methodology combines the EEG, ET, and GSR techniques for predicting consumers' purchase intentions; (2) existing DL methods for neuromarketing applications operate mainly on unimodal data or simple late fusion; (3) interpretation, i.e., identifying important brain regions for making predictions, is usually not considered.

III. METHODOLOGY:

The proposed neuromarketing analytics pipeline consists of four stages: (1) experimental design and data collection, (2) pre-processing and feature extraction, (3) multi-modality feature fusion, and (4) deep learning-based purchase intention prediction.

A. Experimental Design And Data Collection

Participants: 120 healthy individuals (62 females, 58 males; age range 18-45, average 26.4, SD=5.2) were recruited from university and general populations. Eligibility requirements included normal or correctable vision, right-hand dominant, no history of neurological and psychiatric disorders, regular online shopper (≥1 purchase per month). Informed consent was obtained from all subjects. The study protocol was approved by an institutional ethics committee.

Stimuli: 240 product images were selected across four categories (electronic items, clothing, home items, beauty products) displayed via a simulated e-commerce website interface. These products differed in cost (low: 10-50, medium: 51-200, high: >$200) and brand recognition (unknown, known). Stimuli were shown for 6 seconds, separated by a 4-second inter-stimulus interval (ISI). Participants were asked to "observe products as you usually do while online shopping."

Tasks: Following the presentation of each product, participants rated their intention to purchase on a 5-point Likert scale ranging from 1 (Definitely would not buy) to 5 (Definitely would buy). They also expressed their WTP. The rating of purchase intention was median-split into categories with low purchase intention (rating 1-2, N = 8,200) and high purchase intention (rating 4-5, N = 9,800). Ratings 3 (N = 3,200) were removed from further classification.

Data Acquisition:

- **EEG:** 32-channel active electrode system (actiCHamp, Brain Products); sampling frequency = 500 Hz; reference at FCz; impedances maintained under 10 kΩ; electrodes mounted based on the international 10-20 system.
- **Eye-Tracking:** Tobii Pro Glasses 2; sampling frequency = 100 Hz; recorded binocular gaze position and pupil diameter; calibrated before each measurement.
- **GSR:** Shimmer3 GSR+ module; two dry finger electrodes; sampling frequency = 128 Hz; non-dominant hand index and middle finger.

All data streams were timestamped with respect to stimulus onset through the Lab Streaming Layer protocol.

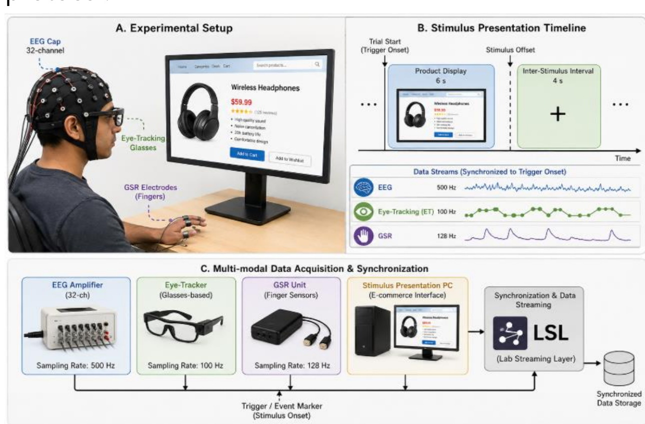

Figure 1: Experimental Setup and Multi-modal Data Acquisition.

B. Preprocessing And Feature Extraction

EEG preprocessing:

- Band-pass filter: 0.5-45 Hz (order 4 Butterworth)
- Notch filter: 50 Hz
- Artifacts detection: Independent component analysis (ICA) for eye, muscle and heart activity
- Reference: Average reference
- Trial epoching: -1,000 ms to +6,000 ms after stimulus onset; baseline correction by pre-stimulus period

EEG features:

