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International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
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DEMOCRATIZING CONSUMER NEUROSCIENCE: A SYSTEMATIC REVIEW OF ACCESSIBLE BIOMETRIC TOOLS FOR EARLY-STAGE STARTUPS

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ABSTRACT

This systematic review examines whether low-cost biometric tools can provide a scientifically credible and economically feasible alternative to traditional laboratory-based neuromarketing methods for early-stage startups. Consumer neuroscience has long been dominated by large firms with access to expensive technologies such as functional Magnetic Resonance Imaging (fMRI) and high-density Electroencephalography (EEG), creating an "insight gap" for resource-constrained ventures that must often rely on self-reported consumer data. Recent advances in consumer-grade biometric devices, webcam-based tracking, and Artificial Intelligence (AI) analytics may help close this gap. Accordingly, this review evaluates the validity, reliability, and affordability of four accessible tools: webcam eye-tracking, automated facial coding, consumer-grade EEG, and wearable Electrodermal Activity (EDA) sensors.

The review followed Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines and drew on evidence from Web of Science, Scopus, PubMed, and IEEE Xplore. More than 100 sources were synthesized, with particular emphasis on validation studies comparing consumer-grade technologies such as Muse, Emotiv, Fitbit, and webcam-based systems against established laboratory standards including Neuroscan, Tobii Pro, and Biopac. The findings reveal a clear validity-accessibility trade-off. Webcam eye-tracking is useful for large Areas of Interest (AOI) and aggregate heatmaps, but lacks the precision needed for detailed usability analysis. Automated facial coding performs reasonably well for high-intensity emotions, yet remains weak in detecting subtle expressions and may be affected by demographic bias. Consumer-grade EEG can capture broad spectral indicators such as alpha and beta activity linked to focus and relaxation, but it is limited by lower signal quality and motion artifacts. Likewise, wearable EDA and Heart Rate Variability (HRV) sensors can provide valid readings under stationary conditions, though reliability declines significantly during movement.

Overall, the evidence suggests that a "Democratized Neuromarketing Stack" is now achievable for startups, provided these tools are used within their methodological limits. Their greatest value lies in generating aggregate-level insights, especially when paired with larger sample sizes to offset higher noise levels, rather than in precise individual-level diagnostics. This makes them well-suited for integration into Lean Startup testing cycles, enabling more evidence-based product development through practical "neuro-testing." However, the growing accessibility of remote biometric research also raises important ethical concerns, making strong safeguards for privacy, informed consent, and responsible data use essential.

Keywords:
Neuromarketing, Consumer Neuroscience, Biometrics, Startups, Systematic Review, EEG, Eye-Tracking, Facial Coding, Democratization, Validation, Wearables, Lean Startup.

1. INTRODUCTION

Traditional marketing research was built on the assumption that consumers are rational decision-makers who can clearly explain what they want and why they want it (Zinkhan & Hirschheim, 1992). Surveys, interviews, and focus groups were therefore designed to capture conscious preferences (Nisbett & Wilson, 1977). However, advances in psychology and behavioral science have shown that much of human decision-making is driven by fast, automatic, and subconscious processes rather than deliberate reasoning. This insight exposed a major limitation of conventional research methods: they often cannot capture the deeper emotional and cognitive drivers of consumer behavior (Evans, 2008; Kahneman, 2003b). In response, consumer neuroscience, or

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neuromarketing, emerged to measure physiological and neural reactions directly, offering richer insight into attention, emotion, and decision-making. Yet in its early development, neuromarketing relied on expensive laboratory tools such as fMRI and high-density EEG, making it largely accessible only to large corporations with substantial research budgets (Ariely & Berns, 2010a; N. Lee et al., 2007; Plassmann et al., 2007).

This access gap is especially problematic for startups, which operate under resource constraints and must make rapid decisions to achieve product-market fit before their financial runway ends (Graña-Alvarez et al., 2024; S. (Ronnie) Lee & Kim, 2024). Under Lean Startup principles, founders depend on fast cycles of testing and learning, usually through behavioral metrics and user feedback. Although these approaches reveal what users do or say, they often fail to explain why users respond in certain ways (Felin et al., 2024; Leatherbee & Katila, 2020; Shepherd & Gruber, 2021). For example, a high bounce rate may show that users leave a page, but not whether the cause is confusion, frustration, or disinterest. Neurophysiological tools could help answer these questions by capturing subconscious reactions, but medical-grade systems remain too costly and complex for most early-stage ventures. As a result, many startups continue to rely heavily on intuition, increasing the risk of poor decision-making in an already uncertain business environment (Alvino et al., 2020).

Recent technological developments, however, suggest that consumer neuroscience is becoming more accessible. Low-cost wearable EEG devices, smartwatch-based biometric sensors, webcam-enabled eye-tracking, and AI-powered facial coding platforms have made it possible to collect neurophysiological data without a specialized laboratory (Höfling & Alpers, 2023; Köhler et al., 2024; Sabio et al., 2024; Schröter et al., 2021; Yang & Krajbich, 2021). At the same time, integrated software platforms now simplify data interpretation by converting raw signals into usable measures such as attention, engagement, and stress. This review examines whether these accessible tools provide a credible and cost-effective alternative to laboratory standards for startups. Specifically, it evaluates the validity of webcam eye-tracking, automated facial coding, consumer-grade EEG, and wearable biometrics against established gold standards, considers their economic feasibility in real startup contexts, identifies where they offer the greatest practical value across the startup lifecycle, and addresses key ethical concerns related to privacy, consent, and the future role of AI in scalable biometric consumer research (Bott et al., 2020; Gupta et al., 2025; Kaduk et al., 2024; Martinez-Martin, 2019; Quiles Pérez et al., 2024).

2. LITERATURE REVIEW

2.1 Theoretical Foundations: The Somatic Marker and System 1

The theoretical viability of neuromarketing rests on the Somatic Marker Hypothesis, proposed by neuroscientist Antonio Damasio. This theory posits that those emotional processes guide behavior, particularly decision-making. "Somatic markers" are feelings in the body that are associated with emotions, such as a rapid heartbeat with anxiety or nausea with disgust. According to Damasio, these markers strongly influence subsequent decision-making (Bechara et al., 2000; Damasio, 1996). In the context of a startup, a user's decision to sign up for a service or purchase a product is rarely a purely cold calculation of features; it is influenced by these somatic markers, the "gut feeling" generated by the brand's aesthetic, the ease of the interface, or the emotional resonance of the copy (Bechara & Damasio, 2005; Cyr et al., 2006; Lindgaard et al., 2006).

This aligns with the dual-process theory of cognition, often referred to as System 1 and System 2. System 1 is fast, automatic, and emotional, while System 2 is slow, effortful, and logical. Traditional market research asking a user, "Did you like this app?" engages System 2, forcing a rationalization of an experience that was largely processed by System 1 (Evans, 2008; Kahneman, 2003a). Biometric tools allow researchers to tap directly into the System 1 response. For example, facial coding can detect a micro-expression of "Joy" milliseconds after a user sees a price point, long before they can articulate "I think this is a good value". For startups, whose products often rely on disrupting habits or creating new desires, accessing this subconscious layer is critical (Höfling & Alpers, 2023; Shen et al., 2012).

