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Neural Response Prediction For Social Media Content: A Survey-Based Framework Using Brain Predictive Models

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Abstract: *The explosion of social media has made it vital to find tools that can anticipate how people will react to digital content before it goes live. Current metrics—likes, shares, and comments—only show up after the fact; they don't capture the subconscious brain activity that actually drives someone to pay attention or click. This paper examines twenty-three studies across four areas: fMRI-based deep learning, neuromarketing, emotion recognition from neural signals, and machine learning for engagement prediction. We look at the methods, data, and gaps in each field. These existing studies show that we can realistically build a system to predict neural engagement. We also look at current hurdles and how these brain models might be used in social media, real estate, and e-commerce..*

Keywords: brain predictive models, fMRI decoding, neuromarketing, social media engagement, neural response prediction, deep learning, EEG emotion recognition, cognitive engagement, TRIBE v2, content analytics

I. INTRODUCTION

Social media is now the primary way we talk and interact with brands online. By 2025, more than five billion people were using these platforms, posting hundreds of millions of times every single day. For anyone managing a brand, the biggest hurdle is knowing how an audience will react to a post before hitting "publish".

Usually, managers wait for likes, shares, or comments to see if a post worked. The problem is this feedback comes too late. You cannot know ahead of time if a specific image will catch someone's eye, if a caption will spark curiosity, or if a promotion will actually trigger a desire to buy. This leads to a slow, expensive cycle of trial and error based more on gut feeling than hard data.

Neuroscience offers a better way. Research shows that our brains react to what we see in milliseconds, long before we consciously decide to act. These reactions happen in areas like the visual cortex and amygdala, creating patterns that reveal attention, emotion, and reward [1]. Thanks to better neuroimaging and deep learning, we can now model these responses without putting a person in a lab scanner.

Meta Research's release of TRIBE v2 in 2026 is a major step forward [2]. It is a model trained on fMRI data from over 700 people that can predict high-resolution brain activity for almost any image, sound, or text. If we use this in a social media workflow, managers could get a clear picture of how an audience's brain will likely respond before they ever post. This paper reviews the research that makes such a system possible. Section II presents the literature survey across four thematic domains. Section III discusses the findings and their collective implications. Section IV outlines future scope and open research directions. Section V concludes the paper.

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II. LITERATURE SURVEY

The research covers four areas that, when combined, show how we can predict neural responses to social media content. Each domain contributes a distinct technical layer to the overall picture.

A. fMRI-Based Brain Encoding and Decoding Using Deep Learning

Computational neuroscience has moved quickly. We now have models that predict brain activity from a stimulus (encoding) and models that can identify what a person is looking at based on their brain activity (decoding). This is the technical core of any neural prediction system.

TRIBE v2 is currently the most important development [2]. It was trained on data from hundreds of volunteers watching videos, listening to podcasts, and reading text. It offers 70x better resolution than older models and works "zero-shot," meaning it can predict responses for new people or languages without needing more training data. Meta has made the code, model weights, and an interactive demo publicly available under a CC BY-NC license, making it directly accessible for academic research.

In 2025, Chen et al. [3] reviewed how deep learning can reconstruct visual and auditory information from fMRI signals. They found that fMRI's high spatial resolution makes it better suited for these tasks than EEG, and that "end-to-end" models—which map brain signals directly to the stimulus representation—outperform modular pipelines that separate feature extraction and alignment into distinct steps. Their survey covered CNNs, variational autoencoders (VAEs), and generative adversarial networks (GANs), finding generative model-based decoding produces the highest-quality reconstructions.

Yin et al. [4] reviewed deep learning architectures for fMRI analysis and found that CNNs are best at capturing where brain activity happens, while RNNs better track how activity changes over time. They also showed that transfer learning from large pre-trained models substantially improves performance when neuroimaging datasets are small—a practically important finding given the cost of fMRI data collection. Wen et al. [5] demonstrated that resting-state fMRI shares enough functional properties with task-based fMRI that resting-state data can serve as a prior for predicting task-evoked neural responses, substantially reducing the data collection burden.

Wang et al. [6] showed that whole-brain convolutional models can generalise across different cognitive task types using transfer learning, which is essential for a real-world system that must handle the full diversity of social media content. Nguyen et al. [7] introduced SwiFUN, a transformer-based model using shifted window self-attention, demonstrating a 27% improvement over existing baselines in predicting emotion-related brain activation maps across two large-scale datasets (UK Biobank, n=7,038 and ABCD, n=4,944).