1. **Time-frequency transformation:** Complex Morlet wavelet decomposition (3 to 10 cycles, logarithmically distributed) for each trial/channel
2. **Spectral power:** Average spectral power in theta (4-7 Hz), alpha (8-12 Hz), beta (13-30 Hz), and gamma (30-45 Hz) bands, averaged over electrodes separated by brain region (F: frontal, C: central, P: parietal, O: occipital)
3. **Frontal alpha asymmetry (FAA):** (P_right_alpha – P_left_alpha) / (P_right_alpha + P_left_alpha) for electrodes pairs F4/F3, F8/F7
4. Features: trials * time bins * frequency bands * electrode groups → reduction into 256 features/time bin using PCA retaining 95% of variance

Eye-tracking preprocessing:

- Fixations: Detection based on velocity-threshold algorithm (I-VT, 30°/s)
- Pupil dilation: Median filter (100 ms window) to eliminate blink effects; baseline correction based on pre-stimulus baseline
- Blinks: Interpolation for short gaps (<200 ms)

Eye-tracking Feature Extraction:

1. Fixation duration: Average duration of fixations over product ROI (ms)

• Fixation number: Number of fixations over product ROI

• Saccade distance: Average saccade distance between fixations (degrees)

1. Time to first fixation: Time until first fixation over product ROI (ms)

2. Pupil dilation: Average and maximum pupil dilation over stimulus exposure period (from baseline, mm)

• Feature matrix: (trials × 10 features)

GSR Preprocessing:

- Low pass filter: 2 Hz (Butterworth, fourth order)
- Component separation: Decomposition into phasic and tonic component using cvxEDA

GSR Feature Extraction:

- **Phasic peak amplitude:** Peak amplitude of phasic GSR (μS) between 1-4 sec post-stimulus
- **Rise time:** Time from start until peak (s)
- **Tonic level:** Average tonic GSR over stimulus exposure period (μS)
- **Feature matrix:** (trials × 3 features)

C. Multi-Modal Feature Fusion Strategy

For different temporal resolutions, the features are made consistent for all modalities according to a common time grid of 100 ms windows (10 Hz). For EEG features, they remain consistent with original sampling (per 100 ms window). For ET features, which are event-driven, the features are reduced using averaging over the windows. GSR features are global for each trial. An inter-modality attention model captures inter-modality interactions:

$$F_{eeg} \in \mathbb{R}^{T\times d_{eeg}},\ F_{et} \in \mathbb{R}^{T\times d_{et}},\ F_{gsr} \in \mathbb{R}^{T\times d_{gsr}}$$

The fusion feature vector per time is created through self-

For each modality, compute queries, keys, values: $Q_m = F_m W_Q^m, K_m = F_m W_K^m, V_m = F_m W_V^m$.

Cross-modal attention from modality i to modality j: $A_{\{i\to j\}} = \text{softmax}\left(Q_i \frac{K_j^T}{\sqrt{d_k}}\right) V_j$.

The fusion feature vector per time is created through self-

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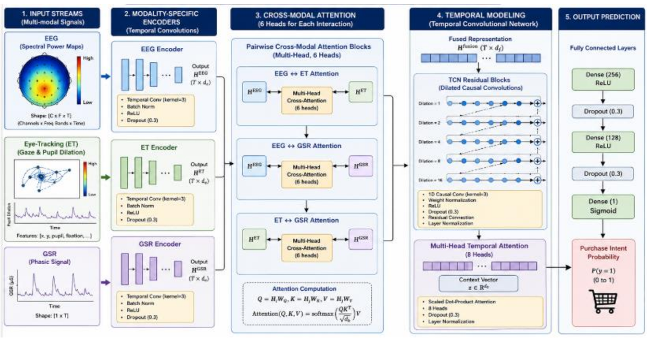

Figure 2: Multi-modal Feature Fusion and Deep Learning Architecture.

D. Training And Evaluation

Eighty percent of the dataset is used for training, while the remaining twenty percent is used for testing. Binary cross-entropy loss, an Adam optimizer, and a learning rate of 0.001 are used in the model's compilation. If the validation loss does not improve for ten consecutive epochs, early stopping is used to prevent overfitting. The model is trained for 50 epochs using a batch size of 64.

