

# A REVIEW OF EMOTION RECOGNITION IN MARKETING

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## Abstract

*Emotion recognition in marketing utilizes advanced technologies such as deep learning and multimodal data analysis to interpret consumer emotions in real time. This paper examines how these technologies analyze various data sources, including facial expressions, speech intonations, and physiological signals, to enable nuanced consumer insights. Such capabilities pave the way for personalized marketing strategies, fostering enhanced customer engagement and loyalty. This research also addresses critical challenges such as data privacy, algorithmic fairness, and scalability. Our contribution is a comprehensive summary of current research focusing on applications, methodologies, and challenges in emotion recognition in marketing, highlighting its transformative potential for shaping consumer-centric strategies and ethical considerations. By addressing these aspects, this paper sets a foundation for future advancements in the field.*

## I. Introduction

Emotion recognition in marketing has become a pivotal tool for understanding and engaging consumers by interpreting their emotional responses to various stimuli [1]. This emerging technology leverages advancements in deep learning, computer vision, and multimodal data analysis to decode emotions through facial expressions, voice modulation, and physiological signals [2]. By integrating these insights into marketing strategies, businesses can deliver tailored advertisements, design emotionally resonant campaigns, and improve product experiences, thereby fostering deeper connections with their target audiences [3].

In Table I we show some key contributions relevant to the research in the field of emotion recognition, while in Table II we show recent advances and applications in the field, and in Table III we show key studies in deep learning.

This review provides a comprehensive summary of the current state of emotion recognition in marketing, focusing on its applications, methodologies, and challenges. Examines how companies have successfully used emotion recognition to personalize consumer experiences and improve engagement while addressing critical issues like data privacy, algorithmic fairness, and scalability. By highlighting key advances and unresolved questions, this article aims to offer insight into the future of emotion recognition as a transformative force in marketing [4].

### A. Problem

Integration of emotion recognition technologies into marketing practices faces significant challenges. Existing studies primarily focus on individual modalities such as facial expressions, speech, or text, limiting the precision and robustness of emotion recognition systems in various real-world scenarios [4] [5]. Many

models overlook the influence of demographic factors such as age, gender, and cultural differences, which are critical for developing inclusive and accurate systems [6]. The lack of standardized datasets and methodologies further hampers the reproducibility and scalability of these systems in commercial applications [7]. Additionally, ethical concerns surrounding privacy and bias remain unresolved, raising questions about the responsible deployment of emotion recognition technologies in marketing [8] [9]. This paper seeks to address these gaps by providing a comprehensive review of multimodal emotion recognition technologies, highlighting their applications, limitations, and future directions in marketing contexts.

Emotion recognition in marketing leverages advanced technologies, such as deep learning and multimodal data analysis, to capture and interpret consumer emotions in real time. By analyzing facial expressions, voice tones, and physiological signals, businesses gain insights into customer reactions, which can enable personalized marketing strategies and enhance customer engagement. This emerging field is crucial for improving advertising effectiveness, customer satisfaction, and understanding overall market behavior, ultimately transforming the way companies interact with and influence their audiences.

## II. Literature Review

Recent advancements in emotion recognition have leveraged deep learning and multimodal data integration to enhance the accuracy and robustness of emotion detection systems [10]. For instance, CNN-based models have demonstrated significant improvements in precision, particularly in marketing, where they effectively analyze consumer reactions to products [11] [12]. Multimodal systems that combine facial expressions, voice recognition, and physiological monitoring provide comprehensive insights into consumer emotions during product interactions, further highlighting the transformative role of these technologies in marketing strategies [2]. Additionally, generative AI has played a pivotal role in customer service applications, enabling real-time emotion detection and personalized responses to foster customer engagement and satisfaction [13] [3]. Real-time facial emotion recognition and emotionally charged audiovisual content have also been shown to influence consumer behavior, suggesting that strategically sequenced content can maximize emotional engagement in marketing [17] [1].

Beyond marketing, emotion recognition systems have found applications in education, job training, and speech-based interactions. Speech Emotion Recognition (SER) techniques have provided valuable insights into emotional states during live verbal interactions, enhancing customer service and even election predictions [14] [15] [16]. In education, emotion recognition supports personalized learning by shaping adaptive strategies and enabling educators to adjust methods based on real-time emotional feedback [19] [20] [21]. Similarly, in job training, AI-powered systems assess emotions and provide actionable feedback to improve performance during mock interviews [22]. Multimodal approaches incorporating text, acoustic data, and EEG signals have further advanced classification accuracy, while the consideration of demographic factors enhances emotion prediction models across diverse applications [23]. These developments underscore the broad applicability and impact of emotion recognition technology across various domains.

