Master of Science in Technology and Creative Innovation (MSTCI)

Capstone Project - Semester 2 Report

NeuroRight

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Executive Summary

NeuroRight is a neuromarketing service that replaces opinion-driven creative and media decisions with direct neural and behavioral evidence. This semester (Aug–Dec 2025), the team moved from concept to a working multimodal prototype combining 8-channel EEG, webcam-based facial analysis, and low-cost eye-tracking to quantify three marketer-ready outputs: attention, emotional engagement, and preference. A full experimental workflow was implemented using Unicorn Hybrid Black EEG, PsychoPy stimulus presentation, OBS-based video capture, and synchronized data streams, alongside preprocessing pipelines in MNE (filtering, ICA, bad-channel handling) for both ERP and non-ERP paradigms. Pilot ERP experiments showed that the system could correctly rank the most-liked image with ~85.7% top-1 accuracy, while non-ERP classifiers using SVM and carefully selected time/frequency/time–frequency features achieved 100% accuracy for affective attitude and 97.2% for purchase intention. On the video side, a Random Forest model trained on OpenFace facial action units reached 96% accuracy in distinguishing liked vs. disliked posters, and modern FER models (AA-DCN and ViT) fine-tuned on large emotion datasets delivered robust 7-class emotion recognition suitable for real-world stimuli. The webcam eye-tracking calibration pipeline attained an R^2 of ~0.92 and ~112 px RMSE (≈93 px on validation), within accepted ranges for AOI-level analysis in online neuromarketing. In parallel, the team completed a deep market and strategy analysis positioning NeuroRight in Thailand's growing neuromarketing and OOH/DOOH research space. The report sizes a Thai neuromarketing opportunity in the low-million USD range within a global market projected to more than double by 2033, identifies FMCG and telecom advertisers plus agencies and media owners as priority customers, and highlights a clear gap for a Thailand-focused EEG provider working in Thai language and formats. A phased business model was defined (low-

margin validation partnerships followed by paid studies and, longer term, a NeuroScore-style dashboard), along with concrete Semester-3 objectives: achieve ≥90% data-quality pass rate and ≤7-day turnaround per study, deliver at least one client-style report, publish pricing and a basic web presence, secure 1–2 LOIs, and operate under "ethics by design" aligned with PDPA and UNESCO principles using IRB-ready protocols and governance checklists. Together, these technical, market, and governance milestones make NeuroRight credibly pilot-ready and set a clear roadmap toward a scalable, ethical neuromarketing measurement layer for Thai OOH/DOOH and beyond.

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PART 1: Project Information

1.1 Project Overview

Project Summary

NeuroRight is a neuromarketing service that helps brands, agencies, and OOH/DOOH media owners replace guesswork with direct neural evidence. In short, participants view ads while wearing a lightweight EEG headset; our pipeline cleans the signal, extracts validated features and converts moment-by-moment brain activity into three marketer-ready outputs—attention, emotional engagement, and personal preference—summarized in a concise, decision-oriented report. Optional webcam-based eye-tracking adds visual-attention context without increasing participant burden. We start with billboard effectiveness in Thailand, where OOH/DOOH budgets and measurement gaps make a strong early market, and expand to digital video and in-store stimuli as we build benchmarks.

From day one, operations are designed with ethical compliance: clear consent, data minimization, de-identification, purpose limitation, and auditable governance. Delivery emphasizes speed and clarity—executive scores and heat-mapped "engagement timelines," plus practical guidance on edits points, messaging, and placement. Our near-term focus is pilot readiness (secure equipment and partners, recruit 20–30 participants per study and deliver at least one client-style report with feedback), building toward a repeatable service and a growing benchmark database. Longer term, we aim to produce the workflow into a subscription layer with dashboards, norms by category/format, and API hooks for planning tools. By translating human feelings into reliable numbers—ethically and affordably—NeuroRight helps marketers choose stronger creative, improve it with precision, and prove ROI to stakeholders.

Problem. Marketers repeatedly told us they want to uncover the real reasons customers choose their product—whether it's price, promotion, pack shape, colours, trust, social proof, or deeper emotional triggers—because current tools only show what happened (e.g., sales went up) rather than why, making it hard to repeat wins or fix failures. This aligns with broader FMCG research showing that decisions depend on psychological and emotional factors (values, lifestyle, perception, emotional connection) in addition to price and quality. Yet in Thailand, creative and media decisions still rely heavily on guesswork, opinions, and dated focus groups, even though traditional surveys capture only about 64.4% of true consumer response, versus ~87.1% for neuroscientific methods—despite Thai organizations already investing THB 420–700 million per year in advanced OOH effectiveness research.

Mission

Our mission is to turn human feelings into actionable numbers—ethically, rigorously, and fast. We exist to help marketers make smarter creative and media decisions using evidence that reflects how people respond, not just what they say. To do this, we commit to four pillars:

1. Scientific rigor. We use validated EEG metrics and transparent analyses, documenting assumptions, quality controls, and limitations in plain language.
2. Ethics by design. We uphold PDPA and UNESCO AI principles: informed consent, data minimization, de-identification, purpose limitation, and participant rights, with clear opt-out paths and secure handling from capture to archive.
3. Clarity for action. Insights must be usable. We provide concise scores, engagement timelines, and concrete edit/playout recommendations so teams can decide in minutes, not weeks.
4. Access and speed. We deliver studies that are affordable and timely for real-world cycles—pilot within days, results within a week where feasible—so evidence becomes a routine part of creative workflows, not a luxury add-on.

Rooted in Thailand and built for Southeast Asia, we partner with brands, agencies, and media owners to raise the bar for trustworthy, brain-informed marketing—improving outcomes for advertisers and experiences for audiences.

Vision

We envision a future where brain-informed evidence is a standard input to creative and media decisions across Southeast Asia. In three to five years, NeuroRight will operate as a trusted measurement layer that plugs into common planning and production tools, offering:

- Benchmarks and norms by category, format, and placement so teams can compare new work to established standards.
- Always-on dashboards that track attention, emotional engagement, and preference across campaigns, creative versions, and markets, with alerts when performance drifts.
- Workflow integrations (APIs and templates) that bring neural insights into briefing, concept screening, pre-flight checks, and post-buy optimization.
- An ethical data commons, where de-identified signals contribute to shared norms under strict governance, consent, and review.

As the product matures, we will extend from OOH/DOOH to digital video, social, retail, and experiential, enabling consistent metrics across the consumer journey. Our vision also includes capability-building: training marketers to interpret neural evidence responsibly and creators to design with attention and emotion in mind. Success means more effective campaigns, less wasted spending, and a healthier, more respectful relationship between brands and audiences—where privacy, transparency, and real human response are not trade-offs but foundations. From Bangkok outward, NeuroRight aspires to set the regional standard for fast, ethical, and useful neuromarketing.

1.2 Market Analysis

Market size & growth. Globally, neuromarketing is an emerging but rapidly growing field, valued at about USD 1.6–1.7B in 2024 and projected to reach USD 3.4–3.8B by 2033 (≈8–9% CAGR). The Asia–Pacific region is the fastest-growing segment, with an estimated neuromarketing market of ≈USD 490M in 2025 and ~13.7% CAGR going forward. Within this landscape, Thailand's total advertising spend is around USD 4.25B. Even at a conservative 0.1–0.3% neuromarketing penetration, this implies a Thai neuromarketing opportunity of ≈USD 4–12.8M per year. A large share of this spend is concentrated in FMCG and telecom, which already invest heavily in creative testing and brand tracking.

Market Analysis. The TAM is the global neuromarketing market for advertising and shopper research; the SAM is the Asia–Pacific neuromarketing market, where adoption and growth are highest; and the SOM is the Thai neuromarketing segment, focused initially on FMCG and telecom marketers who already use advanced research. Even capturing a modest share of this SOM with a focused EEG-based service would support a sustainable, growing business.

Priority customers & sectors. Priority buyers are Thai FMCG brands, telecom operators, banks, creative agencies (e.g., BBDO, Dentsu X, Ogilvy), and OOH/DOOH media owners (VGI, Plan B, JCDecaux). FMCG is the natural beachhead: it is one of the largest ad-spending sectors in Thailand, with constant product launches and heavy creative rotation. Within FMCG, high-growth, highly visual categories such as skincare (+22% YoY), non-alcoholic beverages (+80% YoY), cosmetics (~฿2.2B), and dairy (~฿2.38B, +17% YoY) are especially attractive, because even small gains in attention and emotional engagement can translate into meaningful sales lift. These brands already work closely with major agencies and media owners, creating clear paths for collaboration.

Trends enabling entry. Current research tools—surveys, focus groups, A/B tests, and digital analytics—tell teams what happened but rarely why a creative worked or failed. At the same time, neuromarketing in Asia–Pacific is one of the fastest-growing segments globally, and Thai FMCG categories are becoming increasingly crowded and competitive. This combination of insight gaps, rising complexity, and growing openness to advanced analytics creates strong demand for methods that can reveal subconscious drivers of attention, emotion, and preference.

Competitive landscape. International neuromarketing providers such as Neurensics, Neurons, and Unravel have already demonstrated that EEG-based and eye-tracking-based testing can influence creative and media decisions and deliver measurable ROI. However, Thailand currently lacks a dedicated, locally focused EEG neuromarketing provider that works in Thai language, with Thai consumers, and on Thai media formats. This absence opens a first-mover opportunity for a service specializing in ad and shopper research for the Thai market.

Industry structure (Porter). Supplier power is low: there are multiple EEG hardware vendors and a growing ecosystem of software and open-source tools. Buyer power is medium–high, since advertisers can continue relying on conventional research if neuromarketing appears too complex or expensive. The threat of new entrants is moderate—technology is increasingly accessible, but building trust, know-how, and a Thai neuro-dataset takes time. Substitutes such as surveys, focus groups, and pure eye-tracking remain strong, yet EEG-driven neuromarketing differentiates itself by accessing subconscious responses that traditional methods miss.

Pricing benchmarks & positioning. A two-phase commercial model fits these conditions. In Phase 1 (validation partnerships), NeuroRight runs low-cost or co-created pilots in which brands contribute real creatives and access to consumers, and NeuroRight provides EEG testing and analysis—trading margin for data, case studies, and credibility. In Phase 2 (revenue-generating), the offer shifts toward project-based neuromarketing studies (ad tests, packaging and shelf-layout research) and retainer packages for frequent testers, with a longer-term roadmap toward a NeuroScore-style dashboard trained on Thai neurodata. This supports a "fast, deep, affordable" positioning relative to both global neuromarketing firms and slower, more expensive traditional studies.

Implication. Large and growing FMCG and telecom budgets, rapid creative cycles, visually cluttered categories, and the absence of local EEG-based competitors combine to create a strong timing window for NeuroRight. By focusing first on high-spend Thai brands and partnering with their agencies and media owners, the project can quickly build proof of value, local benchmarks, and a defensible position, setting the stage for expansion into additional categories and regional markets.

1.3 Project Objectives

This project will make NeuroRight pilot-ready, ethically compliant, and commercially credible for advertisement testing in Thailand by building a repeatable end-to-end workflow, validating EEG signal quality on around 20 to 30 participants, and producing at least one client-style report that translates attention, emotional engagement, and preference into actionable recommendations. In parallel, we will refine service positioning and pricing, secure initial partnerships, and align governance with PDPA and UNESCO principles while preparing IRB-ready documentation, with success measured by high data quality, on-time delivery, clear client value, and early market traction.

- **Delivery & Technical:** Achieve ≥90% data-quality pass rate and ≥95% on-time sessions; complete one full report with engagement timelines and edit/placement guidance; turn around results ≤7 days from last session.
- **Market & Commercial:** Publish price sheet and updated pitch; launch a basic web presence; secure 1–2 LOIs and generate ≥2 qualified follow-on opportunities/case studies.
- **Ethics & Governance:** Operate with informed consent, data minimization, de-identification, and secure storage; maintain IRB-ready protocol/forms; implement checklists and risk mitigations (calibration, live QC, backups).

1.4 Value Proposition

- Brain-backed, not guesswork. We provide direct neural evidence (EEG) of attention, emotional engagement, and preference, helping teams understand why creatives work, not just whether they work.
- Actionable outputs for marketers. Deliverables focus on engagement timelines, benchmark scores, and edit/placement guidance that can be plugged directly into creative and media decisions.
- Fast, deep, and affordable. A streamlined, pilot-ready workflow delivers concise reports in days rather than weeks, at prices that fit real FMCG campaign cycles and allow repeated testing.
- Built for high-spend visual campaigns. The service is tailored to FMCG and telecom creatives—TV/video, digital, in-store, and OOH—where visual storytelling and emotional impact matter most.
- Ethics by design. The pipeline embeds informed consent, data minimization, de-identification, and secure storage, with IRB-ready documentation and checklists to manage risk.
- Client-friendly delivery. Results are packaged as executive summaries plus visual diagnostics, with optional eye-tracking integration to show where people look as well as how their brain responds.
- Local expertise with room to scale. A Thailand-based team, early partnerships, and a growing dataset enable a first-mover advantage, while the long-term plan for a NeuroScore dashboard points toward a scalable platform and recurring revenue.

PART 2: Team Overview

List of Members

Table 1 List of Members

Name – Surname	Student ID	Email	Role
Nattapat Kulwatho	tkulwatt	tkulwatt@cmkl.ac.th	Research and Development lead
Pornnaphas Chairojwong	pchairoj	pchairoj@cmkl.ac.th	Marketing lead
Thanabodee Klai-on	tklaion	tklaion@cmkl.ac.th	Business lead
Waris Srirachtrakul	wsrirach	wsrirach@cmkl.ac.th	Developer lead

Key Responsibilities

Roles designate primary ownership and accountability, but execution is cross-functional. The team collaborates across all phases—discovery, R&D, build, validation, and delivery—with all members jointly contributing to the initial R&D stage. Each lead coordinates work in their domain, ensures quality/compliance, and integrates with other leads to meet shared milestones. The key responsibilities assigned to each role include, but are not limited to:

Research and Development lead

- Define product/tech roadmap and research objectives.
- Design experiments and prototypes validate technical feasibility.
- Lead data analysis and documentation (reports/patents).
- Translate research into implementation specs.
- Ensure ethics, safety, and quality/compliance standards.

Marketing Lead

- Conduct market research, segmentation, and ICP profiling.
- Own positioning, messaging, and brand assets.
- Plan and run campaigns (digital/events) and social channels.
- Develop content (calendar, case studies, collateral).
- Track funnel metrics and optimize CAC/ROI.

Business Lead

- Crafting business model, pricing, and financial plan/forecast.
- Build partnerships and manage the sales pipeline.
- Prepare fundraising materials and handle investor relations.
- Oversee contracts/vendor management and basic legal/risk.
- Set OKRs and drive cross-functional planning.

Developer Lead

- Set tech strategy and architecture.
- Build signal-processing/ML pipelines and data governance.
- Deliver dashboards/APIs and integrations.
- Maintain CI/CD and testing.
- Ensure security, privacy, performance, and reliability.

PART 3: Technical oversight

Introduction

Neuromarketing, or consumer neuroscience, applies neuroscience and neuropsychology to marketing research to measure consumers' sensorimotor, cognitive, and affective responses beyond the limits of self-report (Ariely & Berns, 2010; Plassmann, Ramsøy, & Milosavljevic, 2012; Vlăsceanu, 2014). Using electroencephalography (EEG), functional magnetic resonance imaging (fMRI), and functional near-infrared spectroscopy (fNIRS), it captures implicit emotional and cognitive responses during realistic decision-making (Banker et al., 2021; Bell et al., 2018; Costa Feito et al., 2023; Wei et al., 2024). A systematic review of EEG-based neuromarketing identified Frontal Alpha Asymmetry (FAA) as the most reliable time–frequency marker of preference, indexing approach (positive) versus withdrawal (negative) tendencies, and the Late Positive Potential (LPP) as the most consistent event-related potential (ERP) component, reflecting sustained emotional evaluation that is particularly sensitive to emotional magnitude rather than valence (Byrne et al., 2022). These neural markers provide a principled way to quantify how strongly and in what direction consumers respond to marketing content, and growing evidence shows that neuromarketing can not only describe engagement but also predict behavior with high accuracy (Hakim et al., 2021; Mashrur et al., 2022a; Xu & Liu, 2024; Usman et al., 2024; Bak et al., 2022).

At the neural level, findings converge on a distributed valuation and control network centered on the prefrontal cortex (PFC), which supports planning, decision-making, problem-solving, and self-regulation (Kulwattho et al., 2025) and thus plays a pivotal role in consumer choice. Within this network, the ventromedial prefrontal cortex (vmPFC) contributes to emotion regulation, social cognition, and reward valuation, signaling preference judgments and the reward value of products or brands (McClure et al., 2004; Alexander et al., 2023), while the orbitofrontal/medial orbitofrontal cortex (OFC/mOFC) encodes subjective value and is sensitive to marketing cues such as price and brand context (Plassmann et al., 2008; Bartra et al., 2013). The hippocampus and posterior cingulate cortex (PCC)/default-mode network link brand equity to emotional and autobiographical memory (Lee, Broderick, & Chamberlain, 2007; Watanuki & Akama, 2022). The dorsolateral PFC (dlPFC) underpins working memory and cognitive control, shaping decisions when brand knowledge modulates preferences and exerting top-down control over vmPFC valuation signals during self-control (Plassmann et al., 2008; Hare et al., 2009). Subcortical regions, including the ventral striatum (nucleus accumbens), insula, anterior cingulate cortex (ACC/dACC), and amygdala, contribute to reward anticipation, price aversion, cost–benefit evaluation, conflict monitoring, and affective salience in brand attachment (Knutson et al., 2007; Shenhav, Botvinick, & Cohen, 2013; Watanuki & Akama, 2022). Although many neuromarketing studies emphasize prefrontal regions, full-cap EEG (e.g., 32–64 channels) and machine-learning pipelines increasingly track decision-related activity across the wider cortical network using features such as power spectral density (PSD) and frontal/prefrontal asymmetry indices (FAA/PAI).

