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NEUROMARKETING IN EDUCATION: HOW EMOTIONAL CONTENT AFFECTS THE PERCEIVED EFFECTIVENESS OF UNIVERSITY VIDEOS

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ABSTRACT

Purpose of the Research. This study investigates respondents' emotional reactions to Almaty Management University's promotional videos and examines how those reactions influence perceived attractiveness of the videos and recall of their content. Understanding these effects may inform the development of more effective educational-marketing strategies by showing how emotional engagement drives prospective students' interest.

Methodology. The research is based on the observations of the facial expressions of subjects showing two promotional videos developed by the marketing department of Almaty Management University. Twenty prospective students (ages 16–20), who were considering applying to the university, took part in the study. Facial expressions were recorded using FaceReader during video viewing, after which each participant completed surveys to assess ad recall and perceived attractiveness, allowing to examine their relationship with the recorded emotional responses. To predict the memory output and the perceived attractiveness based on FaceReader results machine learning models such as Random Forest and Gradient Boost were employed.

Originality/Value of the Research. By having combined facial expression analysis with predictive analytics, this study intends to serve as a contribution in the growing area of neuromarketing within educational marketing. Contrary to traditional marketing methods which mainly rely on self-report, our research provides an objective evaluation for emotional involvement and its cognitive consequences.

Findings. Positive emotions like joy and sentimentality significantly enhance memory retention and perceived attractiveness of university promo videos. Fear and anger, however, had lower predictive power. According to machine learning models, positive emotion is important for student engagement and recall. Positive emotion-engaging video content will prove a strong tool in educational marketing to increase brand recall and prospective students' decision-making. The results are of practical importance in providing necessary information to universities to better their marketing strategies.

Keywords: Neuromarketing, Educational marketing, Emotional engagement, Memory retention, Perceived attractiveness, FaceReader, Machine learning models (Gradient Boosting, Random Forest), University promo-tional videos

INTRODUCTION

These days, universities are using more multimedia, especially promotional videos to attract students in the competitive education market. Students' decision-making processes are ultimately influenced by their emotional engagement with the multimedia, which is crucial for improving memory retention and perceived attractiveness [1]. Studies also has shown that emotionally engaging content has greater impact on student learning and recall [2].

To improve educational marketing, it's important to measure and optimize emotional responses, especially as emotionally driven content becomes more common. Neuromarketing is one of the new-age interdisciplinary field which integrate marketing, psychology and neurobiology. Through neuromarketing researcher can present advanced approaches in investigating and optimizing emotional engagement [3]. Neuromarketing strategies can also be used for improving the content of universities for enhancing memory recall. In these terms, facial expression analysis is as able to offer insights into how emotionally-driven content can contribute to better memory recall. Facial expression analysis has been popular among neuromarketing tools. It allows real-time detection of emotional responses through micro-expression tracking [4]. Tools like FaceReader, integrated into platform named iMotions, is able to provide a way to measure facial expressions. Understanding these emotional reactions can enhance the effectiveness of educational marketing strategies. [5].

Despite all of this, the effect of emotional engagement in university marketing strategies on cognitive outcomes has not been thoroughly studied. Addressing this gap will pave the way for creating data-driven content strategies for engaging and recruiting prospective students.

Our study seeks to examine emotional responses of respondents to promotional videos, and their relation to memory retention and perceived attractiveness. The main objectives of research are:

1. Identify emotions that impact memory retention and perceived attractiveness.
2. Evaluate the predictive power of machine learning models (such as Gradient Boosting and Random Forest) in analyzing influences of emotions.

This research combines neuromarketing instruments and predictive analytics with the aim of benefiting universities when improving their promotional videos through engagement and better recall.

Neuromarketing and Facial Expression Analysis

Neuromarketing represents the merge of cognitive psychology, neurophysiology, and marketing. It offers valuable insights into how consumer reaction at a subconscious level [6]. One of the advanced tools in neuromarketing is FaceReader. FaceReader serves as an advanced solution for studying human behavior. It enables the collection of precise and reliable data on emotions through facial expression analysis. These expressions are the result of muscle movements beneath the skin, which provide researchers a more profound understanding of consumer behavior and decision-making processes [7]. Besides according previous studies, emotional analysis is considered highly accurate, because emotions directly influence human behavior and are most clearly reflected on the face [8].

Emotional Responses in Advertising

Emotions are generally characterized as fleeting and temporary. They have a key influence on consumer behavior by affecting perceptions, brand choices, and buying decisions. Neuromarketing studies have shown that different marketing stimuli, including product images, logos, advertising stories, and the general store environment, can trigger emotions [9].

Researches have proven that emotionally engaging content has a strong impact on cognitive processes. According to findings of Tyng et al. and Osugi et al. [1,10] perception, attention, learning, memory, reasoning and problem-solving are significantly influenced by emotions. Particularly, they increase memory retention, by making them more vivid and easier to recall.

