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How Emotional Dynamics are Associated with Advertising Recall: Evidence from Facial Expression Analysis in Young Consumers

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Abstract

Background: Emotions elicited by advertisements are known to influence what consumers remember; however, prior studies have often relied on averaged measures. We examined how the dynamics of facial expressions during video advertisements relate to ad recall in young adults.

Methods: In a laboratory experiment, 40 participants watched branded video commercials while their facial expressions were continuously recorded. From these recordings, we derived features capturing emotional intensity and temporal dynamics (e.g., variability, peaks). We then applied correlation analyses and machine-learning classifiers to predict which ads participants would later recall.

Results: Ads with higher recall consistently elicited greater emotional variability. Dynamic facial emotion features accounted for a substantial proportion of the most informative predictors in the final classification model, which achieved an AUC of approximately 0.867. At the same time, overall levels of positive emotion remained a significant predictor of recall, indicating that emotional dynamics complement rather than replace static affective intensity.

Conclusions: Temporal patterns of emotion during ad viewing substantially enhance the prediction of memorability. Monitoring fluctuations in facial expressions provides unique insight beyond static metrics and offers actionable guidance for designing more memorable advertisements.

Keywords: video advertising, machine learning, neuromarketing, facial coding, emotional dynamics

Introduction

Recent transformations in global advertising industry showcases the domination of digital video advertisement in global media balance, e.g. reaching 259 billion dollars in 2024 in USA, showing similar trends in UK, Australia and Kazakhstan as well (IAB UK 2025, IAB Australia 2025, IAB USA, 2025; AACA, 2025). No wonder today's consumers are exposed to an unprecedented volume of advertising messages. In 2025, an average consumer is estimated to encounter between 6,000 and 10,000 ads per day—nearly double the number reported in 2007 (Forbes, 2022). This constant exposure contributes to attentional overload, especially among "digital natives", who switch between media platforms at a rapid pace (MarketingProfs, 2017).

Besides, despite substantial investments in digital video advertising, it remains unclear which ads are remembered by young viewers and which fail to influence memory or behavior (MarketingProfs, 2017). Classic marketing concerns remain unresolved—Wanamaker's famous remark that half of advertising budgets are wasted still resonates today. Currently existing digital metrics (reach, views, impressions etc.) mainly capture exposure, but rarely actual processing. They also do not reflect actual behavioral change—both key for advertising effectiveness. This kind of disconnect between exposure and action emphasizes the need for deeper scientific exploration. And it raises a broader question central to advertising research: which specific aspects of ad exposure actually drive advertising effectiveness like recall, recognition, perceived attractiveness or intention to act?

Given these challenges, the last decades advertising industry has increasingly shifted toward emotions and experiential communication. The "Experience Economy" paradigm posits that sustained brand value stems from emotional impact rather than rational information (Pine & Gilmore, 1998). Empirical work demonstrates that emotionally charged advertisements enhance awareness, recall and loyalty (Byrne et al., 2022). Nonetheless while emotional engagement is recognized as central to persuasive advertising, the mechanisms through which these emotional reactions translate into expected behavioral outcomes remain insufficiently understood. Traditional measures capture only conscious evaluations and dependent on self-report, while a substantial part of emotional processing occurs rapidly, automatically and often outside of conscious awareness. Neuromarketing has emerged as a methodological response by enabling real-time as-

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sessment of consumers' emotional and physiological responses during ad exposure (Byrne et al., 2022). Among its tools, facial-expression-based emotion detection has become one of the most widely used proxy measures, providing a non-invasive and relatively accurate way to track emotional responses during video viewing (Stöckli et al., 2018). Recent literature highlights that such affective signals offer valuable insight into how certain marketing stimuli shape consumer memory and preference, complementing traditional self-report measures (Gupta et al., 2025; Vrtana & Krizanova, 2023).

Despite advances in the field, existing neuromarketing research still faces several gaps. Many studies rely on static or averaged emotional measures across an entire advertisement, overlooking how emotions fluctuate dynamically over time. Systematic reviews emphasize that emotional responses during video ads peak at narrative moments, shift with contextual cues and may or may not align with brand exposure—yet these dynamics are rarely examined in relation to memory outcomes (Gupta et al., 2025). Consequently, it remains unclear whether it is the intensity, timing or temporal trajectory of emotional responses that most strongly associated with advertising effectiveness among viewers.

Therefore, the aim of this exploratory study is to examine how the temporal dynamics of emotional facial expressions during real video advertisements are associated with ad recall among consumers. This study focuses on young digital consumers in Kazakhstan—a rapidly evolving media landscape under-researched in neuromarketing literature.

Based on prior theoretical assumptions, we propose the following exploratory hypotheses:

H1: Dynamic emotional metrics are significantly associated with ad recall among young consumers.

H2: Dynamic emotional features offer better predictive accuracy of ad recall than static average-based emotional metrics.

This study contributes to advertising research by introducing a dynamic approach to measuring emotional responses and by applying facial coding to naturalistic advertising stimuli in a Kazakhstani youth context.

Literature Review

Classic Advertising Effectiveness Metrics and Integration of Neuromarketing Approach

Advertising effectiveness usually refers to how well an ad achieves its intended impact—most commonly evaluated through cognitive, emotional and behavioral outcomes such as recall, preference, attitude, purchase intention (Grigaliunaite & Pileliene, 2016; Prihatiningsih et al., 2024). Nowadays in the context of digital advertising effectiveness is typically measured through metrics like viewability, view-through-rate; more advanced levels include Brand Lift Tests, conversion, incrementality tests, even Marketing Mix Modelling (MMM) to understand how video ads contribute to sales along with other media (IAB, 2014; Google n.d.; Meta n.d.). However, despite their widespread use they provide only a partial view of effectiveness, as they do not fully reflect how deeply an ad was processed or how strongly it is integrated into memory. In adition many of them rely on self-reports which may lack objectivity and does not necessarily reflect actual behavior. Lastly, advanced types like MMM are expensive, require large amount of data and can be limited due to privacy restriction policies. It raises new challenges for marketers and encourages the development of novel approaches to measuring advertising effectiveness in order to address gaps in existing methods.