TABLE I: Summary of fMRI Brain Encoding/Decoding Literature

Ref.	Authors / Year	Method	Dataset / Scale	Key Finding
[2]	Meta Research, 2026	Foundation Model (Transformer)	700+ subjects, images/video/audio/text	Zero-shot high-res fMRI prediction; 70x resolution gain over prior models
[3]	Chen et al., 2025	CNN, VAE, GAN (End-to-End)	Multiple public fMRI datasets	End-to-end models outperform modular; fMRI gives best spatial resolution
[4]	Yin et al., 2021	CNN, RNN, GNN, AE (Review)	ADNI, ABIDE and others	CNN best for spatial; RNN best for temporal; transfer learning critical
[5]	Wen et al., 2018	CNN (Review)	HCP, multiple clinical sets	DL outperforms hand-crafted features; resting-state generalises to task prediction
[6]	Wang et al.,	Whole-brain	HCP S1200	Cross-task generalisation via transfer

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Ref.	Authors / Year	Method	Dataset / Scale	Key Finding
	2018	ConvNet		learning; flexible to data scale
[7]	Nguyen et al., 2025	SwiFUN Transformer	UK Biobank (n=7,038), ABCD (n=4,944)	27% improvement in emotion activation maps; captures individual differences

B. Neuromarketing and Neural Responses to Digital and Social Media Content

Neuromarketing applies neuroscience tools to the study of consumer behaviour and marketing stimuli. Since it measures subconscious reactions directly, it is often more revealing than surveys or self-reports, which are subject to social desirability bias and imprecise recall.

Alsharif et al. [8] conducted a systematic review following the PRISMA framework, analysing 106 articles on neuromarketing tools applied to the marketing mix. They found that emotional engagement, memory retention, attention, and purchase intention are the four dimensions most reliably measurable using neuroimaging methods. fMRI was identified as providing the highest spatial resolution for deep brain structures—such as the reward circuits in the nucleus accumbens—while EEG provides superior temporal resolution for tracking rapid neural dynamics of attention and emotional response.

Zhang and Lee [9] conducted the study most directly relevant to this paper. Using event-related potential (ERP) methodology, they found a specific brainwave pattern combining the P3 component and late positive potential (LPP) that appeared within 300 milliseconds of someone seeing a Facebook post. This pattern reliably distinguished engaging content from non-engaging content, providing direct empirical evidence that neural engagement prediction before a user consciously decides to click is scientifically feasible. The signal was detected in bilateral temporal brain regions associated with semantic processing and emotional evaluation.

Cuadrado-García et al. [10] found that images generally trigger stronger neural reactions than text-based social media content, and that storytelling structures measurably increase brain activity compared to non-narrative posts. They also documented that the brain's social validation circuits activate when users see high like counts or community endorsements—a finding with direct implications for content design. Micu et al. [11] suggested that combining fMRI with EEG and facial coding gives the most complete picture of neural response to social media advertisements, capturing both where and when in the brain a reaction occurs.

Alsharif et al. [12] reviewed cases where fMRI findings directly informed social media campaign decisions, for example guiding brands to select warmer colour palettes and narrative caption structures based on their associated neural engagement signatures. The authors identified personalisation—adapting content to individual neural and psychological profiles—as the most promising next frontier in neuromarketing-informed content strategy.

C. Emotion and Attention Recognition from Neural Signals

Predicting that a stimulus will generate neural activity is one part of the challenge; the other is interpreting what that activity means in human-understandable terms. This field focuses on translating brain signals into specific cognitive-emotional states such as attention, positive valence, and reward anticipation.

Wang et al. [13] conducted a comprehensive review of deep learning methods for EEG-based emotion recognition, covering work from 2017 to 2022. They documented the evolution from simple LSTM-based models to sophisticated architectures including the 3D convolutional attention neural network (3DCANN) and transformer-based encoders. Across standard benchmarks including DEAP, MAHNOB-HCI, and SEED, the most effective models achieved valence classification accuracies exceeding 90% in subject-dependent settings. Cross-subject generalisation was identified as the primary remaining challenge.

Jafari et al. [14] found that Graph Convolutional Networks (GCNs) consistently outperform spatial CNN approaches because they model the brain as a network of interconnected regions rather than isolated activation spots. A single active region tells us less about emotional state than the overall pattern of co-activation across regions. GCN-based

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models explicitly capture these functional connectivity patterns and are therefore more diagnostically accurate for emotion classification.