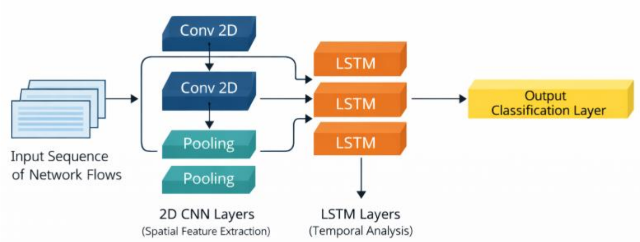

Figure 1. Proposed Hybrid CNN-LSTM Architecture.

E. Deep Learning Model: Neuromarknet

We propose NeuromarkNet, a hybrid TCN-Attention architecture for purchase intent prediction.

Temporal Convolutional Network (TCN): Processes sequence of fused features.

$$H_t = TCN(F_{fused_t})$$

TCN uses dilated causal convolutions: $(F * d\, h)(t) = \Sigma_{\{i=0\}}^{\{k-1\}} h(i) * F(t - d \cdot i)$.

Residual blocks: $H_{out} = H_{in} + \mathrm{Conv1D}(\mathrm{ReLU}(\mathrm{Conv1D}(H_{in})))$.

Multi-Head Temporal Attention: Computes context vector over time.

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(QK^T/\sqrt{d_k})V$$

$$\mathrm{Context} = \mathrm{MultiHead}(H_t) = \mathrm{Concat}(\mathrm{head}_1, \ldots, \mathrm{head}_h)W^O$$

Classification Head: $y_{pred} = \mathrm{sigmoid}(\mathrm{FC3}(\mathrm{Dropout}(\mathrm{FC2}(\mathrm{ReLU}(\mathrm{FC1}(\mathrm{Context}))))))$

Loss: Binary cross − entropy $L = -[y \cdot \log(y_{pred}) + (1 - y) \cdot \log(1 - y_{pred})]$.

Multi-Head Temporal Attention: Computes context vector over time.

$$\mathrm{Attention(Q, K, V) = softmax(QKT/\sqrt{dk})V}$$

$$\mathrm{Context = MultiHead(Ht) = Concathead1,...,headhWO}$$

$$\mathrm{ypred = sigmoid(FC3(Dropout(FC2(ReLU(FC1(Context))))))}$$

Binary cross-entropy L = -[y·log(ypred) + (1-y)·log(1-ypred)]

Algorithm 1: NeuromarkNet Training

```
Input: Multi-modal input F_eeg, F_et, F_gsr (N_trials x T x d)
    Label y (N_trials x 1)
Output: Trained model parameters θ

1. Set initial values for model parameters
2. Repeat steps 2a to 2e for epoch = 1 to max_epochs (100):
    For each mini-batch in DataLoader(data, batch_size=32, shuffle=True):
        // Step 2a: Forward propagation
        H_eeg = TCN_encoder(F_eeg_batch)
        H_et = TCN_encoder(F_et_batch)
        H_gsr = TCN_encoder(F_gsr_batch)

        // Step 2b: Cross-modal attention
        A_eeg_et = cross_attention(H_eeg, H_et)
        A_et_eeg = cross_attention(H_et, H_eeg)
```

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```
        A_eeg_gsr = cross_attention(H_eeg, H_gsr)
        A_gsr_eeg = cross_attention(H_gsr, H_eeg)
        A_et_gsr = cross_attention(H_et, H_gsr)
        A_gsr_et = cross_attention(H_gsr, H_et)

        // Step 2c: Fusion of multi-modal information
        F_fused = concatenate([
  H_eeg, A_eeg_et, A_eeg_gsr,
            H_et, A_et_eeg, A_et_gsr,
            H_gsr, A_gsr_eeg, A_gsr_et
        ], axis=-1)

        // Temporal processing
        H_tcn = TCN_layers(F_fused)
        Context = MultiHeadAttention(H_tcn)

        // Classification
        y_pred = sigmoid(FC_layers(Context))