Memory Retention and Emotional Arousal

Positive emotions like joy and sentimentality, correlate with better recall and higher brand likeability. It has been proven that ad campaigns that evoke positive emotions generate 6 times more brand lift and 20% more ad recall than those with less emotional engagement [11,12]. This phenomenon is also evident in neuromarketing researches. For instance, Vences et al. [13] demonstrate that positive emotions enhance purchase intentions and brand loyalty. They highlight the importance of emotional connection between brands and customers.

On the other hand, negative emotions, while less frequently used, can also create lasting impressions. Studies have shown that campaigns generating strong negative emotions can lead to higher recall rates. It indicates that negative emotional arousal can enhance memory retention [14].

Emotionally charged experiences are encoded more deeply in memory. Advertisements that trigger strong emotional reaction are more likely to be retained in customers' long-term memory. [15]. Moreover, by using consumer neuroscience methods to study emotional responses, marketers and researchers can evaluate the subconscious reactions. It contributes to understanding of connection between emotions and memory retention [16].

These findings highlights the importance of emotional engagement in content creation. Both positive and negative emotions can significantly impact memory retention and consumer perception.

Emotional Engagement in Educational Marketing

Universities are increasingly utilizing video content to attract students and build brand identity. Emotionally engaging content has been shown to strengthen connections between students and institutions, enhancing engagement and recall [1,2]. However, empirical research directly linking emotional responses to cognitive outcomes in educational marketing remains limited, highlighting the need for further studies in this area.

Machine Learning for Emotion and Consumer Behavior Analysis

Recent research has shown that the diversity of emotional reactions is frequently not well captured by conventional statistical techniques. Machine learning models have been rather effective in deeper analysis of consumer behavior. They are able to identify patterns in self-report and physiological metrics, including facial expressions and gaze patterns. For example, research indicates that models like Random Forest and Gradient Boosting outperform other models in predicting customer purchase behavior, by achieving higher accuracy scores. [16,17]

Machine Learning in Educational Marketing

While machine learning has proven itself effective in commercial marketing, its application in educational marketing is still underexplored. Combining facial expression analysis with predictive modeling can help educational institutions to enhance student engagement and memory recall. Previous researches proposed system which uses machine learning models to identify students' facial expressions and define engagement levels. This approach allows to optimize teaching methods and materials, by ensuring they resonate emotionally with students. Their results indicated that use of deep learning techniques has shown promise in accurately assessing engagement levels [18,19].

Literature Gap

Previous studies have begun applying neuromarketing techniques to educational contexts, but none have directly linked emotional facial responses to memory and attractiveness outcomes for university marketing content. For example, a recent multi-campus study used facial expression analysis to evaluate student engagement with online course materials and websites, illustrating the growing role of neuromarketing in higher education branding [20]. However, that work focused on usability and learning engagement rather than on promotional videos or memory recall of marketing messages. Another experiment compared viewer engagement for advertisements with mixed vs. uniform emotional tones using EEG, confirming that varied emotional content can sustain attention [21]. Yet, it did not assess recall or appeal, and it was not specific to education marketing. This research addresses this clear gap. To our knowledge, this is the first study to objectively track prospective students' emotional reactions (via facial coding) to actual university promo videos and examine how those reactions correlate with what information they remember and how attractive they find the video and its message. It also complements earlier survey-based studies in higher-ed marketing that highlighted the importance of emotional connection in shaping college choice [22]. By combining biometric emotion measures with cognitive outcomes, our work provides novel empirical evidence on why emotionally engaging recruitment content is effective. In summary, whereas earlier research either measured emotional engagement or memory in isolation, our study bridges the two. It fills an empirical gap by showing which specific emotions (e.g. joy, sentimentality) are most influential in enhancing recall and attractiveness of university marketing videos – insights that were previously unquantified in the literature.

MAIN BODY

Materials and Methods

This section describes the research approach used in this study. Our study aims to investigate how emotional responses impact memory retention and perceived attractiveness of university promotional videos. The study integrates FaceReader, a facial expression analysis tool by iMotions, with machine learning models (Gradient Boosting and Random Forest) and conducts a quantitative analysis of emotional engagement and its cognitive impact.

Research Questions

The study is guided by the following key research questions:

1. How do specific emotional responses elicited by promotional videos impact memory retention and perceived attractiveness?
2. To what extent can machine learning models (Gradient Boosting and Random Forest) predict the influence of emotional engagement on memory retention and attractiveness?
3. Do positive emotions play a more significant role in perceived attractiveness than in memory retention?

Hypotheses

Based on prior neuromarketing research, this study tests the following hypotheses:

H1: Positive emotions significantly enhance memory retention of video content compared to neutral or negative emotions.

H2: Emotional engagement, measured through facial expressions, is a strong predictor of perceived attractiveness, with higher engagement correlating to higher attractiveness ratings.