In order to mitigate these limitations the use of neuroscience for marketing purposes has gained considerable popularity in last few decades—emerging a new interdisciplinary field known as neuromarketing (Ariely & Berns, 2010). Simply put, neuromarketing is the application of brain science to gain deeper understanding about consumer behavior (Lin et al., 2018; Puprediwar & Tapas, 2024) By employing theories and methods of neurobiology it offers objective and evidence-based insights about "what is actually happening?" in consumers body when they are exposed to certain marketing stimuli (Lim, 2018). Reviews indicate that combining such objective indicators with surveys helps explain how emotional narratives and imagery influence brand memory and preferences, going beyond purely declarative measures (Gupta et al., 2025; Singh et al., 2023; Venkatraman et al., 2015).

Facial Action Coding System

One of those objective indicators employed in neuromarketing studies is knows as Facial Action Coding System. Automated facial coding (AFC) has become a widely used method in advertising research to unobtrusively capture viewers' affective reactions. It's based on Ekman's Facial Action Coding System (FACS) which links specific facial muscle movements (action units) to basic emotions (Ekman, 1972; Ekman & Friesen, 1978). Tools such as FaceReader analyzes facial video streams frame-by-frame and estimate the intensity of six basic emotions (joy, surprise, sadness, fear, disgust, anger; recent models include sentimentality, confusion and contempt as well), valence (positive and negative direction of emotions), and engagement (overall emotional engagement) (iMotion, n.d.). AFC offers several advantages: it is non-invasive, scalable, and allows for high temporal resolution, enabling researchers to track emotional fluctuations in real time (Stöckli et al., 2018). However, key methodological caveats remain. Classifiers are typically trained on exaggerated, posed expressions, which limits their accuracy for spontaneous, low-intensity reactions in naturalistic settings (Baños-González et al., 2020; Büdenbender et al., 2023). Differences across software systems also reduce cross-study comparability, and the method requires controlled lighting and camera positioning to minimize noise (Küster et al., 2020). Nonetheless it's still a validated relatively precise neuromarketing tool broadly applied for emotional assessment (Stöckli et al., 2018).

Role of Emotions in Advertising Effectiveness

Young consumers represent a particularly challenging and relevant segment for digital video advertising. Studies show that individuals born after 1990 change platforms around 27 times per hour—far more frequently than older cohorts—resulting in approximately a 30 % decline in sustained concentration (MarketingProfs, 2017). Advertisers respond with short videos that rely on strong visual and emotional hooks from the very beginning. In this context, visually or/and emotionally salient content tends to stand out, while slower or purely informational ads are quickly skipped, creating an incline towards creative and entertaining ads with emotionally charged messages.

Emotional engagement has long been recognized as a key mechanism driving advertising impact (Byrne et al., 2022; Lewinski et al., 2014). For example, Teixeira et al. showed that ad content eliciting joy and surprise significantly increased viewer attention and engagement (Teixeira et al., 2012). Similarly, Lewinski et al. (2014) found that greater facial expressions of happiness during an ad were associated with more positive attitudes toward the ad and brand (Lewinski et al., 2014). These attitudinal responses (liking of the ad or brand) are one class of outcomes.

A second class involves behavioral or memory outcomes (e.g. later recall of the ad or logo). Emotional memory theory emphasizes that events accompanied by moderate to high arousal are preferentially tagged for long-term storage (McGaugh, 2003). In video advertising, this implies that scenes eliciting laughter, delight or even fear are more likely to be retained and to influence later brand choice (McDuff et al., 2015). Neuromarketing researchers have begun linking emotions to these outcomes. Previous studies indicate that stronger emotional engagement can improve brand and ad recall, and under certain conditions even increase purchase intention (Baldo et al., 2022). Also, Guixeres et al. reported that neural indicators of affect predicted subsequent ad recall, suggesting emotional arousal helps "cement" an ad in memory (Byrne et al., 2022). Emotional engagement has therefore been identified as a key driver of advertising effectiveness: ads that evoke meaningful affective responses are more likely to be processed deeply and remembered (Pine & Gilmore, 1998; Jiang et al., 2023; Vrtana & Krizanova, 2023)

Dynamic Emotional Signatures and Theoretical Framework

However, these findings are often based on emotional scores which were aggregated by average. Russel's Circumplex model highlights that emotions are highly dynamic rather than static (Russell, 1980). Notably, over the course of an advertisement, emotions typically rise and fall, with discrete peaks emerging at narrative turning points, humorous elements or visually striking scenes. This motivates a deeper examination of how dynamic emotional responses during video ads relate to memory outcomes. Dynamic features such as rise time, peak intensity, duration and variability of emotional episodes can therefore provide richer insight than simple averages. Kühn et al. (2016) found that moment-specific neural peaks, particularly during branding segments, were more predictive of real-world sales than average engagement, emphasizing the importance of when emotions occur (Kühn et al., 2016). Kolar et al. (2021) similarly showed that EEG peaks during brand logo appearances predicted recall far better than post-exposure surveys, reinforcing that emotional timing matters (Kolar et al., 2021). McDuff et al. (2014) extended this insight to facial expressions, demonstrating that temporal dynamics of smiles—not just their presence—correlated with ad liking and memory (McDuff et al., 2014). Even though limited works studied dynamic feature of emotion in context of ad effectiveness, existing ones validate our focus on facial expression dynamics for predicting memory outcomes. These findings resonate with broader emotional memory theories, which argue that "emotional peaks" during an episode serve as markers that intensify encoding. While a stable positive tone can support favorable brand attitudes, ads that lack emotional variability risk fading into the background amid competing stimuli. This provides a theoretical basis for focusing on the temporal structure and contrast of emotional responses—key elements in the present study's dynamic emotional signatures.