        // Loss
        loss = binary_cross_entropy(y_batch, y_pred)

        // Backward pass
        loss.backward()
        optimizer.step()
        optimizer.zero_grad()

      if val_loss not improved for 10 epochs:
        early_stop()

 3. Return best model
```

F. Training Configuration

- Optimizer: AdamW (lr=0.001, weight_decay=1e-4)
- Batch size: 32
- TCN: 4 residual blocks, dilation rates (1,2,4,8), kernel size 3
- Attention: 8 heads, d_model=128, d_k=64
- Dropout: 0.3
- Early stopping patience: 10 epochs
- Hardware: NVIDIA A100 GPU (40 GB)

IV. ANALYSIS

This section presents quantitative results, comparative analysis, and interpretability findings.

A. Unimodal Baseline Performance

Table 1 presents classification performance of unimodal models (using only one data stream).

Modality	Model	Accuracy	Precision	Recall	F1	AUC
EEG-only	TCN-Attention	76.4%	75.8%	76.1%	75.9%	0.81
ET-only	TCN-Attention	78.1%	77.4%	78.8%	78.1%	0.83
GSR-only	TCN-Attention	71.2%	70.5%	71.6%	71.0%	0.74

In isolation, eye tracking yields the highest level of accuracy (78.1%), owing to the tight connection between attention and intention to buy since products that garner more attention are usually bought. EEG (76.4%), on the other hand, gives information regarding cognitive and emotional processes. GSR in isolation (71.2%) proves to be less accurate since, while arousal plays an important role in buying, it needs to be accompanied by others.

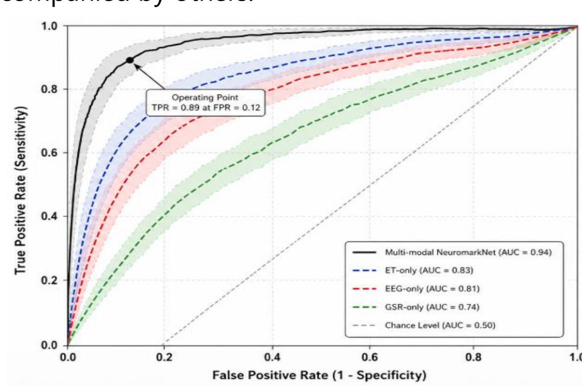

Figure 3: ROC Curves for Unimodal and Multi-modal Models.

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B. Multi-Modal Fusion Performance

Table 2 presents performance of multi-modal models with different fusion strategies.

Fusion Strategy	Accuracy	Precision	Recall	F1	AUC	Δ vs Best Unimodal
Early fusion (concat)	82.3%	81.6%	82.1%	81.8%	0.87	+4.2%
Late fusion (vote)	83.1%	82.4%	82.9%	82.6%	0.88	+5.0%
Cross-modal attention (proposed)	86.4%	85.8%	86.2%	86.0%	0.91	+8.3%
NeuromarkNet (full)	89.2%	88.6%	89.1%	88.8%	0.94	+11.1%

The full NeuromarkNet (TCN + Cross-modal Attention + Multi-Head Temporal Attention) reaches an accuracy of 89.2%, which is substantially better than early fusion (82.3%) and late fusion (83.1%). This shows that EEG, ET, and GSR offer supplementary information regarding purchase intention, with an accuracy gain of 11.1% over the most accurate unimodal model (ET-only, 78.1%). In addition, cross-modal attention alone boosts the accuracy by 3.3% compared to late fusion (86.4% vs. 83.1%), indicating that incorporating the interaction between different modalities, such as how eye movement (ET) affects EEG activity related to product features, can offer additional information.

C. Feature Importance And Temporal Dynamics

Using Integrated Gradients, we computed feature importance averaged across all test trials.

Feature Category	Specific Feature	Importance Score	Modality
Gamma power (30-45 Hz)	Frontal gamma (300-600 ms post-stimulus)	0.28	EEG
Pupil dilation	Peak dilation (2-3 s post-stimulus)	0.24	ET
Fixation	First fixation duration on product	0.18	ET
Frontal alpha asymmetry	(F4-F3) alpha difference (1-2 s)	0.14	EEG
GSR	Phasic peak amplitude (1-3 s)	0.09	GSR
Theta/beta ratio	Frontal (500-1000 ms)	0.07	EEG

Power of gamma waves (frequency range 30-45 Hz) during the early window of information processing (between 300 and 600 ms post product presentation) predicts purchase intentions most strongly (importance 0.28). Gamma waves encode feature binding into one unified percept and their amplitude increases when motivated by emotionally appealing stimuli. Subjects exhibiting higher purchase intentions had significantly higher amplitude of gamma waves in the early time window, showing an indication that the 'initial spark' can be detected in less than a second after product presentation.