Research Design

This study adopts a quantitative experimental approach to evaluate the relationship between emotional responses and cognitive outcomes. After participants were informed of the study's aims and provided written informed consent, they watched two university promotional videos while their facial expressions were recorded in real time using FaceReader. Subsequently, each participant completed memory recall tests and rated the perceived attractiveness of the videos on a Likert scale.

Participant Selection

The sample consisted of 20 prospective students (10 females, 10 males), aged 16-20 years, who had expressed interest in Almaty Management University. Participants were recruited through the university's admissions office to ensure contextual relevance. According to ESOMAR guidelines, sample composition should reflect the natural target audience to enhance relevance and interpretability [23]. Although our sample size (n = 20) is smaller than typical thresholds for large-scale surveys, it aligns with standard neuromarketing practice, where focused cohorts often produce reliable physiological and emotional insights [24]. Vozzi et al. (2021) demonstrated in a neuromarketing context that meaningful and interpretable results can be obtained from as few as 16 participants when analyzing biometric metrics such as EEG, eye movements, or facial expressions; subgroups of this size still showed moderately strong correlations with full-sample outcomes [25]. Nevertheless, future work should recruit larger and more diverse samples to strengthen the generalizability of these findings.

Experimental Procedure

The study followed a structured experimental protocol:

1. Pre-Experiment Survey: Participants rated their likelihood of choosing the university on a scale of 1 to 10.
2. Video Exposure: Participants watched two university promotional videos.
3. Emotional Response Measurement: FaceReader recorded micro-expressions in real time.
4. Memory Test & Attractiveness Ratings: Participants completed memory recall tests and rated video attractiveness on a Likert scale.
5. Post-Experiment Survey: Participants re-evaluated their university preference after viewing the videos.

Experimental Equipment

The FaceReader software, via the iMotions platform, was used to automatically categorize participants' facial expressions into distinct emotional states. Specifically, FaceReader detects the six basic emotions defined by Ekman – Joy (Happiness), Sadness, Anger, Fear, Disgust, Surprise – as well as Neutral (no strong emotion). In addition, the version used includes Contempt (as a seventh fundamental expression) and two advanced affective states: Sentimentality (a warm, nostalgic emotional response) and Confusion. This yields a total of 9 classified emotional states. Alongside these categories, the system computes an "Engagement" metric reflecting the level of expressiveness or intensity of the facial reactions, and a "Valence" score indicating overall positive vs. negative emotional tone [26]. These measures were captured at ~30 frames per second as participants watched the videos. As recommended by the manufacturer, we calibrated the software with each participant's neutral expression at baseline to improve accuracy [27]. The FaceReader tool has been validated in prior research for reliably recognizing facial expressions and micro-expressions corresponding to the above emotion categories [28]. We thus obtained a time-series of probabilities for each emotion per participant, which were later averaged per video or used to compute features (e.g., peak "Joy" level) for our analysis.

Research Materials

The stimuli used for this study consisted of two short promotional videos lasting 1 minute and 10 seconds, and 31 seconds respectively. These videos, provided by the university's marketing department, showcased essential information about available programs and highlighted the benefits of attending the university, aiming to engage and attract prospective students.

Data Collection and Preprocessing

The study collected two types of data:

- Facial Expression Data: Captured via FaceReader (emotion intensities recorded in real-time).
- Survey & Memory Test Data: Post-video recall scores and attractiveness ratings.

Data preprocessing included:

- Filtering out outliers in emotional responses.
- Standardizing values for model training.
- Splitting data into training (80%) and testing (20%) sets.

Data analysis and Machine Learning Models

To quantify the relationship between recorded emotional responses and cognitive outcomes, two supervised learning algorithms were employed. Additionally, hyperparameters described below were selected to balance model expressiveness and overfitting risk. A Random Forest regressor was configured with 100 decision trees (n_estimators=100), a maximum depth of 10 (max_depth=10), and the Gini impurity criterion (criterion='gini'), reflecting common defaults shown to perform well in small-to-medium sized datasets. The Gradient Boosting regressor was initialized with 100 boosting stages (n_estimators=100), a learning rate of 0.1 (learning_rate=0.1) to ensure gradual improvement, and a maximum tree depth of 3 (max_depth=3) to prevent overfitting. Data were randomly divided into training (80 %) and testing (20 %) sets (random_state=42), and model stability was further assessed via 5-fold cross-validation on the training data. Both models' predictive performance was evaluated on the held-out test set using Mean Squared Error (MSE) and the coefficient of determination (R^2); detailed results for each model and media condition are reported in Section Results. Given the modest sample size (n = 20), these hyperparameter choices help mitigate overfitting while preserving sufficient model complexity. Future studies with larger and more diverse cohorts should explore tuning these parameters further to optimize predictive accuracy.

