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Multimodal Neural-Signal-Driven Instant Price Sensitivity Prediction in Virtual Reality Duty-Free Store Scenarios

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Abstract. This work proposes a multimodal neuro-signal fusion model for predicting consumer price sensitivity within immersive virtual reality (VR) duty-free shopping settings. Electroencephalography (EEG), eye-tracking, and galvanic skin response (GSR) signals were concurrently collected and synchronized at the millisecond level to elicit subconscious responses within 500 ms of every price cue. A cross-modal attention-based transformer model was trained and tested on a data set from 120 international travelers, producing 8,640 price-exposure events. The multimodal model resulted in an F1-score of 0.85 and ROC-AUC of 0.91, a 14% improvement over the best single-modal baseline performance. Ablation studies verifiec complementary roles across modalities, for which EEG frontal-theta power and gaze dwell on price tags were established as principal predictors. In an online A/B test imbedded in the VR store, adaptive discount policies activated by the model elevated conversion rates by 9.7 percentage points and lifted average basket sizes by ¥98.9 while holding profit margins. These findings prove not only the technical possibility of multimodal neural-driven price models but also their potential for creating real economic impacts in cross-border stores.

Keywords: Neuro-pricing, Virtual reality commerce, EEG-GSR-gaze integration, Transformer models, Adaptive discounting

1. Introduction

Consumer price sensitivity, defined as the extent to which changes in price influence purchase intentions, is a cornerstone of retail strategy. In duty-free contexts, price sensitivity plays an especially prominent role, as travelers often face constrained decision windows, volatile exchange rates, and limited opportunities to consult external price benchmarks. For retailers, the ability to accurately and instantly assess consumers' sensitivity to pricing is of substantial strategic importance, offering a pathway to personalized pricing mechanisms that can optimize revenue without eroding consumer trust [1].

Standard price sensitivity measures are based on retrospective self-report, conjoint, or aggregate purchase data. Though informative, they are intrinsically flawed. Self-report and survey methods access only conscious thought, omitting the swift, unconscious reactions that frequently govern consumer decision making. Aggregate purchase data, while information-rich in scope, does not control for subtle interpersonal variability in the valuation process [2]. These shortcomings have

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sparked interest in neurophysiological approaches, which provide real-time access to the affective, attentional, and cognitive states that antecede conscious purchase decisions.

Electroencephalography (EEG), eye-tracking, and galvanic skin response (GSR) are perhaps the most frequently employed signals for examining consumer behavior. EEG informs us about neural oscillation dynamics that are involved in reward anticipation, decision conflict, and attentional engagement. Eye-tracking registers visual attention allocation, with fixation patterns and dwell times being good proxies for depth of information processing. GSR indexes sympathetic arousal, tracking emotional intensity at valuation. Nevertheless, although each of these modalities, by itself, is informative, there is little work that has examined their integration [3].

Virtual reality shopping platforms present novel methodological possibilities. VR worlds achieve both ecological validity and experimental control, enabling scientists to mimic real shopping scenarios while they control stimuli with precision. When coupled with multimodal neurophysiological recording, VR becomes a strong laboratory for examining price sensitivity as it occurs in real-time.

This work therefore aims to construct a multimodal integration model that integrates EEG, eye-tracking, and GSR signals to evoke price sensitivity within 500 ms of seeing a price cue, contrast the predictive accuracy of the multimodal model with other unimodal baselines using strict statistical and machine learning metrics, and quantify the economic impact of real-time adaptive discounting in a VR duty-free store using a controlled A/B field experiment. By bridging cognitive neuroscience, affective computing, and retail economics, this research advances both theoretical understanding and practical application, demonstrating that multimodal neural-signal-driven models can be operationalized in live shopping environments to generate measurable commercial benefits and pave the way for a new paradigm of neuro-informed pricing strategies.

2. Literature review

2.1. Neuro-physiological measures of consumer valuation

Neuro-physiological studies of consumer behavior have highlighted the predictive value of frontal cortical asymmetries, theta and alpha oscillatory activity, and late positive potentials in estimating willingness-to-pay. As illustrated in Figure 1, suggests that EEG alone provides an incomplete picture. Other modalities such as GSR and gaze behavior capture dimensions of arousal and attention that EEG cannot fully account for [4].