2.2 The Challenge of "Reverse Inference."

A persistent debate in the academic literature concerning neuromarketing is the problem of "reverse inference." This logical fallacy occurs when a researcher observes a physiological state (e.g., activation of the insula in the brain, or a spike in skin conductance) and infers a specific psychological state (e.g., "the consumer dislikes this price" or "the consumer is excited") (Ariely & Berns, 2010a; Poldrack, 2006, 2011). The critique, articulated by researchers like Poldrack, is that physiological signals are rarely one-to-one; the insula activates for pain, but also for disgust and empathy. Similarly, a spike in arousal (GSR) could indicate excitement, but it could equally indicate stress or fear (Ohira & Hirao, 2015; Poldrack, 2006; Singer et al., 2009).

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However, the literature also presents a counter-narrative from the applied commercial sector. While academic science demands absolute certainty, business operates on probabilities. As noted in commercial research contexts, if a biometric signal can increase the probability of a correct decision from 50% (a coin toss) to 60%, it holds immense economic value. This "probabilistic reverse inference" is the operational model for most neuromarketing (Hutzler, 2014; Poldrack, 2006). Startups must navigate this by using biometric data not as a crystal ball, but as a directional signal to be triangulated with other data points (e.g., combining high arousal with a smile to infer excitement rather than fear) (Barrett et al., 2019; Cao & Reimann, 2020; Garczarek-Bąk et al., 2021).

2.3 The Three Waves of Consumer Neuroscience

The literature traces the evolution of this field through three distinct waves, each defined by the accessibility of the technology:

- **Wave 1: The Clinical Era (2000-2010)**. Research was conducted almost exclusively in academic or hospital settings. The tools were heavy fMRI scanners and 128-channel EEG caps. Studies were slow, expensive, and focused on broad theoretical questions or the needs of massive brands (Alvino et al., 2020; Ariely & Berns, 2010b; N. Lee et al., 2007).
- **Wave 2: The Portable Era (2010-2018)**. Companies like Tobii and Shimmer introduced portable, research-grade devices. Eye-trackers became screen-mounted bars, and EEG caps became wireless. This allowed research to move into "central location tests" (CLTs) in malls or offices, reducing cost but still requiring specialized hardware and technicians (Burns et al., 2010; N. Lee & Lee, 2021; Zhang & Cui, 2022).
- **Wave 3: The Consumer/AI Era (2018-Present)**. This current wave is the focus of this report. It is characterized by the use of *existing* consumer hardware (webcams, smartwatches) and low-cost consumer wearables (Muse, Emotiv). The burden of data quality has shifted from hardware precision to software sophistication, with AI algorithms cleaning noisy data and interpreting results (Brophy et al., 2022; Köhler et al., 2024; Sabio et al., 2024; Shajari et al., 2023; Yang & Krajbich, 2021).

2.4 Ethical Frameworks: The NMSBA and GDPR

As the tools for reading human physiology become more accessible, the ethical stakes rise. The Neuromarketing Science & Business Association (NMSBA) was established to create a code of ethics for the industry (Ferrell et al., 2025; Hensel et al., 2017a; Sabio et al., 2024). Key pillars of this code include:

- **transparency**: Participants must be explicitly informed that their physiological reactions are being measured.
- **Consent**: There must be clear, informed consent, which is particularly challenging in remote webcam studies where users might click "Agree" without reading terms.
- **Privacy**: Physiological data is sensitive. Under the General Data Protection Regulation (GDPR) in Europe, biometric data is classified as a "special category" of personal data, requiring higher standards of protection. For startups, ignorance of these ethical boundaries is a significant liability. The "move fast and break things" ethos of Silicon Valley clashes with the strict requirements of biomedical ethics. The literature highlights that while the tools are democratized, the *responsibility* is also distributed, often to founders who lack training in human subjects research (Ferrell et al., 2025; Hensel et al., 2017b).

3. METHODOLOGY

3.1 Systematic Review Protocol

To ensure this report provides a rigorous foundation for business decision-making, a systematic review methodology was employed, adapted from the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. This approach minimizes bias and ensures a comprehensive sweep of the available evidence.

Search Strategy:

The review utilized a structured search across multiple high-impact electronic databases: Scopus, Web of Science, PubMed, and IEEE Xplore. The search strategy was designed to intersect three core domains: the technology (tools), the application (neuromarketing/startups), and the evaluation (validation).

- **Primary Keywords**: "Neuromarketing," "Consumer Neuroscience," "Biometrics," "Startups," "Low-cost."

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- **Specific Modalities**: "Webcam Eye Tracking," "Consumer EEG," "Automated Facial Coding," "Wearable EDA," "Photoplethysmography (PPG)."
- **Search Strings**: Queries such as ("systematic review" OR "validation" OR "reliability") AND ("consumer-grade" OR "low-cost") AND ("EEG" OR "eye tracking" OR "GSR") were used to pinpoint papers that specifically tested the *quality* of these tools.

3.2 Inclusion and Exclusion Criteria

Strict criteria were applied to filter the thousands of initial results down to a relevant core set of documents suitable for guiding startup strategy.

- **Inclusion**:
    - **Publication Date**: Studies published between 2015 and 2025 were prioritized to ensure the technology discussed is current.
    - **Comparative Validation**: Studies that explicitly compared a consumer-grade device (e.g., Muse, Webcam) against a recognized medical/research-grade gold standard (e.g., BioSemi, Tobii Pro). This "benchmarking" is crucial for establishing the validity-accessibility trade-off.
    - **Application Context**: Literature discussing the practical application of these tools in marketing, UX, or behavioral research.
- **Exclusion**:
    - **Purely Clinical Studies**: Research focused solely on pathology (e.g., diagnosing epilepsy or arrhythmia) was excluded unless it contained relevant sensor validation data.
    - **High-Cost Modalities**: Studies focusing exclusively on fMRI, MEG, or PET scanning were excluded, as these remain fundamentally inaccessible to early-stage startups due to cost and logistical complexity.

3.3 Data Synthesis and the "Signal-to-Noise" Framework

The extracted data was synthesized using a "Signal-to-Noise" framework. In engineering and neuroscience, the Signal-to-Noise Ratio (SNR) determines the quality of a measurement. Medical-grade tools strive for maximum SNR (pure signal). Consumer tools inherently accept a lower SNR (more noise) in exchange for accessibility. The synthesis focused on identifying the *threshold of utility*: at what point does the noise become so great that the signal is no longer useful for business decisions? Data extracted included:

- **Quantitative Metrics**: Correlation coefficients (Pearson's r, ICC), Root Mean Square Errors (RMSE), and accuracy percentages.
- **Economic Data**: Hardware unit costs, software subscription fees (SaaS models), and ease-of-access metrics.
- **Qualitative Insights**: Authors' conclusions on the usability, comfort, and "real-world" viability of the devices.