Because social media content combines images, video, and text, multimodal emotion recognition is particularly relevant. Sadeghi et al. [15] found that models integrating brain signals with audiovisual data reach up to 94% emotion classification accuracy, with cross-modal attention mechanisms proving most effective for fusing heterogeneous signal types. Zhao et al. [16] demonstrated that pre-training on large unlabelled datasets using contrastive learning then fine-tuning on emotion-labelled data yields superior generalisation to new subjects—directly supporting the use of large pre-trained models like TRIBE v2. Peng et al. [17] showed that visual stimuli can be reliably decoded from fMRI activity patterns using a combined 3D CNN and GCN architecture, establishing a direct technical pathway from visual content to brain response to content category classification.

TABLE II: Summary of Neuromarketing and Neural Emotion Recognition Literature

Ref.	Authors / Year	Method / Signal	Dataset	Key Finding
[8]	Alsharif et al., 2023	fMRI, EEG, Eye-tracking (Review)	106 papers (PRISMA)	Emotional engagement, memory, attention are most measurable; fMRI best for spatial depth
[9]	Zhang & Lee, 2022	ERP (EEG)	Social media consumer lab study	P3+LPP brainwave distinguishes engaging vs. non-engaging FB posts within 300ms
[10]	Cuadrado-Garcia et al., 2020	Theoretical review	2000-2020 literature	Images > text; narrative arc elevates neural activity; social proof activates validation circuits
[11]	Micu et al., 2021	fMRI, Eye Tracking, Facial Coding	Social media ad studies	Multimodal neuro gives fuller picture; facial coding cost-effective complement
[12]	Alsharif et al., 2023	Neuromarketing strategy (Review)	Case studies	Warm colours and narrative captions guided by fMRI; personalisation is next frontier
[13]	Wang et al., 2023	LSTM, 3DCANN, Transformer (Review)	DEAP, MAHNOB-HCI, SEED	>90% valence accuracy (subject-dependent); cross-subject generalisation remains a challenge
[14]	Jafari et al., 2023	GCN, CNN, RNN (Review)	DEAP, SEED, MAHNOB	GCNs outperform spatial CNNs by capturing distributed emotion networks across brain regions
[15]	Sadeghi et al., 2025	Multimodal EEG + AV (Review)	Multiple benchmark datasets	Cross-modal attention best fusion; multimodal reaches 94% accuracy; contrastive pre-training effective
[16]	Zhao et al., 2024	Contrastive Learning + Cross-modal Attn	Custom EEG + video/audio dataset	Pre-training + fine-tuning generalises across subjects; multimodal outperforms unimodal
[17]	Peng et al., 2022	3D CNN + GCN	Visual fMRI dataset (11 ROIs)	Visual stimuli reliably decoded from fMRI via GCN on functional connectivity of visual ROIs

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D. Machine Learning-Based Social Media Engagement Prediction

This area looks at how engagement—likes, shares, and comments—is currently predicted using standard behavioural and content-level data. While these models do not use brain data, they define the prediction benchmarks that a neural system must match or exceed.

Amara et al. [18] found that emotionally charged content—especially posts with high arousal—gets significantly more engagement. Using a dataset of 600 annotated songs and their social media performance metrics, they trained a gradient-boosting model on log-transformed engagement ratios and found that emotional valence and arousal are among the strongest predictors of comments and likes respectively. They also found that the features driving comments differ from those driving likes, suggesting different types of engagement are driven by different emotional properties.

Devi and Kumar [19] showed that deep learning models, specifically bidirectional LSTMs, outperform traditional methods including random forests and gradient boosting in predicting social media consumer behaviour across Facebook, Twitter, LinkedIn, Instagram, and Pinterest. Deep models better captured the non-linear interactions between posting time, content type, sentiment, and prior interaction history. Peters et al. [20] demonstrated that context—location, time of day, weather—significantly improves engagement prediction, raising model accuracy from $R^2=0.345$ to $R^2=0.522$ in a study of over 100 million Snapchat sessions.

Govindankutty and Jain [21] and Sadeque and Xu [22] have each noted that purely behavioural features may have reached a performance ceiling, and that integrating neural and cognitive models is the next logical step to meaningfully improve prediction accuracy. Govindankutty [23] also presented a hybrid deep learning framework combining socially restricted Boltzmann machines with bidirectional LSTMs (SRBM-DPSO-BiLSTM) that provides a competitive behavioural benchmark against which future neurologically-grounded predictions should be evaluated.