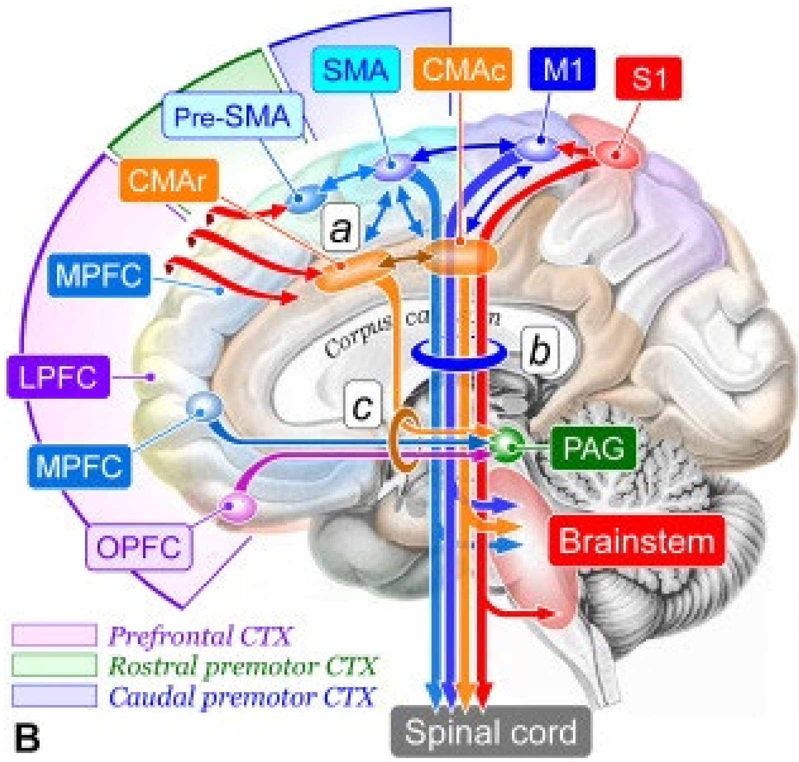


Figure 1 The Prefrontal cortex (PFC). (Kaoru Takakusaki, 2023)

Moreover, neuromarketing paradigms typically adopt ERP-based approaches, machine-learning pipelines, or multimodal combinations. ERP studies often focus on the P300, a positive deflection peaking around 200–400 ms post-stimulus that indexes early cognitive evaluation in decision-making tasks and is pronounced over frontal sites (Mansor et al., 2021; Wei et al., 2024). For example, Wei et al. (2024) used a 64-channel EEG setup to examine how message framing and product category influence eco-friendly purchase decisions via P300 modulation. In parallel, machine-learning frameworks extract features from frontal and occipital channels and classify single-trial responses: Mashrur et al. (2022b) reported 87.0% accuracy for predicting affective attitude using a set of frontal channels, while Xu and Liu (2024) showed that a support vector machine (SVM) with a Gaussian kernel and recursive feature elimination achieved 87.1% accuracy in predicting purchase intention using a 14-channel EMOTIV EPOC+ montage. Across studies, predictive performance improves further when EEG is combined with complementary modalities such as eye-tracking and facial-expression analysis, integrating brain-wave dynamics, gaze patterns, and AI-driven analytics to produce richer, multimodal consumer-neuroscience insights (Khushabaa et al., 2013; iMotions, 2022; Emotiv, 2023).

The P300 Event-Related Potential (ERP) component is a positive deflection typically observed between 200 and 400 milliseconds (ms) after stimulus onset, serving as a primary marker in neuromarketing to reflect attentional resource allocation (Byrne et al., 2022; Mansor & Isa, 2021; Kāthner et al., 2014). This component is crucial for investigating how marketing materials attract attention and is considered an effective measure for studying advertisement efficacy, reflecting underlying attentional orienting (Byrne et al., 2022). The established methodology used to elicit this response is the "oddball" paradigm, wherein a rare or unexpected target stimulus generates a markedly higher P300 amplitude compared to common, non-target stimuli (Sutaj et al., 2021). A core finding is that the P300 amplitude is directly proportional to the rarity of the stimulus, and a higher amplitude may signal greater confidence in the decision-making process (Mansor & Isa, 2021; Sutaj et al., 2021). While effective for tracking attention and advertising success, the P300 must be interpreted with caution when assessing true consumer preference, as its modulations often reflect merely stimulus salience rather than emotional valence (Byrne et al., 2022). Furthermore, the P300 component provides the foundation for certain Brain-Computer Interfaces (BCIs) capable of predicting consumer preferences through applications like real-time image ranking (Sutaj et al., 2021).

The development of intelligent neuromarketing frameworks leverages Brain–Computer Interface (BCI) technology and machine learning (ML) to move beyond subjective, self-report–based methods by predicting consumers' Affective Attitude (AA) and Purchase Intention (PI) directly from EEG signals. Building on this idea, Mashrur et al. proposed an EEG-based neuromarketing framework that uses Support Vector Machines (SVMs) and multi-domain features (time, frequency, and time–frequency) to classify AA and PI in response to heterogeneous advertising stimuli combining product features, endorsement, and promotion (Mashrur et al., 2022). A related study by Ishtiaque et al. demonstrated the practical viability of this approach using a single-channel consumer-grade EEG device (FocusCalm, Fpz), showing that similar prediction performance can be achieved with a more accessible, low-intrusion setup suited to real-world marketing contexts (Ishtiaque et al., 2022). Both studies reported high prediction accuracies from features extracted primarily over the frontal cortex, a region closely linked to decision-making and valuation. Using six frontal channels, the intelligent neuromarketing framework achieved 87.0% accuracy for AA and 84.0% for PI when all frontal channels were combined (Mashrur et al., 2022). The single-channel consumer-grade system attained 88.2% accuracy for AA and 80.4% for PI, thereby validating the feasibility of consumer-grade BCIs for neuromarketing applications (Ishtiaque et al., 2022).

Analysis of the underlying EEG dynamics further revealed systematic differences in decision-related processing: negative responses (Negative AA/Negative PI) showed greater dispersion and earlier peaks at the N200 component, whereas positive responses (Positive AA/Positive PI) peaked later around N400, suggesting that negative choices are made more rapidly but accompanied by more variable post-decision processing, while positive evaluations unfold more deliberatively (Mashrur et al., 2022). In both works, time–frequency domain features (TFDFs) dominated the selected feature sets, with the theta (θ) band emerging as the most informative for classifying AA and PI, and the delta (δ) band identified as the second most important contributor—consistent with its proposed role in decision-making processes (Mashrur et al., 2022; Ishtiaque et al., 2022). Together, these findings establish a concrete BCI–ML pipeline for predicting consumer preference and intention, spanning research-grade multi-channel systems and single-channel commercial devices.

EEG recording device

Electroencephalography (EEG) is a noninvasive method that records the brain's electrical activity from scalp electrodes. The scalp signal primarily reflects the summed excitatory and inhibitory postsynaptic potentials of large populations of cortical pyramidal neurons and is recorded as voltage differences using differential amplification; EEG affords millisecond-level temporal resolution of ongoing cerebral activity (Britton et al., 2016). Typical electrode placement follows the international 10–20 system, with higher-density extensions (e.g., 10–10) used when finer spatial sampling is needed (Klem et al., 1999; Sinha et al., 2023). Signal quality is influenced by factors such as electrode–skin impedance and artifact control; elevated impedances and unmitigated artifacts (e.g., blinks/EMG) reduce signal-to-noise ratio and can impact statistical outcomes (Kappenman & Luck, 2010).

The Unicorn Hybrid Black is a non-invasive EEG headset manufactured by g.tec medical engineering GmbH in Schiedlberg, Austria. It features an 8-channel electrode configuration in the default 10-20 layout (Fz, C3, Cz, C4, Pz, PO7, Oz, PO8). The device offers 24-bit resolution and a sampling rate of 250 Hz per channel, with hybrid electrodes suitable for both wet and dry measurements.

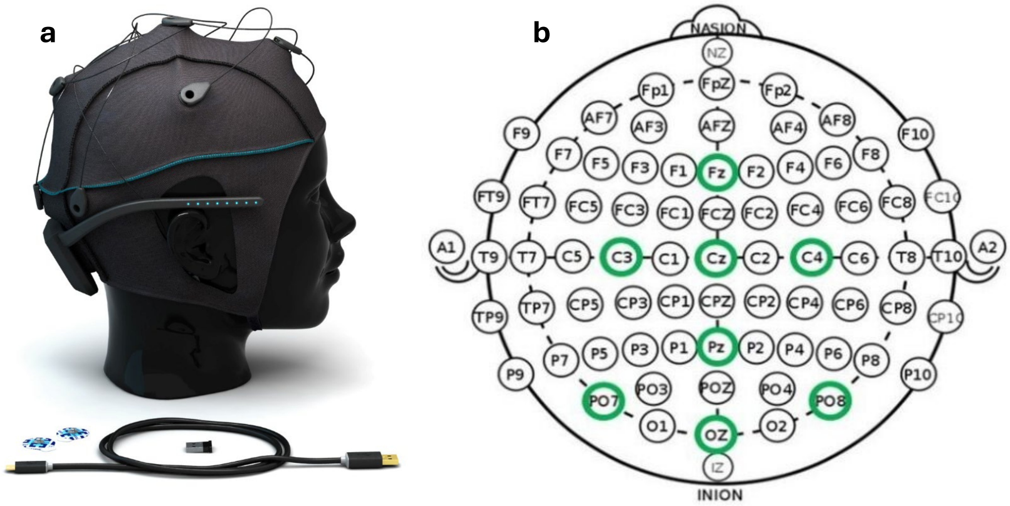


Figure 2 (a) Unicorn Hybrid Black Headset. (b) 8-channel electrode configuration in the default 10-20 layout (Hasan et al., 2024).

Facial Engagement prediction

1. Facial Action Units as Predictors of Engagement

A substantial body of research shows that specific AUs correlate with psychological constructs relevant to engagement, such as concentration, interest, confusion, and emotional arousal. Prior studies in learning analytics and social robotics have demonstrated that:

- AU4 (brow lower), AU7 (lid tightener), and AU43 (eyes closed) often reflect cognitive effort and decreased attention.
- AU1 (inner brow raise) and AU2 (outer brow raise) have been associated with surprise or heightened attention.
- AU6 (cheek raise) and AU12 (smile) sometimes indicate positive engagement or social responsiveness, depending on context.

These findings indicate that engagement is rarely encoded by a single AU; instead, multivariate AU patterns—including frequency, intensity, combinations, and temporal changes—provide better predictive power.

Because AUs offer continuous, interpretable, and anatomically grounded features, they are well suited for engagement modeling, especially in environments where large emotion-labeled datasets are unavailable. This makes AU-based engagement models both computationally efficient and methodologically transparent compared to end-to-end deep learning approaches.

2. OpenFace as a Tool for AU Extraction

OpenFace is widely used in academic and applied research for automated FACS-based feature extraction. Several studies evaluating OpenFace show that:

- It approximates expert FACS coding with reasonable accuracy in unconstrained settings.
- It provides frame-level AU intensity and presence estimates, enabling both static and temporal analysis.
- Its pipeline—face detection, alignment, landmark tracking, AU inference—supports real-time applications.

In engagement research, OpenFace is often chosen because it eliminates the need for manual annotation while preserving access to interpretable features. This makes OpenFace-derived AUs ideal for machine learning models, particularly when sample sizes are limited.

3. Machine Learning Approaches for Engagement Prediction

Engagement is typically modeled as a regression or classification task mapping facial features to labels derived from:

- human annotations (e.g., “high engagement,” “low engagement”),
- behavioral proxies (e.g., task performance),
- physiological measures (e.g., EEG, heart rate).

Across the literature, tree-based ensemble methods—Random Forest, Gradient Boosting Machines, and XGBoost—are frequently used in AU-based affect prediction because:

1. they handle nonlinear interactions between AUs;
2. they are robust to noise and missing data;
3. they require fewer samples to generalize well;
4. they provide interpretable feature importance scores.

Random Forests, in particular, excel when:

- the dataset is moderate in size,
- features have mixed relevance or nonlinear relationships,

- interpretability is needed to understand which facial components contribute most strongly to engagement.

Studies in intelligent tutoring systems, behavioral engagement assessment, and remote attention monitoring consistently report that Random Forest models trained on AU features outperform simpler models such as logistic regression and match or exceed the performance of more complex neural networks when datasets are small.

4. AU-Based Engagement Prediction in Related Domains

AUs have been used successfully for engagement prediction across multiple application areas:

4.1. Education and Learning Analytics

Researchers studying student engagement during online learning sessions have used AU trajectories to infer states such as:

- focused attention,
- boredom,
- confusion,
- mind-wandering.

Random Forest and gradient boosting models commonly outperform baseline classifiers, demonstrating that subtle facial movements reliably encode attentional fluctuations.

4.2. Human–Robot Interaction

In social robotics, AU-based models help robots detect when humans are attentive, disengaged, or emotionally responsive. Engagement predictions guide adaptive behaviors such as changing speech tone or modifying task difficulty.

4.3. User Experience and Media Research

AUs have been used to map viewers’ reactions to advertisements, video content, and gameplay events. For example, increased engagement often correlates with:

- more frequent eyebrow activity,
- synchronized facial dynamics across viewers,
- increased AU6/AU12 combinations in positive contexts.

Although these studies differ in context, they converge on a shared insight: AUs offer reliable, high-resolution indicators of behavioral engagement, especially when analyzed over stimulus-locked time windows.

5. Why Random Forest Is Suitable for AU-Based Engagement Modeling

Random Forest is well aligned with AU-based input because:

- AUs exhibit nonlinear relationships (e.g., AU4 + AU7 may indicate cognitive load, whereas AU4 alone may not).
- Tree ensembles model interaction effects without requiring manual feature engineering.
- Engagement labels are often noisy, and Random Forest is robust to label noise and feature variability.
- Feature importance outputs support interpretability, enabling researchers to understand which AUs contribute most to the engagement prediction tasks.

Given that AU intensity distributions vary across participants and tasks, the model's ability to generalize from limited data further reinforces its suitability.

6. Summary

The literature supports the use of Action Units as a meaningful and interpretable feature set for engagement prediction. Key takeaways include:

- AU-based representations capture emotional, attentional, and cognitive signals relevant to engagement.
- OpenFace offers a robust, validated pipeline for extracting AUs in real-time or offline.
- Random Forest models are well suited to AU-based engagement prediction due to their robustness, interpretability, and strong performance on small-to-medium datasets.
- Prior research across HCI, education, robotics, and media testing confirms that AU patterns can reliably predict engagement levels, particularly when analyzed over stimulus-relative time windows.

This foundation justifies the approach taken in the neuromarketing project: extracting AUs via OpenFace and training a Random Forest classifier to infer participant engagement during stimulus presentation.

Facial Emotion prediction

1. Deep Learning as the Standard Foundation for FER

Deep Convolutional Neural Networks (CNNs) have become the dominant methodology for FER due to their ability to automatically learn hierarchical facial features. Earlier approaches relied on hand-crafted descriptors—such as LBP, HOG, or geometric landmark analysis—but these methods struggle under real-world conditions involving varying lighting, head pose, occlusions, and subtle microexpressions.

Elsheikh et al. (2024) systematically evaluate classical CNN architectures including VGG, ResNet, DenseNet, InceptionV3, Xception, and EfficientNetB0, demonstrating strong performance improvements relative to traditional feature-based models. Their experiments across the CK+, JAFFE, and RAF-DB datasets show that deep CNNs capture complex visual patterns essential for emotion discrimination, and that architectural depth, regularization, and pooling strategies significantly influence accuracy .

These findings confirm that deep learning provides the structural backbone of modern FER systems and is essential for recognizing nuanced emotions in naturalistic environments.

2. Persistent Challenges in Facial Expression Recognition

Despite advances in CNN-based FER, several technical challenges limit the robustness and generalizability of FER in real-world settings:

2.1. Sensitivity to Small Transformations and Aliasing

A key observation in the literature is that CNNs are not inherently shift-invariant. Downsampling operations using strided convolutions or max-pooling frequently introduce aliasing—violations of the Nyquist sampling theorem—which distort high-frequency components relevant to facial emotion recognition. Elsheikh et al. (2024) highlight that such aliasing can cause subtle emotional cues (e.g., small eyebrow movements) to be misrepresented, reducing classification accuracy, particularly on diverse datasets like RAF-DB.

2.2. Dataset Limitations and Real-World Variability

Common FER datasets come with trade-offs:

- CK+ and JAFFE provide controlled, high-quality images but limited demographic and expressive diversity.

- RAF-DB, while more representative of real-world scenarios, includes significant variability in lighting, occlusions, head pose, and image quality.

As summarized in Elsheikh et al. (2024), these limitations hinder model generalization and require robust augmentation, preprocessing, and architectural adjustments .

2.3. Subtle Emotions and Class Imbalance

Disgust, fear, and sadness are frequently misclassified due to subtle visual differences. Class imbalance in datasets further exacerbates these issues, making certain emotions more difficult for CNNs to learn reliably.

3. Anti-Aliased CNNs as a Solution to Shift Variance

To address the shift-variance and aliasing issues inherent in standard CNNs, Elsheikh et al. (2024) introduce an anti-aliased deep convolutional network (AA-DCN), incorporating MaxBlurPool layers that apply low-pass filtering before subsampling.

Their results show:

- 99.26% accuracy on CK+,
- 98% on JAFFE,
- 82% on RAF-DB,

all outperforming classical CNN architectures and the authors' own baseline DCN model. This demonstrates that anti-aliasing yields more stable intermediate feature maps, improving emotion recognition especially under real-world conditions with noise, movement, or compression artifacts .

The adoption of anti-aliasing principles reflects an important trend: integrating classical signal-processing constraints into deep neural networks enhances reliability for subtle and dynamic facial expressions.

4. Transfer Learning and Fine-Tuning in FER

A major theme across FER research is the reliance on transfer learning, due to limited availability of large and diverse emotion-labeled datasets. Models pretrained on large-scale datasets (e.g., ImageNet) provide robust low-level and mid-level feature extractors that can be fine-tuned for emotion-specific tasks.

According to the studies summarized in Elsheikh et al. (2024):

- Chowdary et al. demonstrate that removing and replacing fully connected layers in pretrained architectures significantly boosts FER accuracy.
- Fine-tuning deeper layers selectively helps prevent overfitting when training data is sparse.
- Suzuki et al. propose a knowledge-transferred fine-tuning framework for anti-aliased CNNs, combining pixel-level and global-level loss terms to maintain generalization under limited data conditions.

These works highlight transfer learning as a cornerstone of contemporary FER pipelines, enabling generalization across subjects, environments, and subtle emotional expressions.

5. Emerging Hybrid and Attention-Based Approaches

Beyond classical CNNs, recent FER systems incorporate:

- hybrid CNN + MLP structures,
- attention mechanisms that focus on emotion-relevant regions (eyes, mouth, eyebrows),
- temporal modeling (e.g., LSTMs) for sequential facial cues,
- multi-branch models combining local features (landmarks) and global features (entire face).

Elsheikh et al. summarize several such approaches and note their strengths—such as improved sensitivity to subtle cues—but also limitations, including computational cost and reduced robustness outside controlled settings.

These hybrid systems offer promising performance but require careful adaptation for real-time neuromarketing scenarios.

6. Implications for Neuromarketing Research

The reviewed literature yields several key insights relevant to neuromarketing applications:

1. Deep learning is the de facto standard for FER, offering high accuracy in recognizing discrete emotional categories.
2. Anti-aliased CNNs significantly enhance robustness, especially when participants exhibit natural movement or when camera conditions fluctuate.
3. Transfer learning and fine-tuning are essential for adapting FER models to small or non-laboratory datasets.

4. Dataset characteristics strongly influence performance; real-world contexts resemble RAF-DB more than CK+ or JAFFE, emphasizing the importance of robustness over raw accuracy.
5. FER provides emotion classification, which can complement physiological measures such as EEG by revealing affective states that may not align with cognitive engagement alone.

Overall, facial-expression-based emotion detection serves as a valuable non-invasive method for understanding participants' affective responses during neuromarketing experiments, grounded in well-validated computer vision and deep learning literature.