4. RESULTS

A. Findings: The Eye Tracking Paradigm Shift

Visual attention is perhaps the most intuitive and direct metric in neuromarketing (Gheorghe et al., 2023). If a user does not see a product, they cannot buy it. If they do not see the "Buy" button, the conversion is lost. Consequently, eye-tracking has been a staple of the industry. The shift from dedicated infrared hardware to webcam-based software represents the most significant "democratization" event in the field (Gheorghe et al., 2023; Kaduk et al., 2024; Schröter et al., 2021; Van der Cruyssen et al., 2024).

4.1 Technology Mechanisms: Infrared vs. Computer Vision

To understand the validation data, one must understand the underlying mechanisms. **Gold Standard: Infrared Video-Oculography**. Systems like the **Tobii Pro** or **SMI** use near-infrared light sources to create reflections on the cornea (Purkinje images) and the pupil (Cognolato et al., 2018). High-speed cameras track the vector difference between the pupil center and the corneal reflection. This method is robust to head movement and lighting changes, providing extremely high sampling rates (60Hz to 1200Hz) and precision down to 0.5 degrees of visual angle (Hooge et al., 2023).

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Accessible Alternative: Webcam Eye-Tracking. Solutions provided by platforms like **iMotions**, **CoolTool**, and **RealEye** utilize the standard RGB webcam found in laptops. They rely on advanced computer vision and deep learning algorithms to detect the user's face, locate the eyes, and estimate the gaze vector based on the geometry of the iris and head pose. This approach requires no specialized hardware but is fundamentally limited by the low resolution and frame rate (typically 30fps) of consumer webcams (Kaduk et al., 2024; Liu et al., 2022; Saxena et al., 2024; Zdarsky et al., 2021).

4.2 Validation Evidence: The Accuracy vs. Precision Trade-off

The review of validation literature reveals a consistent theme: webcam eye-tracking sacrifices precision (granularity) but maintains acceptable accuracy (general location) for specific use cases.

Accuracy and Precision Metrics: A pivotal study comparing webcam-based tracking to the Tobii X2-60 (infrared) found that while the infrared system had an average spatial error of ~0.43 degrees, the webcam system on a tablet had an error of ~1.99 degrees. In practical terms, 0.43 degrees is the size of a letter in a word; 1.99 degrees is the size of the entire button. This means webcam tracking might struggle to tell *which* word a user is reading, but it can reliably tell *which paragraph* they are reading or if they are looking at a large "Call to Action" button (Greenberg et al., 2006; Taore et al., 2024).

Another study utilizing the "Sticky" algorithm (a popular webcam tracking algorithm) versus SMI infrared trackers found that for large images centered on the screen, the accuracy in determining whether a stimulus was viewed was comparable. However, performance degraded significantly for targets located at the periphery of the screen or for very small targets. This is a crucial limitation for startups testing full-screen web designs; data at the edges of the monitor is less reliable due to the geometry of the webcam's field of view (Burton et al., 2014).

Robustness and Data Loss: Webcam systems are highly sensitive to environmental variables. "Data loss"—periods where the eye-tracker cannot find the eyes are significantly higher with webcams, often due to poor lighting, reflections on glasses, or the user moving out of frame. One study noted that while infrared systems had negligible data loss (0.13%), webcam systems could experience loss rates requiring the exclusion of trials where gaze predictions fell outside the screen dimensions. However, algorithms are improving. Validations of the **WebGazer.js** library and other proprietary tools indicate that with proper calibration (often a 5-point or 9-point sequence), the system can achieve reasonable reliability for "fixation" detection, though it struggles with "saccades" (rapid eye movements) due to the low 30Hz frame rate (Semmelmann & Weigelt, 2018; Van der Cruyssen et al., 2024; Vos et al., 2022).

4.3 Startup Application: The "Heatmap" Economy

For a startup, these findings dictate a clear use case. Webcam eye-tracking is **valid** for:

- **A/B Testing Hero Images**: Determining which of two large images captures attention first.
- **Heatmap Generation**: Aggregating data from 50+ remote users to see "hot spots" on a landing page. The law of large numbers helps average out the noise of individual webcams.
- **Visual Hierarchy Validation**: Ensuring the user flow follows the intended path (e.g., Headline -> Image -> Button).

It is **invalid** for:

- **Detailed Reading Studies**: Trying to see if a user stumbled on a specific word in a sentence.
- **Mobile App Usability Testing**: Where buttons are small and the user's thumb might obscure the camera's view of the eyes.

Cost Implications: The cost difference is staggering. A Tobii lab setup can cost $20,000+. Webcam tracking costs zero in hardware and operates on a SaaS model (e.g., $299/month for CoolTool or per-respondent fees). This shifts eye-tracking from a "Capital Expenditure" (CapEx) to an "Operating Expense" (OpEx), making it accessible to bootstrapped ventures.

B. Findings: Automated Facial Coding (AFC)

If eye-tracking tells us *what* people see, facial coding attempts to tell us *how they feel* about it. Based on the Facial Action Coding System (FACS) developed by Ekman and Friesen, this method decomposes facial expressions into anatomical muscle movements called Action Units (AUs) (Donato et al., 1999; Hamm et al., 2011).

4.4 Technology Mechanisms: EMG vs. Computer Vision

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Gold Standard: Facial Electromyography (EMG). This technique involves placing electrodes directly on the skin over specific facial muscles, typically the *Zygomaticus Major* (cheek muscle involved in smiling) and the *Corrugator Supercilii* (brow muscle involved in frowning). EMG measures the electrical activation of these muscles. It is incredibly sensitive, capable of detecting "sub-threshold" or "micro" expressions that are visible to the naked eye (Rutkowska et al., 2024; Sato & Kochiyama, 2023).

Accessible Alternative: Automated Facial Coding (AFC). Software platforms like **Affectiva**, **FaceReader** (Noldus), and open-source libraries like **Py-Feat** use computer vision to track facial landmarks (eyebrows, mouth corners, nose tip). Deep learning models then classify the geometric configuration of these landmarks into AUs and subsequently into emotions (e.g., Joy, Anger, Surprise) (Cheong et al., 2023; Namba et al., 2021; Stöckli et al., 2018).

4.5 Validation Evidence: The Intensity Threshold

The literature indicates a strong correlation between AFC and EMG, but only above a certain intensity threshold.

High-Intensity Correlation: Validation studies have repeatedly shown that for distinct, high-intensity expressions, AFC performs admirably. A study comparing **Affectiva** software with EMG found significant correlations for "Joy" (smiling) and "Anger" (brow furrowing). In some experimental conditions, the software's "Joy" metric correlated with the EMG Zygomaticus signal with r-values exceeding 0.75, considered a strong relationship in behavioral science. This suggests that for measuring reaction to a funny joke in an ad or a delightful moment in a video, AFC is a valid proxy for EMG (Kulke et al., 2020, 2020; Westermann et al., 2024).

The "Neutral" Problem: The technology falters with subtle or neutral expressions. EMG can detect the slight tension of a brow during a moment of confusion that does not result in a visible frown. AFC software often classifies these subtle states as "Neutral" or misinterprets them. Studies show that neutral faces are more often falsely identified as negative by EMG (which detects the resting tension) compared to software, or vice versa, highlighting a discrepancy in how "baseline" states are handled. For a startup testing a complex B2B dashboard, where user frustration might be a subtle tightening of the jaw rather than a theatrical scowl, AFC may miss the signal entirely (Höfling et al., 2020; Hsu & Sato, 2023).