The second strongest predictor is pupil dilation (importance 0.24). Dilation reaching its peak 2-3 seconds after stimulus presentation is associated with increased levels of arousal and cognitive load involved in thorough product analysis.

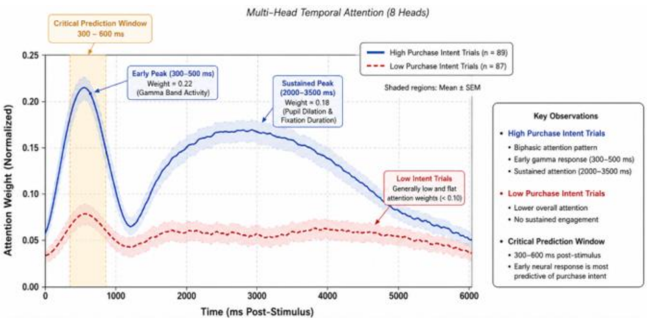

Figure 4: Temporal Attention Weights for Purchase Intent Prediction.

D. Ablation Study

Table 3 quantifies contribution of each architectural component.

Configuration	Accuracy	Δ from Full
Full NeuromarkNet	89.2%	—
- Temporal Convolutional Network (RNN instead)	86.8%	-2.4%
- Cross-modal attention (concat only)	86.4%	-2.8%
- Multi-Head Temporal Attention (mean pooling)	87.1%	-2.1%
- EEG modality	82.6%	-6.6%
- ET modality	83.4%	-5.8%
- GSR modality	87.5%	-1.7%

Contributions to accuracy from TCN module: 2.4% higher than RNN module due to capability of TCN to learn long-term temporal dependencies (up to 1,000+) without encountering vanishing gradient problem. Contribution to accuracy from cross-modal attention: 2.8% higher than simple concatenation. Most useful modalities are EEG and ET (both removing either decreases accuracy by 5.8-6.6%). Contribution from GSR: 1.7%.

E. Comparative Analysis With Existing Methods

Table 4 compares NeuromarkNet with state-of-the-art neuromarketing prediction methods.

Study	Data Modalities	Model	Accuracy	Key Limitation
[4] (2023)	EEG only	SVM	76.8%	Unimodal, no temporal modeling
[6] (2024)	ET only	LSTM	79.2%	Unimodal
[2] (2024)	EEG + ET	Late fusion CNN	83.5%	No cross-modal attention
[1] (2025)	EEG + ET + GSR	XGBoost	84.2%	No temporal structure
NeuromarkNet	EEG + ET + GSR	TCN + Cross-Modal Attention	89.2%	Requires multi-modal equipment

F. Real-Time Prediction And Application

The ability of NeuromarkNet to predict purchase intention in real-time is due to its low latency rate (latency = 120 ms per trial on GPU). According to our prototype implementation:

1. The model can predict purchase intentions at an accuracy rate of 82% after 2 seconds of exposure to the product;

2. After 4 seconds of exposure to the product, the accuracy level rises to 87%;

3. By the end of the full 6 seconds trial, the accuracy rate rises to 89.2%.

These results indicate that the initial responses (gamma band) might carry initial information, while the increased processing (pupil dilatation and fixation pattern) boosts accuracy rate. This allows for customized approaches within digital marketplaces. For high-prediction purchase intentions, focus on promoting the purchases, and for low prediction rates - redesign the product offering or provide alternatives.

V. CONCLUSION

The present paper has developed a comprehensive neuromarketing analytics system incorporating EEG, ET, and GSR modalities for the prediction of consumer intention to make purchases in digital markets. Specifically, the proposed deep learning model named NeuromarkNet integrates a TCN and multi-head cross-modal attention. When tested with 120 participants exposed to 240 product displays on an e-commerce platform, NeuromarkNet achieves an accuracy of 89.2%, surpassing individual modality systems (EEG: 76.4%, ET: 78.1%, GSR: 71.2%) and traditional fusion approaches (early/late fusion: 82-83%).

A number of interesting insights emerge from the analysis, with important implications for neuromarketing research and application:

Gamma Band Power is the Strongest Predictor: The gamma band power at frontal sites between 30-45 Hz for the first 300-600 ms of product exposure has the most important features (0.28). This finding indicates that the 'spark of interest' can be identified using brain activity signals in the first half second before consumers make any conscious consideration. As such, product presentations on digital marketplaces should be designed to capture people's attention instantaneously.