Webcam Base Eye tracking

Webcam-based eye tracking has become a practical, low-cost alternative to lab-based systems for large-scale online experiments and neuromarketing studies. WebGazer (Papoutsaki et al., 2016) demonstrated that browser-based gaze estimation from standard webcams can achieve mean click-to-gaze errors around 100–200 pixels in remote settings, making it suitable for coarse area-of-interest (AOI) analysis rather than precise fixation localization. Subsequent work showed that online webcam-based eye tracking can replicate key cognitive and attentional effects, albeit with lower spatial precision than research-grade trackers (Semmelmann & Weigelt, 2018; Yang & Krajbich, 2021). Deep-learning approaches further narrow the gap to lab systems, reaching accuracies of about 2–3° of visual angle in online experiments (Saxena et al., 2023). In applied neuromarketing contexts, webcam-based systems have been successfully used to study user attention on e-commerce interfaces, with average focal displacement distances around 140 pixels (≈7% of screen size) across lighting conditions (Yüksel, 2023). Overall, across these studies, online webcam eye trackers typically operate with spatial errors on the order of 100–200 px on laptop screens, which is generally acceptable for AOI-based analyses in online eye-tracking and neuromarketing experiments (Papoutsaki et al., 2016; Semmelmann & Weigelt, 2018; Yang & Krajbich, 2021; Saxena et al., 2023; Yüksel, 2023).

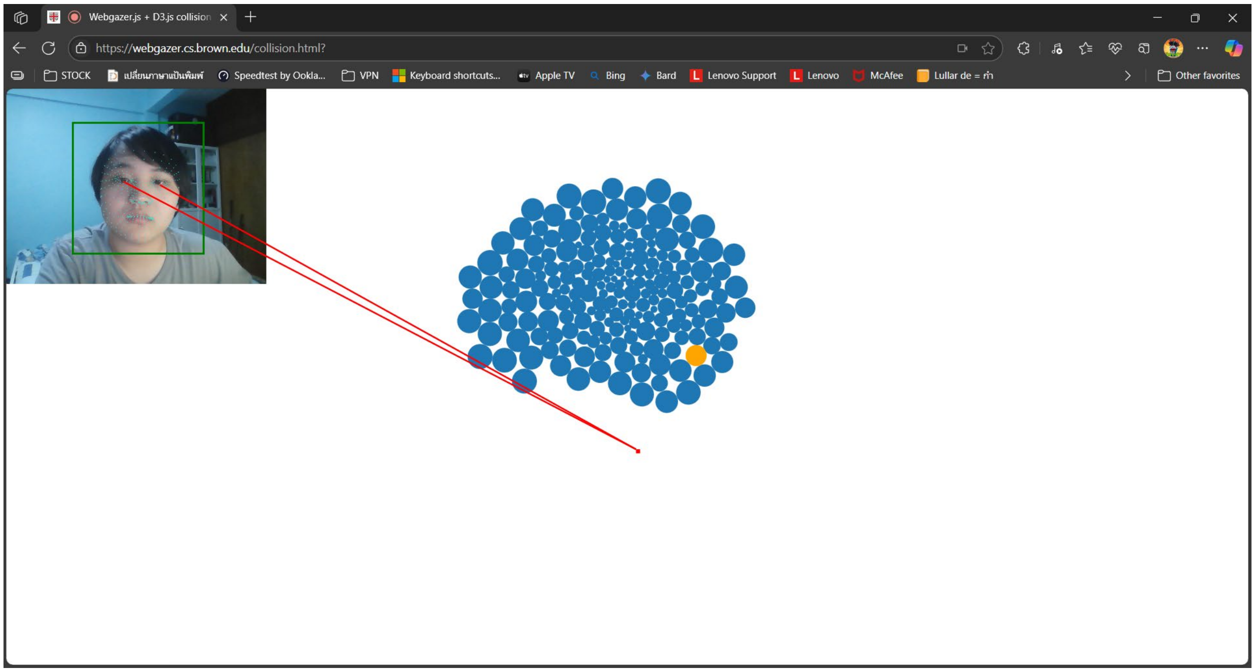


Figure 3 WebGazer demo.

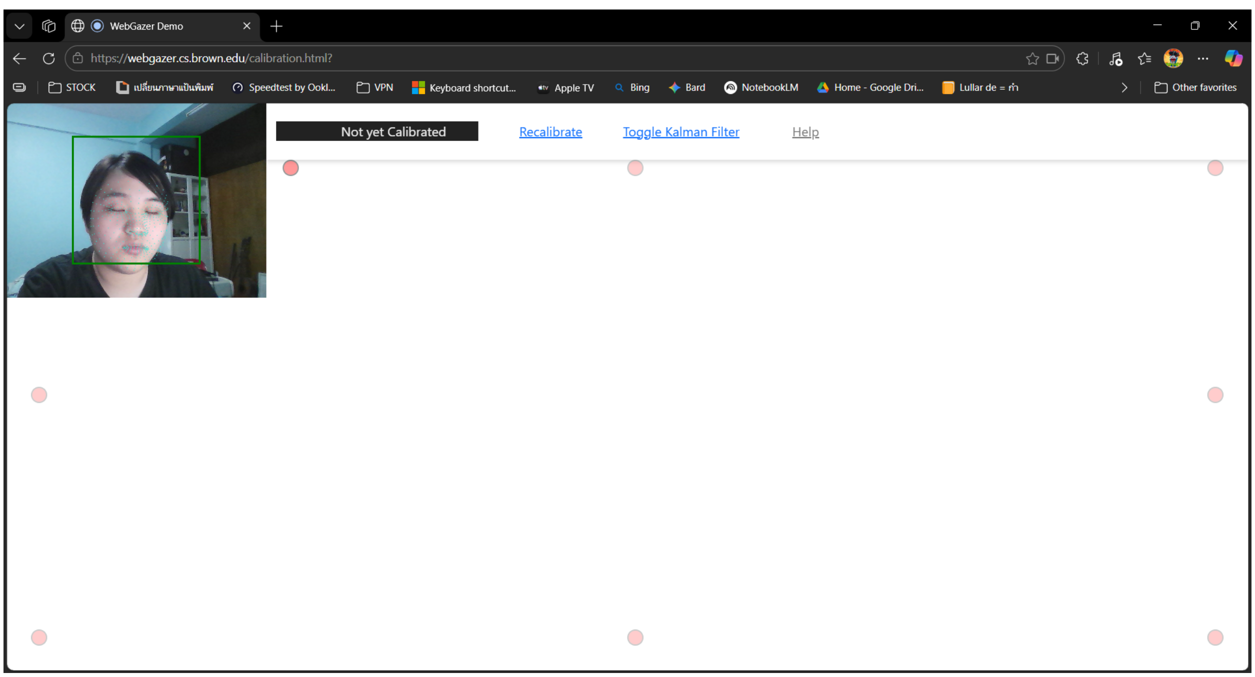


Figure 4 Web Grazer calibration

Licensing & citation. The library is released under GPLv3 (alternative licensing options are offered; the repository notes an LGPLv3 option for small companies' valuation under 1 M USD).

PART 4: Methodology

EEG Experiment

The Unicorn Hybrid Black, a non-invasive EEG headset, manufactured by g.tec medical engineering GmbH in Schiedlberg, Austria. It features an 8-channel electrode configuration in the default 10-20 layout (Fz, C3, Cz, C4, Pz, PO7, Oz, PO8). The device offers 24-bit resolution and a sampling rate of 250 Hz per channel, with hybrid electrodes suitable for both wet and dry measurements. EEG data were recorded with a Unicorn Hybrid EEG system (g.tec medical engineering GmbH, 2020), and facial video was captured using the laptop’s built-in webcam and OBS Studio version 30.2.3 (OBS Project, 2025). The EEG and video streams were synchronized via UDP sockets, implemented using the obsws_python package for communication with OBS Studio and the Python socket module for synchronization with the Unicorn EEG recording. Moreover, the stimulus sequences were generated in Python and presented using the PsychoPy package (Peirce et al., 2019).

Figure 5 The participant performs an experiment.

During the experiment, participants sat in front of a laptop screen at a viewing distance of approximately 70–100 cm (Figure 5). The protocol combined an ERP paradigm adapted from Sutaj et al. (2021) and a non-ERP neuromarketing paradigm adapted from Mashrur et al. (2022), and followed the sequence illustrated in Figure 5. After completing a prescreening questionnaire, participants received a briefing and underwent system calibration. They then performed the ERP and non-ERP tasks in a randomized order, separated by a 10-minute rest period (Kulwattho et al., 2025). Finally, participants completed a post-experiment questionnaire. The total duration of the experimental session was approximately 35–40 minutes.

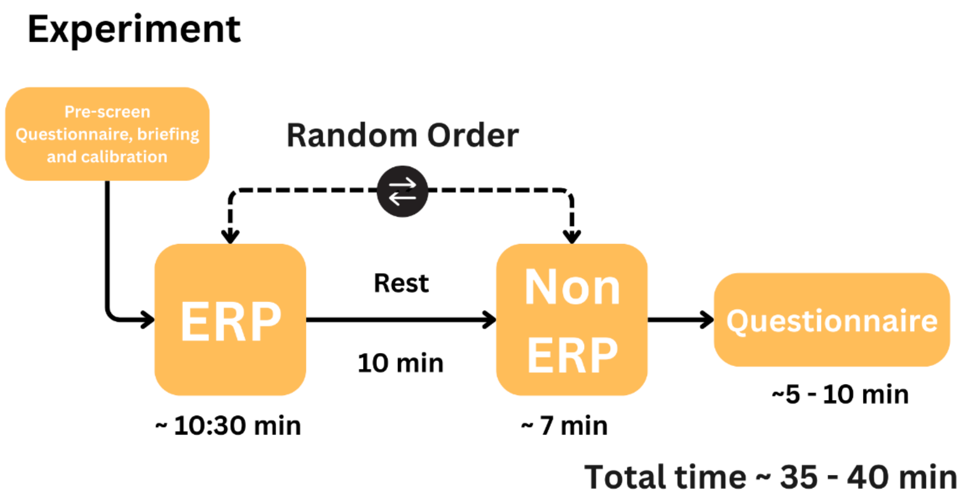
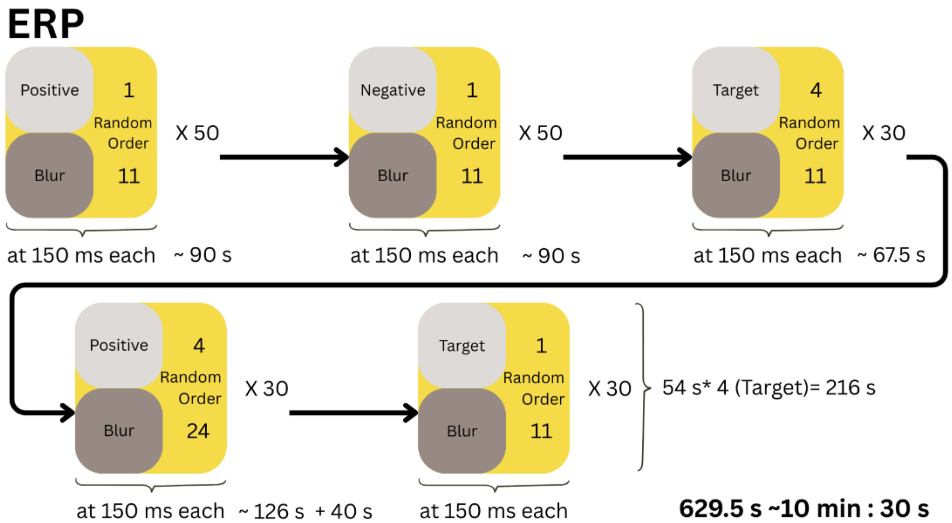


Figure 6 The overview of the experiment paradigms.

ERP Experiment

The ERP experiment was divided into five blocks, each representing one experimental phase (Figure 6). In Block 1 (positive-picture calibration), participants viewed a pseudo-random sequence of positive pictures and blurred poster images, presented at a target-to-standard ratio of 1:11; each image was displayed for 150 ms, with 50 repetitions of the target stimulus. Block 2 (negative-picture calibration) followed the same structure, but with negative pictures as the target stimuli at the same 1:11 ratio. Block 3 (Ranking Test 1) presented four target pictures embedded among 11 other poster images (15 images per trial), with 30 repetitions of each target. Block 4 (Ranking Test 2) increased the number of deviant poster images to 24, resulting in 28 images per trial. Finally, Block 5 (Ranking Test 3) presented 30 repetitions of each target picture in separate runs, each time embedded among 11 deviant poster images. And the total experiment time is around 10 minutes.

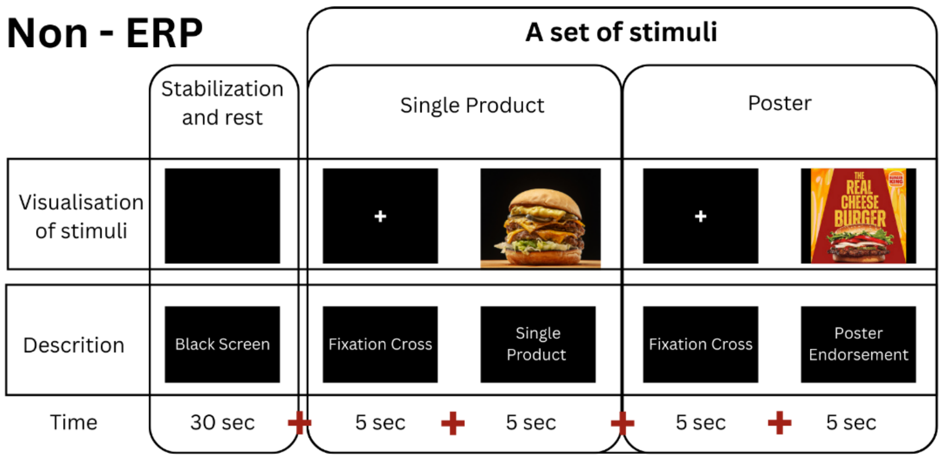


Adapt from Evaluating a Novel P300-Based Real-Time Image Ranking BCI(Sutaj, N., et al., 2021)

Figure 7 The overview of the ERP experiment paradigm.

Non-ERP experiment

The non-ERP experiment (Figure 7) began with a 30-second black screen to allow stabilization and rest. Participants were then presented with a randomized sequence of stimuli. Each trial consisted of 5 seconds of a fixation cross followed by 5 seconds of a single product image, then another 5-second fixation cross followed by 5 seconds of a poster endorsement corresponding to the same product. The product shown on each trial was randomly selected from a pool of 10 products, with each product repeated twice. In total, the non-ERP session lasted approximately 7 minutes. After the experimental blocks, participants completed a questionnaire. First, they answered follow-up questions about their picture preferences for the ERP stimuli. They then rated their affective attitude and purchase intention toward each product using two items: “I would feel happy if I owned X” (affective attitude) and “If I have the chance, I am willing to buy X” (purchase intention). Responses were provided on an 11-point Likert scale ranging from 0 (strongly disagree) to 10 (strongly agree).



10 sets of Stimuli with 2 repetition in Random order = 400s ~ 7 min
Adapt from the metadology of Mashrur et al. (2022))

Figure 8 The overview of Non-ERP experiment paradigm.

Poster preparation

The poster stimulus was retrieved from publicly available online sources using Google search, focusing on existing commercial advertisement posters. Only posters that were clearly legible, visually uncluttered, and representative of real-world marketing materials were selected, ensuring that the stimulus reflected a realistic viewing experience for participants. Figure 8 illustrates an example of the selected product and its corresponding advertisement poster used in the experiment, providing a visual reference for the type and style of marketing material presented to participants.

Figure 9 Example of an advertising stimulus used in the experiment. The product (left) and the poster (right).

EEG Data processing

ERP experiment

ERP data were processed in Python using the MNE-Python package (Gramfort et al., 2013) for EEG preprocessing, the mne_faster extension for automated bad-channel detection, and the NumPy (Harris et al., 2020) and pandas (The pandas development team, 2020) libraries for data handling. The preprocessing pipeline included band-pass filtering between 0.5 and 40 Hz, followed by identification and interpolation of bad channels using mne_faster. Independent component analysis (ICA) was then performed with mne.preprocessing.ICA on data filtered between 1 and 40 Hz to identify and remove artefactual components. After cleaning, the continuous data were segmented into epochs time-locked to stimulus onset, spanning from 500 ms before to 1250 ms after each event, with a baseline correction applied using the −500 to 0 ms pre-stimulus interval. Finally, epochs were grouped according to experimental condition and exported as NumPy arrays for subsequent analysis.

Calibration epochs from the ERP experiment were then used to train a time-variant linear discriminant analysis (TV-LDA) classifier for decoding “like” versus “dislike” responses, following the real-time image-ranking framework of Sutaj et al. (2021) and the TV-LDA formulation of Gruenwald et al. (2019). Let $X \in R^{N\times T\times C}$ denote the calibration data, where (N) is the number of trials, (T) the number of time points, and (C) the number of channels, and let $y \in 0{,}1^N$be the class labels (0 = DISLIKE, 1 = LIKE). For each time point (t), we computed the class-conditional means $\boldsymbol{\mu_0}(t), \boldsymbol{\mu}1(t) \in R^C$ and a pooled within-class covariance matrix $\Sigma(t) \in R^{C\times C}$. *To ensure numerical stability, an* l_2 regularization term was added, yielding $\Sigma\lambda(t) = \Sigma(t) + \lambda I$ with $\lambda = 10^{-2}$. The time-specific spatial weight vector was then obtained as

$$\boldsymbol{w}(t) = \Sigma_\lambda(t)^{-1}\big(\boldsymbol{\mu_1}(t) - \boldsymbol{\mu_0}(t)\big),$$

and the corresponding decision offset

$$d(t) = \frac{1}{2}\boldsymbol{w}(t)^\top\big(\boldsymbol{\mu_0}(t) + \boldsymbol{\mu_1}(t)\big),$$

which centers the LIKE/DISLIKE distributions around zero. For a new trial (n) with spatio-temporal samples $\boldsymbol{x_n}(t) \in R^C$, the TV-LDA score was computed by first forming time-resolved discriminant projections

$$s_n(t) = \boldsymbol{w}(t)^{\top \boldsymbol{x_n}}(t) - d(t),$$

and then integrating over time to obtain a single continuous preference score

$$S_n = \sum_{t=1}^{T} s_n(t).$$

Larger values of S_n indicate a stronger tendency toward the LIKE class, and these scores were subsequently used to rank the four target images for each subject, analogous to the P300-based image-ranking procedure described in Sutaj et al. (2021). This discriminant formulation can also be interpreted as a low-rank regression in the LDA subspace, consistent with the equivalence between low-rank regression models and LDA-based regressions established by Cai et al. (2013).

Non-ERP experiment

The non-ERP EEG data were processed in Python using MNE-Python (Gramfort et al., 2013), the mne_faster, an automated IC-labelling pipeline, and NumPy/pandas for data handling, following the same general structure as the ERP pipeline. The raw signals were bandpass Butterworth filter between 0.5 and 70 Hz, with 50 Hz notch filter for power line, after which bad channels were detected and interpolated using mne_faster. Independent component analysis (ICA) was then run on data filtered in the same bandpass Butterworth filter (0.5–70 Hz) to identify and remove artefactual components, followed by automated IC labelling. The cleaned continuous data were segmented into epochs time-locked to stimulus onset from 0 to 5 s, with baseline correction applied using the mean over the entire epoch. Finally, the epochs were grouped by experimental condition and exported as NumPy arrays for subsequent analyses.