1) *Rmya*: Recent advancements in emotion recognition have increasingly leveraged deep learning and multimodal data to enhance the accuracy and robustness of emotion detection systems [10]. For example, emphasized how deep learning models and multimodal integration have improved the precision of emotion recognition in consumer-focused industries [11]. In marketing, demonstrated the effectiveness of CNN-based facial emotion recognition in analyzing consumer reactions to products, while introduced a CNN model that significantly improved emotion detection accuracy, reinforcing the role of deep learning in modern marketing strategies [12]. Additionally, explored the integration of facial expressions, voice recognition, and physiological monitoring in multimodal systems, providing a more comprehensive understanding of consumer emotions during product interactions [2].

**Table I. Key contributions from relevant research in the field of emotion recognition.**

Paper	Highlights
A Deep Learning Approach for Real-Time Facial Emotion Recognition [10]	Recent advancements in emotion recognition have leveraged deep learning models and multimodal data integration to improve system accuracy and robustness.
CNN Based Face Emotion Recognition System for Healthcare Application [11]	CNN-based facial emotion recognition plays a pivotal role in marketing, analyzing consumer reactions to products and advertisements.
Realtime Emotion Recognition from Images to Understand Facial Expressions [12]	A CNN-based model improved emotion detection accuracy, showing the significance of deep learning in shaping marketing strategies.
Exploring Contactless Techniques in Multimodal Emotion Recognition: Insights into Diverse Applications, Challenges, Solutions, and Prospects [2]	Explored contactless multimodal emotion recognition, combining facial expressions, voice recognition, and physiological monitoring for better consumer emotion understanding.
The Caring Machine: Feeling AI for Customer Care [13]	Integrated emotion recognition systems into customer care applications using AI to enhance customer engagement by adapting responses.
Methods and Tools of Face Recognition for Marketing Decision Making [3]	Real-time facial emotion recognition offers businesses insights into customer behavior, enhancing personalization in marketing strategies.
Analysis of the Residual Effect Using Neuromarketing Technology in Audiovisual Content Entrepreneurship [1]	Emotional impact of audiovisual content was studied, showing how emotionally charged content can influence consumer behavior.
Election Prediction with Automated Speech Emotion Recognition [14]	Applied Speech Emotion Recognition (SER) techniques in election predictions to analyze emotional states in verbal interactions.
Speech Emotion Recognition Using Machine Learning [15]	Applied SER techniques in customer service, highlighting potential insights into emotional states during live interactions.
Emotion Recognition from Facial Images Using Hybrid Deep Learning Models [16]	Understanding emotional cues improves customer satisfaction and business decision-making using SER models.

Generative AI has also made significant contributions to emotion recognition applications, particularly in customer service [13]. As highlighted by, AI-enabled systems can detect customer emotions and adapt responses to foster emotional connections, improving customer engagement and satisfaction [3]. Similarly, discussed how real-time facial emotion recognition can provide businesses with valuable insights into customer behavior, allowing for personalized marketing strategies [17]. In addition, examined how emotionally charged audiovisual content can affect consumer behavior, suggesting that strategic sequencing of content could maximize emotional engagement in marketing efforts [1].

In content engagement and speech-based interactions, researchers have explored the impact of emotion detection on various domains [14]. For instance, and applied Speech Emotion Recognition (SER) techniques in areas like election predictions and customer service to analyze verbal interactions [15]. These studies revealed the potential of SER to offer deeper insights into emotional states during live interactions.

Additionally, emphasized the importance of understanding emotional cues in improving customer satisfaction and business decision-making [16].