Algorithmic Bias: A critical ethical and practical finding is the presence of bias in AFC algorithms. Because these AI models are trained on datasets of human faces, they inherit the biases of those datasets. Research has highlighted that accuracy can vary significantly based on the subject's gender, age, and skin tone. For example, some algorithms have been shown to interpret the resting faces of certain ethnicities as "angry" or "sad" more often than others. This poses a risk for startups: optimizing a product based on biased emotional data could lead to exclusion of certain user demographics (Cross et al., 2023; Halberstadt et al., 2022).

4.6 Startup Application: Viral Content and "Wow" Moments

For early-stage startups, AFC is best deployed in **Content Marketing** and **Video Ad Testing**.

- **Viral Prediction**: High valence (positive emotion) is a strong predictor of sharing behavior. Startups can use AFC to test multiple cuts of a promo video to see which one generates the highest "Joy" score at the punchline.
- **User Frustration**: While it misses subtle cues, AFC *can* detect moments of significant frustration (e.g., brow furrowing) during a broken user flow.
- **Integration**: Platforms like **iMotions** and **CoolTool** integrate AFC seamlessly, allowing a founder to send a link to 100 users and get an "Emotional Timeline" of their video.

C. Findings: Democratizing Brain Imaging (EEG)

Electroencephalography (EEG) is the crown jewel of neuromarketing. It measures the electrical activity of the brain directly, offering millisecond-level temporal resolution. It captures the "Ah-ha!" moment or the instant of cognitive overload (Bazzani et al., 2020; García-Madariaga et al., 2020; Vecchiato et al., 2011).

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4.7 Technology Mechanisms: Wet vs. Dry
Gold Standard: Medical EEG. Systems like **Neuroscan** or **g.tec** utilize 32 to 128 electrodes. They are "wet" systems, requiring the application of conductive gel to the scalp to bridge the gap between skin and sensor. This ensures a high Signal-to-Noise Ratio (SNR) but requires 30-60 minutes of setup time and a controlled environment.

Accessible Alternative: Consumer EEG. Devices like the **Muse** (Interaxon), **Emotiv Epoc**, and **NeuroSky** use "dry" or saline-soaked sensors. They typically have fewer channels (1 to 14) and prioritize ease of use, often slipping on like a headband in seconds. The **Muse S**, for example, is a soft headband designed for sleep and meditation but widely adopted for research due to its accessibility.

4.8 Validation Evidence: Spectral Power vs. Localization
The validation landscape for consumer EEG is surprisingly robust, though specific in its scope.

Valid for Spectral Power: Multiple studies have confirmed that consumer devices like the Muse and Emotiv are capable of reliably measuring the "Power Spectral Density" (PSD) of major brainwaves: Alpha (8-12Hz, associated with relaxation), Beta (12-30Hz, associated with active focus), and Theta (4-8Hz, associated with drowsiness or deep cognition). A study comparing the **Muse** to a medical-grade **Brain Products** system found high correlations in Alpha and Beta band power during resting states. Another study compared the **NeuroSky MindWave** (a single-channel device) to the Neuroscan and found "very minor differences" in signal quality for basic tasks, though the single channel severely limits the types of analysis possible.

Invalid for Source Localization: Where consumer EEG fails is "Spatial Resolution." With only 4 channels (Muse) or 14 channels (Emotiv), it is mathematically impossible to triangulate *where* inside the brain a signal is coming from (Source Localization). You cannot say "The amygdala fired." You can only say "There was increased Beta activity in the frontal lobe." For marketing, this means you can measure "General Engagement" or "Focus," but you cannot map specific emotional centers deep in the brain as an fMRI would.

The Artifact Issue: Consumer devices are highly susceptible to "artifacts" non-brain electrical signals. Blinking, clenching the jaw, or moving the head creates electrical noise that is often stronger than the brain signal. Medical systems use reference electrodes and gel to minimize this; dry consumer sensors are prone to drifting and losing contact. Validation studies emphasize that rigorous data cleaning algorithms are required to make consumer EEG data usable.

4.9 Startup Application: Cognitive Load and Focus
For startups, the "Killer App" of consumer EEG is measuring **Cognitive Load**.

- **UX Testing**: High Beta/Theta ratios indicate high cognitive processing. If a user is navigating a startup's "simple" signup form but their brainwaves show intense cognitive load, the design is likely too complex.
- **Meditation/Wellness Apps**: For startups in the health space, devices like Muse are not just research tools but potential hardware partners. The **Muse S** has been validated for sleep and stress tracking, providing a direct route to product efficacy validation.
- **Cost**: A Muse headset costs ~$250. An Emotiv Epoc+ is ~$800 plus licensing. This is accessible for even the leanest budget.

D. Findings: Wearable Biometrics (EDA & HRV)
Electrodermal Activity (EDA), also known as Galvanic Skin Response (GSR), measures the electrical conductance of the skin, which varies with sweat gland activity. It is a pure measure of physiological arousal, the intensity of emotion (but not the valence/direction). Heart Rate Variability (HRV) is a measure of the variation in time between heartbeats and is a robust indicator of stress and Autonomic Nervous System (ANS) state (Posada-Quintero & Chon, 2020; Shaffer & Ginsberg, 2017).

4.10 Technology Mechanisms: Clinical vs. Consumer Wearable
Gold Standard: Desktop/Research Units. Devices like **Biopac** or **Shimmer GSR+** use silver-chloride electrodes attached to the fingers or palm (the most sweat-gland-dense areas). They offer high sampling rates (e.g., 64Hz-2000Hz) and are the benchmark for accuracy.

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Accessible Alternative: Smartwatches and Wristbands. The **Empatica E4** is a specialized research wearable that measures EDA and PPG (blood volume pulse) from the wrist. Consumer devices like the **Fitbit Sense** and **Apple Watch** also now include EDA sensors and HRV tracking capabilities.

4.11 Validation Evidence: The Location Problem
The primary challenge for wearables is the measurement site. The wrist has fewer sweat glands than the fingers/palm.

Empatica E4 Validation: The Empatica E4 is widely considered the "Gold Standard" of *wearable* (as opposed to desktop) devices. Validation studies show it has excellent concordance with laboratory ECG for Heart Rate (ICC = 0.93) and good agreement for HRV metrics like SDNN. However, for EDA, correlations are moderate to high in resting states but degrade during movement. One study noted that while E4 is reliable for HR/HRV, its EDA data is less sensitive than finger-based measurements.

Fitbit and Apple Watch: The **Fitbit Sense**, a mass-market device, has been tested against the Empatica E4 and Shimmer. Results show a positive correlation for EDA features, but significantly lower reliability and higher error rates (NRMSE). The **Apple Watch** is highly accurate for heart rate (deviation ~1.3 bpm vs medical ECG) and can detect mild mental stress via HRV, but it does not typically offer raw EDA data access to developers in the same way research devices do.