Summary and Research Gap

In summary, existing literature agrees that emotions play a central role in advertising effectiveness by enhancing attention, encoding and recall. Neuromarketing approaches, and automated facial coding in particular, provide objective, time-resolved measures of viewers' emotional responses and have been successfully linked to evaluative outcomes such as ad liking and brand attitude. Nevertheless, several gaps remain. First, the temporal dynamics of emotional reactions are rarely examined systematically: many studies rely on static or averaged measures, overlooking how emotion fluctuates across narrative segments and branding moments. Second, although previous studies suggest these mechanisms, facial dynamics in youth-focused ad contexts remain underexplored and under-theorized. Lastly, relatively few studies directly connect dynamic facial responses to subsequent memory outcomes. These gaps justify the present quantitative exploratory study, which uses automated facial coding to capture the temporal dynamics of emotional expressions during youth-oriented video advertisements and links these dynamic emotional signatures to ad recall and other self-reported effectiveness measures. By focusing on the intensity and variability of facially expressed emotions, the study aims to clarify how dynamic emotional responses relate to advertising effectiveness and to assess whether such indicators can complement traditional evaluation methods. This framework directly underlies the two hypotheses formulated in the Introduction.

Methods

Research design and ethical considerations

This study adopts an exploratory, quantitative, lab-based design aimed at examining how dynamic emotional responses to video advertising relate to self-reported measures of advertising effectiveness among young consumers. Facial-expression-based emotion tracking (FaceReader) was combined with post-exposure survey measures. The study represents a pilot stage within a broader project on developing a behavioral model of communicative effectiveness in digital advertising. The experiment was conducted in Almaty Management University. The study was conducted by researchers with prior training in neuromarketing, with no affiliation to any of the brands or stimuli presented, minimizing personal or commercial bias.

All procedures adhered to institutional guidelines, national regulations, and international standards for minimal-risk behavioral research. According to the Model Rules of Scientific Ethics of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Ministry of Science and Higher Education of the Republic of Kazakhstan, 2024) and the Code of Scientific Ethics of the National Academy of Sciences (National Academy of Sciences of the Republic of Kazakhstan, 2023), researchers must ensure informed consent, confidentiality, voluntary participation, and minimization of risks to human subjects. Given the non-invasive design, absence of sensitive content, and stimuli comparable to everyday media exposure, the study falls under the category of minimal-risk research as defined by international guidelines (ESOMAR & GRBN, 2020; U.S. Department of Health and Human Services, 2023). In accordance with both national and international definitions of minimal-risk research, and institutional policy, no formal ethics board review was required. Two participants were aged 17 and provided written assent. In line with ESOMAR-GRBN guidance for research with young people aged 14–17, and given the minimal-risk and non-sensitive nature of the content, parental permission was not deemed obligatory under prevailing ethical standards (ESOMAR & GRBN, 2020). All participants consented voluntarily, signed informed consent, data were anonymized, and post-study debriefings were conducted.

Participants

The sample comprised 40 young people aged 17–21. This age group was chosen because late teens and emerging adults constitute the core active audience for social media and online video platforms in Kazakhstan, and thus represent a natural target for digital advertising (Tribune, 2025). Participants were recruited on a voluntary basis among students of Almaty Management University. All participants self-reported daily use of social media and frequent exposure to online video advertising. The sample was gender-balanced and included students from diverse majors, providing heterogeneity in educational background within a relatively homogeneous age and media-consumption profile. The sampling strategy was one of convenience rather than probabilistic recruitment, which limits statistical generalizability. However, such sample sizes and recruitment procedures are common in neuromarketing and psychophysiological research, where each participant is exposed to multiple stimuli and the focus is on exploratory pattern detection rather than population-level estimation (Vozzi et al., 2021; Kazybaeva, 2022). In this study, each participant viewed all advertising stimuli, producing a participant-stimulus dataset of 240 observations after data cleaning. The findings should therefore be interpreted as indicative rather than definitive and will require replication on larger and more diverse samples in future work.

Advertising stimuli

Six video advertisements for fast-moving consumer goods (FMCG) were selected as experimental stimuli. FMCG brands were chosen because they are major investors in video advertising in Kazakhstan (K-Research Central Asia, 2025). All ads were real, locally relevant commercial videos used in the market, rather than artificially constructed stimuli, to preserve ecological relevance. The selection followed several criteria. First, the videos differed in emotional tone and creative strategy, including humorous, sentimental, dynamic/action-oriented and more neutral executions, to elicit a broad range of affective responses. Second, the ads were comparable in basic format: short videos of approximately 30 seconds, horizontal 16:9 ratio and HD quality, which helped to standardize viewing conditions. Third, all ads clearly presented the brand and product and were in a language understandable to all participants. The content was appropriate for a youth audience and did not contain explicit or age-inappropriate material. Together, these criteria ensured sufficient variability in emotional impact while controlling for obvious confounds such as extreme length, technical quality or incomprehensible content.