Ethical considerations

This study was conducted in accordance with international and national research ethics guidelines. All participants (and parents/guardians for minors) gave informed consent prior to participation. We followed the ICC/ESOMAR Code and the Neuromarketing Science & Business Association (NMSBA) Code of Ethics, which emphasize voluntary participation, privacy, and protection of participants' welfare [29, 30]. The procedures (watching short publicly available university videos and answering questions) presented no more than minimal risk, comparable to everyday media consumption. According to the Common Rule's definition of minimal risk, the probability and magnitude of any harm or discomfort in our research were not greater than those ordinarily encountered in daily life [31]. In line with this and APA ethical standards for minimal-risk research, the study did not require formal ethics committee review[32]. Nevertheless, we adhered to legal requirements on data protection: no personal identifiers were retained, and data were analyzed in aggregate. This is consistent with GDPR-aligned Kazakhstan law, which mandates informed consent and secure handling of personal data [33]. All experimental protocols (recruitment, data collection, and storage) were designed to ensure participants' rights and well-being were fully respected.

RESEARCH RESULTS

The results include descriptive statistics, model performance comparisons and a detailed examination of the predictive power of emotional variables. This integrated approach offers key insights into the role of emotions in shaping consumer engagement.

General Findings From Survey Responses And Face-Reader Emotional Valence Analysis

Table 1 presents the key metrics for Media 1 and Media 2, such as preference ratings for universities before-after exposure, media attractiveness score, emotional valence based on survey and Face-Reader and memory test results. Such summary outlines a significant scene for further discussion.

The university preference ratings remained consistent at 8.32 for both media before the experiment. However, after exposure of medias there was a slight increase in ratings, with Media 2 scoring 8.74 compared to

Media 1 with score 8.58 on scale 1 to 10. It may indicate that Media 2 had a stronger impact on respondents' preference. While both videos were rated highly in terms of attractiveness, Media 2 showed a slight advantage over Media 1 (8.95 vs. 8.84). Regarding emotional valence, the survey revealed that Media 1 had a higher positive emotional response (84.2%) compared to Media 2 (78.9%), which is consistent with FaceReader results (Media 1 – 5,42; Media 2 – 2,51). Additionally, based on survey results, Media 2 showed a higher proportion of neutral responses (21% compared to 15.7% for Media 1). This pattern is also consistent with FaceReader data. It may indicate that Media 1 evoked higher engagement.

Table 1 - General Findings From Survey Responses And Face-Reader Emotional Valence Analysis

Category	Media 1	Media 2
University Preference Before Experiment on scale from 1 to 10 (survey)	8.32	8.32
Media Attractiveness on scale from 1 to 10(survey)	8.84	8.95
Positive Emotional Valence (%)(survey)	84.21	78.95
Negative Emotional Valence (%)(survey)	0.00	0.00
Neutral Emotional Valence (%)(survey)	15.79	21.05
Correct Memory Test Answers (%)(survey)	84.20	80.30
Valence AVG. (FaceReader)	5.41	2.51
University Preference After Media on scale from 1 to 10 (survey)	8.58	8.74
Note - Compiled by the authors based on research findings.		

Detailed Face-Reader-based Emotional Data Comparison Across Media Types (AVG. Values)

Figure 1 presents the average emotional responses (AVG) triggered by Media 1 and Media 2, provided by Face-Reader. It offers deeper understanding of respondents' emotional engagement. The chart includes all key emotional metrics, including engagement and neutral response. This comprehensive approach provides a more holistic view of how participants emotionally responded to each media type

Media 1 consistently triggered stronger emotional reactions. Particularly, it is observed in terms of positive emotion, with Joy averaging 7,16. The higher engagement score of 15,40 for Media 1 suggests that respondents were more attentive. It further enhances emotional impact of first media. In contrast, Media 2 evoked lower Joy (2,56), slightly higher Sentimentality (2,40) in contract to Media 1 (2,28). The lower engagement level (10,66) indicates lower emotional response. Negative emotions also varied between the two media types. Media 1 recorded higher levels of Contempt (3,08) and Disgust (0,52) compared to Media 2 (2,6 and 0,05 respectively). The lower engagement in Media 2 reflects a less emotionally charged viewing experience, potentially leading to weaker memory retention and lower perceived attractiveness.

Overall, these findings highlight that Media 1 fostered a stronger emotional connection. The higher engagement and valence, lower neutrality of Media 1 suggest that it had a more significant cognitive and emotional impact on respondents compared to Media 2.