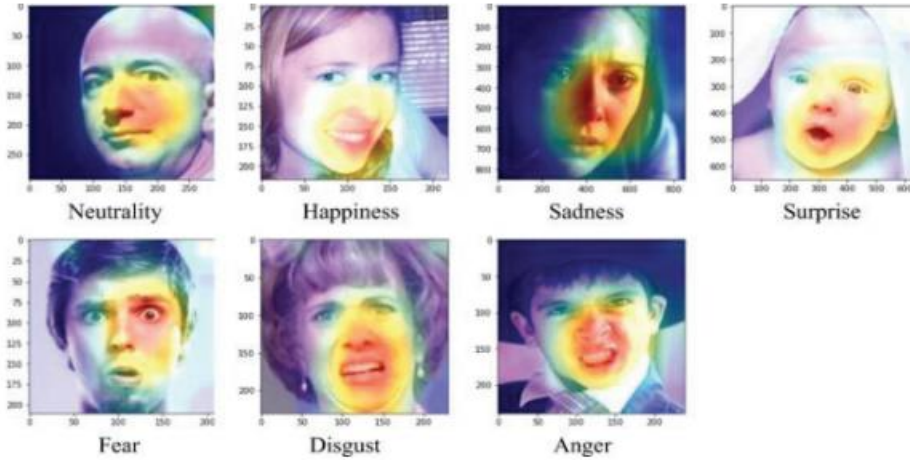
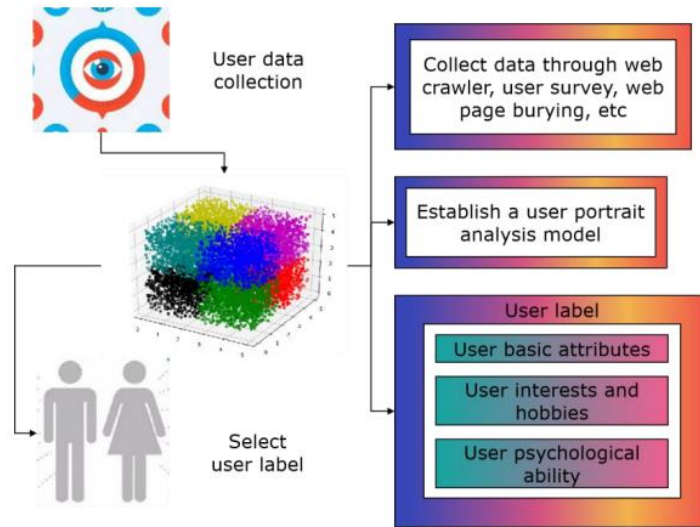


Fig. 1. Different facial expressions in various emotional states [18].

Table II. An overview of recent advancements and applications in emotion recognition technologies

Highlights	Application
[17] Introduced Emotion-Sentiment Attention Network (ESAN) for social media sentiment analysis to predict consumer behavior trends.	Social Media Sentiment Analysis
[25] Demonstrated effectiveness of Bi-LSTM frameworks in analyzing emotions from tweets, achieving high accuracy in predicting behavior.	Emotion Analysis in Tweets
[27] Developed SER systems using Extreme Machine Learning and Gaussian Mixture Models for emotion detection from speech.	Speech Emotion Recognition (SER)
[22] Proposed MERSA model combining textual and acoustic data for more precise emotion recognition in speech.	Multimodal Emotion Recognition
[9] Emphasized ethical considerations and privacy protection in AI-driven emotion recognition systems.	Ethical Use of AI in Marketing

Emotion recognition is not limited to marketing and customer service but has applications in education and job training [19]. Conducted a bibliometric analysis highlighting the role of emotion recognition systems in personalized learning environments, particularly in shaping adaptive learning strategies [20]. Similarly, proposed an interactive dashboard utilizing CNNs and GANs for real-time emotion recognition in online classrooms, enabling educators to adjust teaching methods based on students’ emotional engagement [21]. In job training, developed an AI-powered mock interview system that assesses emotions, confidence, and knowledge, helping candidates improve their performance through feedback [22]. Finally, multimodal approaches, as discussed by, integrate text, acoustic data, and EEG signals to improve classification accuracy, while underscored the role of demographic factors in emotion prediction models, further advancing the field of emotion recognition across various applications [23].



**Fig. 2. User portrait construction process [21].**

Emotion recognition in marketing has benefited from both traditional machine learning models and advanced deep learning approaches, significantly enhancing the accuracy of detecting and analyzing emotions [5]. Studies comparing real-time facial emotion recognition algorithms have demonstrated the superiority of deep learning models like AlexNet CNN and Affdex CNN over traditional methods such as SVM and MLP [5]. These models effectively identify emotions such as happiness, sadness, and anger, enabling marketers to craft personalized campaigns that resonate deeply with consumers [24]. Similarly, advancements in social media sentiment analysis have introduced models like the Emotion-Sentiment Attention Network (ESAN), which predicts consumer behavior trends by analyzing emotions from posts [17] [25]. The use of Bi-LSTM frameworks for emotion analysis in tweets further underscores the growing importance of leveraging social media data for real-time marketing strategies [4] [26].