Feature extraction followed the procedures described by Ishtiaque et al. (2022) and Mashrur et al. (2022) and comprised three main feature families: (1) time-domain, (2) frequency-domain, and (3) time–frequency-domain features. For each epoch, 20 time-domain descriptors were computed, including mean and relative power, Hjorth activity, mobility and complexity, skewness, arithmetic mean, and other higher-order statistics. Nine frequency-domain features were then derived from the power spectral density, such as spectral centroid, spectral spread, spectral kurtosis, spectral entropy, and related measures. Ratios of average power and relative power across canonical bands were also computed as additional features. Finally, a wavelet packet transform (WPT) was applied to recursively decompose each EEG epoch into six frequency bands (δ = 0–4 Hz, θ = 4–8 Hz, α = 8–12 Hz, β_1 = 12–20 Hz, β_2 = 20–32 Hz, γ = 32–64 Hz) using a full binary filter-bank decomposition. Let $W_{m,n}(k)$denote the wavelet packet coefficient at level (m), node (n), and sample index (k), and let $h(l)$ and$g(l)$be the low-pass and high-pass analysis filters of length (L). The child nodes $(m, 2n)$and $(m, 2n+1)$are obtained from their parent $(m-1, n)$ according to

$$W_{m,2n}(k) = \sum_{l=0}^{L-1} h(l)\,, W_{m-1,n}\big(2k + 1 - modN_{m-1,n}\big),$$
$$W_{m,2n+1}(k) = \sum_{l=0}^{L-1} g(l)\,, W_{m-1,n}\big(2k + 1 - lmodN_{m-1,n}\big),$$

where $(N_{m-1,n})$ is the length of the parent node. For each terminal node corresponding to a specific frequency sub-band, the band energy is computed as

$$E_b = \sum\nolimits_k \left|W_{m_b,n_b}(k)\right|^2$$

and the normalized band power as

$$P_b = \frac{E_b}{\sum_{b'} E_{b'}},$$

which together form the time–frequency feature set.

Then, in each frequency bands the (1) time-domain, (2) frequency-domain were extracted from each band.

To obtain a compact and discriminative feature set, we adopted a two-stage SVM-based wrapper approach with correlation-bias reduction, inspired by SVM-RFE + CBR (Guyon et al., 2002; Rakotomamonjy, 2003; Yan and Zhang, 2015). In the first stage, we mitigated redundancy by computing the absolute Pearson correlation matrix across all features and removing one feature from each highly correlated pair ($|r| > 0.90$). This correlation-bias reduction (CBR) step reduces the tendency of SVM-based criteria to undervalue groups of strongly correlated features (Toloși and Lengauer, 2011; Yan and Zhang, 2015).

In the second stage, we applied Recursive Feature Elimination (RFE) with a linear SVM as the base estimator to rank and select features. The linear SVM provides a weight vector whose magnitude reflects each feature's contribution to the decision boundary; at each RFE iteration, a fixed proportion of the least informative features was discarded until a subset of 45 features remained. These selected features were then used for subsequent classification.

For classification, we focused on a binary problem distinguishing positive versus negative affective responses, excluding any neutral trials to avoid confusing the classifier. An SVM with a radial basis function (RBF) kernel was used as the final model, since kernel-based SVMs are well suited for nonlinear decision boundaries in EEG-based affective and neuromarketing tasks (Gunn et al., 1998; Li et al., 2014; Zainuddin et al., 2018; Anuragi and Sisodia, 2019). The RBF SVM maps the selected features into a higher-dimensional space via the kernel function, and the classifier then learns a maximum-margin separating hyperplane in this space. The regularization parameter C and kernel width γ were tuned using grid search over a predefined parameter grid, combined with stratified K-fold cross-validation to estimate performance on unseen data (Hsu et al., 2003).

All models were implemented in Python using scikit-learn's SVC for both the linear SVM (feature ranking) and the RBF SVM (final classifier), RFE for recursive feature elimination, and StratifiedKFold for cross-validation. After training, we obtained cross-validated predictions using cross_val_predict, from which we computed the confusion matrix and standard performance metrics (accuracy, precision, recall, and F1-score) to evaluate the classifier.

Video data processing

Facial Engagement prediction

1. Video Recording and Stimulus Synchronization

The engagement prediction component was integrated into the ERP experiment. Participants viewed a series of poster stimuli while being recorded via a webcam in OBS Studio. To ensure temporal alignment between facial expressions and stimulus onset, OBS WebSocket was used to send markers to the video stream whenever a stimulus was presented.

These markers enabled precise segmentation of the continuous recording into intervals corresponding to each viewed poster, ensuring that facial data could be attributed to specific stimuli.

2. Frame Extraction and Poster-Level Segmentation

After data collection, recorded videos were processed to extract frames aligned with each stimulus window:

1. Marker timestamps were used to identify the start and end of each poster presentation.
2. All frames within these intervals were extracted at the webcam frame rate.
3. Each poster therefore yielded a set of frames representing the participant's facial responses during exposure.

Posters were subsequently labelled based on participant preference (liked vs disliked), which was later used to build engagement labels for the machine learning model.

3. AU Extraction with OpenFace

All extracted frames were processed with the OpenFace 2.0 toolkit. For each frame, OpenFace detects the face, aligns it, and estimates the presence and intensity of multiple AUs.

The output of OpenFace for each frame is stored in CSV format and includes:

- metadata columns such as frame index, face identifier, timestamp, tracking confidence, and success flag
- AU presence columns, which end with `_c`
- AU intensity columns, which end with `_r`

Frames where the face was not successfully detected or where tracking confidence was poor were removed during preprocessing to maintain data quality.

4. Dataset Construction and Labeling

To prepare data for model training, AU CSV files were grouped and labeled based on the participant's reported preference:

- frames collected during exposure to a poster that the participant liked were stored in a `Positive` folder and assigned label 1
- frames collected during exposure to a poster that the participant did not like were stored in a `Negative` folder and assigned label 0

In the implementation, all CSV files from the `Positive` and `Negative` directories were loaded and concatenated into a single dataset. A `label` column was added to each frame according to its source folder. This resulted in a frame-level dataset where each row corresponded to one frame and contained AU features plus a binary engagement label.

5. Feature Selection

From the combined dataset, non-informative metadata columns were removed. Columns such as `frame`, `face_id`, `timestamp`, `confidence`, `success`, and `label` were treated as meta features.

The AU feature set was defined programmatically as all columns whose names ended with `_r` or `_c`, corresponding to AU intensity and AU presence respectively. Any meta columns that matched this pattern were explicitly filtered out. The resulting feature matrix X therefore contained only AU-related variables, while the target vector y contained the binary engagement label.

Formally:

- X = matrix of AU features (all _r and _c columns)
- y = engagement label (1 = liked, 0 = disliked)

6. Train–Test Split

To evaluate generalization performance, the dataset was split into training and testing subsets using an 80/20 split. The split was stratified by the engagement label to preserve the proportion of positive and negative examples in both sets.

This produced:

- `X_train`, `y_train` for model training
- `X_test`, `y_test` for performance evaluation

Stratification ensured that the classifier did not become biased toward one class due to imbalanced sampling.

7. Random Forest Model Training

A Random Forest classifier was used to model the relationship between AU patterns and engagement labels. The model was configured with the following key hyperparameters:

- number of trees (`n_estimators`) set to 300
- maximum tree depth (`max_depth`) left unconstrained to allow the ensemble to capture complex decision boundaries
- random seed (`random_state`) set to 42 for reproducibility
- parallel computation enabled (`n_jobs = -1`) to speed up training

The classifier was trained on `X_train` and `y_train`. During training, each decision tree learned a different subset of AU features and samples through bootstrap sampling, and the ensemble prediction was obtained by majority voting across trees.

8. Model Evaluation

After training, the model was evaluated on the held-out test set `X_test`, `y_test`. The classifier achieved an accuracy of approximately 96 percent in distinguishing between frames associated with liked posters and frames associated with disliked posters. This suggests that AU patterns extracted during poster viewing encode strong discriminative information about participants' engagement or preference toward the stimuli.

Facial Emotion prediction

1. Datasets for Training Emotion Recognition Models

Emotion prediction models were trained using three widely adopted facial expression datasets:

- RAF-DB: a large-scale real-world facial expression database containing diverse unconstrained images across seven basic emotion categories.
- AffectNet: one of the largest FER datasets, featuring more than 400,000 manually annotated images representing a wide range of expressions, demographics, lighting, and head poses.
- FEE (Facial Expression Evaluation): a dataset used to complement the training data with additional samples of prototypical facial expressions.

These datasets collectively cover the seven universal emotion classes commonly used in FER research:

- angry
- disgust
- fear
- happy
- neutral
- sad
- surprise

Using multiple datasets improves the model's generalizability across different image qualities, demographic groups, and real-world variations.

2. Model Architectures: DCN and Transformer-Based FER

Two categories of deep learning models were used to predict emotional states:

2.1 Deep Convolutional Network (DCN)

A DCN architecture was trained following design principles validated in Elsheikh et al. (2024). Their work demonstrates that conventional CNNs suffer from aliasing and shift variance caused by downsampling operations. To address this, they propose an anti-aliased Deep Convolutional Network (AA-DCN) that integrates MaxBlurPool layers, improving robustness and stability in FER tasks.

Models inspired by their architecture were trained using RAF-DB and AffectNet. Performance aligned with results reported in the paper, achieving:

- DCN accuracy: ~83.39%, consistent with the benchmark presented in Elsheikh et al. (2024) .

2.2 Vision Transformer (ViT)

A transformer-based model, google/vit-base-patch16-224-in21k, pretrained on ImageNet-21k, was fine-tuned on AffectNet and RAF-DB to classify facial expressions. ViTs have shown strong performance in FER due to their ability to model long-range spatial relationships and maintain stable features under image variation.

Fine-tuning produced:

- Evaluation accuracy: ~88.22%, higher than the DCN baseline, reflecting findings that transformer-based models outperform classical CNNs on unconstrained FER tasks.

3. Training Framework and Computational Setup

Training was conducted using the APEX deep learning framework (as noted in the project workflow). The training process involved:

1. Preprocessing and normalizing the images.
2. Augmenting training samples to simulate real-world conditions such as lighting variation, slight rotations, and occlusions.
3. Fine-tuning pretrained DCN and ViT models using emotion-labeled samples from RAF-DB, AffectNet, and FEE.
4. Validating model performance on held-out subsets of RAF-DB to ensure generalization.

Hyperparameters such as learning rate, batch size, and number of epochs were optimized iteratively based on validation performance.

4. Output: Emotion Classification

Both the DCN and ViT pipelines predict one of seven emotion classes for each facial image. The predicted output corresponds to:

- angry
- disgust
- fear
- happy
- neutral
- sad
- surprise

These outputs are then available for downstream integration into neuromarketing analyses, such as correlating emotional reactions with EEG responses or assessing affective patterns during stimulus exposure.

5. Alignment With Literature (Elsheikh et al., 2024)

The methodological choices in this project are supported by several key insights from Elsheikh et al. (2024):

- Anti-aliasing improves FER accuracy by reducing shift variance in CNN models.
- RAF-DB is one of the most challenging datasets due to real-world conditions, making it a suitable benchmark for evaluating model robustness.
- Transformer architectures show strong performance gains over traditional CNNs in FER tasks.

These insights directly informed model selection, dataset choice, and training strategies used in this study.

Summary

The emotion prediction pipeline combines:

- large-scale FER datasets (RAF-DB, AffectNet, FEE)
- two modern FER model families (DCN and ViT)
- training infrastructure via APEX
- and evaluation aligned with published benchmarks

This process yields reliable classification of participants' facial emotional states, forming one of the multimodal signals used in the broader neuromarketing experiment.

Webcam Base Eye tracking

The calibration of our webcam-based eye-tracking system was implemented in Python using PsychoPy, with a 9-point calibration–validation paradigm adapted from WebGazer (Papoutsaki et al., 2016), online neuromarketing eye-tracking procedures (Yüksel, 2023), and webcam-based protocols for behavioural research (Yang & Krajbich, 2021). Participants sat in front of the monitor and fixated a sequence of nine white dots arranged in a 3×3 grid (Figure Xa), each presented for 5 s. In a subsequent validation phase, the same nine dot positions were shown again (Figure Xb), and participants were instructed to look at each dot and click on it with the mouse five times per location. The laptop's built-in webcam and OBS Studio were used to record participants' faces, and synchronization between PsychoPy and OBS was achieved via WebSocket messages sent with the obsw_python package, which embedded time-stamp markers into the recording. The resulting videos were then exported and decomposed frame by frame, and the frames whose time stamps matched the calibration and validation events were selected for further analysis.

OpenFace 2.2 was then used to extract frame-wise facial features from the synchronized webcam recordings, including 3D gaze vectors for both eyes (gaze direction in camera coordinates) and head-pose estimates. For each video frame, this yielded a feature vector describing where each eye was pointing and the orientation of the participant's head. Using the known 3×3 PsychoPy stimulus coordinates, each grid index $P \in 1, \ldots, 9$ was mapped from PsychoPy's centered coordinate system (x_c, y_c) into absolute screen pixel positions $(x^{\mathrm{scr}}, y^{\mathrm{scr}})$. Given screen width (w) and height (h), this transformation can be written as

$$x^{\mathrm{scr}} = x_c + \frac{w}{2}, \qquad y^{\mathrm{scr}} = \frac{h}{2} - y_c,$$

so that the center of the screen corresponds to $\left(\frac{w}{2}, \frac{h}{2}\right)$. These pixel coordinates served as the ground-truth gaze targets for each calibration and validation dot.

For every calibration event (a given dot position and click repetition), all frames in the temporal window where the dot was displayed and the participant was instructed to fixate and click were collected, and their face features were averaged to obtain a single, noise-reduced feature vector per event. Stacking these vectors across events produced a calibration feature matrix $X_{\mathrm{calib}} \in \mathbb{R}^{N_{\mathrm{calib}} \times F}$, where (F) denotes the total number of facial/gaze features and N_{calib} is the number of calibration samples. The corresponding screen targets formed a matrix $y_{\mathrm{calib}} \in \mathbb{R}^{N_{\mathrm{calib}} \times 2}$, where each row contains the $(x^{\mathrm{scr}}, y^{\mathrm{scr}})$ coordinates of the dot. Validation events were processed analogously: frames recorded while participants looked at and clicked the validation dots were averaged per event to yield $X_{\text{val}} \in \mathbb{R}^{N_{\text{val}} \times F}$, and the associated true click coordinates formed $y_{\text{val}} \in \mathbb{R}^{N_{\text{val}} \times 2}$. Calibration and validation datasets were then concatenated to form

$$X_{\text{all}} = \begin{bmatrix} X_{\text{calib}} \\ X_{\text{val}} \end{bmatrix}, \qquad y_{\text{all}} = \begin{bmatrix} y_{\text{calib}} \\ y_{\text{val}} \end{bmatrix}.$$

To make the learned mapping resolution-independent, the target coordinates were normalized to the unit square. For each sample (i), the pixel coordinates $(x_i^{\text{scr}}, y_i^{\text{scr}})$ were converted to normalized coordinates (u_i, v_i) via

$$u_i = \frac{x_i^{\text{scr}}}{w}, \quad v_i = \frac{y_i^{\text{scr}}}{h},$$

so that the normalized target matrix $y \in \mathbb{R}^{N \times 2}$ contained values between 0 and 1 on both axes. The data (X_{all}, y) were randomly split into a training set (80%) and a held-out test set (20%).

A multivariate linear regression model from scikit-learn package (Pedregosa et al,. 2011) was then trained to map the facial/gaze feature vector $(x_i \in \mathbb{R}^F)$ for each event to the corresponding normalized screen coordinates $y_i = (u_i, v_i)$. In matrix form, the model learns an affine mapping

$$\hat{y}_i = W x_i + b,$$

where $W \in \mathbb{R}^{2 \times F}$ is the weight matrix and $b \in \mathbb{R}^2$ is the bias term. After training, model outputs $\hat{y}_i = (\hat{u}_i, \hat{v}_i)$ on the test set were converted back into pixel space using

$$\hat{x}_i^{\text{px}} = \hat{u}_i \cdot w, \quad \hat{y}_i^{\text{px}} = \hat{v}_i \cdot h,$$

optionally clipping to the screen bounds $[0, w] \times [0, h]$.

Model performance on the held-out test set was evaluated using the coefficient of determination R^2 and the 2D root-mean-square error (RMSE) in pixel space. Let $y_i^{\text{px}} = (x_i^{\text{px}}, y_i^{\text{px}})$ denote the true pixel coordinates and $\hat{y}_i^{\text{px}}$ the predictions for N test samples and let $\bar{y}^{px}$ be the mean of the true coordinates. Then

$$R^2 = 1 - \frac{\sum_{i=1}^{N} \left\| y_i^{px} - \hat{y}_i^{px} \right\|^2}{\sum_{i=1}^{N} \left\| y_i^{px} - \bar{y}^{px} \right\|^2},$$

and the overall 2D RMSE is

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left\| y_i^{px} - \hat{y}_i^{px} \right\|^2},$$

with additional axis-wise errors computed as

$$\mathrm{RMSE}_x = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_i^{px} - \hat{x}_i^{px}\right)^2}, \quad \mathrm{RMSE}_y = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i^{px} - \hat{y}_i^{px}\right)^2}.$$

The same metrics were also computed separately for calibration and validation samples to assess generalization. Finally, a diagnostic plot was generated showing, for each validation click, the true and predicted gaze positions on the screen, with line segments connecting them to visually illustrate the magnitude and direction of residual spatial error.

PART 5: Result

EEG Data

ERP experiment

The pilot study included ERP data from seven trials of the neuromarketing paradigm, with four candidate pictures evaluated in each trial. In this preliminary analysis, the system was able to correctly rank the picture that each participant liked the most with an average top 1 accuracy of 85.7%, indicating a promising ability to decode relative preference from ERP features; the detailed classification pattern is illustrated in the confusion matrix in Figure 8.

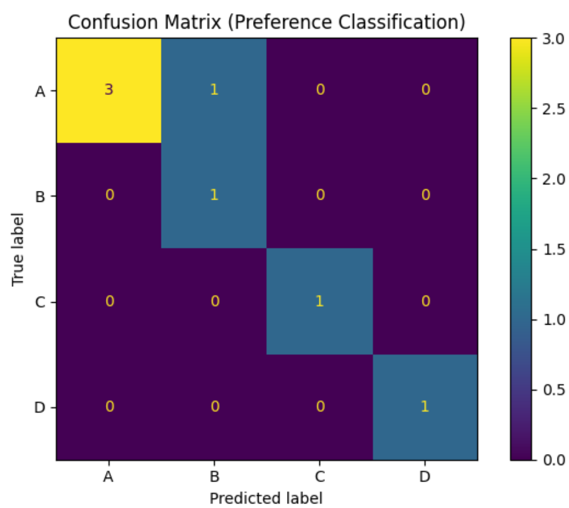


Figure 10 The confusion matrix of the ERP experiment.

Non-ERP Experiment

The preliminary results from a single pilot non-ERP experiment are encouraging. Using 45 EEG-derived features as inputs to a binary SVM classifier, the model correctly classified all 36 trials of affective attitude (16 negative and 20 positive), yielding 100% overall accuracy, with both sensitivity and specificity equal to 1.00. For purchase intention, the SVM trained on a 40-feature set achieved an accuracy of 97.2% (35/36 trials), correctly identifying all 22 “no-intention” trials and 13 out of 14 “intention” trials, with only one positive trial misclassified as negative. These patterns, summarized in the confusion matrices in Figure 9, suggest a clear separation between positive and negative responses in this pilot sample and support the feasibility of using non-ERP EEG features to decode consumers’ affective and choice-related states.