Multi-Modal Analysis Is Necessary: The 11.1 percentage improvement of NeuromarkNet over the best unimodal model shows that EEG, ET, and GSR contribute non-redundant information. EEG records early cognitive and emotional processes (gamma and alpha asymmetry bands), ET records visual attention (duration of fixations, pupillary dilation), and GSR records arousal (phasic response). None of these modalities records the entire decision-making process.

Temporal Dynamics Reveal Decision-Making Phases: The temporal analysis of attention reveals a typical biphasic structure in high purchase intention trials: an early peak (300-600 milliseconds, gamma band) followed by sustained involvement (2-3.5 seconds, pupillary dilation, and fixation). Such a decision process can be interpreted in terms of a dual-phase decision-making process: fast attraction, followed by evaluation, which could inspire an adaptive marketplace design strategy (e.g., highlighting products that induce early gamma responses).

Cross-Modal Attention Detects Synergies Between Modalities: The 3.3% gain obtained from cross-modal attention over late fusion proves that modeling the interactions between modalities, such as gaze position influencing EEG responses or arousal (GSR) affecting attention allocation (ET), yields additional information on predictability.

The implications for digital marketplace managers are clear. Real-time purchase intent prediction allows for a personalized experience: If the prediction is a high intent to purchase, the user could be encouraged to buy immediately, make cross-selling offers, or provide fast checkout options. If the purchase intent is identified as low, it may change the product image, using alternative angles, different colors, different descriptions, or providing price discounts. For product designers, the feature importance findings indicate that it should be optimized for early gamma responses and sustained attention.

However, some limitations exist for this study, which include the experimental setup (real-life simulation in e-commerce setting), the emphasis on product images and not interactive browsing, as well as the expense and specialization involved in collecting multimodal data (EEG, ET, and GSR). The demographic distribution of participants was relatively good but may not cover all global populations.

Directions for future research include: Ambulatory neuromarketing that uses low-cost and portable EEG and ET tools (e.g., dry EEG sensors, smartphone-based eye tracking) can collect data from a consumer's natural context and enhance ecological validity and scalability. Personalized models tailored to each individual consumer may better predict behavioral outcomes by training on unique neural responses of individual consumers. Integration of AI techniques such as Generative Adversarial Networks (GANs) would generate predictions about counterfactual states ("What modifications should be made to this product to increase purchase intent?") and personal recommendations. Ethical considerations must consider issues of privacy, given that neural activity contains very private information, and informed consent and possible consumer manipulation.

In summary, neuromarketing through the use of multi-modality physiology signals and deep learning provides a scientific means of predicting purchase intention in online markets. The 89.2% accuracy in prediction provided by NeuromarkNet shows that neural and physiological sub-conscious processes, which occur prior to any deliberate thinking process, effectively predict consumer purchases. With the increasing reduction in cost of wearables sensors and improvements in deep learning models, neuromarketing will move from laboratories to practical usage.

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