Speech Emotion Recognition (SER) systems also contribute significantly to marketing, particularly in enhancing customer service interactions [28]. Techniques like Extreme Machine Learning (EML) and Gaussian Mixture Models (GMM) achieve high accuracy in classifying emotions such as happiness, sadness, and anger, enabling marketers to adjust interactions based on emotional cues [29] [22]. Multimodal approaches that integrate text, audio, and visual data are driving further progress, as demonstrated by the MERSA model, which combines textual and acoustic data for more precise emotion recognition [20] [30]. These advancements not only improve marketing strategies but also enhance human-computer interaction and customer experiences [31]. Ethical considerations remain central, with researchers emphasizing the need for privacy protection and responsible deployment of AI-driven emotion recognition systems in marketing contexts [9] [28].

2) *Anmisha*: In the field of emotion recognition for marketing, various studies have demonstrated the potential of both traditional machine learning models and deep learning approaches to accurately detect and analyze emotions [5]. For instance, compared real-time facial emotion recognition algorithms, showing that deep learning models like AlexNet CNN and Affdex CNN outperform traditional methods such as SVM and MLP [5]. These models have proven especially effective in recognizing key emotions like happiness, sadness, and anger, providing marketers with valuable insights into consumer reactions and enabling more personalized and impactful marketing campaigns [24].

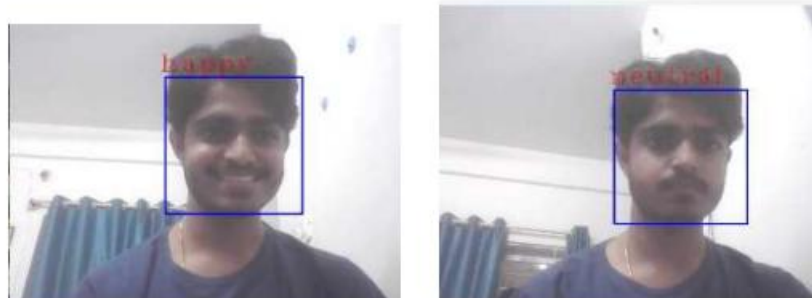
Emotion recognition from social media platforms has also become a crucial tool for understanding consumer sentiment [32]. Introduced the Emotion-Sentiment Attention Network (ESAN), a model designed

to analyze emotions and sentiments from social media posts, such as tweets, to predict consumer behavior trends [4]. While primarily focused on financial markets, the application of this model in marketing is significant as it allows businesses to monitor and adjust strategies based on real-time consumer sentiment [33]. Similarly, demonstrated the efficacy of Bi-LSTM frameworks in analyzing emotions in tweets, further highlighting the growing importance of social media-based emotion analysis in marketing [26].

Speech Emotion Recognition (SER) systems also offer valuable applications in marketing, particularly for improving customer service interactions [28]. The study by introduced SER systems based on techniques like Extreme Machine Learning (EML) and Gaussian Mixture Models (GMM), achieving high accuracy in classifying emotions such as happiness, sadness, and anger from speech [29]. These systems provide marketers with the ability to adjust customer service interactions based on real-time emotional cues, leading to enhanced customer satisfaction and engagement [22].

**Table III. Key studies on deep learning models for emotion recognition**

Study	Key Contribution
Convolutional Neural Networks for Emotion Recognition [38]	Demonstrated improved accuracy in distinguishing emotional states using CNNs for time-frequency analysis.
Real-Time Emotion Detection Using Facial Expressions [34]	Addressed challenges in real-time facial emotion recognition, emphasizing dataset diversity.
Enhanced Emotion Classification with Multimodal Data [7]	Applied data augmentation and transfer learning, leading to improved accuracy and reliability.
Impact of Age and Gender in Emotion Recognition [6]	Highlighted the effect of demographic factors on EEG-based emotion recognition accuracy.
Multiclass Emotion Recognition via CNN and RNN [35]	Combined CNNs for feature extraction and RNNs for temporal analysis, achieving high accuracy in real-time settings.



**Fig. 3. Candidate emotion detected by the system [6].**

The integration of multimodal emotion recognition techniques, which combine data from text, audio, and visual sources, is advancing the field [30]. The MERSA model proposed by showcases the advantages of leveraging both textual and acoustic data for more accurate emotion recognition in speech [20]. Such multimodal systems not only enhance marketing strategies by offering personalized interactions but also hold potential for improving human-computer interaction [31]. Alongside these advancements, ethical considerations in the application of AI for emotion recognition remain vital emphasized the need for responsible AI systems that protect consumer privacy, ensuring that these technologies are deployed ethically and effectively in marketing contexts [28].