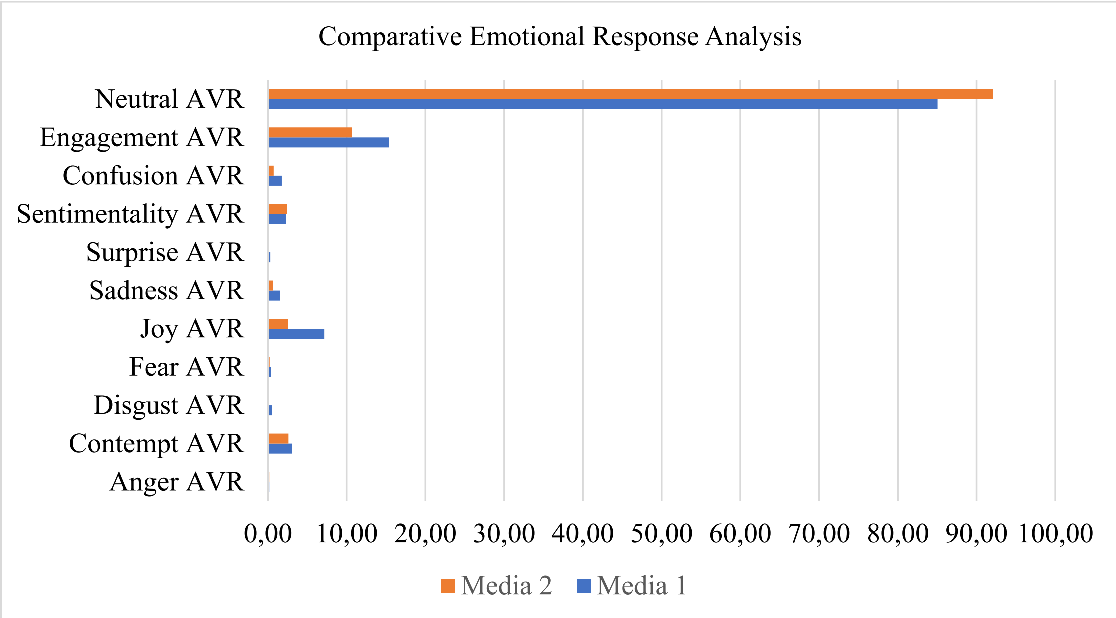

Figure 1 - Comparative Emotional Response Analysis for Media 1 and Media 2

Note - Compiled by the authors based on emotional response data captured using FaceReader analysis.

Machine Learning Model Performance for Memory and Attractiveness

To predict memory retention and perceived attractiveness the study employed Random Forest (RF) and Gradient Boosting (GB) models. The findings showed different levels of model performance. It provides insights into feature importance, models' predictive ability and their limitations.

The analysis of machine learning models reveals varying predictive ability in assessing memory retention and perceived attractiveness for the two medias. For memory retention, both models showed lower predictive accuracy, with negative R-squared values. It indicates limited predictive ability, which can be explained by small sample size and complex, non-linear relation of memory with different factors. However Sentimentality, Contempt, and Joy emerged as key predictors, suggesting that emotionally charged content influences viewers' recall.

For perceived attractiveness, the models performed better, particularly for Media 2, where GB achieved the highest R^2 (0.41) and lowest MSE (1.00), indicating a stronger predictive relationship. Joy, Sentimentality, and Surprise were primary contributors to attractiveness perceptions, reinforcing the role of positive and emotionally engaging content in shaping viewer preferences. The Random Forest model for Media 1 underperformed, with negative R^2 (-0.58) and higher MSE (1.19), suggesting that attractiveness perception in this media type was influenced by additional factors beyond the emotional features captured.

Table 2 - Summary Table of Model Performance Metrics

Model	Media	Variable	MSE	R-squared	Top Features (Importance), %	Average APE (%)
Random Forest	1	Memory Retention	205.69	-0.76	Sentimentality (36.5), Contempt (30.3), Joy (8.3)	-
Random Forest	1	Perceived Attractiveness	1.19	-0.58	Joy (31.5), Surprise (19.2), Sentimentality(8.5)	-
Random Forest	2	Memory Retention	367.91	-0.18	Joy (15.9), Fear (15.3), Sadness (11.7)	-
Random Forest	2	Perceived Attractiveness	1.35	0.20	Joy (23.8), Anger (20.8), Surprise (16.8)	-
Gradient Boosting	1	Memory Retention	235.31	-1.01	Contempt (51.9), Sentimentality (37.2), Joy (10.9)	12.50

Gradient Boosting	1	Perceived Attractiveness	1.24	-0.65	Joy (52.0), Sadness (22.1), Contempt (12.4)	10.71
Gradient Boosting	2	Memory Retention	605.30	-0.94	Sentimentality (39.8), Disgust (28.6), Joy (14.2)	21.52
Gradient Boosting	2	Perceived Attractiveness	1.00	0.41	Sentimentality (37.4), Joy (22.3), Confusion (19.5)	7.35
Note - Compiled by the authors based on research findings.						

Overall, the results suggest that while emotions significantly impact attractiveness perceptions, their role in memory retention is less straightforward, requiring further refinement of predictive models and possibly incorporating additional cognitive and contextual variables.