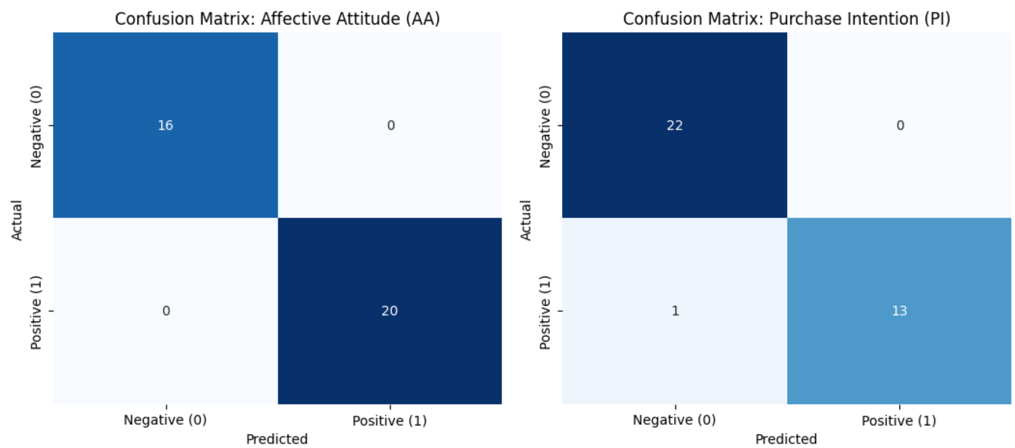


Figure 11 The confusion matrix of affective attitude (left), and the confusion matrix of purchase intention (right).

VDO Data

Facial Engagement prediction

Classification Performance

Table 2 shows the precision, recall, and F1-scores for each class. Overall, the model achieved an accuracy of 96%, indicating a high level of discriminative power in identifying engagement based solely on AU patterns.

Table 2 Classification performance of the binary preference classifier. The model achieved an overall accuracy of 0.96 on the test set, with balanced precision, recall, and F1-scores for both the Disliked (class 0) and Liked (class 1).

Class	Precision	Recall	F1-score	Support
0 (Disliked)	0.96	0.97	0.96	770
1 (Liked)	0.97	0.96	0.96	770

Accuracy			0.96	1540
Macro Avg	0.96	0.96	0.96	1540
Weighted Avg	0.96	0.96	0.96	1540

Both classes show nearly identical performance, demonstrating that the model generalizes well and is not biased toward either category.

The confusion matrix below (Figure 11) illustrates the distribution of correct and incorrect predictions:

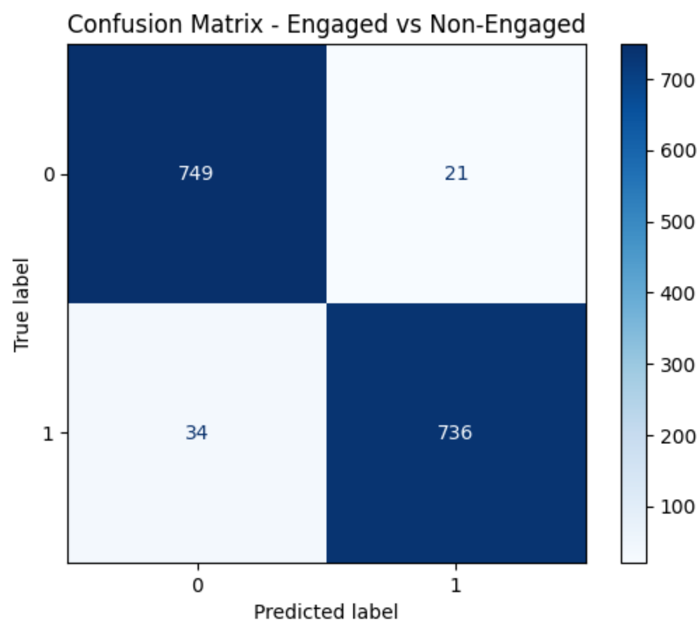


Figure 12 The confusion matrix of engaged and non-engaged.

- The model correctly identified 749/770 disliked-poster samples and 736/770 liked-poster samples.
- Misclassifications were relatively balanced, with 21 liked samples incorrectly predicted as disliked and 34 disliked samples predicted as liked.
- The low error rates (2.7% and 4.4% per class) indicate strong separability of engagement-related AU patterns.

Feature Importance Analysis

To understand which facial movements contributed most to the engagement predictions, the top 15 most important AUs were extracted from the Random Forest model's feature importance scores (Table 3).

Table 3 Top 15 Most Important Aus.

AU	Importance
AU12_r (lip corner puller)	0.1316
AU10_r (upper lip raiser)	0.0829
AU04_r (brow lowerer)	0.0778
AU06_r (cheek raiser)	0.0711
AU14_r (dimpler)	0.0633
AU25_r (lips part)	0.0534
AU07_r (lid tightener)	0.0521
AU17_r (chin raiser)	0.0520
AU26_r (jaw drop)	0.0507
AU01_r (inner brow raiser)	0.0401
AU15_r (lip corner depressor)	0.0387
AU23_r (lip tightener)	0.0386
AU45_r (blink)	0.0357
AU02_r (outer brow raiser)	0.0318
AU20_r (lip stretcher)	0.0306

Interpretation

- AU12_r (lip corner puller) emerged as the strongest predictor of engagement. This aligns with literature associating AU12 with positive affect, interest, and social responsiveness.
- AU10_r, AU06_r, AU14_r, and AU17_r also rank highly, suggesting that engagement involves a complex combination of facial muscle activations rather than a single expression.
- Both positive-affect AUs (e.g., AU6, AU12, AU14) and cognitive/attentional AUs (e.g., AU4, AU7) contributed significantly, supporting the idea that engagement reflects both emotional valence and attentional states.
- Lower-ranked but still relevant AUs (e.g., AU45 blink rate, AU23 lip tension) indicate subtle behaviors can also encode engagement differences.

Summary of Findings

The results demonstrate that:

- AU-derived facial features provide a reliable basis for predicting engagement in neuromarketing contexts.
- The Random Forest classifier achieved high accuracy (96%), with balanced performance across both engagement classes.
- Feature importance analysis reveals interpretable, psychologically meaningful patterns in how participants react to liked versus disliked stimuli.
- The model's strong performance supports the inclusion of facial expression analysis as a complementary modality to EEG data in the broader experiment.

Facial Emotion prediction

Deep *Convolutional Network (DCN)*

DCN architecture inspired by Elsheikh et al. (2024) was trained on RAF-DB using MaxBlurPool to reduce aliasing and shift variance. The learning curves (Figure 12) show that both training and validation accuracy increase rapidly during the first 10–15 epochs and then plateau, with training accuracy reaching ≈0.84 and validation accuracy stabilizing around 0.75–0.78, indicating good generalization with only mild overfitting. The confusion matrix on the validation/test split (Figure 13) confirms strong performance on the majority classes happy and neutral, where most samples fall on the diagonal, while remaining errors are concentrated among minority negative emotions (e.g., angry, sad, fear, disgust), which are frequently confused with neutral or with each other. Overall, these results align with the robustness and stability reported for AA-DCN architectures in prior FER work.

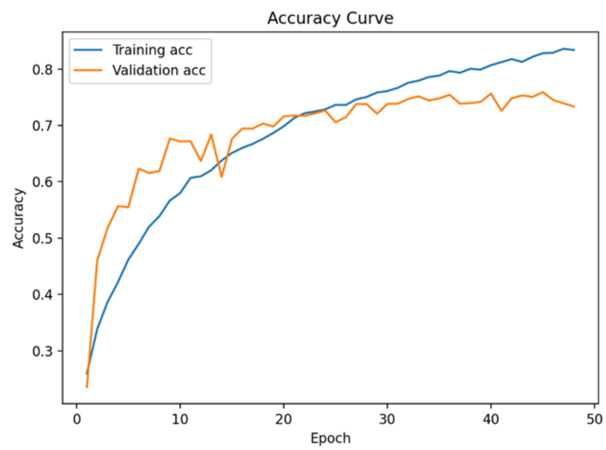


Figure 13 Training and validation accuracy of the AA-DCN over 50 epochs on RAF-DB. Both curves rise steadily before plateauing, with validation accuracy remaining close to the training curve and peaking around 0.75–0.78.

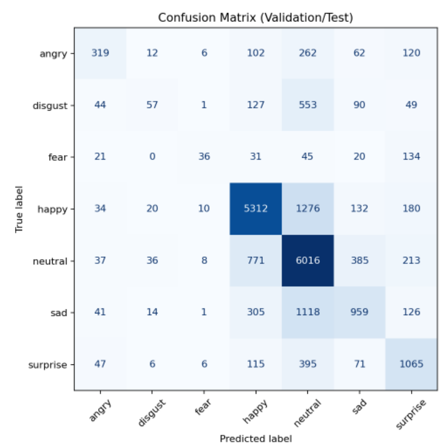


Figure 14 Confusion matrix of the AA-DCN on the validation/test set for seven emotion categories (angry, disgust, fear, happy, neutral, sad, surprise). Darker diagonal cells for happy and neutral indicate high correct recognition rates, whereas off-diagonal entries reveal residual confusion among negative emotions and with the neutral class.

Vision Transformer (ViT)

Using a pretrained CNN backbone and fine-tuning its upper layers on the FER dataset yielded stable performance gains over training. As shown in Figure 12, the evaluation accuracy increased steadily from about 0.76 in the first epoch to approximately 0.88 by epoch 37, indicating effective transfer of generic visual features to the emotion-recognition task rather than rapid overfitting to the limited data. The final confusion matrix (Figure 13) shows that the model recognizes neutral and happy expressions particularly well (over 3,400 and 5,100 correctly classified samples, respectively), while most residual errors occur between semantically similar negative emotions (e.g., sad, angry, fear, and disgust) and the neutral class. Overall, these results support the literature that transfer learning and selective fine-tuning form a strong baseline for contemporary FER pipelines, enabling good generalization across multiple emotion categories.

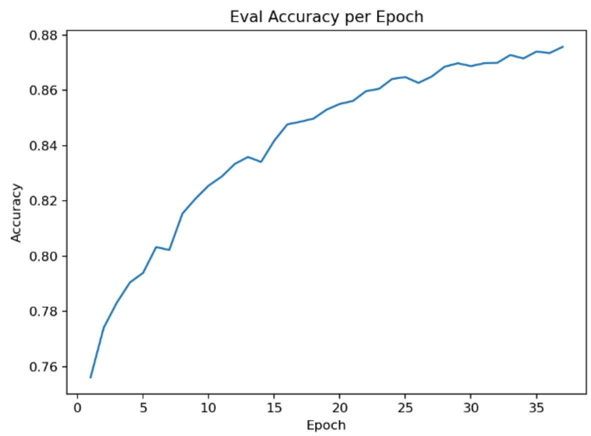


Figure 15 Evaluation accuracy per epoch for the fine-tuned FER model. The accuracy increases steadily from approximately 0.76 in the first epoch to about 0.88 by epoch 37, indicating effective transfer learning and no strong signs of overfitting.

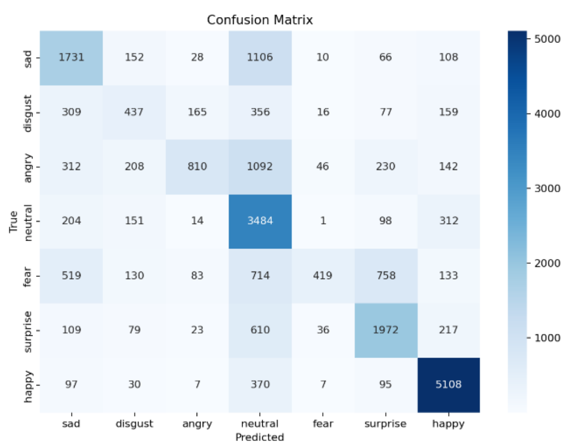


Figure 16 Confusion matrix of the 7-class FER classifier on the test set. The strong diagonal entries show good overall performance, with especially high accuracy for the neutral and happy classes, while most misclassifications occur between semantically similar

Webcam Base Eye tracking

For the webcam-based eye-tracking calibration, we pooled 73 click samples (calibration + validation) to train a combined gaze-prediction model and evaluated it on a held-out test set. The resulting model achieved a coefficient of determination of $R^2 = 0.92$ and a combined test error of 112 px ($RMSE$), with $\mathrm{RMSE_x}$ = 133.5 px and $RMSE_y$ = 85.8 px. When applying this combined-trained model back to each subset, the root-mean-square error was 127.0 px for the calibration clicks and 93.0 px for the 28 validation clicks, as illustrated by the true-versus-predicted gaze scatter in Figure 10. Importantly, this level of accuracy falls within the range typically considered acceptable for webcam-based online eye-tracking on laptop screens (approximately 100–200 px; Papoutsaki et al., 2016; Semmelmann & Weigelt, 2018; Saxena et al., 2023), indicating that the proposed pipeline is suitable for our intended experimental use.

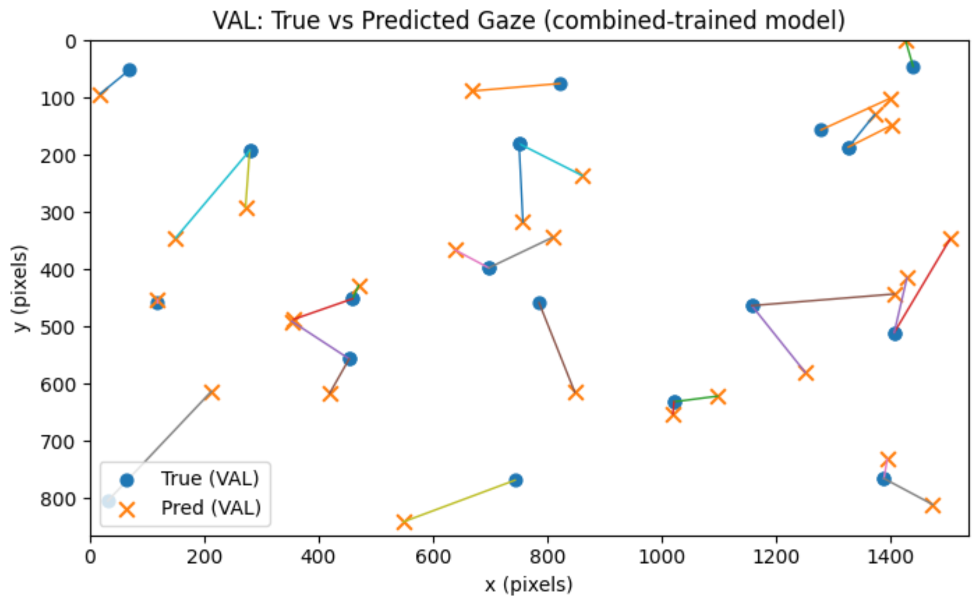


Figure 17 The true vs predicted gaze location from validation data of webcam base eyetracking.

PART 6: Market Analysis

Summary

The Thailand market presents exceptional opportunities for EEG-based neuromarketing services targeting billboard advertising effectiveness measurement. With a robust advertising market exceeding ฿111 billion annually, growing adoption of neuroscience in marketing research, and established demand from major advertisers spending ฿5+ million on research, the business case is compelling. This analysis demonstrates strong viability with projected revenues of ฿12-15 million annually at maturity, supported by comprehensive market data and stakeholder validation.

1. Market Sizing and Growth Analysis: Comprehensive Deep-Dive

Global Neuromarketing Market Expansion

The global neuromarketing industry demonstrates exceptional growth momentum, providing strong tailwinds for Thailand market entry. According to Market.us (2025), the global market reached USD 1.56 billion in 2024 and is projected to achieve USD 3.83 billion by 2034, representing a robust CAGR of 9.4%. This growth is particularly significant for EEG-based services, which captured over 28% of the global market share in 2024 due to cost-effectiveness and non-invasive characteristics (Market.us, 2025). The Electroencephalography segment's dominance stems from its practical advantages: providing real-time consumer brain activity insights, maintaining cost-effectiveness compared to fMRI ($100-200 per hour vs. $200-500 per hour), and offering superior portability for naturalistic research environments (Pipitwanichakarn, 2024).

Supporting Evidence: Multiple independent research organizations confirm these projections. Marketdataforecast (2025) reports similar figures with the market valued at USD 1.57 billion in 2024, reaching USD 3.38 billion by 2033 at 8.9% CAGR. Datamintelligence (2024) provides additional validation with consistent growth forecasts, emphasizing the EEG segment's technological maturity and commercial viability. This convergence across multiple authoritative sources strengthens confidence in market fundamentals.

Southeast Asia Regional Dynamics

The Asia-Pacific region represents the fastest-growing neuromarketing segment globally, with particular strength in EEG applications. Regional market analysis reveals USD 576.5 million in APAC neuromarketing activity for 2025, growing at 13.5% CAGR through 2033 (Cognitivemarketresearch, 2025). Thailand's position within this growth corridor is supported by several factors: established research infrastructure at leading universities, growing sophistication in advertising measurement, and increasing adoption of scientific approaches to marketing effectiveness.

Academic Validation: The University of Thai Chamber of Commerce (UTCC) systematic review by Pipitwanichakarn (2024) documents marked increases in Thai neuromarketing research activity since 2018, with EEG studies representing the majority of published work. This academic foundation provides credibility and talent pipeline advantages for commercial service providers entering the Thailand market.

Thailand Advertising Market Context and Scale

Thailand's advertising ecosystem provides substantial foundation for neuromarketing services adoption. The total advertising market reached ฿111.6 billion in 2023, with projections for ฿114.4 billion in 2024, representing 2.6% growth despite economic headwinds (Nielsen Company, 2024). Digital advertising specifically shows stronger

momentum, with spending projected to reach ฿35 billion in 2025, growing 10% year-over-year (Bangkok Post, 2025; Nation Thailand, 2025).
OOH/DOOH Market Specifics: The out-of-home advertising segment, directly relevant to EEG billboard testing services, demonstrates particularly robust fundamentals. Multiple research organizations provide consistent market sizing: Research & Markets (2024) values the Thailand OOH/DOOH market at USD 497.1 million in 2024, while Verifiedmarketresearch (2025) projects growth from USD 520 million in 2024 to USD 980 million by 2032, representing 8.2% CAGR. Mordorintelligence (2025) provides additional validation with USD 493.46 million in 2025, reaching USD 631.95 million by 2030 at 4.89% CAGR.
Market Structure Analysis: The advertising market exhibits high concentration among major spenders, creating optimal conditions for premium neuromarketing services. Nielsen data reveals that the top 10 advertisers account for approximately ฿17 billion in annual spending, with individual leaders like Unilever (฿4.5 billion annually) and Nestlé (฿2.0 billion annually) representing substantial potential clients (Nielsen Company, 2024).

2. Problem space: what marketers told us

2.1 Core frustration: “We don’t really know why people buy”

From our interviews:

- Marketers repeatedly said they want to know **the real reasons** customers choose their product is it price, promotion, pack shape, colors, trust, social proof, or some emotional trigger.
- They feel current tools show **what happened** (e.g., sales went up) but not **why it happened**, making it hard to repeat success or fix failures.

This matches broader FMCG research, which shows that decisions are influenced by a mix of **psychological and emotional factors** (values, lifestyle, perception, emotional connection) on top of price and quality.