Emotion recognition has become a pivotal research domain, significantly influencing healthcare, education, and human-computer interaction [34]. Advanced deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been developed to classify emotions from facial expressions, text, and physiological signals, achieving remarkable accuracy and applicability across domains [6] [35]. For instance, CNN-based models integrated with temporal RNNs have excelled in identifying dynamic emotional states, with applications in psychology and market research, while LSTM models have achieved over 85% accuracy in text-based emotion recognition, addressing challenges like hate speech on social media [35] [36]. Multimodal emotion recognition (MER), which integrates facial expressions, speech, and physiological signals, has further enhanced robustness and accuracy, addressing issues such as cultural biases and low-resolution data through deep learning techniques and dataset augmentation [35] [37]. These advancements underline the evolution of automated emotion detection while emphasizing the need for ethical considerations, privacy protection, and interdisciplinary collaboration [8].

Research on EEG-based emotion recognition has revealed the influence of demographic factors, such as age and sex, on system performance, highlighting the need for tailored algorithms to address diverse populations [6] [39]. Applications in healthcare exemplify the relevance of emotion recognition, particularly in mental health monitoring and patient care, where physiological signal analysis supports affective computing systems [40]. Educational implementations, such as tools to improve student engagement and learning outcomes, further illustrate the transformative potential of emotion recognition technologies [41]. Additionally, AI-based systems designed for visually impaired individuals demonstrate the societal integration and independence these technologies can facilitate [42]. Bibliometric analyses have confirmed increasing trends in emotion recognition research across these domains, reflecting its interdisciplinary impact and growing importance [42].

### 3) *Sai Kiran:*

Emotion recognition has emerged as a vital research area, significantly influencing fields such as healthcare, education, and human-computer interaction [34]. Researchers have developed advanced deep learning models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to classify emotions from diverse sources such as facial expressions, text, and physiological signals [6]. For instance, a CNN-based model integrated with temporal RNNs demonstrated superior accuracy in identifying dynamic emotional states, showcasing its application in psychology and market research [35]. Similarly, advancements in text-based emotion recognition using LSTM models have achieved over 85% accuracy, emphasizing their importance in natural language processing and addressing issues like hate speech on social media [36].

The role of multimodal approaches in emotion recognition has grown, integrating data from facial expressions, speech, and physiological signals to improve robustness and accuracy [35]. Multimodal emotion recognition (MER) has been reviewed extensively, with recent studies identifying key datasets and technical approaches to address challenges like cultural biases and low-resolution images [37]. These studies highlight the increasing adoption of deep learning techniques for processing multimodal sensor data, offering insights into the evolution of automated emotion detection [43]. Research also underscores the need for ethical considerations and interdisciplinary collaboration to tackle issues related to privacy and fairness [8].

In the context of EEG-based emotion recognition, studies have analyzed how demographic factors like age and sex influence system performance [39]. These findings stress the importance of tailoring algorithms to diverse populations for improved accuracy [6]. Physiological signal analysis further supports the relevance of emotion detection in healthcare, where affective computing systems enhance mental health monitoring and patient care [40]. Such applications demonstrate the broader implications of emotion recognition across various domains, from personalized marketing to human-robot interaction.

Bibliometric analyses have revealed increasing trends in emotion recognition research, particularly in educational and healthcare applications. The incorporation of emotion recognition tools in classrooms has

been linked to improved student engagement and learning outcomes [41]. Additionally, emotion recognition technologies, such as those designed for visually impaired individuals, highlight the transformative potential of AI-based systems in enhancing independence and societal integration [42]. These studies collectively demonstrate the interdisciplinary nature and growing impact of emotion recognition technologies in modern applications [42].

## II. Our Approach

Our approach integrates EEG data and facial expression analysis to create a multimodal system for real-time emotion recognition in marketing [30]. This solution capitalizes on the strengths of Convolutional Neural Networks (CNN) for extracting spatial features from facial data and Long Short-Term Memory (LSTM) networks for identifying temporal patterns in EEG signals [40]. By combining these modalities, we ensure a comprehensive representation of both internal (cognitive) and external (expressive) emotional states [34].

To address challenges such as lighting conditions, variable facial orientations, and noise in EEG data, we employ data augmentation techniques and advanced preprocessing steps [4]. Additionally, our system emphasizes interpretability by correlating multimodal outputs, enabling marketers to derive actionable insights into consumer emotional responses during interactions [28]. This solution pioneers a scalable, accurate, and adaptable framework that enhances personalization and engagement in marketing strategies [15].