Motion Artifacts: A critical finding across all wearable studies is the impact of motion. "In the wild" testing (e.g., walking through a store) introduces massive noise. Validation studies suggest that for reliable EDA/HRV data, the subject should be relatively stationary. This limits the utility of these tools for testing "active" products (e.g., fitness apps) unless sophisticated noise-correction algorithms are applied.

4.12 Startup Application: Stress and Emotional Arousal
- **Gaming/Entertainment**: Startups in gaming can use EDA to measure "Excitement" levels during gameplay.
- **Health/Therapy**: Startups building stress-reduction apps can use the Apple Watch's HRV validation to prove their app actually lowers physiological stress.

Pricing: The Empatica E4 is expensive (~$1,600) and targeted at academics. The **Shimmer3 GSR+** is a middle ground at ~€650. The Apple Watch is likely already owned by the user, representing zero hardware cost if the startup builds an app to harvest the HealthKit data.

5. DISCUSSION

5.1 The Validity-Accessibility Trade-off
The synthesis of findings clearly delineates a trade-off. Democratization does not mean "equal quality for less money"; it means "sufficient quality for specific questions at a drastically lower cost."
- **High Validity/High Access**: Webcam Eye-Tracking for Heatmaps. The data is noisy, but the "Law of Large Numbers" allows a startup to aggregate 50 noisy webcams into one highly accurate heatmap.
- **Moderate Validity/High Access**: Automated Facial Coding for "Joy." Good for checking if a joke landed; poor for subtle nuance.
- **Moderate Validity/Moderate Access**: Consumer EEG. Requires more technical know-how to interpret than the other tools. The hardware is accessible, but the *insight* is still somewhat gated by the need for signal processing expertise.

5.2 The Software Ecosystem: The Real Enabler
The hardware is useless without the software to interpret it. The rise of integrated SaaS platforms is the true catalyst for this democratization.
- **iMotions**: Offers a "Lab in a Box" solution, integrating EEG, Eye Tracking, and Facial coding. While powerful, its pricing (starting ~$3,600/module) can still be high for pre-revenue startups.
- **CoolTool**: Represents the "low-end" disruption. By offering a subscription model (~$299/mo) and integrating webcam eye-tracking and implicit tests into a SurveyMonkey-style interface, it makes neuromarketing accessible to non-experts.

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- **Neurons Inc**: Represents the "AI Prediction" model. Instead of testing humans, startups upload creative assets to an AI trained on thousands of eye-tracking studies. This provides instant results (95% accuracy on attention prediction) without the logistical hassle of recruiting participants.

5.3 The "Black Box" Problem and Epistemic Risk

A significant risk identified in the discussion is the "Black Box" nature of these SaaS tools. Startups are often given a simplified metric, e.g., an "Engagement Score" of 7.5. They do not know how this is calculated. Is it Beta waves? Is it pupil dilation? Is it a combination? This obscurity increases the risk of **Reverse Inference**. A founder might see a high "Engagement" score and assume it means "Purchase Intent," when in reality, the user was just confused (high cognitive load) or stressed. Without the neuroscientific training to interrogate the data, startups risk making confident business decisions based on misinterpreted biological signals.

5.4 Ethical Implications in the "Wild"

Moving neuroscience out of the lab and into the wild (users' homes) creates new ethical minefields.

- **Informed Consent**: In a lab, a participant signs a form and talks to a researcher. In a remote webcam study, they click a box. Do they truly understand that their facial micro-expressions are being analyzed?
- **GDPR and Biometrics**: The collection of gaze and facial data is strictly regulated in the EU. Startups must ensure they are not just "checking a box" but actively protecting this sensitive data. The penalties for mishandling biometric data under GDPR are severe, posing an existential legal risk to fragile startups.

6. CONCLUSION

This systematic review demonstrates that consumer neuroscience is no longer confined to large corporations or highly specialized laboratories. A practical and increasingly accessible neuromarketing toolkit now exists for early-stage startups, allowing them to capture meaningful insights into attention, emotion, cognitive load, and stress through lower-cost technologies such as webcam-based eye-tracking, automated facial coding, consumer EEG devices, and wearable sensors. Although these tools do not match the precision of traditional lab-grade systems in every context, the literature indicates that they can still provide substantial value when applied appropriately. They are most effective for identifying broad patterns, validating user experience designs, assessing emotional responses to content, and supporting evidence-based marketing decisions in resource-constrained environments.

At the same time, the review makes clear that democratization does not eliminate complexity. The effectiveness of these accessible tools depends heavily on careful study design, realistic interpretation, and ethical implementation. Environmental variability in remote testing, device limitations related to battery life and connectivity, algorithmic bias, and the rapid pace of consumer hardware development all constrain reliability and generalizability. Moreover, because published studies may overrepresent successful validation outcomes, researchers and practitioners should remain cautious when translating academic findings into commercial practice. These technologies should therefore be viewed as decision-support instruments rather than definitive truth-generating systems. Their outputs can guide strategic judgment, but they should be complemented by qualitative feedback, customer interviews, and domain expertise.

Looking ahead, the field offers considerable promise for future innovation and scholarship. Emerging directions such as generative AI, synthetic users, metaverse-based biometric environments, and multimodal sensor fusion may further expand the reach and sophistication of startup-friendly neuromarketing. Especially promising is the possibility that combining several affordable sensors may produce a more robust and holistic understanding of consumer behavior than any single device alone. Ultimately, the review concludes that accessible biometric tools can help founders move beyond self-reported preferences and toward a richer understanding of how users respond in real time. However, their true value lies not in replacing human-centered marketing wisdom but in strengthening it through responsible, informed, and context-sensitive use.

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7. APPENDIX

Table 1: The Startup Neuromarketing Toolkit - A Validity & Cost Matrix

Tool Category	Recommended Device/Software	Approx. Cost	Key Metrics	Validated Use Cases	Limitations
Eye Tracking	Webcam (CoolTool, iMotions, RealEye)	$299/mo (SaaS)	Heatmaps, TTFF (Time to First Fixation)	A/B Testing Landing Pages, Ad Creative	Low precision, poor dwell time accuracy
Facial Coding	Affectiva (via iMotions), Py-Feat	Integrated / Free (Open Source)	Valence (Pos/Neg), Joy, Anger	Video Ad Testing, Viral Content Prediction	Fails on subtle emotions, bias risks
EEG	Muse S, Emotiv Epoc X	$250 - $900	Alpha/Beta Power (Focus/Relaxation)	Meditation Apps, Cognitive Load in UX	No source localization, sensitive to noise
Wearables	Apple Watch, Empatica E4	$300 - $1600	HRV (Stress), EDA (Arousal)	Health/Wellness App Validation, Gaming	Motion artifacts, wrist measurement less sensitive
AI Prediction	Neurons Inc (Predict)	Subscription	Predicted Attention Heatmaps	Pre-testing designs instantly	Simulation only (no real human data)