Procedure

The study was conducted individually in a university classroom setting. After consent, each participant received a brief instruction stating that they would watch several short video ads and then answer questions about each one. The advertising content and specific study hypotheses were not disclosed to avoid biasing responses. Each participant then viewed the six video ads in randomized order to control for potential order effects. The videos were presented on a computer screen at a comfortable viewing distance. A webcam positioned above the screen recorded the participant's face throughout the session. FaceReader (iMotion 10, Affectiva) ran in parallel, automatically analyzing facial expressions in real time and storing a frame-by-frame record of emotional indices at approximately 30 frames per second. Within the constraints of an exploratory laboratory design and limited sample size, facial coding represents a methodologically appropriate compromise between temporal resolution, ecological validity, and feasibility. After each video, participants completed a brief questionnaire assessing ad recall: reflecting the perceived memorability of the advertisement. Rating was provided on 10-point Likert-type scales. This measure served as the primary dependent variable both in correlation analysis and in exploratory predictive modelling. After all six ads and questionnaires were completed, participants were debriefed and given an opportunity to ask questions. This allowed for time-resolved alignment between emotional response and evaluative outcomes at the stimulus level.

Data Preparation and Analysis

Dataset Construction and Preprocessing*:* The raw dataset combined frame-by-frame facial expression recordings with post-exposure survey responses. First, dependent variable—Ad Recall—was examined and transformed as needed. For classification tasks, each outcome was binarized via median split (e.g., high vs. low recall), creating roughly balanced classes. Demographic variables were prepared by converting Gender into binary indicators and treating Age as a numeric feature. The facial expression data (captured by FaceReader software) were cleaned by removing frames with no detected face or all emotion values missing, and categorical identifiers (participant ID, video ID, etc.) were standardized for consistency. Each participant's continuous facial emotion time-series for a given ad was then aggregated into a single exposure-level observation by merging it with that individual's survey outcomes on the same ad.

Feature Engineering—Average (Static) and Dynamic Emotions: To quantify emotional responses, a comprehensive set of features was derived from the facial expression time-series. Static features summarized overall emotional levels during the ad (e.g., the mean intensity of "Joy", "Valence", "Engagement" across the ad). Specifically, for each emotion channel, we computed the average (mean) intensity. By contrast, dynamic features captured temporal patterns and variability in the emotional response. These included the standard deviation of each emotion's intensity over time (as an index of volatility), the range (max-min contrast) of each emotion, and the linear slope of emotion intensity over the ad's duration (indicating rising or falling trajectories) and 90th percentile, and other aggregate metrics. We also recorded the relative timing of peak expression (e.g., the fraction of the ad's duration at which the maximum joy occurred) and split the ad into three equal segments to compute segment-wise emotion means (e.g., Joy_seg1_mean for the first third of the ad, etc.). These temporal features were designed to reflect hypotheses about emotional dynamics. All engineered features were inspected for outliers and missing values: any infinite values (from slope calculations or entropy measures) were replaced with NaN, and then rows with missing data in any predictor or outcome were dropped to ensure a complete-case dataset for modeling.

Before predictive modeling, we conducted a comprehensive statistical analysis to examine associations between facial emotion-derived features and advertising effectiveness outcomes. Two complementary approaches were used: (1) nonparametric Spearman and parametric Pearson correlations, and (2) one-way ANOVA tests on quantile-based outcome groupings. Emotional predictors were grouped into static (mean-based) and dynamic (variability- and time-sensitive) features. Multiple testing corrections (Bonferroni and FDR) were applied to control for false positives, and post-hoc Tukey tests identified pairwise group differences where applicable.

Train-Test Split and Class Imbalance Handling: After feature extraction, the data were divided into training and testing sets for predictive modeling. We used an 80/20 stratified split, ensuring that the class ratio (e.g., high vs low recall) was preserved in both sets. Stratification was important given a slight class imbalance in outcomes like Ad Recall (approximately 50 % "high" recall vs 50 % "low", with minor deviations). To further address class imbalance during model training, we implemented a sample weighting strategy. Each training instance was weighted inversely to its class frequency (using scikit-learn's class_weight='balanced' formula), so that the classifier paid relatively more attention to minority-class examples. These weights were supplied to the model's training routine (via the sample_weight parameter) to mitigate bias without discarding or oversampling any data. By preserving all observations and applying weights, we aimed to improve the model's recall for the under-represented class while maintaining overall performance.

Modeling Approach and Hyperparameter Tuning: Based on prior testing of several algorithms, we selected an XGBoost gradient-boosted tree classifier as the primary model for predicting binary ad outcomes. XGBoost was chosen for its ability to handle feature heterogeneity and its built-in robustness to collinearity and scale differences in features. An initial grid search was conducted on the training data to fine-tune key hyperparameters. Using 5-fold cross-validation within the training set, we exhaustively searched over combinations of tree depth, number of trees, learning rate, and tree subsampling fractions. The optimization criterion was the mean cross-validated ROC AUC score, reflecting the model's ability to discriminate between classes. The grid search identified an optimal configuration (for Ad Recall prediction) with relatively shallow trees (max depth = 3), a lower learning rate (0.01), and a moderate number of trees (approximately 100 boosting rounds). These tuned hyperparameters were then fixed for the final model training. During training, the sample weights (as described above) were applied, and a validation subset was monitored to prevent overfitting (with early stopping if performance ceased improving). The final XGBoost classifier was thus trained on the weighted training set with tuned settings and then evaluated on the 20 % hold-out test set.