III. DISCUSSION

A. Synthesis of Findings Across Domains

The research across these four fields converges on a consistent message: a neural engagement prediction system for social media content is technically feasible today. Models like TRIBE v2 [2] can predict high-resolution brain activity for arbitrary stimuli. Neuromarketing research [9] has confirmed that social media content generates measurable neural signals distinguishing engaging from non-engaging content within 300 milliseconds. Deep learning models [13]–[17] can classify those signals into meaningful cognitive-emotional states with accuracy exceeding 90%. And machine learning research [18]–[23] has established that emotional content features are strong predictors of behavioural engagement, creating a bridge between neural responses and observable outcomes.

B. Identified Research Gap

Despite this convergent evidence, no existing work has integrated brain response prediction, neural activation interpretation, and social media content evaluation into a unified, scalable pre-publication system. Current social media analytics are exclusively post-publication and behavioural. Current neuromarketing studies are laboratory-bound and do not scale to real-world workflows. Current brain decoding models have not been applied to social media evaluation pipelines. This integration gap is the central unsolved problem that future research must address.

IV. FUTURE SCOPE

Based on the synthesis of the reviewed literature, several clear and high-impact research directions emerge for applying brain predictive models to real-world content domains.

- **Social Media Content Evaluation:** The most direct application is a pre-publication neural engagement tool for platforms like Instagram, Facebook, and YouTube. A content administrator uploads a draft post—image, caption, or reel—and the system processes it through TRIBE v2 to generate predicted fMRI activation patterns. These are interpreted to produce a Neural Engagement Score covering attention capture, emotional valence, and reward anticipation, allowing the admin to refine the content before publishing [2], [9].

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• **Real Estate Listings:** Property listing platforms such as 99acres, MagicBricks, and Zillow present buyers with photographs, floor plans, and descriptions. Agents and developers could test multiple versions of a property photograph—different lighting, angles, or staging—and select the version predicted to generate the strongest reward and interest response. The same system could evaluate property descriptions for the narrative engagement they generate [10], [12].

• **E-Commerce and Digital Advertising:** Advertisers currently use slow, expensive A/B testing to compare creative variants. Neural pre-screening would allow dozens of variants to be evaluated before any budget is committed, selecting the version most likely to activate attention and purchase intent at a neural level. Neuromarketing research [8], [11] has already demonstrated that fMRI and EEG can predict advertisement effectiveness; a brain predictive model extends this to any creative asset without laboratory infrastructure.

• **Neural Response Datasets for Social Media:** A prerequisite for validating these systems is the creation of publicly available datasets pairing social media content with measured neural responses. This requires subjects to view curated sets of posts during fMRI or EEG recording. Such a dataset would enable training and evaluation of neural interpretation models and provide ground truth for assessing TRIBE v2's prediction accuracy on social media stimuli [5], [13].

• **Ethical and Regulatory Frameworks:** The capacity to predict subconscious neural responses at scale carries significant ethical risks. Neural-optimised content could exploit cognitive vulnerabilities or manipulate emotions without user awareness. Future work must develop governance frameworks distinguishing legitimate engagement optimisation from neurological manipulation, and establish transparency norms for content that has been neural-tested [10], [21].

V. CONCLUSION

This survey reviewed twenty-three peer-reviewed papers across four areas—fMRI brain encoding and decoding, neuromarketing and social media neural responses, emotion recognition from brain signals, and ML-based engagement prediction—to lay the groundwork for neural engagement prediction systems.

What the literature makes clear is that the building blocks are already there. Brain predictive models can now generate high-resolution fMRI predictions for arbitrary stimuli without needing lab subjects. Social media content triggers measurable neural responses within 300ms that correlate with real behavioural engagement. Deep learning can classify brain activity into cognitive-emotional states with over 90% accuracy. And emotional content features consistently rank among the strongest predictors of engagement across platforms.

The gap isn't capability—it's integration. Each of these technical pieces exists and has been validated independently, but nobody has put them together yet. That's where we see the opportunity. The next steps are building social media neural response datasets, fine-tuning classifiers on real content, and validating neural engagement scores against behavioural ground truth across domains like social media, real estate, and e-commerce.

Neural engagement prediction shifts the game from measuring what users did after seeing content to predicting what their brains will do before it's even published. The science is there—now it's an engineering problem.

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