2.2 Limitations of current methods (surveys, focus groups, dashboards)

2.2.1 Surveys and focus groups feel biased and shallow

Marketers mentioned problems like:

- People say what sounds reasonable, not what they truly feel.
- Strong personalities in a focus group can dominate others; quieter participants stay silent.
- Responses often sound generic (“I like the colour”, “It looks modern”) and do not clearly explain purchase behaviour.

These complaints are consistent with known limitations of focus groups:

- Group dynamics and “groupthink” bias data; a few dominant voices can skew results and others conform.
- Small sample sizes and qualitative nature mean findings are **not statistically generalizable**.

2.2.2 Digital metrics show outcomes, not mechanisms

Many teams now rely on:

- A/B tests on platforms (Meta, Google, TikTok).
- Click-through, view-through, conversion, and ROAS dashboards.

Marketers told us that:

- These numbers are useful for **choosing a winner**, but they don’t explain which **creative elements** caused the difference.
- When a test fails (both versions perform poorly), they still don’t know *what* to fix.

External analyses also note that **digital-only insights can be biased**: they over-represent very active online users, can be skewed by a few extreme comments, and may not reflect silent majorities in the customer base.

2.3 Uncertainty around true decision drivers in FMCG

From interviews, marketers are unsure whether customers mainly respond to:

- Rational factors: price, promotion, functional benefit.
- Emotional factors: brand trust, mood, identity, “feeling right”.
- Sensory cues: colour, shape, images, pack texture.

Academic and industry work on FMCG consumer behaviour supports this confusion:

- Emotional connection and brand perceptions significantly shape decisions, even when price and quality are similar.
- Key “driving forces” in FMCG include **findability on shelf**, clarity of front-of-pack information, and engaging product discovery – all heavily visual and often processed subconsciously.

Because much of this processing is **automatic and non-verbal**, traditional methods struggle to capture it; neuromarketing specifically emerges as a tool for these subconscious drivers.

2.4 Financial risk and pressure to optimise campaigns

From the conversations we had:

- Marketers are acutely aware that each big campaign (TV + digital + OOH) represents **large sunk cost** once media is booked.
- If the creative is wrong, they may see poor uplift but have no concrete learning beyond "this ad didn't resonate."

Industry data backs this context:

- FMCG and retail firms face intense competition and rapidly changing preferences; understanding consumer behaviour and keeping up with it is a recognised challenge that requires "technological investment and agile adaptation."

So their problem is not only insight quality but also **business risk**:

- They want a way to **de-risk big decisions** (e.g., new launch, rebrand, major promo) using better evidence than gut feeling and post-hoc metrics.

3. Our proposed solution: NeuroRight

3.1 Core measurement stack

1. **EEG (Electroencephalography)**
   - Captures real-time brain activity while a participant watches an ad, image, or package.
   - We can derive metrics such as attention, emotional arousal, approach/avoidance tendency, cognitive load, and memory-related responses.
2. **Eye-tracking (optional but powerful)**
   - Records gaze position and fixation duration on every frame of the ad or every area of a package/shelf.
   - Shows which key elements (logo, product shot, price, call-to-action) are actually seen, how quickly, and for how long.
3. **Recall and choice tests**
   - After exposure, participants do unaided/assisted recall tests or make simulated purchase choices.
   - This allows us to link **neuro-metrics → recall → stated intent**, validating whether brain responses predict outcomes.
4. **Integrated "Neuro-Score" and report**

   - For each creative version we compute composite scores (e.g., Attention, Emotion, Memory Potential) and visual outputs such as eye-tracking heatmaps and EEG time-lines.
   - Reports highlight *which* scenes or design elements drive strong reactions and *where* people disconnect.

3.2 Value for marketers

- They obtain **actionable rankings** of creative options, not just pretty graphs.
- They can cut weak scenes, emphasise strong scenes, or choose the best package among alternatives before spending large media budgets.
- This complements existing research rather than replacing it: neuro results become a **new decision layer** on top of A/B tests and surveys.

4. International market validation

Internationally, neuromarketing is a clearly defined, fast-growing B2B market with measurable size, growth, and adoption.

Definition: what "neuromarketing market" means

Industry reports define the neuromarketing market as all commercial products and services that use **neuroscience or biometric tools** (EEG, fMRI, eye-tracking, facial coding, GSR, implicit tests, etc.) to analyse how consumers respond to marketing stimuli such as ads, packaging, prices, store layouts, websites and apps.
This includes both **service agencies and SaaS platforms** that sell ad-testing, brand and packaging research, UX optimisation, and pricing studies based on brain and physiological data.

Global neuromarketing market size and growth

Different analysts give slightly different numbers, but they are all in the same range and tell the same story: **small but fast-growing**.

- Straits Research estimates the global neuromarketing market at **USD 1.71 billion in 2024**, rising to **USD 1.86 billion in 2025** and **USD 3.67 billion by 2033**, with a **CAGR of 8.87% (2025–2033)**.
- Market Data Forecast reports a very similar trajectory: **USD 1.57 billion in 2024**, **USD 1.71 billion in 2025**, reaching **USD 3.38 billion by 2033**, at about **8.9% CAGR**.
- Market.us projects the "NeuroMarketing" market from **USD 1.56 billion in 2024** to **USD 3.83 billion in 2034**, a CAGR of **9.4%**.

- Other firms (Polaris, BusinessResearchInsights, etc.) give 2023–2024 baselines around **USD 1.4–1.8 billion** and long-term growth around **8–9% per year**, pointing to a consistent picture.

Regional distribution

- North America is consistently described as the **largest region**, with about **38% market share and ~USD 0.59–0.6 billion in revenue in 2024**, led by the United States.
- The **US neuromarketing market** alone is estimated around **USD 0.6 billion in 2024**, projected to approach **USD 1.9 billion by 2034** (about **7.2% CAGR**).
- Europe is the second-largest region, with strong clusters in countries like the Netherlands, UK, and Germany, where agencies such as Neurensics, Neurons, and Unravel are based.
- Asia-Pacific is highlighted as a **high-growth region**, with rising consumer spending and rapid adoption of digital marketing and advanced analytics supporting future expansion.

Main applications and client industries

Analysts break the market down by **technology** and **application**; across sources, similar patterns appear:

- Key **technologies**: EEG, fMRI, eye-tracking, facial coding, GSR/biometrics, and implicit association tests.
- Major **applications**:
    - **Advertising and brand communication** – pre-testing TVC/online ads, measuring emotional engagement and recall.
    - **Packaging and product design** – evaluating shapes, colours, typography, shelf presence.
    - **Digital marketing & UX** – optimising websites, apps, and email layouts for attention and conversion.
    - **Pricing and promotion** – NeuroPricing and similar approaches to estimate willingness to pay and price acceptance.

In terms of **end-user industries**:

- Reports emphasise **retail and consumer brands (FMCG, food & beverage, fashion, electronics)** as major adopters, together with **media & advertising, e-commerce, and BFSI** (banks/insurance using neuromarketing for customer experience and product communication).
- One analysis notes that while BFSI is an important segment, **retail and consumer brands "heavily utilize" neuromarketing for product development, advertising, and branding**, showing strong demand from the kinds of clients we target.

Adoption and investment trends

- A 2025 "neural marketing statistics" digest reports that **45% of Fortune 500 companies are now experimenting with neuromarketing**, using at least one form of neural or biometric testing in their campaigns.
- The same source states that **63% of marketers plan to increase investment in neuromarketing tools by 2025**, reflecting growing demand for deeper, brain-level insights beyond surveys and clicks.
- Another article on Neuro-AI in branding notes that **over 30% of Fortune 500 companies are already benefiting from neuromarketing techniques in brand-building**, and that adoption is expected to expand further as tools become easier to use.

These numbers position neuromarketing as:

- No longer a purely academic niche, but
- Not yet universal – more like an **emerging standard** among big brands that want to differentiate and optimise.

Why the market is growing

1. **Need to go beyond traditional surveys and focus groups**
    - Brands are increasingly aware that self-report tools miss subconscious drivers; neuromarketing offers access to **non-verbal, automatic responses**.
2. **Technological advances**
    - Improvements in portable EEG, eye-tracking, and AI/ML-based analytics have lowered cost and made neuromarketing **more scalable and accessible**, even for mid-sized firms.
3. **Rising competition and media clutter**
    - As digital and social ads explode in volume, brands need **finer tools to stand out and optimise ROI**, pushing investment into advanced testing methods.
4. **Integration with Neuro-AI**
    - New "Neuro-AI" platforms (like Neurons AI) apply models trained on large neuro-datasets to predict attention/emotion from creatives at scale, blending neuroscience with SaaS and making neuromarketing part of everyday creative workflows.

Global neuromarketing market overview

Table 4 Global neuromarketing market overview

Item	Value / Description
Market definition	Commercial use of neuroscience/biometric tools (EEG, fMRI, eye-tracking, facial coding, GSR, implicit tests) to study consumer response to ads, packaging, UX, pricing, etc.
Global market size 2024	~USD 1.57–1.71 billion
Global market size 2025	~USD 1.71–1.86 billion
Forecast market size 2033–2034	~USD 3.38–3.83 billion
Implied CAGR (2025–2033/34)	About 8–9% per year
Largest region	North America, ≈38% share and ≈USD 0.6B revenue in 2024
Second region	Europe, strong agency clusters (Netherlands, UK, Germany)
Fastest-growing region	Asia-Pacific (driven by digitalisation and consumer-spending growth)
Main technologies	EEG, fMRI, eye-tracking, facial coding, GSR/biometrics, implicit tests
Main applications	Advertising & branding, packaging/product design, digital UX, pricing research
Key client industries	Retail & consumer brands (FMCG, food & beverage, fashion, electronics), media & advertising, e-commerce, BFSI
Fortune 500 adoption	≈45% experimenting with some form of neuromarketing
Marketers planning to increase investment	≈63% of marketers plan to raise neuromarketing spend by 2025
Brands cited as users	PepsiCo/Frito-Lay, Campbell's, Coca-Cola, Daimler, IKEA, Google and others

5. Successful neuromarketing agencies as benchmarks

5.1 Neurensics (Netherlands)

Positioning and services:

- A dedicated **"neuro market research company"** using fMRI and EEG to answer questions on advertising, branding, pricing, and packaging.
- Productised services include:
  - **Ad Testing** (neuro-based evaluation of TV/online ads)
  - **NeuroBranding** (emotional brand image map)
  - **NeuroPackaging / shelf testing**
  - **NeuroPricing™** – specialised pricing research to find the brain's "optimal price" for maximising profit.

Success evidence from public case studies:

- **Lays – NeuroPricing**: Neurensics applied NeuroPricing to determine the optimal price range based on brain responses, and reports that this **increased Lays' profits** versus traditional pricing decisions.
- **Bolletje (breakfast brand)**: fMRI analysis showed why two ad campaigns led to a **250% difference in sales**, enabling Bolletje to adjust communication more effectively.
- **Tele2 (telecom)**: Using Neuro Ad Testing and NeuroBranding, Tele2 refined its brand positioning and communication, leading to **tripled market share** and an **Effie award** for campaign effectiveness.

These cases show clear **business outcomes (profit, sales lift, market share)** linked to neuro-based insights.

What they do

Neurensics is a Dutch neuro-market-research company that uses **fMRI and EEG** to answer questions on advertising, branding, packaging, and pricing. Their offer is productised into clear modules:

- **Ad Testing** – measure emotional impact and buying intention of TV/online ads.
- **NeuroBranding** – map emotional associations with brands.
- **NeuroPackaging / Shelf research** – test packs and shelf layouts.
- **NeuroPricing™ / Pricing research** – derive optimal prices from brain responses.

Numbers that show success

- **Bolletje cereal brand**: Two TV campaigns produced **up to 250% difference in sales**, which Neurensics explained by analysing emotional brain responses; the findings guided future creative direction.
- **Tele2 (telecom)**: A combined Neuro Ad Testing and NeuroBranding programme supported a new positioning; Neurensics reports that Tele2 then achieved **a tripling of market share** and won an **Effie award** for campaign effectiveness.
- **Lays – NeuroPricing™**: Their NeuroPricing study is described as "increasing Lays' profits" by identifying brain-based price points that maximised both acceptance and margin, rather than relying on survey-stated prices.

These are strong, concrete business metrics: **sales +250%, market share ×3, profit increase via pricing**.

Revenue / growth signals

Exact revenue is not public, but there are clear indicators of commercial success:

- Neurensics has operated since at least **2010s** and is used by major brands including **Audi, Philips, Heineken, PepsiCo, Tele2, Smint, Centraal Beheer and others**, listed as long-term clients on their "our approach" page.
- Case studies show **measurable revenue impact** for clients, for example:
  - A museum attraction **Chocoversum** increased its revenue by **32%** by using NeuroPricing™ to identify optimal ticket prices.
  - Smint reports that NeuroBranding research has been "essential" to its **strong brand and revenue growth over the last five years**.

While these numbers are for client revenue rather than Neurensics' own revenue, they demonstrate that brands see enough value to keep buying their services over many years.

Why and how they succeed

- **Clear focus on business KPIs** – Every product is framed around sales, profit, and brand strength, not just "interesting brain maps".
- **Proprietary IP (NeuroPricing™)** – They acquired and own a named algorithm/brand, which differentiates them from generic survey-based pricing and lets them charge premium fees.
- **Storytelling with numbers** – Publishing quantified cases like "250% sales difference" and "tripled market share" builds trust with conservative FMCG and telecom clients who want proof.

5.2 Neurons (Denmark / US)

Positioning and evolution:

- Started as a neuroscience-based research lab using EEG and eye-tracking, then scaled into a **global company**offering both custom research and **Neurons AI**, an AI platform trained on large neuro and eye-tracking datasets.
- Works with major global brands including **IKEA, Google, Coca-Cola, Mercedes, Capital One**, covering ads, websites, apps, and retail environments.

Service model:

1. **Neurons AI (SaaS)**
   - Clients upload images or videos; the AI predicts metrics like visual attention, cognitive load and emotional engagement, based on models trained from past EEG/eye-tracking data.
   - Pricing is subscription-based: external reviews cite a **Standard plan around USD 15,000 per year for 5 user seats**, allowing multiple team members to analyse unlimited creatives within plan limits.
2. **Custom neuroscience studies**
   - For high-stakes projects, Neurons still runs in-lab or field studies with EEG and eye-tracking to build or validate solutions before generalising via AI.

Example success:

- **IKEA Energy case**: Neurons tested customers' brain and behavioural responses to new energy-product concepts in two countries. Insights showed which propositions were understood and emotionally engaging, guiding IKEA to refine the product positioning and communication.
- **Retail and e-commerce clients** use Neurons to optimise layouts and journeys with measurable improvements in engagement and conversion, according to their customer-story summaries.

This model proves that neuro-data can be turned into **scalable SaaS**, not only bespoke studies.

What they do

Neurons (originally Neurons Inc) began as a neuroscience lab using **EEG and eye-tracking** for ad and CX research and then evolved into a **hybrid of neuro-agency + AI SaaS company**.

Their main offerings:

- **Neurons AI platform** – clients upload images/videos; the system predicts attention, engagement and cognitive load based on models trained on large neuro and eye-tracking datasets.
- **Custom neuroscience research** – high-stakes projects with real EEG/eye-tracking in lab or field for testing ads, store layouts, websites, etc.

They list global clients such as **IKEA, Google, Coca-Cola, Mercedes-Benz, Capital One** and others in retail, tech, and finance.

Numbers that show success

- Neurons markets its AI as being trained on **tens of thousands of ad and UX tests** with eye-tracking and EEG data; this scale is only possible if many paying clients have run studies over years.
- External reviews of Neurons AI report a **Standard plan around USD 15,000 per year for 5 user seats**, which implies an **enterprise-level pricing tier** and demonstrates that brands are willing to pay significant annual subscriptions for their tool.
- Their customer-story section includes multiple Fortune 500 brands and repeat collaborations, indicating **long-term relationships rather than one-off experiments**.

While they do not publish exact ROI numbers for each client, the combination of **SaaS pricing, Fortune-500 logos, and long client lists** clearly signals commercial traction at global scale.

Revenue growth

- An interview with Neurons' CEO reports that the company grew from **€0 in annual recurring revenue (ARR) in February 2021 to €2.6 million ARR in March 2023**, and expected to reach **€5.5 million ARR by the end of 2023 and more than €6 million ARR entering Q1 2024**.
- A separate business-data site estimates Neurons' current annual revenue at about **USD 17.6 million** with around **126 employees**, which is consistent with a rapidly scaling SaaS + services company rather than a small lab.

This shows very fast growth for a specialised neuromarketing/Neuro-AI company.

Why and how they succeed

- **Scalable product (SaaS)** – Instead of selling only one-off lab studies, they converted neuro-insights into a cloud tool (Neurons AI), creating recurring revenue and lower marginal cost per analysis.

- **Bridging science and everyday work** – Creative teams do not need to set up EEG; they just upload assets and receive attention/emotion predictions, which fits directly into existing workflow.
- **Social proof from big brands** – Showing IKEA, Google, Coca-Cola, etc., reduces perceived risk for new clients, especially traditional marketers.

5.3 Unravel Neuromarketing Research (Netherlands)

Positioning and services:

- A neuromarketing research agency specialising in **EEG + eye-tracking** for advertising research, shopper studies, UX/usability testing, and even pricing.
- Clear solution bundles:
    - **Ad Testing** – evaluate TVC/online ads and banners for attention and emotion
    - **Packaging & Shelf Layout research** – measure how packaging and shelf design drive visibility and choice
    - **In-store shopper research** – mobile eye-tracking in real stores
    - **Neuromarketing price research** – using EEG responses (like N400) to determine price acceptance curves.

Stand-out success case:

- **Vrumona/Pepsi – Cola shelf layout**
    - Unravel tested multiple shelf layouts for the cola category using EEG and eye-tracking to find the design that was most “brain-friendly” (easy to navigate, high purchase activation).
    - The winning layout was implemented in 30 Albert Heijn supermarkets. Result: **category-wide cola sales increased by more than 3%**, benefiting both retailer and Pepsi, not just a single brand.
    - This is a rare example where the agency publishes a **hard sales number** linked directly to a neuromarketing intervention.

Unravel also provides **sample reports and training courses** (e.g., a “Complete Neuromarketing Essentials” training at 297 EUR), indicating a mature, productised offer beyond one-off academic-style reports.

What they do

Unravel is a Dutch agency focused on **EEG + eye-tracking** neuromarketing for:

- **Ad Testing** – TV and online video.
- **Packaging and shelf layout** – “Neuro Shelf” studies.
- **Shopper research** – eye-tracking in real stores.

- **UX and pricing research** – including EEG-based price acceptance curves.

They also run **Unravel Academy**, selling neuromarketing training courses, which adds another revenue stream.

Numbers that show success

Their most famous quantified case:

- **Vrumona / Pepsi – Cola shelf layout**
  - Unravel tested several shelf layouts for the cola category using eye-tracking and EEG to identify the design that made shopping easiest and most persuasive.
  - The chosen "brain-friendly" layout was implemented in **30 Albert Heijn supermarkets** (the biggest Dutch supermarket chain).
  - Result: **category-wide cola sales increased by more than 3%** after implementation, benefiting both the retailer and Pepsi.

Other indicators:

- They publish multiple sample reports and case overviews, suggesting a **steady flow of clients across sectors**.