Evaluation and Interpretation Procedures: We evaluated classification performance with several standard metrics: overall accuracy, F1-score (the harmonic mean of precision and recall for the positive class), and Area Under the ROC Curve (AUC) for probabilistic performance. In addition, we examined the confusion matrix on test data to understand the distribution of true vs. predicted positives and negatives. Alongside raw performance, we extracted the model's internal feature importance values (based on information gain) to identify which input features contributed most to the predictions. To add an interpretable layer to the results, we employed SHAP (SHapley Additive exPlanations) analysis on the final model. Using TreeSHAP, we computed contribution scores for each feature for every prediction. This allowed us to generate a global SHAP summary plot (ranking features by average absolute impact on the model's output) and to visualize local explanations for individual instances (illustrating how specific feature values increased or decreased the predicted probability). All analysis steps were conducted in a reproducible Python environment, and the data preparation and modeling pipeline were codified such that the process could be repeated or extended with new data. By the end of this phase, we had a cleaned and feature-rich dataset, a tuned and validated predictive model (XGBoost), and a suite of interpretability tools to help understand the model's decisions.

Results

To test the association between emotional features and ad recall, both correlational and variance-based statistical methods were employed.

Table 1 presents the results of a Pearson correlation analysis between emotional features and the dependent variable Ad Recall. Only features that met the predefined significance threshold ($p < 0.05$) and demonstrated a correlation magnitude of at least $|0.2|$ are included. The table distinguishes between static and dynamic features, with the majority of statistically significant correlations emerging from dynamic metrics. The strongest associations were observed for standard deviation, 90th percentile, and contrast-based indicators across the Joy, Engagement, and Valence emotion channels.

Table 1. Pearson correlation analysis

№	Aggregation type	Feature	Pearson corr.	p-value
1	*2*	*3*	*4*	*5*
1	Static	Joy_mean	0.215	0.0008
2	Static	Engagement_mean	0.210	0.0011
3	Static	Valence_mean	0.216	0.0007
4	Dynamic	Contempt_max	0.209	0.0011
5	Dynamic	Contempt_contrast	0.210	0.0011
6	Dynamic	Joy_max	0.257	0.0001
7	Dynamic	Joy_p90	0.266	0.0000
8	Dynamic	Joy_std	0.283	0.0000
9	Dynamic	Joy_contrast	0.257	0.0001
10	Dynamic	Engagement_max	0.272	0.0000
11	Dynamic	Engagement_p90	0.239	0.0002
12	Dynamic	Engagement_std	0.272	0.0000
13	Dynamic	Engagement_contrast	0.272	0.0000
14	Dynamic	Engagement_seg1_mean	0.203	0.0016
15	Dynamic	Valence_max	0.276	0.0000
16	Dynamic	Valence_p90	0.279	0.0000
17	Dynamic	Valence_std	0.292	0.0000
18	Dynamic	Valence_contrast	0.267	0.0000

Table 2 summarizes the outcome of one-way ANOVA tests conducted on quantile-based groupings of Ad Recall scores. The features listed passed false discovery rate (FDR) correction at the $\alpha = 0.05$ level. For each feature, raw p-values, Bonferroni-adjusted p-values, and FDR-adjusted p-values are reported, along with binary significance indicators. Notably, multiple dynamic features related to Joy, Engagement, and Valence retained statistical significance after correction.

Table 2. One-way ANOVA test

	Feature	**p_raw**	**Bonferroni**	**FDR**	**Significant_raw**	**Significant_Bonf**	**Significant_FDR**
1	2	3	4	5	6	7	8
1	Joy_max	0.000875	0.086597	0.007872	True	False	True
2	Joy_p90	0.000233	0.023077	0.005769	True	True	True
3	Joy_std	0.000149	0.014721	0.004907	True	True	True
4	Joy_contrast	0.000874	0.086557	0.007872	True	False	True
5	Engagement_max	0.000623	0.061700	0.006860	True	False	True
6	Engagement_p90	0.003336	0.330263	0.027522	True	False	True
7	Engagement_std	0.000590	0.058457	0.006860	True	False	True
8	Engagement_contrast	0.000624	0.061739	0.006860	True	False	True
9	Engagement_seg1_mean	0.005695	0.563766	0.043367	True	False	True
10	Valence_max	0.000513	0.050765	0.006860	True	False	True
11	Valence_p90	0.000139	0.013738	0.004907	True	True	True
12	Valence_std	0.000106	0.010452	0.004907	True	True	True
13	Valence_contrast	0.000479	0.047406	0.006860	True	True	True

Model Performance Across Stages

We evaluated the XGBoost classifier's performance on predicting high vs. low advertising outcomes at three key stages: the initial baseline model, after hyperparameter tuning, and after addressing class imbalance with weighting. Even though, initially 2 types of models were built—using dynamic and static emotional features to test Hypothesis 2—in the end combined model was chosen for further investigation and improvement since it showed better performance among all 3 types. Table 3 summarizes the classification metrics for Ad Recall (the focal outcome) in each stage. The baseline model—trained with default XGBoost parameters on the full feature set—achieved moderate discrimination, with a cross-validated ROC AUC around

0.65 and test-set accuracy about 0.60 (for Ad Recall). After performing a grid search and hyperparameter tuning, the tuned XGBoost reached an AUC of approximately 0.72 on the test set, alongside an accuracy of ~0.70 and a positive-class F1-score of ~0.73 (see Table 3).

Table 3. Summary of model performance across stages

№	Stage	AUC	Accuracy	F1 Score
1	2	3	4	5
1	Baseline model	0.66	0.63	0.62
2	Tuned model	0.72	0.70	0.73
3	Weighted model	0.86	0.75	0.75

Further the class-weighting strategy was implemented. Training the model with sample weights yielded a small uptick in overall accuracy (to ~75 %) and substantially improved the recall for the positive class. As a result, the weighted model achieved an AUC of about 0.86 on the hold-out test set. In the final weighted model, the number of correctly identified high-recall instances increased while false negatives decreased, without inflating false positives. Figure 1's confusion matrix shows that true positives and true negatives comfortably outnumber misclassifications, a pattern not seen in the baseline model.