8. REFERENCES

[1] Alvino, L., Pavone, L., Abhishta, A., & Robben, H. (2020). Picking Your Brains: Where and How Neuroscience Tools Can Enhance Marketing Research. *Frontiers in Neuroscience*, *14*, 577666. https://doi.org/10.3389/fnins.2020.577666
[2] Ariely, D., & Berns, G. S. (2010a). Neuromarketing: The hope and hype of neuroimaging in business. *Nature Reviews. Neuroscience*, *11*(4), 284–292. https://doi.org/10.1038/nrn2795
[3] Ariely, D., & Berns, G. S. (2010b). Neuromarketing: The hope and hype of neuroimaging in business. *Nature Reviews. Neuroscience*, *11*(4), 284–292. https://doi.org/10.1038/nrn2795
[4] Barrett, L. F., Adolphs, R., Marsella, S., Martinez, A., & Pollak, S. D. (2019). Emotional Expressions Reconsidered: Challenges to Inferring Emotion From Human Facial Movements. *Psychological Science in the Public Interest : A Journal of the American Psychological Society*, *20*(1), 1–68. https://doi.org/10.1177/1529100619832930
[5] Bazzani, A., Ravaioli, S., Trieste, L., Faraguna, U., & Turchetti, G. (2020). Is EEG Suitable for Marketing Research? A Systematic Review. *Frontiers in Neuroscience*, *14*, 594566. https://doi.org/10.3389/fnins.2020.594566

[6] Bechara, A., & Damasio, A. R. (2005). The somatic marker hypothesis: A neural theory of economic decision. *Games and Economic Behavior, Special Issue on Neuroeconomics*, *52*(2), 336–372. https://doi.org/10.1016/j.geb.2004.06.010
[7] Bechara, A., Damasio, H., & Damasio, A. R. (2000). Emotion, Decision Making and the Orbitofrontal Cortex. *Cerebral Cortex*, *10*(3), 295–307. https://doi.org/10.1093/cercor/10.3.295
[8] Bott, N. T., Madero, E. N., Glenn, J. M., Lange, A. R., Anderson, J. J., Newton, D. O., Brennan, A. H., Buffalo, E. A., Rentz, D. M., & Zola, S. M. (2020). Device-Embedded Cameras for Eye Tracking-Based Cognitive Assessment: Implications for Teleneuropsychology. *Telemedicine Journal and E-Health: The Official Journal of the American Telemedicine Association*, *26*(4), 477–481. https://doi.org/10.1089/tmj.2019.0039
[9] Brophy, E., Redmond, P., Fleury, A., De Vos, M., Boylan, G., & Ward, T. (2022). Denoising EEG Signals for Real-World BCI Applications Using GANs. *Frontiers in Neuroergonomics*, *2*. https://doi.org/10.3389/fnrgo.2021.805573
[10] Burns, A., Doheny, E. P., Greene, B. R., Foran, T., Leahy, D., O'Donovan, K., & McGrath, M. J. (2010). SHIMMER: An extensible platform for physiological signal capture. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference*, *2010*, 3759–3762. https://doi.org/10.1109/IEMBS.2010.5627535
[11] Burton, L., Albert, W., & Flynn, M. (2014). A Comparison of the Performance of Webcam vs. Infrared Eye Tracking Technology. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *58*(1), 1437–1441. https://doi.org/10.1177/1541931214581300
[12] Cao, C. C., & Reimann, M. (2020). Data Triangulation in Consumer Neuroscience: Integrating Functional Neuroimaging With Meta-Analyses, Psychometrics, and Behavioral Data. *Frontiers in Psychology*, *11*, 550204. https://doi.org/10.3389/fpsyg.2020.550204
[13] Cheong, J. H., Jolly, E., Xie, T., Byrne, S., Kenney, M., & Chang, L. J. (2023). Py-Feat: Python Facial Expression Analysis Toolbox. *Affective Science*, *4*(4), 781–796. https://doi.org/10.1007/s42761-023-00191-4
[14] Cognolato, M., Atzori, M., & Müller, H. (2018). Head-mounted eye gaze tracking devices: An overview of modern devices and recent advances. *Journal of Rehabilitation and Assistive Technologies Engineering*, *5*, 2055668318773991. https://doi.org/10.1177/2055668318773991
[15] Cross, M. P., Acevedo, A. M., & Hunter, J. F. (2023). A Critique of Automated Approaches to Code Facial Expressions: What Do Researchers Need to Know? *Affective Science*, *4*(3), 500–505. https://doi.org/10.1007/s42761-023-00195-0
[16] Cyr, D., Head, M., & Ivanov, A. (2006). Design aesthetics leading to m-loyalty in mobile commerce. *Information & Management*, *43*(8), 950–963. https://doi.org/10.1016/j.im.2006.08.009
[17] Damasio, A. R. (1996). The somatic marker hypothesis and the possible functions of the prefrontal cortex. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, *351*(1346), 1413–1420. https://doi.org/10.1098/rstb.1996.0125
[18] Donato, G., Bartlett, M. S., Hager, J. C., Ekman, P., & Sejnowski, T. J. (1999). Classifying Facial Actions. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *21*(10), 974. https://doi.org/10.1109/34.799905
[19] Evans, J. S. B. T. (2008). Dual-processing accounts of reasoning, judgment, and social cognition. *Annual Review of Psychology*, *59*, 255–278. https://doi.org/10.1146/annurev.psych.59.103006.093629
[20] Felin, T., Gambardella, A., Novelli, E., & Zenger, T. (2024). A Scientific Method for Startups. *Journal of Management*, *50*(8), 3080–3104. https://doi.org/10.1177/01492063231226136
[21] Ferrell, M. L., Beatty, A., & Dubljevic, V. (2025). The Ethics of Neuromarketing: A Rapid Review. *Neuroethics*, *18*(1), 19. https://doi.org/10.1007/s12152-025-09591-8
[22] García-Madariaga, J., Moya, I., Recuero, N., & Blasco, M.-F. (2020). Revealing Unconscious Consumer Reactions to Advertisements That Include Visual Metaphors. A Neurophysiological Experiment. *Frontiers in Psychology*, *11*, 760. https://doi.org/10.3389/fpsyg.2020.00760
[23] Garczarek-Bąk, U., Szymkowiak, A., Gaczek, P., & Disterheft, A. (2021). A comparative analysis of neuromarketing methods for brand purchasing predictions among young adults. *Journal of Brand Management*, *28*(2), 171–185. https://doi.org/10.1057/s41262-020-00221-7
[24] Gheorghe, C.-M., Purcărea, V. L., & Gheorghe, I.-R. (2023). Using eye-tracking technology in Neuromarketing. *Romanian Journal of Ophthalmology*, *67*(1), 2–6. https://doi.org/10.22336/rjo.2023.2