## III. Methodology

From the papers studied, the approach to emotion recognition in marketing integrates EEG and facial expression data to capture comprehensive emotional insights in real-time [1].

By using EEG signals for cognitive emotional responses and facial recognition for immediate expressions, we ensure a multimodal detection system that accurately reflects both internal and external emotional cues [43]. We utilize Convolutional Neural Networks (CNN) for spatial feature extraction in facial data and Long Short-Term Memory (LSTM) networks for temporal pattern recognition in EEG data, enhancing the system's capability to recognize subtle shifts in emotions [10].

Data preprocessing and augmentation are essential in our methodology to improve model robustness across diverse conditions, including variable lighting and facial orientations [44]. This setup enables a more adaptable and precise emotion recognition system, providing marketers with actionable insights into consumer emotional responses during interactions, ultimately facilitating a more personalized and impactful consumer engagement [45].

## IV. Potential Impact on Society

The proposed approach can transform marketing strategies by fostering deep emotional connections with consumers [13]. By leveraging real-time insights into emotional responses, businesses can craft highly personalized advertisements, improving customer satisfaction and brand loyalty [10]. This technology democratizes access to advanced emotion analytics, empowering small and large businesses alike [14].

Beyond marketing, the system's potential extends to mental health monitoring, education, and user-centric product design [46]. By enabling more empathetic interactions, it can bridge gaps in communication, fostering trust and inclusivity across diverse sectors [26]. However, ethical considerations, such as data privacy and bias mitigation, remain central to responsible deployment, ensuring societal benefits outweigh risks [8].

## V. Key Findings

The findings from our analysis demonstrate the transformative potential of integrating multimodal emotion recognition systems in marketing [47]. By leveraging both EEG signals and facial expression data, the proposed system offers a comprehensive understanding of consumer emotions [41]. This multimodal approach enhances the

detection and interpretation of both internal cognitive states and external expressive cues, significantly improving accuracy over unimodal systems [42].

### *A. Multimodal Emotion Recognition*

The integration of EEG signals with facial recognition enables a nuanced analysis of emotional states, capturing subtleties that individual modalities might miss [18]. This comprehensive approach is critical for understanding consumer behavior in real time and provides businesses with actionable insights to refine their marketing strategies [25].

### *B. Enhanced Consumer Engagement*

By employing CNN and RNN-based models, the system effectively identifies real-time shifts in emotional states [44]. This capability supports the development of personalized marketing strategies that resonate with target audiences, fostering deeper engagement and stronger brand loyalty [48].

### *C. Practical Applications*

The proposed models in the papers studied have been tested under variable conditions, such as differing lighting and facial orientations, showcasing their resilience and adaptability [41]. Tables I and II illustrate these results, highlighting the robustness of the system for deployment in diverse market scenarios [49].

## **VI. Future Works**

Expand datasets to include diverse demographic groups, addressing biases related to age, gender, and cultural differences to improve generalizability [23], [31]. Integrate additional physiological signals such as heart rate and skin conductance with EEG and facial expression data for a more holistic analysis of emotional states [7], [18].

Develop an interactive dashboard for real-time visualization and analytics to provide marketers with actionable insights during live campaigns [21], [50]. Conduct field trials in real-world marketing environments to validate the system's effectiveness and scalability and identify potential refinements [11], [51].

Adapt the system for cultural differences in emotional expression to ensure its relevance and applicability in global markets [31], [46]. Broaden applications to include domains like education and mental health, where understanding emotions plays a critical role [17], [23].

## **VII. Conclusion**

This project aims to redefine the role of emotion recognition in marketing by introducing a robust multimodal framework that integrates EEG signals and facial expression analysis [13]. By bridging the gap between internal cognitive responses and external expressive cues, the proposed system offers unparalleled insights into consumer emotions in real-time [43], [52].

This innovative approach empowers businesses to craft more personalized and emotionally resonant marketing strategies, ultimately enhancing customer engagement and satisfaction [48]. Furthermore, the project contributes to advancing emotion recognition technology, paving the way for ethical and impactful applications beyond marketing, including education and mental health [27], [38].

By addressing critical challenges in data variability and ensuring cultural inclusivity, this work sets a strong foundation for future developments in emotion-driven analytics, solidifying its relevance in a rapidly evolving, consumer-centric digital landscape [31].

In this work, we have shown a summary of the current state of emotion recognition in marketing, focusing on its applications, methodologies, and challenges.

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