Discussion

The findings of this study highlight the intricate relationship between emotional engagement, memory retention, and perceived attractiveness in the context of promotional media. By employing facial expression analysis and machine learning models, this study provides insights into how different emotional reactions influence cognitive and perceptual outcomes. The discussion below synthesizes the key patterns observed, compares findings with existing literature, and outlines theoretical and practical implications.

Emotional Engagement and its Impact on Memory Retention

Findings from the analysis show that Media 1 triggered a greater emotional response comparing to Media 2. For example: Joy (7,16), Sadness (1,54), and Engagement (15,40) scores. Additionally, the higher valence (5.41) of Media 1 suggests that participants had a more positive and emotionally immersive experience compared to Media 2, which had a significantly lower valence (2.51). This aligns with previous studies emphasizing that emotionally charged content enhances memory retention by strengthening encoding processes in the brain [14,15].

According to memory test results positive emotions correlated with better recall performance. However, the predictive power of machine learning models in terms of memory retention was relatively weak, with negative R-squared values across both RF and GB. This suggests that memory formation may not be solely dependent on emotional valence or engagement but also on other cognitive and contextual factors, such as narrative complexity, prior knowledge, or personal relevance [1].

The Role of Emotional Responses in Perceived Attractiveness

The results indicate that perceived attractiveness of the media content was more strongly influenced by emotions than memory retention. Machine learning models consistently identified Joy, Sentimentality, and Surprise as key predictors of attractiveness perception. This aligns with neuromarketing research, which suggests that positively valenced emotions contribute to higher consumer engagement and brand appeal [11,12].

A notable observation was that Media 2 was rated slightly higher in attractiveness (8.95) than Media 1 (8.84), despite eliciting weaker emotional engagement. This indicates that attractiveness ratings may be moderated by something other than emotional engagement. Sequential viewing of both media could also have had a hand in this. Since participants viewed Media 1 first, their perception of Media 2 may have been shaped by a contrast effect, making it appear relatively more engaging or appealing. Overall, these findings suggest that media characteristics, as well as ordering effects, must be taken into consideration in the interpretation of attractiveness judgments.

Interestingly, Surprise played a larger role in attractiveness perceptions than in memory retention, particularly in Media 1 (19.2% importance in the Random Forest model). This aligns with research suggesting that unexpected emotional elements can heighten engagement and make content more appealing [34]. However, its role in memory retention remained limited, indicating that surprise alone is not sufficient for deep cognitive encoding.

Comparative Model Performance and Predictive Insights

The predictive models yielded varying levels of accuracy, with perceived attractiveness being more reliably predicted than memory retention. The Random Forest model for memory retention in Media 1 produced a weak R^2 (-0.76) and MSE (205.69), suggesting that memory retention is influenced by additional cognitive factors beyond emotional expressions. In contrast, Gradient Boosting performed better for perceived attractiveness, especially in Media 2 ($R^2 = 0.41$, MSE = 1.00), reinforcing the idea that affective engagement plays a crucial role in attractiveness perception.

A striking result was that Sentimentality was a dominant predictor across multiple models, with a significant impact on both memory and attractiveness outcomes. This suggests that content evoking warm, nostalgic, or emotionally complex reactions may be particularly effective in influencing consumer perceptions. Additionally, the relatively high contribution of Contempt in memory retention models (30.3% in RF and 51.9% in GB for Media 1) highlights that not all negative emotions hinder cognitive processing—some may enhance attention and recall under specific conditions.

Theoretical and Practical Implications

These findings have several implications for both theoretical models of consumer engagement and practical marketing applications:

Theoretical Contribution: The study contributes to neuromarketing literature by demonstrating that memory retention and attractiveness perception are influenced by distinct emotional dynamics. While positive emotions like Joy and Sentimentality enhance attractiveness, memory retention is more complex, requiring a balance between arousal, engagement, and cognitive relevance.

Marketing Implications: For educational marketing, these results suggest that emotionally engaging promotional videos may be more effective in influencing prospective students' perceptions of an institution's brand. However, simply increasing emotional intensity may not be sufficient for memory retention, strategic storytelling and personalized engagement strategies should be considered.

Machine Learning Applications: The study highlights both the potential and limitations of machine learning in neuromarketing. Both models successfully identified key emotional predictors. However due to their lower predictive ability in terms of memory retention, it is suggested to incorporate additional cognitive and contextual factors into future studies.