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

[25] Graña-Alvarez, R., Gomez-Conde, J., Lopez-Valeiras, E., & González-Loureiro, M. (2024). Management control systems, business financial literacy and financial leverage in business-incubated start-ups. *The British Accounting Review*, *56*(6), 101427. https://doi.org/10.1016/j.bar.2024.101427
[26] Greenberg, S. N., Inhoff, A. W., & Weger, U. W. (2006). The impact of letter detection on eye movement patterns during reading: Reconsidering lexical analysis in connected text as a function of task. *Quarterly Journal of Experimental Psychology (2006)*, *59*(6), 987–995. https://doi.org/10.1080/17470210600654776
[27] Gupta, R., Kapoor, A. P., & Verma, H. V. (2025). Neuro-insights: A systematic review of neuromarketing perspectives across consumer buying stages. *Frontiers in Neuroergonomics*, *6*. https://doi.org/10.3389/fnrgo.2025.1542847
[28] Halberstadt, A. G., Cooke, A. N., Garner, P. W., Hughes, S. A., Oertwig, D., & Neupert, S. D. (2022). Racialized emotion recognition accuracy and anger bias of children's faces. *Emotion*, *22*(3), 403–417. https://doi.org/10.1037/emo0000756
[29] Hamm, J., Kohler, C. G., Gur, R. C., & Verma, R. (2011). Automated Facial Action Coding System for Dynamic Analysis of Facial Expressions in Neuropsychiatric Disorders. *Journal of Neuroscience Methods*, *200*(2), 237–256. https://doi.org/10.1016/j.jneumeth.2011.06.023
[30] Hensel, D., Iorga, A., Wolter, L., & Znanewitz, J. (2017a). Conducting neuromarketing studies ethically-practitioner perspectives. *Cogent Psychology*, *4*(1), 1320858. https://doi.org/10.1080/23311908.2017.1320858
[31] Hensel, D., Iorga, A., Wolter, L., & Znanewitz, J. (2017b). Conducting neuromarketing studies ethically-practitioner perspectives. *Cogent Psychology*, *4*(1), 1320858. https://doi.org/10.1080/23311908.2017.1320858
[32] Höfling, T. T. A., & Alpers, G. W. (2023). Automatic facial coding predicts self-report of emotion, advertisement and brand effects elicited by video commercials. *Frontiers in Neuroscience*, *17*, 1125983. https://doi.org/10.3389/fnins.2023.1125983
[33] Höfling, T. T. A., Gerdes, A. B. M., Föhl, U., & Alpers, G. W. (2020). Read My Face: Automatic Facial Coding Versus Psychophysiological Indicators of Emotional Valence and Arousal. *Frontiers in Psychology*, *11*, 1388. https://doi.org/10.3389/fpsyg.2020.01388
[34] Hooge, I. T. C., Niehorster, D. C., Hessels, R. S., Benjamins, J. S., & Nyström, M. (2023). How robust are wearable eye trackers to slow and fast head and body movements? *Behavior Research Methods*, *55*(8), 4128–4142. https://doi.org/10.3758/s13428-022-02010-3
[35] Hsu, C.-T., & Sato, W. (2023). Electromyographic Validation of Spontaneous Facial Mimicry Detection Using Automated Facial Action Coding. *Sensors (Basel, Switzerland)*, *23*(22), 9076. https://doi.org/10.3390/s23229076
[36] Hutzler, F. (2014). Reverse inference is not a fallacy per se: Cognitive processes can be inferred from functional imaging data. *NeuroImage*, *84*, 1061–1069. https://doi.org/10.1016/j.neuroimage.2012.12.075
[37] Kaduk, T., Goeke, C., Finger, H., & König, P. (2024). Webcam eye tracking close to laboratory standards: Comparing a new webcam-based system and the EyeLink 1000. *Behavior Research Methods*, *56*(5), 5002–5022. https://doi.org/10.3758/s13428-023-02237-8
[38] Kahneman, D. (2003a). A perspective on judgment and choice: Mapping bounded rationality. *The American Psychologist*, *58*(9), 697–720. https://doi.org/10.1037/0003-066X.58.9.697
[39] Kahneman, D. (2003b). Maps of Bounded Rationality: Psychology for Behavioral Economics. *American Economic Review*, *93*(5), 1449–1475. https://doi.org/10.1257/000282803322655392
[40] Köhler, C., Bartschke, A., Fürstenau, D., Schaaf, T., & Salgado-Baez, E. (2024). The Value of Smartwatches in the Health Care Sector for Monitoring, Nudging, and Predicting: Viewpoint on 25 Years of Research. *J Med Internet Res 2024;26:E58936 Https://Www.Jmir.Org/2024/1/E58936*. https://doi.org/10.2196/58936
[41] Kulke, L., Feyerabend, D., & Schacht, A. (2020). A Comparison of the Affectiva iMotions Facial Expression Analysis Software With EMG for Identifying Facial Expressions of Emotion. *Frontiers in Psychology*, *11*, 329. https://doi.org/10.3389/fpsyg.2020.00329
[42] Leatherbee, M., & Katila, R. (2020). The lean startup method: Early-stage teams and hypothesis-based probing of business ideas. *Strategic Entrepreneurship Journal*, *14*(4), 570–593. https://doi.org/10.1002/sej.1373