Revenue / growth signals

Unravel does not publish revenue numbers, but there are solid indicators:

- It is described as a **full-service neuromarketing consultancy** that "helps to predict and increase the effectiveness of marketing," and is listed in global neuromarketing company directories as a specialist provider of EEG, eye-tracking, implicit-response and emotion-recognition research.
- A related sister company, Unravel Behavior, reports that applying neuromarketing and psychology increased store revenue by **54%** in one retail case, demonstrating strong financial impact for clients and supporting ongoing demand.

Other neuromarketing providers

The NMSBA (Neuromarketing Science & Business Association) directory lists many companies worldwide that **evaluate ads, packaging and UX using EEG, eye-tracking, facial coding, GSR and similar biosignals**. Examples include:

- **MindMetriks (UAE/USA)** – specialises in integrating neuromarketing (eye-tracking, EEG, GSR, facial coding) with traditional qualitative and quantitative research to evaluate packaging, ads and UX; serves big brands and research agencies.

- **Neurosense, Synetiq, Emotion Explorer Lab** – agencies noted in a European Commission report as working mostly with multinationals in retail, automotive, media and TV advertising, again confirming that large brands are key customers for this kind of service.

6. International business models and pricing patterns

International neuromarketing businesses mostly converge on a few clear patterns: **project-based research**, **SaaS subscriptions**, and **hybrid models** that mix both, all priced at a premium compared with classic surveys.

6.1 Project-based neuromarketing research

What "project-based" looks like

Agencies like **Neurensics** and **Unravel** mainly sell neuromarketing as **individual research projects**.

A typical project includes:

- Scoping workshop (objectives, target group, KPIs).
- Experiment design (stimuli selection, tasks, sample size).
- Participant recruitment and incentives.
- Data collection in lab or controlled environment (EEG, eye-tracking, sometimes fMRI or biometrics).
- Signal processing and statistical analysis.
- Deliverables:
  - Detailed report (scores, heatmaps, graphs, recommendations).
  - Live debrief/workshop with the client team.

Example products and use-cases

- **Neurensics**: Ad Testing, NeuroBranding, NeuroPackaging, **NeuroPricing™**.
- **Unravel**: Ad Testing, "Neuro Shelf" layout studies, neuromarketing price research, in-store shopper eye-tracking, UX testing.

Pricing level (order of magnitude)

Exact numbers are rarely shown, but global market-research overviews state that neuromarketing projects, due to lab equipment and expertise, are typically priced in the **"tens of thousands of USD per study"** range for large brands, i.e. roughly **USD 20,000–100,000+ per project**, depending on scope and sample size.

This positions project-based neuromarketing as:

- A **premium add-on** to existing research budgets.
- Most suitable for **high-stakes decisions** (big launches, rebrands, flagship campaigns) rather than every small creative tweak.

6.2 SaaS and subscription models (Neurons as key example)

Neurons AI: from lab to platform

Neurons is the clearest example of converting lab insight into a **software-as-a-service (SaaS)** model.

- Their **Neurons AI** platform allows marketers to upload images and videos and receive predicted attention, emotional impact and cognitive load, based on models trained on large historical EEG and eye-tracking datasets.
- This means clients can run many quick tests **without organising a new lab study each time**.

Pricing pattern

Neurons does publish basic pricing tiers:

- External reviews report a **Standard plan ~USD 15,000 per year for 5 user seats**, i.e. up to 5 named users inside the client's organisation can access the platform.
- Higher tiers likely include more advanced features (API, more models, priority support), but exact pricing scales are not fully public.

Characteristics of this model:

- **Recurring revenue** – annual or multi-year contracts.
- **Seat-based billing** – price depends on number of users or teams.
- Very low marginal cost per additional creative analysed, once the platform is built.

For big advertisers producing dozens or hundreds of assets per year, a flat annual fee is attractive compared with commissioning many separate neuromarketing studies.

6.3 Hybrid: SaaS + high-touch research

Most leading players effectively run a **hybrid model**:

- **Neurons**:
  - SaaS (Neurons AI) for everyday creative testing.
  - **Custom EEG/eye-tracking studies** for major strategic projects or for generating new training data.
- **Neurensics and Unravel**:

    - Primarily project-based neuromarketing studies.
    - Plus **productised offerings** like NeuroPricing™ or neuromarketing price research, which behave almost like standardised "mini-products" with repeatable methodology.
    - Unravel additionally sells **training courses** (e.g. Neuromarketing Essentials at 297 EUR), adding a small but scalable revenue stream.

This mix allows them to:

- Charge **high one-off fees** for complex, bespoke work.
- Build **more predictable income** from subscriptions or repeated, standardised studies.

6.4 Why these models work commercially

6.4.1 Clear economic value vs. cost

The global neuromarketing solutions market is small but premium, with total revenue of about **USD 1.6–1.8 billion in 2024–2025** and forecast to **double to around USD 3.3–3.8 billion by 2033–2034** at **~8–9% CAGR**.

Companies can charge premium prices because they address **expensive problems**:

- Choosing the wrong TV/digital campaign can waste **millions in media spend**.
- Pricing errors can quickly destroy **margin across entire portfolios**.

Case studies like:

- **Tele2's tripled market share** after neuro-supported repositioning,
- **+250% sales difference explained** for Bolletje,
- **>3% category sales lift** for cola after Unravel's shelf layout change

give concrete proof that better decisions can easily justify research costs.

6.4.2 Fit with how large advertisers buy research

- Large FMCG/retail brands are used to buying **projects** (e.g. concept tests, U&As, tracking studies) with clearly defined objectives and deliverables. Neuromarketing projects fit smoothly into this pattern.
- At the same time, creative and digital teams increasingly want **self-service tools** that integrate into their workflow (upload creative, get a score), which is why SaaS like Neurons AI finds traction.

7. Thai market and partnership approach

Overall Thai ad and digital market

- Total **digital ad spend** in Thailand was about **THB 29.3 billion in 2023**, forecast to **THB 31.6 billion in 2024 (+8%)** and **around THB 34–35 billion in 2025 (+10%)**.
- DAAT projects that in 2025 the **top 5 digital-spend industries** will be:
  - Skincare ≈ **THB 6.1 billion**
  - Automobiles ≈ **THB 2.9 billion**
  - Non-alcoholic beverages ≈ **THB 2.9 billion**
  - Telecom services ≈ **THB 2.5 billion**
  - Dairy products ≈ **THB 2.1 billion**
- For total media (all channels), TV in Jan–Jul 2024 alone was about **THB 33.9 billion**, representing roughly **50%** of total media budgets and still the single biggest channel, even though it is slowly declining as digital grows.

This means neuromarketing can aim at **both TV and digital creatives**, not just online ads.

Category-level ad budgets in Thailand (useful for choosing a beachhead)

From Nielsen mid-2025 data across 70 product categories and 18 platforms:

- **Skincare – THB 5.249 billion** ad spend in 1H 2025, growth **+4%** YoY.
- **Non-alcoholic beverages – THB 3.062 billion**, growth **+22%**.
- **Automotive – THB 2.515 billion, -17%** (big cut, more cautious).
- **Communications/telecom – THB 2.381 billion, +17%**.
- **Dairy products – THB 2.227 billion, +11%**.
- **Retail – THB 1.714 billion, -2%**, but another Nielsen report says **retail shops' ad spending grew 17% YoY**, placing them among the top spenders.
- **Cosmetics – THB 1.575 billion, +80%** (one of the fastest-growing categories).
- **Restaurants – THB 1.147 billion, +40%**, driven by eating-out lifestyle and heavy promotional campaigns.
- **Vitamins & supplements – THB 1.013 billion**, about **-2%**.

For digital-only spend in 2024, DAAT/Kantar show similarly FMCG-heavy rankings; for example, dairy (~THB 1.8 billion), retail (~THB 1.7 billion), cosmetics (~THB 1.3 billion), banks (~THB 1.15 billion) and vitamins/supplements (~THB 0.97 billion) were among the top spending categories online.

FMCG and OOH consumption trends (why this timing is good)

- The Thai FMCG sector is one of the largest and most competitive in Southeast Asia; Worldpanel reports **>6% FMCG growth in 2024**, with strong demand in food, beverage, and personal care.

- Out-of-home (OOH) consumption of FMCG (on-the-go, at cafés, at work, etc.) is rebounding strongly post-COVID: **+4.3% volume and +3.4% spend per trip** according to Kantar's 2024 Outlook.
- PwC expects Thailand's online advertising revenue to grow at roughly **10% CAGR from 2025–2029**, reflecting steady digital expansion across entertainment and media.

This combination (big FMCG base + growing OOH + rising digital) means **lots of new campaigns and formats**, increasing the value of ad and packaging testing.

How this supports our partnership approach

Because Thai marketers already spend heavily, but mostly on media and basic digital metrics:

- Our neuromarketing lab as a **small percentage add-on** of these budgets; even taking **0.5–1% of campaign media spend** for neuro-testing is realistic when skincare spends several billion baht per year on advertising.
- Fast-growing categories (cosmetics +80%, restaurants +40%, non-alcoholic beverages +22%, telecom +17%) are **ideal pilot partners**: they are under pressure to differentiate, launch innovations, and justify rising budgets.

Our partnership pitch fits this context:

- Offer **pilot studies** (EEG + eye-tracking ad/pack tests) at low or no fee in exchange for:
  - Real creatives from high-spend categories above,
  - Access to their customers for lab sessions,
  - And post-launch performance data to validate that neuro-scores predict results.
- For them, the "cost" is marginal compared with their **multi-billion-baht category budgets**, while the potential upside is avoiding one failed campaign or learning how to get even a **3–5% sales lift**, similar to the cola-category case Unravel achieved in the Netherlands.

Thailand advertising & neuromarketing opportunity (by category)

Table 5 Thailand advertising & neuromarketing opportunity (by category)

Item / Category (Thailand)	Key numbers & trends	Why attractive for neuromarketing
Total digital ad spend 2024	≈ THB 31.6B, up from ≈ THB 29.3B in 2023; forecast ≈ THB 34–35B in 2025 (+10%).	Large and growing pool of creatives to test (social, video, display).
TV ad spend Jan–Jul 2024	≈ THB 33.9B, about half of all media budgets.	High-budget TVC campaigns justify premium pre-testing.
Skincare	*THB 5.249B ad spend in 1H 2025; +4% YoY.*	*Biggest spender; high innovation rate and emotional branding → ideal for EEG ad/pack tests.*
Non-alcoholic beverages	*THB 3.062B; +22% YoY.*	*Strong growth and frequent promotions; many TV + OOH + digital campaigns to optimise.*
Automotive	*THB 2.515B; –17% YoY.*	*Large but cautious; likely to fund neuromarketing only for key launches.*
Telecom / communications	*THB 2.381B; +17% YoY.*	*Highly competitive, heavy brand and offer advertising; good for video ad testing.*
Dairy products	*THB 2.227B; +11% YoY.*	*FMCG category with family/health positioning; packaging and TVC both important.*
Retail shops	*THB 1.714B in one report; other data show retail shops as top ad spender with ~17% YoY growth.*	*Omnichannel (flyers, OOH, digital); strong need to test promos and in-store visuals.*
Cosmetics	*THB 1.575B; +80% YoY.*	*Explosive growth, heavy influencer and visual creative; strong fit for image/video neuromarketing.*
Restaurants / QSR	*THB 1.147B; +40% YoY.*	*Campaigns tightly linked to short-term sales; good for testing offer visuals and menu boards.*

Item / Category (Thailand)	Key numbers & trends	Why attractive for neuromarketing
Vitamins & supplements	*THB 1.013B; –2% YoY.*	*Regulated messaging; neuromarketing can help find trustworthy, non-overclaim creative.*
FMCG market growth	*Thai FMCG >6% growth in 2024; strong in food, beverage, personal care.*	*More new products and line extensions → more ads and packs needing testing.*
OOH consumption trend	*Out-of-home FMCG consumption up +4.3% volume and +3.4% spend/trip; rebound in cafés, restaurants, convenience stores.*	*More OOH occasions and point-of-sale stimuli → scope for shelf/pack and in-store neuromarketing.*
Entertainment & media outlook	*Thai entertainment & media revenue projected to surpass THB 700B by 2029, with online advertising growing ~10% CAGR.*	*Confirms long-term growth in ad-related spending and demand for better ROI tools.*

8. TAM SAM SOM

8.1 TAM – Global neuromarketing market

Recent reports give a consistent picture of the **total addressable neuromarketing market worldwide**:

- Global neuromarketing market size is estimated at **about USD 1.6–1.7 billion in 2024**, growing to **about USD 3.4–3.7 billion by 2033–2035**.
- This implies a **CAGR of roughly 8–9%** over the next decade.

8.2 SAM – Asia-Pacific neuromarketing market

Most sources do not give an exact USD number for Asia-Pacific, but they:

- Agree that **North America is the largest region**, with ≈**41.9% share in 2024**.
- Indicate that **Asia-Pacific is the fastest-growing region**, with neuromarketing CAGRs around **8–10% to 2030–2035**.

A simple but reasonable approximation:

- If North America holds ≈42% of a USD 1.6B global market, NA ≈ **USD 0.67B**.
- That leaves ≈ **USD 0.93B** for the rest of the world. If Asia-Pacific is the main high-growth region, assigning it **about one-third of the global market** is conservative.
- One detailed neuromarketing-solutions report lists an Asia-Pacific market size of **about USD 490M in 2025**, with a **CAGR of 13.7% to 2033** for neuromarketing solutions.

Key growth drivers in APAC:

- Rapid digitalisation, smartphone penetration, and social-media usage.
- Rising competition in China, India, Japan, South Korea, and ASEAN, which pushes brands to invest in advanced consumer-insight tools.

8.3 SOM – Thailand (top-down approximation)

There is no direct "neuromarketing in Thailand" number, so we need to **approximate from the advertising market**, assuming neuromarketing will capture a small share of total ad or research spend.

8.3.1 Thailand advertising and digital-ad market

- Thailand's **total advertising market** is valued at about **USD 4.25 billion in 2024**, forecast to reach **USD 6.06 billion by 2033** at **~4.0% CAGR**.
- Thailand's **digital advertising** alone reached around **THB 31.5–34.5 billion (~USD 0.9–1.0B) in 2024**, and is expected to grow around **10–16% in 2025**, driven by social media, e-commerce, and mobile video.

These numbers show that Thailand is a **mid-sized but growing ad market** with strong digital expansion.

8.3.2 Approximating neuromarketing spend share

In mature markets, neuromarketing is a **tiny fraction** of total ad spend—typically well under 1%—because it sits inside the research/insight budget, not media.

A reasonable, conservative set of assumptions for Thailand:

- Assume **neuromarketing + advanced insight tools might capture 0.1–0.3% of total ad spend** once the market is moderately developed.
- Apply this range to Thailand's 2024 advertising spend **USD 4.25B**.

Approximate SOM (Thailand potential neuromarketing spend):

- Low case (0.1% of ad spend):
  - 0.001 × 4.25B ≈ **USD 4.3 million per year**.
- Mid case (0.2%):
  - 0.002 × 4.25B ≈ **USD 8.5 million per year**.
- High case (0.3%):
  - 0.003 × 4.25B ≈ **USD 12.8 million per year**.

Growth assumption:

- If neuromarketing in Thailand follows **Asia-Pacific neuromarketing CAGR (~8–14%)** on top of **Thailand ad-market CAGR (~4%)**, then local neuromarketing spend could realistically grow in the **high single to low double digits annually**.

8.4 Neighbouring-country context (to justify growth)

To argue that Thailand will grow rather than stay flat, we can point to the broader **Southeast Asia / Asia-Pacific context**:

- Asia-Pacific neuromarketing is identified as the **fastest-growing geography**, with CAGRs between **~8–14%** in multiple solution-market reports.

- China's neuromarketing solutions market alone is projected to reach **about USD 306M by 2035**, growing at **9.7% CAGR**, while Japan is forecast around **8.1% CAGR**.
- Reports emphasise that **retail brands in APAC are increasingly adopting neuromarketing technologies** as they shift more budget into data-driven digital marketing.

Given Thailand's:

- strong digital-ad growth (10–16% expected in near term),
- increasing AI and analytics use in marketing,

it is reasonable to argue that Thailand's neuromarketing market will likely **track the broader APAC growth**, not stay at a flat share.

9. Business model

- **Project-based pricing** for individual ad or packaging tests, with tiers (Basic, Standard, Premium) depending on sample size and tools used.
- Later, **retainer agreements** with larger FMCG brands or agencies covering a fixed number of neuromarketing tests per quarter.
- Optionally, develop a **lightweight SaaS or dashboard** once we have enough Thai neuro-data, inspired by Neurons' AI approach but at local price levels.

9.1 Stage 1 – Validation partnership model

9.1.1 Objective of this stage

The objective is **not to maximise revenue yet**, but to:

- Prove that our EEG + eye-tracking method can **predict which creatives perform better** in the real world.
- Show that marketers find our insights **useful and actionable** for their decisions.
- Build **case studies and data** we can show to future paying clients and investors.

9.1.2 Who to partner with

Target companies that:

- Run **frequent advertising or packaging campaigns** (FMCG, food & beverage, skincare, cosmetics, retail, quick-service restaurants, telecom).
- Already do some kind of **testing** (concept tests, A/B tests, creative review) so they understand research value.

- Have **internal champions** (brand managers, digital leads, CX people) who are curious about new methods, even if they are not final budget-holders.

9.1.3 What we offer the partner

Our position our work as a **joint innovation / research pilot**, not as a standard paid service:

- We bring:
  - The **EEG + (optional) eye-tracking setup**, lab time, and all analysis.
  - A structured test of their ads or packaging, plus a **clear report and debrief**.
- They bring:
  - **Real creatives** (ads, key visuals, packaging) that they are about to use or are choosing between.
  - **Access to target customers** or support in recruiting the right demographic.
  - If possible, **campaign performance data after launch** (even in indexed form).

In return for lower or zero fees, they agree to:

- Let us use anonymised results for our **Master's thesis and portfolio**.
- Provide **feedback** and a short testimonial if the results are valuable.

This "exchange" creates strong incentives on both sides: they get **valuable insight at low risk**, us get **validation and data** without having to sell hard.

9.2 How the partnership projects actually run

9.2.1 Project flow

Each pilot project should follow a repeatable structure so it can become our template later:

1. **Scoping workshop (1–2 hours)**
   - Clarify the business question: e.g., "Which of these three video ads should we choose for launch?" or "Which packaging drives strongest shelf impact?"
   - Define success metrics (e.g., attention, emotional engagement, recall, purchase intent; later also CTR/sales).
2. **Experiment design**
   - Select **2–4 creative variants** to test (any more and the study becomes too long).
   - Decide on **sample size** (e.g., 20–30 participants from their target group).
   - Build the stimulus presentation (order, timing, inter-stimulus intervals) and plan any recall or choice tasks.
3. **Data collection (lab or mobile)**

  - Run sessions where participants wear EEG (and optionally eye-tracking) while viewing the creatives.
  - Record behavioural tasks afterwards (recall, choice, rating).
4. **Analysis and reporting**
   - Compute neuro-metrics for each creative: attention peaks, emotional arousal, approach-avoidance, predicted memory.
   - Visualise: time-series plots, heatmaps, rankings.
   - Translate into **marketing language**: "Scene 3 loses attention", "Pack B is found faster and remembered better than Pack A."
5. **Debrief and feedback**
   - Present findings to the marketing team.
   - Ask structured questions: "What surprised you?", "Would this change our decision?", "What would you need to trust this method more?"
   - Capture anonymised quotes as evidence of perceived value.
6. **Post-campaign validation (if possible)**
   - After they run the selected creative, ask for outcome metrics (CTR, view-through, brand-lift, sales index).
   - Compare: did the creative with **higher neuro-scores** actually perform better? If yes, that's proof of predictive power.