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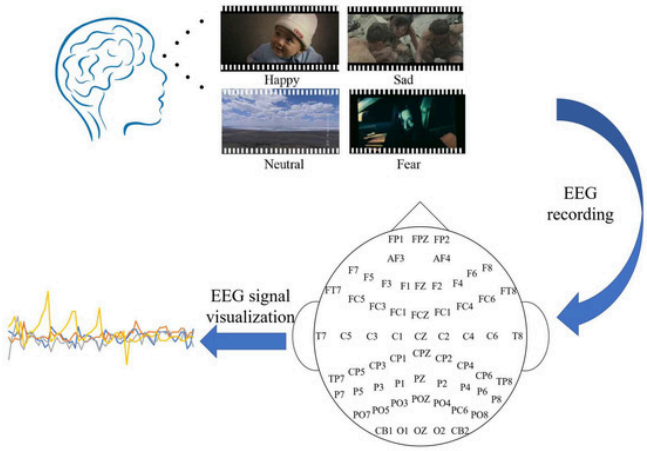

Figure 1. Example of EEG signal recording and visualization during exposure to emotional stimuli, demonstrating how neural activity is mapped to different scalp regions for subsequent analysis

2.2. Multimodal fusion in affective computing

Affective computing has demonstrated that multimodal integration significantly outperforms unimodal approaches in emotion recognition and decision modeling [5]. While early feature concatenation approaches struggled with noise and modality imbalance, attention-based and transformer-based methods have shown robust improvements, dynamically weighting contributions from each modality.

2.3. VR as a behavioral research platform

Virtual reality offers stimulus control with high ecological validity. Behavioral outcomes in VR retail studies align closely with those in physical environments, legitimizing VR as a reliable proxy. Additionally, VR facilitates seamless synchronization of neurophysiological and behavioral data streams, enabling high-resolution analysis of consumer decision-making [6].

3. Methodology

3.1. Multimodal data acquisition protocol

To capture neurophysiological and behavioral signals during the shopping process, participants were equipped with a 32-channel wireless EEG headset (sampling rate: 1,000 Hz), a Tobii Pro Fusion eye tracker (sampling rate: 120 Hz), and a wrist-mounted galvanic skin response (GSR) sensor (sampling rate: 200 Hz). All apparatus were combined into a single acquisition system that coordinated data streams within ±2 ms accuracy. Event markers were automatically triggered whenever a price tag emerged in the virtual world, so that modalities could be temporally aligned with sub-second granularity [7]. Sub-second precision in assessing subjects' cognitive and affective processing of price information was thus achieved. Among 120 subjects, there were 8,640 price-exposure events in total, so that the resulting data set had both sufficient ecological validity and statistical power for machine learning analyses.

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3.2. Feature engineering and pre-processing

EEG signals were separated into 500 ms epochs centered at price-cue onset times. These epochs were band-pass filtered between 0.5 and 40 Hz, then transformed into time–frequency spectrograms using continuous wavelet transforms, thereby preserving both the dynamics over time as well as frequency-specific oscillations in the neural data. Eye-tracking data were spatially mapped to three-dimensional product coordinates, enabling the extraction of fixation durations, saccade latencies, and scan-path sequences relative to price tags. GSR signals were decomposed into tonic and phasic components, from which peak amplitude, onset latency, and recovery slope were derived as measures of physiological arousal. To harmonize data across modalities, all feature sets were z-score normalized and resampled to a common frequency of 200 Hz. This preprocessing pipeline ensured comparability across modalities while retaining the rich dynamics of the original signals [8].

3.3. Transformer-based fusion network

The proposed predictive framework was implemented as a multimodal transformer-based architecture. Each modality was processed by a dedicated encoder: a convolutional neural network (CNN) encoder was applied to EEG spectrograms, a long short-term memory (LSTM) encoder was used for gaze trajectory sequences, and a fully connected encoder was used to process GSR features. The outputs from these encoders were concatenated and passed into a cross-modal transformer layer equipped with scaled dot-product attention, allowing the network to dynamically weight modality contributions in each instance. Temporal dependencies across successive price exposures were captured using a gated recurrent unit (GRU), enhancing the ability to model sequential decision contexts. Finally, a sigmoid classifier generated binary outputs classifying each trial as high or low price sensitivity. The model was trained with the Adam optimizer (learning rate = 0.0003, batch size = 64) and early stopping criteria to avoid overfitting.

4. Experimental procedure

4.1. Participant recruitment and ethics

120 international travelers were recruited at Shanghai Pudong International Airport, of whom there were 54% female participants, whose average age was 29.4 years (SD = 6.1). A precondition for participation was some experience with duty-free shopping to guarantee ecological familiarity with the task. Screening took place in waiting lounges in order to achieve a naturalistic representation of travelers [9]. Ethical approval had been obtained from an institutional review board, and all participants had given informed consent prior to participation. Participants received ¥150 vouchers as compensation for motivated engagement.