International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

[43] Lee, N., Broderick, A. J., & Chamberlain, L. (2007). What is ‘neuromarketing’? A discussion and agenda for future research. *International Journal of Psychophysiology, Cognitive Neuroscience: Contributions from Psychophysiology*, *63*(2), 199–204. https://doi.org/10.1016/j.ijpsycho.2006.03.007
[44] Lee, N., & Lee, J. (2021). Comparison of Home Use Tests with Differing Time and Order Controls. *Foods*, *10*(6). https://doi.org/10.3390/foods10061275
[45] Lee, S. (Ronnie), & Kim, J. D. (2024). When do startups scale? Large-scale evidence from job postings. *Strategic Management Journal*, *45*(9), 1633–1669. https://doi.org/10.1002/smj.3596
[46] Lindgaard, G., Fernandes, G., Dudek, C., & Brown, J. (2006). Attention web designers: You have 50 milliseconds to make a good first impression! *Behaviour & Information Technology*, *25*(2), 115–126. https://doi.org/10.1080/01449290500330448
[47] Liu, J., Chi, J., Yang, H., & Yin, X. (2022). In the eye of the beholder: A survey of gaze tracking techniques. *Pattern Recognition*, *132*, 108944. https://doi.org/10.1016/j.patcog.2022.108944
[48] Martinez-Martin, N. (2019). What Are Important Ethical Implications of Using Facial Recognition Technology in Health Care? *AMA Journal of Ethics*, *21*(2), 180–187. https://doi.org/10.1001/amajethics.2019.180
[49] Namba, S., Sato, W., Osumi, M., & Shimokawa, K. (2021). Assessing Automated Facial Action Unit Detection Systems for Analyzing Cross-Domain Facial Expression Databases. *Sensors (Basel, Switzerland)*, *21*(12), 4222. https://doi.org/10.3390/s21124222
[50] Nisbett, R. E., & Wilson, T. D. (1977). *Telling more than we can know: Verbal reports on mental processes*. https://hdl.handle.net/2027.42/92167
[51] Ohira, H., & Hirao, N. (2015). Analysis of skin conductance response during evaluation of preferences for cosmetic products. *Frontiers in Psychology*, *6*, 103. https://doi.org/10.3389/fpsyg.2015.00103
[52] Plassmann, H., Ambler, T., Braeutigam, S., & Kenning, P. (2007). What can advertisers learn from neuroscience? *International Journal of Advertising*, *26*(2), 151–175. https://doi.org/10.1080/10803548.2007.11073005
[53] Poldrack, R. A. (2006). Can cognitive processes be inferred from neuroimaging data? *Trends in Cognitive Sciences*, *10*(2), 59–63. https://doi.org/10.1016/j.tics.2005.12.004
[54] Poldrack, R. A. (2011). Inferring Mental States from Neuroimaging Data: From Reverse Inference to Large-Scale Decoding. *Neuron*, *72*(5), 692–697. https://doi.org/10.1016/j.neuron.2011.11.001
[55] Posada-Quintero, H. F., & Chon, K. H. (2020). Innovations in Electrodermal Activity Data Collection and Signal Processing: A Systematic Review. *Sensors (Basel, Switzerland)*, *20*(2), 479. https://doi.org/10.3390/s20020479
[56] Quiles Pérez, M., Martínez Beltrán, E. T., López Bernal, S., Horna Prat, E., Montesano Del Campo, L., Fernández Maimó, L., & Huertas Celdrán, A. (2024). Data fusion in neuromarketing: Multimodal analysis of biosignals, lifecycle stages, current advances, datasets, trends, and challenges. *Information Fusion*, *105*, 102231. https://doi.org/10.1016/j.inffus.2024.102231
[57] Rutkowska, J. M., Ghilardi, T., Vacaru, S. V., van Schaik, J. E., Meyer, M., Hunnius, S., & Oostenveld, R. (2024). Optimal processing of surface facial EMG to identify emotional expressions: A data-driven approach. *Behavior Research Methods*, *56*(7), 7331–7344. https://doi.org/10.3758/s13428-024-02421-4
[58] Sabio, J., Williams, N. S., McArthur, G. M., & Badcock, N. A. (2024). A scoping review on the use of consumer-grade EEG devices for research. *PLOS ONE*, *19*(3), e0291186. https://doi.org/10.1371/journal.pone.0291186
[59] Sato, W., & Kochiyama, T. (2023). Crosstalk in Facial EMG and Its Reduction Using ICA. *Sensors*, *23*(5). https://doi.org/10.3390/s23052720
[60] Saxena, S., Fink, L. K., & Lange, E. B. (2024). Deep learning models for webcam eye tracking in online experiments. *Behavior Research Methods*, *56*(4), 3487–3503. https://doi.org/10.3758/s13428-023-02190-6
[61] Schröter, I., Grillo, N. R., Limpak, M. K., Mestiri, B., Osthold, B., Sebti, F., & Mergenthaler, M. (2021). Webcam Eye Tracking for Monitoring Visual Attention in Hypothetical Online Shopping Tasks. *Applied Sciences*, *11*(19). https://doi.org/10.3390/app11199281
[62] Semmelmann, K., & Weigelt, S. (2018). Online webcam-based eye tracking in cognitive science: A first look. *Behavior Research Methods*, *50*(2), 451–465. https://doi.org/10.3758/s13428-017-0913-7
[63] Shaffer, F., & Ginsberg, J. P. (2017). An Overview of Heart Rate Variability Metrics and Norms. *Frontiers in Public Health*, *5*, 258. https://doi.org/10.3389/fpubh.2017.00258

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

[64] Shajari, S., Kuruvinashetti, K., Komeili, A., & Sundararaj, U. (2023). The Emergence of AI-Based Wearable Sensors for Digital Health Technology: A Review. *Sensors (Basel, Switzerland)*, *23*(23), 9498. https://doi.org/10.3390/s23239498
[65] Shen, X., Wu, Q., & Fu, X. (2012). Effects of the duration of expressions on the recognition of microexpressions. *Journal of Zhejiang University. Science. B*, *13*(3), 221–230. https://doi.org/10.1631/jzus.B1100063
[66] Shepherd, D. A., & Gruber, M. (2021). The Lean Startup Framework: Closing the Academic–Practitioner Divide. *Entrepreneurship Theory and Practice*, *45*(5), 967–998. https://doi.org/10.1177/1042258719899415
[67] Singer, T., Critchley, H. D., & Preuschoff, K. (2009). A common role of insula in feelings, empathy and uncertainty. *Trends in Cognitive Sciences*, *13*(8), 334–340. https://doi.org/10.1016/j.tics.2009.05.001
[68] Stöckli, S., Schulte-Mecklenbeck, M., Borer, S., & Samson, A. C. (2018). Facial expression analysis with AFFDEX and FACET: A validation study. *Behavior Research Methods*, *50*(4), 1446–1460. https://doi.org/10.3758/s13428-017-0996-1
[69] Taore, A., Tiang, M., & Dakin, S. C. (2024). (The limits of) eye-tracking with iPads. *Journal of Vision*, *24*(7), 1. https://doi.org/10.1167/jov.24.7.1
[70] Van der Cruyssen, I., Ben-Shakhar, G., Pertzov, Y., Guy, N., Cabooter, Q., Gunschera, L. J., & Verschuere, B. (2024). The validation of online webcam-based eye-tracking: The replication of the cascade effect, the novelty preference, and the visual world paradigm. *Behavior Research Methods*, *56*(5), 4836–4849. https://doi.org/10.3758/s13428-023-02221-2
[71] Vecchiato, G., Astolfi, L., De Vico Fallani, F., Toppi, J., Aloise, F., Bez, F., Wei, D., Kong, W., Dai, J., Cincotti, F., Mattia, D., & Babiloni, F. (2011). On the Use of EEG or MEG Brain Imaging Tools in Neuromarketing Research. *Computational Intelligence and Neuroscience*, *2011*, 643489. https://doi.org/10.1155/2011/643489
[72] Vos, M., Minor, S., & Ramchand, G. C. (2022). Comparing infrared and webcam eye tracking in the Visual World Paradigm. *Glossa Psycholinguistics*, *1*(1). https://doi.org/10.5070/G6011131
[73] Westermann, J.-F., Schäfer, R., Nordmann, M., Richter, P., Müller, T., & Franz, M. (2024). Measuring facial mimicry: Affdex vs. EMG. *PLOS ONE*, *19*(1), e0290569. https://doi.org/10.1371/journal.pone.0290569
[74] Yang, X., & Krajbich, I. (2021). Webcam-based online eye-tracking for behavioral research. *Judgment and Decision Making*, *16*(6), 1485–1505. https://doi.org/10.1017/S1930297500008512
[75] Zdarsky, N., Treue, S., & Esghaei, M. (2021). A Deep Learning-Based Approach to Video-Based Eye Tracking for Human Psychophysics. *Frontiers in Human Neuroscience*, *15*, 685830. https://doi.org/10.3389/fnhum.2021.685830
[76] Zhang, L., & Cui, H. (2022). Reliability of MUSE 2 and Tobii Pro Nano at capturing mobile application users' real-time cognitive workload changes. *Frontiers in Neuroscience*, *16*. https://doi.org/10.3389/fnins.2022.1011475
[77] Zinkhan, G. M., & Hirschheim, R. (1992). Truth in Marketing Theory and Research: An Alternative Perspective. *Journal of Marketing*, *56*(2), 80–88. https://doi.org/10.1177/002224299205600207