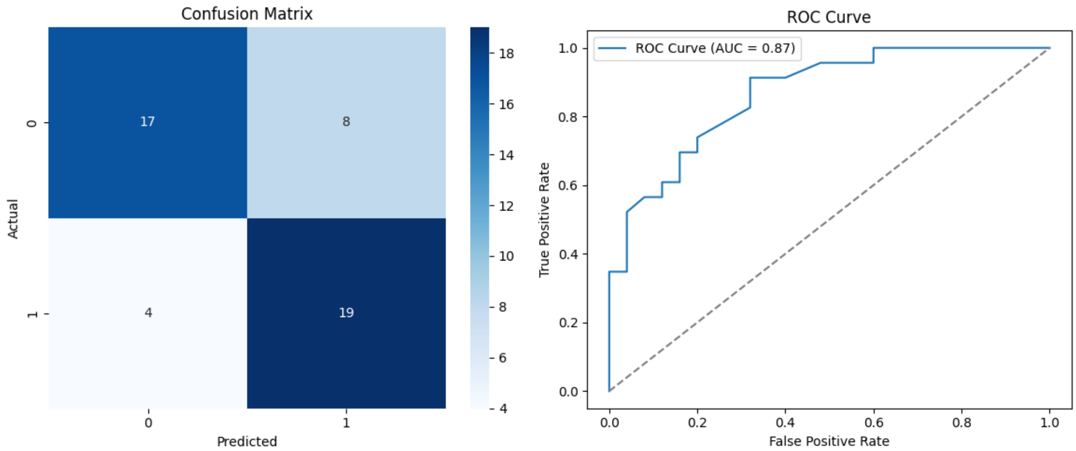

Figure 1. Confusion matrix of the weighted model

Overall, the classification framework outperformed regression attempts (which yielded near-zero or negative R^2 on test sets), affirming that a binary approach (e.g. distinguishing high vs low recall) was more viable given the data characteristics.

Feature Importance Analysis

Feature importance was assessed using SHAP (SHapley Additive exPlanations), which quantifies the contribution of each feature to the model's prediction for individual cases. Figure 2 presents a SHAP summary plot for the final Ad Recall classifier, showing both the direction and magnitude of each feature's impact.

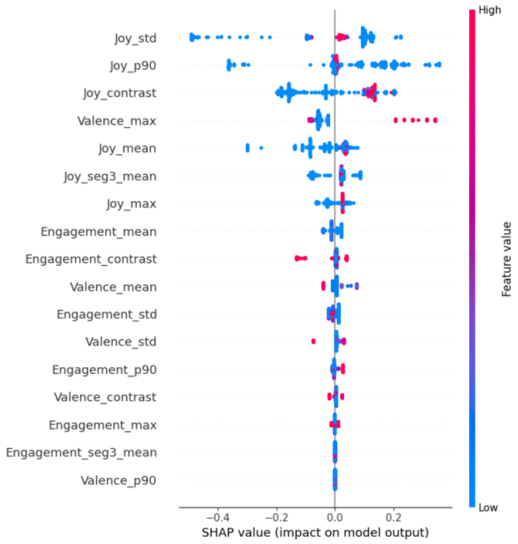

Figure 2. Global SHAP values

Each dot represents one sample's SHAP value for a given feature. The x-axis indicates the direction and strength of the feature's effect on the model output: values to the right increased the likelihood of high recall, while values to the left decreased it. Color denotes the original feature value, from low (blue) to high (red). Several features—such as Joy_std, Joy_p90, and Joy_contrast—display wide horizontal dispersion, indicating strong and variable contributions across instances. For these features, high values (in red) generally align with positive SHAP values, suggesting a tendency to push predictions toward the high-recall class. Conversely, features near the bottom (e.g., Valence_p90, Engagement_seg3_mean) show low dispersion and tightly clustered values around zero, indicating limited influence on predictions regardless of their value range. The overall pattern suggests that specific high-magnitude emotional signals—especially those related to joy and its temporal variability—had the most consistent and substantial impact on the classifier's output.

In addition to global explanations, we examined local SHAP values for individual predictions to illustrate the model's decision logic. The SHAP waterfall plot in Figure 3 visualizes the additive contributions of individual features toward the model's predicted probability for a single high-recall observation. The base value (E[f(x)])—the mean model output across the dataset—is 0.008, the final prediction reached 0.725. Feature contributions are displayed in descending order of impact. Valence_max exerted the strongest positive influence, shifting the output by +0.31, followed by Joy_contrast (+0.14) and Valence_mean (+0.04). Additional moderate contributions were observed from Engagement_contrast, Joy_mean, Joy_std, Valence_std, Engagement_p90, and Joy_max, each contributing between +0.03 and +0.04. Features with negligible effect were grouped under "8 other features". The length of each horizontal bar represents the absolute magnitude of the feature's contribution to the prediction. The annotated values on the left of each bar correspond to the raw input value for the given feature. The cumulative visualization highlights the sequential aggregation of effects that led the model from the baseline prediction to the final output.