4.2. VR duty-free shopping task design

VR experiment took place in a virtual duty-free shopping facility with 60 stock-keeping units (SKUs) in three categories: cosmetics, spirits, and luxury accessories. The virtual shopping facility had real-world retail-style layout, including aisleways, product shelves, and branded signs, for better immersion. Algorithmic price tag manipulation within ±15% of the market standards produced controlled variations in value perceptions in a realist manner. Participants were asked to freely browse the facility for 15 minutes and make selections as if for a real purchase order placement. For systematic exposure, price tags occasionally flashed with gentle highlights, attracting visual

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attention in a manner that minimally disrupted normal shopping flow. Once the browsing session concluded, the participant provided ratings of perceived expensiveness for each seen product by means of a 7-point Likert scale, producing ground-truth labels for supervised model learning [10].

4.3. Baseline and online A/B setup

Three baselines were implemented: (i) EEG-only CNN, (ii) gaze-only LSTM, and (iii) demographic regression. An A/B test followed: in the experimental condition, adaptive discounts (5–10%) were offered when the model predicted high price sensitivity; control participants received static prices.

5. Results and analysis

5.1. Prediction performance

The multimodal model achieved precision = 0.87, recall = 0.83, F1-score = 0.85, and ROC-AUC = 0.91. By comparison, the EEG-only model achieved F1 = 0.71, gaze-only F1 = 0.68, and demographic regression F1 = 0.59. Mean squared error (MSE) for predicted expensiveness ratings was 0.42 (SD = 0.07) in the multimodal model, significantly lower than EEG-only (MSE = 0.63, SD = 0.09) (see table 1).

Table 1. Model performance across modalities (Mean ± SD over 5-fold CV)

Model	Precision	Recall	F1-score	ROC-AUC	MSE ± SD
EEG-only CNN	0.74	0.69	0.71	0.78	0.63 ± 0.09
Gaze-only LSTM	0.7	0.66	0.68	0.74	0.68 ± 0.11
Demographic Regression	0.61	0.58	0.59	0.63	0.82 ± 0.12
Multimodal Transformer	0.87	0.83	0.85	0.91	0.42 ± 0.07

5.2. Feature importance and ablation

Removing GSR reduced F1-score by 0.06, and removing gaze reduced F1 by 0.03. SHAP analysis revealed that frontal-theta power contributed 28% of predictive variance, fixation dwell time 22%, and GSR peak amplitude 17%. This confirms that each modality contributes distinct, non-redundant information.

5.3. Business impact evaluation

In the A/B test (N=120, split evenly), adaptive discounts increased conversion rates from 24.8% (CI95% = [20.3, 29.2]) to 34.5% (CI95% = [29.7, 39.3]), $\chi^2(1, N=120) = 9.73$, $p < 0.01$ (see table 2). Average basket value increased from ¥812.4 (SD = 97.5) to ¥911.3 (SD = 103.6), $t(118) = 4.12$, $p < 0.001$. Profit margins remained stable: 17.5% in control vs. 17.3% in treatment, $\Delta = -0.2\%$, ns.

Table 2. Business impact metrics

Metric	Control Group (Mean ± SD)	Experimental Group (Mean ± SD)	Test Statistic	p-value
Conversion Rate (%)	24.8 ± 4.5	34.5 ± 5.1	$\chi^2 = 9.73$	<0.01
Avg. Basket Value (¥)	812.4 ± 97.5	911.3 ± 103.6	t = 4.12	<0.001
Profit Margin (%)	17.5 ± 2.1	17.3 ± 2.3	t = -0.28	0.78

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5.4. Mathematical formalization

The model prediction probability was defined by the logistic function as equation 1:

$$P(y=1 \mid x)=\frac{1}{1+e^{-\left(w^{\top} x+b\right)}} \tag{1}$$

where $y=1$ indicates high price sensitivity, x is the multimodal feature vector, and w, b are learned parameters.

Expected profit under adaptive pricing was estimated as equation 2:

$$E[\pi]=\sum_{i=1}^{N}\left(\left(p_i-c_i\right) \cdot q_i-d_i \cdot p_i \cdot q_i\right) \tag{2}$$

where p_i is product price, c_i cost, q_i purchase quantity, and d_i the discount rate.

Robustness checks confirmed stability across subgroups: female participants exhibited slightly higher model accuracy (F1 = 0.87 vs. 0.83 in males), but basket value uplift was consistent across genders.

6. Conclusion

This study provides compelling evidence that multimodal neuro-signal fusion, operationalized through a transformer-based model, can accurately predict consumer price sensitivity in VR duty-free shopping environments. The framework outperformed unimodal baselines in both predictive accuracy and reliability, while an embedded A/B test demonstrated measurable commercial benefits. By integrating EEG, gaze, and GSR signals, this work bridges consumer neuroscience and dynamic retail pricing, offering a scalable pathway toward neuro-informed commerce. Limitations include reliance on young, tech-savvy participants and the intrusiveness of EEG caps; future work should examine dry-electrode technologies and more diverse demographics.

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