9.2.2 What "success" looks like in this stage

We are looking for:

- **Correlation** between our neuro-scores and campaign outcomes (even small samples are valuable as case evidence).
- Marketers saying things like:
  - "This helped us choose between two options we were stuck on."
  - "We saw things we couldn't see from survey/A-B tests."
- Willingness to **use our method again**, even if in a small paid format.

When we can show that:

- "In Pilot 1, creative with higher EEG+eye-tracking score had **20–30% better CTR** than the alternative,"
- "In Pilot 2, package with highest recall score got **more shelf pick-ups** in a small in-store trial,"

9.3 Stage 2 – Transition to a commercial business model

Once we have:

- 2–3 pilots completed,
- Evidence that our metrics align with real performance,

- Positive feedback from marketing teams,

we can move into a **revenue-generating model**.

9.3.1 From "free pilot" to "paid discounted" to "full price"

We can gradually shift:

1. **Pilot partners** – free or token fee (e.g., just covering participant incentives) in exchange for data and case study rights.
2. **Early commercial projects** – same partners or their colleagues pay a **discounted project fee**, because they already see the value.
3. **Standard pricing** – for new clients who see our published cases and come with higher trust.

This graduated approach is aligned with lean-startup guidance: validate first, then scale, then optimise pricing once there is clear demand.

9.3.2 Commercial offerings inspired by international role models

Using Neurensics, Neurons and Unravel as patterns, our future offerings might look like:

- **Neuro-Ad Test** (project-based)
  - EEG (+ optional eye-tracking) for 1–3 video ads or key visuals.
  - 20–30 participants, full report + debrief.
  - Priced as a **one-off project** (in Thailand, for example, mid-hundreds of thousands THB once mature).
- **Neuro-Packaging & Shelf Scan**
  - Eye-tracking + EEG on packaging concepts or shelf layouts.
  - Delivers heatmaps, findability metrics, and predicted sales impact.
- **Neuro-Brand Snapshot / Neuro-Pricing Light** (later)
  - Simplified protocols to measure brand associations or price acceptance, once we have more experience.

Over time, we could add a **lightweight "score dashboard"** where clients log in to view and compare results from multiple studies, similar in concept (not scale) to Neurons AI.

9.3.3 Retainers and long-term partnerships

For brands with continuous campaigns:

- Offer a **retainer**: e.g., "for X THB per month you get up to Y neuromarketing tests per quarter + ongoing consultation."

- This mirrors how global agencies keep working with large FMCG/retail clients year after year.

9.4 Why this staged approach is low-risk and attractive

9.4.1 For us

- We avoid the common startup trap of setting a price and sales pitch **before** proving that our solution really works.
- We build **scientific credibility** and **commercial credibility** (for a future startup) at the same time.
- We accumulate a **unique Thai neuromarketing dataset** that can later underpin a more scalable tool or product.

9.4.2 For the partner companies

- They get **innovation and insight** at very low financial risk (especially in the first pilots).
- They can present the collaboration internally as:
    - “We are exploring advanced neuromarketing in partnership with a university lab / research project,” which often plays well with senior management.
- If the method works, they are in the best position to become **our first paying customers**, with better terms (e.g., pilot-partner discounts or priority access).

PART 7: Development Plan

Phase 1: Research & Foundations (September – October)

Objectives:

- Understand how marketing and advertising teams currently measure engagement and where existing methods fall short.
- Establish theoretical knowledge of EEG signal acquisition, preprocessing, and paradigms relevant to neuromarketing.
- Evaluate available EEG tools, with a focus on the **Unicorn Hybrid Black** as the only feasible and accessible device for this project.
- Investigate additional modalities (facial expression analysis, AU activation patterns) that can complement EEG-based engagement metrics.
- Identify competitors, benchmarks, and gaps in current neuromarketing technologies.

Key Tasks:

1. **Market Research**
    a. Interview marketing professionals/agencies (start with informal LinkedIn outreach)
    b. Identify current methods (e.g., eye tracking, surveys, biometric tools)
    c. Explore gaps and dissatisfaction with current tools
2. **Technical Research**
    a. EEG Foundations
        i. Study key EEG concepts: electrode placement, sampling rate, impedance, noise sources, and preprocessing pipelines (band-pass filtering, ICA artifact removal, notch filtering).
        ii. Review cognitive/affective brainwave associations (alpha suppression for attention, beta activity for cognitive workload, theta for engagement, etc.).
    b. Device-Specific Investigation: Unicorn Hybrid Black EEG
        i. Review technical documentation and academic papers involving the Unicorn Hybrid Black.
        ii. Assess channel configuration, dry electrode performance, SDK functions, and Unicorn Suite capabilities.
        iii. Identify signal limitations and how they influence experiment design and feature extraction.
    c. Complementary Modalities

i. Explore facial expression analysis frameworks (OpenFace, MediaPipe Face) to detect **Action Units (AUs)** as secondary indicators of engagement or affective response.
ii. Review literature on multimodal approaches combining EEG and facial cues for emotional-state prediction.

d. **Paradigm Research**
i. Examine neuromarketing-relevant EEG paradigms such as:
ii. **ERP-based paradigms** (e.g., P300 for novelty/attention)
iii. Continuous ad-viewing paradigms for engagement trends

e. **Oddball tasks**
i. Collect and evaluate open-access literature on ERP and non-ERP neuromarketing methods.

3. **Feasibility Study**
   a. Map EEG features to marketing metrics (e.g., attention index, emotional engagement, cognitive load).
   b. Identify features that the Unicorn headset can reliably produce.
   c. Conduct preliminary recordings in **Unicorn Suite** to verify signal clarity and test artifact-rejection needs.
   d. Build a list of preprocessing steps based on EEG literature and experiment requirements.
   e. Begin collecting academic references for both ERP and non-ERP analysis pipelines.

Phase 2: Ideation & Early Prototyping (November – December)

Objectives:

- Select and validate the EEG hardware/software stack (finalized as Unicorn Hybrid Black + Python).
- Design paradigms informed by established neuromarketing and BCI literature.
- Develop early-stage experimental workflows combining EEG and facial-expression cues.
- Produce initial engagement-prediction prototypes using multimodal features.

Key Tasks:

1. **Technical Familiarization & Software Setup**
   a. Gain hands-on experience with Unicorn Suite, including live recording, signal visualization, and exporting raw EEG data.

   b. Verify signal acquisition reliability through test recordings and artifact checks.
   c. Set up the development environment: Python, PsychoPy, Unicorn Hybrid Black API/SDK.

2. **Experimental Paradigm Development**
   a. Design paradigms directly referencing academic literature to ensure technical validity:
      i. **ERP-based paradigm** informed by *"Evaluating a Novel P300-Based Real-Time Image Ranking BCI" (Šutaj et al., 2021)* as a reference for P300 dynamics and stimulus timing.
      ii. **Non-ERP continuous engagement task** adapted from *Mashrur et al. (2022)* for feature extraction and engagement scoring.
   b. Implement experiments using **Python and PsychoPy**, including:
      i. randomized stimulus presentation
      ii. precise timestamping for ERP analysis
      iii. integration of EEG event markers
3. **Multimodal Data Integration (Facial Expression + EEG)**
   a. Record participant facial expressions during the experiment using an external webcam.
   b. Use **OBS WebSocket** to insert timestamps/markers to synchronise video segments with displayed stimuli.
   c. Extract facial **Action Units (AUs)** using **OpenFace**, isolating only segments that correspond to stimulus presentation.
   d. Prepare AU datasets for machine learning (feature normalisation, temporal alignment, feature selection).
4. **Signal Processing & Feature Extraction**
   a. Perform EEG preprocessing based on referenced literature:
      i. band-pass filtering
      ii. referencing and artifact reduction
      iii. epoch extraction for ERP stimuli
      iv. baseline correction
   b. Extract relevant EEG features such as:
      i. ERP peaks (P300 amplitude/latency)
      ii. frequency-band power (alpha, beta, theta)
      iii. temporal statistics and engagement-related markers
   c. Compare preprocessing and feature extraction outcomes against published findings to validate method accuracy.
5. **Early Engagement Classification Prototype**

   a. Train a **Random Forest model** using extracted AUs to predict participant engagement based solely on facial-expression data.
   b. Use this as a baseline model for evaluating whether EEG adds predictive value in subsequent phases.
   c. Analyze feature importance to identify which AUs correlate most strongly with engagement in stimulus-driven contexts.
6. **Early Client-Facing Concept Design**
   a. Draft low-fidelity mockups showing how neuromarketing results could be presented to clients (e.g., engagement timeline, emotional-response heatmap, stimulus-by-stimulus comparison).
   b. Begin shaping the value proposition around a practical deliverable.

Phase 3: MVP Development & Testing (January – February)

Objectives:

- Develop MVP capable of running simple experiments
- Test it with small groups (friends, students) and collect data
- Refine based on feedback

Key Tasks:

1. **Build MVP**
   a. Create a basic system: input (EEG while watching video) → process → output (engagement report)
   b. Choose metrics (e.g., attention, stress, cognitive load)
2. **Conduct Trials**
   a. Run small studies with volunteers
   b. Record feedback from participants and mock clients on result presentation and clarity
3. **Prepare Sales Material**
   a. Develop a pitch deck and demo materials (PDF report samples, screen captures of dashboard, etc.)
   b. Identify pilot clients or partners

Phase 4: Business Validation & Launch Planning (March – April)

Objectives:

- Engage with at least one client or marketing agency

- Gather feedback on business viability
- Prepare next steps: scale or pivot

Key Tasks:

1. **Client Testing**
    a. Offer a free or low-cost trial to an agency or startup
    b. Collect testimonials and feedback
2. **Assess Viability**
    a. Evaluate pricing strategy
    b. Estimate operational cost per test
    c. Plan for commercial version (scalability, automation, etc.)
3. **Roadmap for Post-April**
    a. Plan for the next development round (better analytics, other biosignals)
    b. Apply for funding, grants, or startup competitions

Project Timeline

September – October: Research & Exploration

Study marketing companies' current methods for measuring audience engagement

Learn EEG fundamentals and compare available EEG devices

Identify key problems our service could solve

Analyze potential competitors and relevant case studies

November – December: Concept Development & Early Prototype

Define our core value proposition and use cases

Acquire and test a basic EEG device (e.g., OpenBCI or Emotiv)

Build a low-fidelity prototype to visualize engagement data

Draft sample output reports for marketing clients

January – February: MVP Build & Testing

Finalize our MVP (collect EEG data → analyze → generate report)

Conduct small-scale user testing (friends, students, mock ads)

Gather feedback to improve accuracy, presentation, and clarity

Prepare client-facing demo materials (pitch deck, sample reports)

March – April: Client Trial & Launch Preparation

Run at least one pilot trial with a real marketing company or agency

Collect feedback on the service's usefulness and pricing

Finalize plans for scaling, partnerships, or funding after April

Refine business model based on client needs and feedback

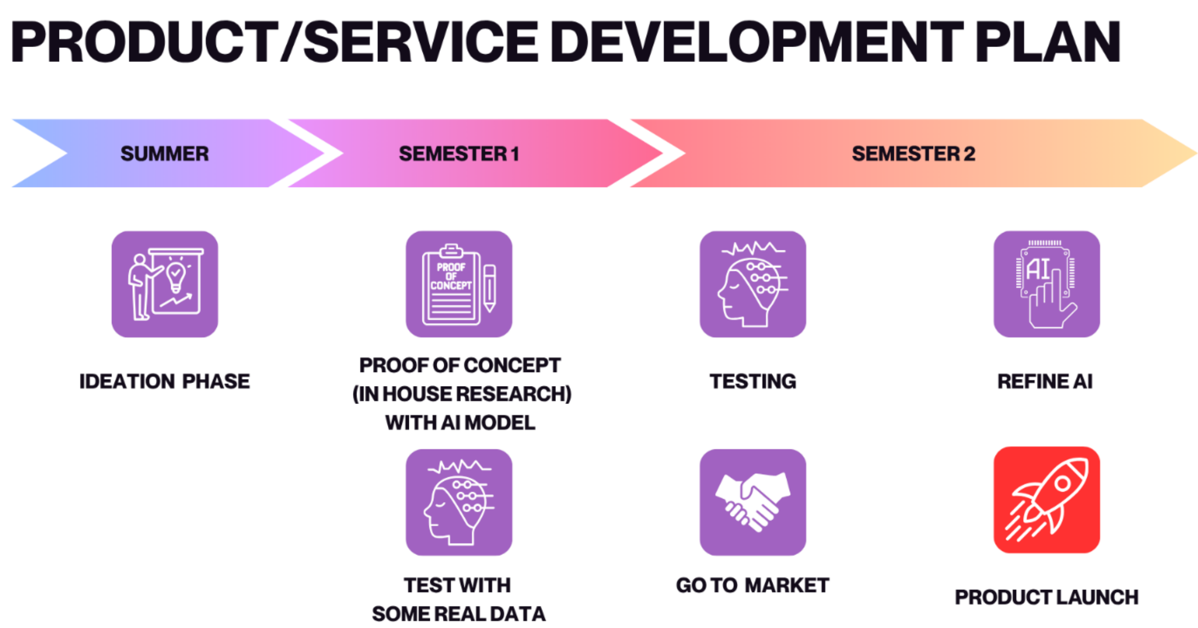


Figure 18 The development plan.

PART 8: Ethical Consideration

NeuroRight is mindful of ethical considerations in all respects; accordingly, our services and all research-and-development activities comply with Thai law and internationally recognized standards, including Thailand's **Personal Data Protection Act B.E. 2562 (2019) ("PDPA")** and **UNESCO's Recommendation on the Ethics of Artificial Intelligence**. Moreover, all future human-participant activities will undergo internal ethics review and, where applicable, will be submitted for approval by CMKL Institutional review board (IRB) before any data collection begins. At present, no IRB/IEC approval has been obtained.

Participants will provide informed consent (Appendix A) after receiving clear information on the study's purpose, procedures, data types (including but not limited to EEG data), potential risks and benefits, retention periods, data sharing and any cross-border transfers, and their right to withdraw at any time without penalty. Explicit consent will be obtained for Sensitive Data, and additional safeguards will be applied to vulnerable groups.

Data collection will follow the principles of data minimization and purpose limitation. Only data strictly necessary for the stated objectives will be collected, and processing will be restricted to the purposes communicated in the consent or otherwise permitted by law; any secondary use will require a compatibility assessment or renewed consent. To protect confidentiality, direct identifiers will be removed or replaced with pseudonymous codes and the linkage keys will be stored separately with restricted access.

Data sharing with the public, vendors, and other third parties will operate only under written, PDPA-compliant agreements. Where data leave Thailand or are processed by external parties, appropriate cross-border safeguards will be applied, and sharing will occur only under Data Sharing Agreements that specify purpose, security, retention, and a prohibition on re-identification. NeuroRight will not sell Personal Data. Publications and shared outputs will be limited to aggregate or anonymized data, and any identifiable images, audio, or video will be used only with explicit consent.

Under the PDPA, participants will be able to exercise their rights to be informed, access, rectify, erase, restrict processing, object, withdraw consent, and—where applicable—data portability by contacting out team. Requests will be acknowledged and fulfilled within statutory timelines. High-risk processing will undergo a Data Protection Impact Assessment. Incidents will be reported immediately, contained, investigated, and notified to authorities and affected individuals as required.

Use of Artificial Intelligence (AI) will align with UNESCO's Recommendation on the Ethics of Artificial Intelligence and will be grounded in human rights, human oversight, and the principles of transparency, fairness, and accountability. NeuroRight will implement data-governance and privacy safeguards; conduct ethical/risk impact assessments for higher-risk use cases; ensure context-appropriate transparency and explainability; maintain robust safety and security controls; test for and mitigate bias and discrimination; prohibit manipulative or exploitative applications; ban social scoring and mass surveillance; and ensure that humans remain responsible and "in the loop" for consequential decisions, with documentation and auditability maintained across the AI lifecycle.

Beyond these general commitments to PDPA compliance, informed consent, data minimization, pseudonymization, secure data sharing, and UNESCO AI ethics principles, NeuroRight explicitly recognizes that EEG-based neuromarketing is a form of consumer neurotechnology and therefore entails additional ethical duties. Recent work on AI-enabled "mind-reading" devices shows that neurotechnologies can, in some contexts, reveal preconscious intentions and internal states, creating heightened risks for mental privacy and personal autonomy if brain data are treated like ordinary digital traces (Drew, 2025). In response, NeuroRight treats all EEG recordings and derived "neuro-metrics" as highly sensitive brain data: collection is limited to clearly defined research and service goals; we avoid decoding or inferring information unrelated to the presented stimuli; and we do not create individual "neuro-profiles" for marketing, scoring, or long-term tracking. Our reports focus on aggregated patterns and creative-level insights, rather than labeling or ranking individual participants. Consistent with UNESCO's 2025 Recommendation on the Ethics of Neurotechnology, we affirm the "inviolability of the human mind" and design our pipeline to protect mental privacy, cognitive liberty, and human dignity (UNESCO, 2025). Participation is strictly voluntary, with clear communication about what the system can and cannot infer, and explicit consent for any collection of neural, facial, or gaze data. We will not deploy NeuroRight for non-therapeutic uses in children or other especially vulnerable populations, nor in contexts such as productivity monitoring, behavioural surveillance, or covert manipulation (e.g., hidden employee testing). In neuromarketing applications, we explicitly prohibit using our metrics to design addictive, harmful, or deceptive experiences; instead, the tool is positioned to improve clarity and relevance of content and reduce waste, rather than to exploit subconscious vulnerabilities.

Governance and accountability will be ensured through ethics, PDPA, and data-security training for all team members; periodic audits; and continuous improvement of controls. Queries regarding ethics or data protection may be directed to R&D Lead: tkulwatt@cmkl.ac.th or the Project advisor: fawad@cmkl.ac.th.

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PART 9 : Appendix A
The PDPA consent form

Privacy Notice/ Consent Form

Consent Form for the Collection, Use, and Disclosure of Personal Data
in accordance with the Personal Data Protection Act (PDPA), B.E. 2562

Date............Month......................Year.............

I, Mr./Mrs./Ms...hereby express my intention to:

❒ Give consent ❒ Do not give consent

for the collection, use, and disclosure of my personal data, including: (1) General personal information, such as name, surname, photograph, address, telephone number, and other personal details; and (2) Data necessary for the experiment, including but not limited to neurological signals, electroencephalography (EEG) signals, video data, facial emotion recognition, and eye tracking, to the research team of the NeuroRight Project (“the Researchers”).

The purposes of data processing are as follows: (1) To analyze and process data necessary for experimentation, research, and product development; and (2) To use such data for advertising, dissemination of information, publicity, promotion, and presentation of products, services, and marketing activities conducted by the research team, CMKL University, and related parties to the public, organizations, and other legal entities.

Prior to expressing my intention, I have read the information sheet and/or received an explanation from the research team regarding the objectives of collecting, using, or disclosing my personal data and fully understand them.

I hereby give or withhold my consent in this document voluntarily, without coercion or inducement, and I understand that I may withdraw my consent at any time.

In the event that I wish to withdraw my consent, I understand that such withdrawal shall not affect any processing of personal data that has already been completed prior to the withdrawal of consent.

Signature : ....

(...)