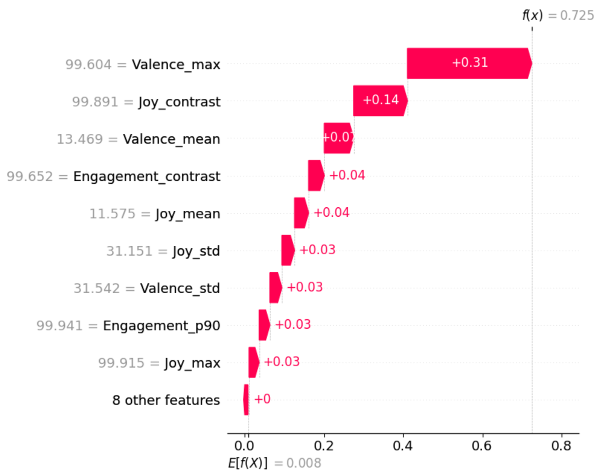

Figure 3. Local SHAP values

Discussion

The results of this study provide clear support for our core hypotheses about emotional dynamics in advertising. First, consistent with Hypothesis 1, we found that dynamic facial expression patterns are significantly associated with advertising effectiveness—most notably with Ad Recall. Both correlation analyses and group comparisons showed that participants who remembered ads tended to exhibit greater emotional variability and intensity during viewing, compared to those with lower recall. This confirms that it's not just whether an emotion is elicited, but how it unfolds over time that matters for memory. For example, high-recall ads were characterized by pronounced surges in joy and engagement, validating the idea that emotional peaks contribute to stronger memorability. This finding aligns well with prior work by Lewinski et al. (2014), who reported that viewers' smiling (a proxy for joy) was positively correlated with their liking and recall of commercials. Our study extends such findings by demonstrating that not only the average level of smiling, but also its dynamics—how much one's smile intensity fluctuates or reaches a climax—is a critical predictor of what ads stick in memory.

The comparative performance of static versus dynamic features addresses Hypothesis 2, which posited that dynamic emotion metrics would enhance predictive power beyond static summaries. The evidence here is nuanced. On one hand, dynamic features (such as standard deviations, contrasts, and temporal slopes) clearly offered additional explanatory value: they dominated the machine learning model's feature importance rankings and improved classification performance for certain outcomes. Models using dynamic features outperformed those using only static means, suggesting that fluctuations in emotions (like moments of surprise or spikes of engagement) differentiate how much an ad entices the viewer. This resonates with Teixeira et al. (2012), who found that temporal patterns of surprise and joy in video ads were key drivers of viewers' continued attention and eventual persuasion. Our results similarly indicate that an ad capable of taking the viewer on an emotional ride—for example switching emotional tone toward a positive resolution—tends to be more effective by certain measures. On the other hand, we also observed that static features retained significant predictive power for Ad Recall, as it was observed in both correlation and feature importance analysis. This suggests that the general valence and engagement level an ad elicits (high vs low overall enjoyment) is still important for memory encoding. The dynamic features then add a finer layer of discrimination: given two ads that are equally positive on average, the one that manages emotional variation or a strong finish will be remembered better. In summary, Hypothesis 2 is partially supported: dynamic measures improve prediction when emotional responses are complex, but basic positive reactions (captured by static means) remain a necessary foundation.

Another notable insight from our study is the particular importance of joy and valence dynamics. Joy (often manifested as smiling or laughter) emerged as the single most influential emotion across analyses. This reinforces a well-established observation in advertising literature: ads that elicit happiness are more likely to engage, as they elicit a rewarding emotional experience (Lewinski et al., 2014; McDuff et al., 2015; Teixeira et al., 2012). Our contribution lies in showing that it is not merely the presence of joy, but its temporal profile that counts. This observation aligns with psychological theories discussed in literature review suggesting that emotional intensity and fluctuation—rather than mere presence—enhance memory encoding. Viewers may not recall content based on a steady emotional state, but are more likely to remember experiences marked by noticeable shifts in affective intensity. In our findings, higher variability and contrast in joy-related expressions were consistently associated with greater ad recall, supporting the idea that dynamic emotional contours, including brief but pronounced surges of positive emotion, contribute to memorability. Thus, our results provide empirical validation, within a facial coding framework, for a principle that creative professionals have long embraced: not just making viewers feel good, but allowing emotional responses to evolve meaningfully over time.

Implications for Theory and Practice

The confirmation that dynamic emotional cues predict ad recall has implications on several fronts. Theoretically, it reinforces the idea that models of advertising effectiveness should incorporate time-based affective factors. Traditional advertising models often include attention, emotion, and memory as linked constructs; our results specify that the temporal structure of emotion (like engagement oscillations or late-emotion peaks) is a critical element linking exposure to memory. This advocates for an integrative framework where emotional dynamics are considered alongside content and frequency effects when explaining why certain ads succeed. Practically, the results offer guidance for advertising practitioners and evaluators. First, the strong performance of joy and engagement metrics implies that facial coding can serve as a valuable early indicator of ad effectiveness. Agencies can use facial expression analysis in pre-test sessions to identify whether an ad elicits the desired emotional ride. If an intended “feel-good” ad only produces mild, flat reactions, it may signal poor memorability—prompting creative rework such as adding a humorous twist or a heartfelt moment to elevate the emotional curve. Second, our use of an interpretable ML model (XGBoost with SHAP explanations) demonstrates a path forward for explainable AI in marketing analytics. Rather than treating predictive models as black boxes, we show that it’s feasible to extract human-readable insights (e.g., “variability in smiling is a top predictor of success”) that can be fed back into creative strategy. This approach increases trust in AI-driven ad testing tools and helps bridge the gap between data scientists and creative teams via a common understanding of what emotional signals matter. Lastly, the findings suggest that advertisers should focus not only on maintaining a positive emotional tone, but also on designing emotionally dynamic narratives with identifiable peaks that coincide with key branding moments.