Limitations and Future Research

This exploratory study has several limitations that open avenues for future 6 research. First, our sample size (N=20) was small. While common in neuromarketing pilot studies, such a sample yields limited statistical power and may inflate certain effects [35]. Minor variations in individual reactions can disproportionately impact results when groups are this small [36]. Future studies should include a larger and more diverse sample to increase the robustness and generalizability of the findings – for instance, recruiting 50–100 participants across multiple universities. Larger samples would also permit more fine-grained analysis (e.g., segmenting by demographic or prior familiarity with the university). Second, participants watched the videos in a controlled setting, free of distractions. However, Gen Z prospects in the real world often encounter university ads amid the clutter of social media, and their attention spans are notably short – often cited around 8 seconds on average [37]. Thus, future research should test emotional engagement with promotional videos in situ on platforms like Instagram, YouTube, or TikTok. Metrics like view duration, skip rates, or click-through could be combined with facial coding to see how emotions translate to behavior in natural viewing environments. The platform and delivery medium might moderate the impact of emotional content. For example, an emotional story might captivate in a YouTube pre-roll but be overlooked in a fast-scrolling TikTok feed. Adapting our methodology to field experiments on social media will help validate these findings in ecologically valid settings. Third, It should be noted that while actual university choice also involves rational criteria such as tuition fees or institutional rankings, this study deliberately isolates emotional responses - holding those factors constant and leaving their integration for future research - so our results reflect the role of emotions ceteris paribus. Moreover, our findings pertain only to the specific promotional videos tested (with respect to their length, style, and a Gen Z sample) and do not include a formal content analysis of narrative, music, or pacing; different formats (e.g., social-media clips or long-form presentations), other content elements, or demographic cohorts may therefore elicit distinct emotional patterns, warranting dedicated follow-up studies. Furthermore, main focus of this study was on facially expressed emotions and two self-reported outcomes, but did not capture other physiological or cognitive measures. Emotions are only one piece of the decision puzzle. Future work should integrate multi-modal measures – such as eye-tracking (to see where attention is focused), galvanic skin response or heart rate (for arousal), and post-viewing interviews or surveys (to assess rational impressions). Notably, combining neurophysiological indicators with traditional self-report has been shown to greatly improve prediction of real-world behavior [38]. For university marketing, this means correlating emotional engagement data with later outcomes like whether the student actually applies or requests more information. Finally, our predictive models showed that emotional facial features alone did not reliably predict memory retention, implying that recall depends heavily on other variables (e.g., prior interest, video relevance, or individual differences in information preference). We recommend future studies include these rational and contextual factors. For example, a "dual-path" model could be tested, where emotional engagement (facial expressions, etc.) and cognitive evaluation (knowledge gained, perceived informational value) are both used to predict outcomes like recall, attractiveness, and eventually decision-making. Investigating the interplay between the emotional and rational appeals – perhaps by comparing an emotion-centric video with a fact-centric video – would provide deeper insight into optimal messaging strategies. In summary, addressing these limitations – larger samples, real-world testing, multi-modal data, and inclusion of rational metrics – will build on our findings and further advance the application of neuromarketing in the educational field.

CONCLUSION

This study examined the role of emotional engagement in memory retention and perceived attractiveness of university promotional videos, applying facial expression analysis and machine learning models to assess viewer responses. The findings reveal that positive emotions, particularly Joy and Sentimentality, significantly enhance perceived attractiveness, whereas memory retention is influenced by a more complex interplay of emotional states, including Sentimentality and Contempt.

Machine learning models demonstrated higher predictive accuracy for attractiveness than for memory retention, suggesting that cognitive recall processes involve additional contextual and psychological factors beyond emotional valence alone. While Media 1 elicited stronger emotional engagement, Media 2 was rated slightly higher in attractiveness. It suggests that factors beyond emotional arousal may have influenced the results. Moreover, the sequential exposure to both media could have contributed to this effect.

The results support the hypotheses only partially. In H1, it was found that positive emotional engagement correlated with recall; however, H1 presented mixed support in terms of memory retention prediction modeling. Strong support was obtained for H2, whereby emotional engagement predicted attractiveness since both self-rating of attractiveness and machine learning models identified Joy and Sentimentality as predominant predictors.

This study highlights the need to produce emotionally engaging content in order to appeal to the brand. Universities may leverage neuromarketing and predictive analytics to assess factors that allow promotional products to elicit necessary emotions that trigger engagement and recall. The main limitations of this study are its small sample size, the absence of additional physiological measures, and the lack of formal content analysis of the promotional videos. Building from this, future experiments should include more biometric data, a larger sample size, and exploration of contextual variables to overcome these shortcoming.

In general, the present study emphasizes the increasing relevance of emotionally engaging marketing strategies within higher education contexts. It provides insight into how affective engagement can influence prospective students' perceptions and decision-making.

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БІЛІМ БЕРУ САЛАСЫНДАҒЫ НЕЙРОМАРКЕТИНГТІҢ ҚОЛДАНЫСЫ: УНИВЕРСИТЕТТІК ВИДЕОЛАРДЫ ҚАБЫЛДАУ ТИІМДІЛІГІНЕ ЭМОЦИЯЛЫҚ КОНТЕНТТІҢ ЫҚПАЛЫ

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АҢДАТПА

Зерттеу мақсаты. Бұл зерттеу Алматы Менеджмент Университетінің жарнамалық видеоларына қатысушылардың эмоционалдық реакцияларын талдап, сол реакциялар бейнелердің тартымдылығына және олардың мазмұнын есте сақтауға қалай әсер ететінін қарастырады. Бұл әсерлерді түсіну болашақта тиімдірек білім беру маркетинг стратегияларын әзірлеуге, яғни эмоциялық қатысу арқылы үміткер студенттердің қызығушылығын арттыру жолдарын көрсетуге мүмкіндік береді.

Әдіснама. Зерттеуде алматылық басқару университеті маркетинг бөлімі әзірлеген екі жарнамалық видеоны қарау кезінде қатысушылардың бет-әлпет қозғалыстары бақылауға алынды. Зерттеуге 16–20 жас аралығындағы, университетке түсуді ойлаған жиырма респондент қатысты. Видео қарау кезінде бет-әлпет көріністері FaceReader бағдарламасы арқылы тіркелді, содан кейін әрбір қатысушы есте сақтау және тартымдылықты бағалау мақсатында сауалнама толтырды. Осылайша, жазылған эмоциялық көрсеткіштердің есте сақтау мен тартымдылыққа қалай байланысатыны зерттелді. Сондай-ақ, FaceReader нәтижелері негізінде есте сақтау көрсеткіштері мен тартымдылықты болжау үшін Random Forest және Gradient Boosting секілді машиналық оқыту модельдері қолданылды.

Зерттеудің бірегейлігі/құндылығы. Дәстүрлі маркетингтік зерттеулерден айырмашылығы, бұл зерттеу эмоциялық қатысу мен оның когнитивті әсерін объективті бағалайды.

Зерттеу нәтижелері. Қуаныш пен сентименталдылық есте сақтау мен бейненің тартымдылығын арттырды, ал ашу мен қорқыныш әлсіз әсер көрсетті.

Қорытынды: эмоционалды видеоконтент Университеттердің маркетингінің тиімділігін арттырып, университет брендін қабылдауды жақсартады. Бұл зерттеу университеттерге есте қаларлық жарнамалық материалдар әзірлеу бойынша ұсыныстар береді

Түйін сөздер: Нейромаркетинг, білім беру маркетингі, эмоционалдық тарту, есте сақтау қабілеті, тартымдылық, FaceReader, машиналық оқыту модельдері (Gradient Boosting, Random Forest), университеттік жарнамалық бейнероликтер.

НЕЙРОМАРКЕТИНГ В ОБРАЗОВАНИИ: ВЛИЯНИЕ ЭМОЦИОНАЛЬНОГО КОНТЕНТА НА ЭФФЕКТИВНОСТЬ ВОСПРИЯТИЯ УНИВЕРСИТЕТСКИХ ВИДЕОРОЛИКОВ

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АННОТАЦИЯ

Цель исследования. В настоящем исследовании анализируются эмоциональные реакции респондентов на промо-видео Алматы Менеджмент Университета и изучается, как эти реакции влияют на восприятие привлекательности видео и запоминание их содержания. Понимание этих эффектов может способствовать разработке более эффективных стратегий образовательного маркетинга, демонстрируя, как эмоциональная вовлечённость повышает заинтересованность будущих студентов.

Методология. В исследовании фиксировались мимические реакции участников при демонстрации двух промо-видео, разработанных маркетинговым отделом Университета. В нём приняли участие двадцать потенциальных абитуриентов в возрасте 16–20 лет. Во время просмотра видео с помощью программы FaceReader регистрировались выражения лица, после чего каждый участник заполнял опросники для оценки запоминания видеоконтента и его привлекательности. Это позволило изучить взаимосвязь между зафиксированными эмоциональными данными и опросными результатами. Кроме того, на основе выходов FaceReader для прогнозирования показателей запоминания и восприятия привлекательности использовались модели машинного обучения Random Forest и Gradient Boosting.

Оригинальность/ценность исследования. В отличие от традиционных маркетинговых исследований, основанных на самодекларируемых данных, это исследование предлагает объективную оценку эмоционального вовлечения и его влияния на когнитивные процессы.

Результаты исследования. Данные показали, что радость и сентиментальность значительно улучшают запоминание и восприятие привлекательности видео, тогда как гнев и страх оказали слабое влияние.

Эти выводы подтверждают, что эмоционально насыщенный видеоконтент может стать эффективным инструментом образовательного маркетинга, улучшая восприятие бренда и влияя на выбор студентов. Исследование предлагает практические рекомендации университетам по созданию запоминающихся и эффективных промо-материалов.

Ключевые слова: Нейромаркетинг, образовательный маркетинг, эмоциональное вовлечение, запоминание информации, привлекательность, FaceReader, модели машинного обучения (Gradient Boosting, Random Forest), университетские рекламные видеоролики.

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