Limitations

This research is among the first to systematically combine dynamic facial expression analysis with machine learning to predict advertising success, and it benefits from a rich, granular dataset (frame-level emotion readings across multiple ads). However, several limitations must be acknowledged. One limitation is the sample and stimulus scope: our data were collected on a specific set of video ads and a specific audience. The ads were all of moderate length and from similar genres (e.g., all consumer product commercials), and the viewers were from one country and roughly within a certain age bracket. This homogeneity helped control extraneous variance but also means the results may not generalize to, say, longer narrative advertisements or to viewers from vastly different cultural backgrounds. Another limitation is the reliance on self-reported effectiveness measures which doesn’t necessarily reflects actual behavior. Additionally, there are technical limitations in the emotion measurement itself. Facial expression analysis with tools like FaceReader provides a convenient and non-intrusive metric of audience emotion, but it only captures outward expressions. It may miss internal emotions not expressed on the face, and it can sometimes misclassify facial actions (for example, mistaking a nervous smile for genuine joy). This could attenuate the observed relationships—meaning the true effect of emotional dynamics might be even stronger than we detected, if measured with perfect accuracy. Finally, our predictive model, while performing above chance, is not perfect. Even with tuning and weighting, the best AUC of ~0.86 for recall prediction indicates that some recalled ads were indistinguishable from non-recalled ones based on facial expressions alone. This reminds us that advertising effectiveness is a multi-dimensional phenomenon: factors like narrative clarity, branding, viewer motivation, and even audio/music components play roles that facial metrics can’t capture. We treat our model as a proof-of-concept for incorporating emotional dynamics, not as a standalone tool to guarantee an ad’s success.

It worth noting that these findings should be understood within the broader view that emotions represent internal, multifaceted states, as noted by Anderson & Adolphs (Anderson & Adolphs, 2014). While the current study does not attempt to exhaustively measure emotion, it provides a useful behavioral proxy for exploring their temporal structure.

Future Directions

Building on this work, future research could explore a few promising avenues. One direction is to incorporate additional modalities to complement facial coding—for instance, physiological sensors (heart rate, skin conductance) could capture arousal changes that the face doesn’t show, potentially improving predictive power for high-arousal emotions like fear or excitement. And implementing self-declared emotional assessment could validate FaceReader results and provide more holistic picture of internal emotional state. Another extension would be to apply sequence modeling techniques (such as recurrent neural networks or time-series clustering) to the emotion trajectories, rather than reducing them to summary features. This could reveal if specific temporal patterns (e.g., a sequence of surprise→joy→sentimentality) universally lead to better outcomes. We also suggest investigating the causal aspect: experimental studies could manipulate the emotional arc of an ad (creating different edit versions of the same ad—one with a flat emotional profile, one with a rising profile) to directly test the impact on recall and persuasiveness. Such research would solidify whether the correlations we observed indeed reflect causation. Last, but not least, future studies should consider including mediating or moderating variables as well, for example cultural, contextual factors’ impact on emotions, and whether cultural differences in emotional expressiveness impact the predictive models.

In conclusion, this study underscores the value of looking beyond static “smile sheets” and instead focusing on the ebbs and flows of emotion. By doing so, it contributes both to academic understanding of how advertising works and to practical techniques for creating and evaluating more emotionally resonant advertisements.

Conclusion

This research set out to deepen our understanding of how emotional dynamics, as captured through facial expression analysis, relate to advertising effectiveness—within a context of this research—ad recall. In pursuit of this aim, we combined a facial coding dataset of ad viewings with state-of-the-art machine learning and explainability methods. The findings offer several key contributions. Methodologically, we demonstrated a rigorous approach to quantify not only the presence of emotions during ads but also their temporal patterns—introducing features like emotional variability, slopes, and timing of peaks. We showed that these dynamic features can be successfully integrated into predictive models (exemplified by a tuned XGBoost classifier) to forecast which ads will be remembered or rated favorably. Our use of SHAP explanations further provided a blueprint for how to open the "black box" of such models, allowing marketing analysts to trace predictions back to intuitive emotional signals. Substantively, the study's results highlight that moment-to-moment emotional expressions play a pivotal role in an ad's impact. Ads that elicited a strongly positive and engaging emotional trajectory—especially those that built up to a peak of joy—were considerably more likely to be recalled by viewers. This underscores a practical implication for advertisers: crafting an emotional storyline with highs can enhance an advertisement's memorability. It's not only the overall sentiment of an ad that matters, but how that sentiment evolves and culminates. For academic researchers, these findings enrich advertising theory by empirically confirming that dynamic affective responses are as important as static content factors in driving outcomes like recall, thus bridging a gap between psychological theories of emotion dynamics and applied advertising research.

Despite its contributions, this study is not without limitations. We examined a specific collection of ads and a relatively small sample of viewers, which may constrain the generalizability of the absolute performance of our model. The predictive accuracy we achieved (AUC in the 0.7-0.8 range for most tasks) is respectable but also indicates that facial expressions capture only one facet of effectiveness—future work should consider complementary data for a more holistic prediction. Additionally, the facial coding technology, while advanced, may misinterpret certain expressions, and thus some emotional nuance could have been lost in our features. These limitations point to future research directions. Expanding the sample to include diverse demographics and ad types would test the robustness of our findings across contexts. Integrating other behavioral or neural measures could improve predictions and offer deeper insight into the mechanisms. Another promising direction is to apply our analytic framework in real marketing settings—for instance, using emotional dynamics to predict ad campaign success in-market, or to personalize ad delivery. Finally, research might explore interventions: can we systematically increase an ad's effectiveness by editing its emotional arc, and do the models correctly forecast the improvement? Addressing these questions would further validate and extend the practical utility of emotional dynamics.

In conclusion, this study provides evidence that "how we feel, moment by moment, as we watch an ad" profoundly shapes what we take away from it. Emotional expressions are more than a reaction; they are part of the advertising process that can amplify or dampen an ad's resonance. By capturing these transient dynamics and linking them to outcomes, we move towards a more emotionally intelligent form of advertising evaluation. Marketers armed with these insights can design content that not only evokes emotion but does so in the right pattern—aiming for that impactful crescendo that leaves viewers with a lasting impression.

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