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Automated emotion recognition in marketing research: A systematic literature review of current image and video-based methods

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Abstract

This study reviews the recent literature on Automated Emotion Recognition (AER), focusing on image and video-based methods applied in marketing research. The literature overview highlights the transformative potential of AER, including real-time, unobtrusive, and scalable applications. It identifies key tools, including Noldus' FaceReader and iMotions' Facial Expression Analysis, as significant contributors to insights in diverse contexts such as e-commerce, social media, and online platforms. The analysis also addresses theoretical challenges, such as the limitations of Ekman's basic emotion theory and the contextual dependence of facial expressions. Practical recommendations for AER use include incorporating multimodal approaches and ensuring cultural and contextual inclusivity in training datasets. Thus, the current work advances the discourse on leveraging AER for refined marketing strategies.

Keywords: Automated Emotion Recognition (AER), Marketing research, Basic emotions, Facial emotion recognition, Systematic literature review (SLR)

JEL Classification: M31, M37

1. Introduction

Understanding consumer emotions can be a powerful tool for marketers, shaping perceptions, behaviors, and purchase decisions (Bagozzi et al., 2020). The study of consumers' emotional responses to marketing stimuli has long been a key focus, particularly in today's digital landscape. On the internet, consumers tend to process images before text (Lindgaard et al., 2006), making visual elements crucial for capturing attention and fostering emotional engagement. The dynamic nature of these environments further amplifies this importance.

Traditional methods to capture emotions like surveys often fail, but advancements in Automatic Emotion Recognition (AER) offer new possibilities. However, its application in marketing research remains complex, with diverse methods and goals that leave marketers uncertain about which approaches or software solutions to apply to specific management challenges.

To address this complexity, this study conducts a systematic literature review (SLR) to explore how image—and video-based AER methods have recently been applied in marketing research. The findings are discussed alongside decision aids and a summary of available software solutions. The study concludes with actionable recommendations for overcoming current challenges, maximizing AER's potential as a marketing research tool, and exploring overlooked avenues for future research.

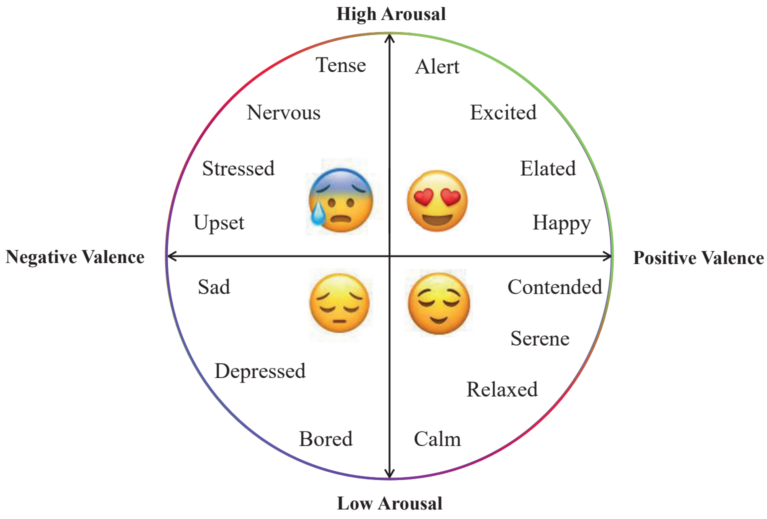
2. Theoretical Background

2.1 The way of emotion theories to AER

Emotions are rapid affective reactions triggered by external stimuli or internal thoughts (Bagozzi et al., 1999). These reactions occur instantly without prior cognitive processing (Zajonc, 1980) and manifest physically through facial expressions, voice, and body language (Mehrabian, 2017). Theories like *discrete* vs. *dimensional* emotion models (Fernández-Abascal et al., 2010) explore how emotions are categorized. Ekman et al.'s (1982) model, grounded in evolutionary theory, identified six basic emotions: anger, fear, joy, sadness, disgust, and surprise, each with a specific and unambiguous form of facial expression (Fernández-Abascal et al., 2010). Alternatively, Lang et al. (1990) proposed two bipolar dimensions: valence and arousal. Specifically, *affective valence* refers to whether a stimulus is perceived as pleasant or unpleasant, ranging from negative (e.g., sad) to positive (e.g., happy), while *arousal*, sometimes called intensity, measures the impact of the stimulus on the person, ranging from low (e.g., calm) to high (e.g., surprise) (Watson & Tellegen, 1985). These dimensions are usually used to classify the different emotions, as seen in the *circumplex model* (Posner et al., 2005; Watson & Tellegen, 1985). Figure 1 illustrates an example.

Figure 1

Circumplex model for valence and arousal



Note: Adapted from the circumplex model of affect (Posner et al., 2005).

Building primarily on these theories, numerous methods for emotion recognition have been developed, from self-report measures (e.g., the Positive and Negative Affect Schedule by Watson et al. (1988), the manual Facial Action Coding System (FACS) (e.g., Paul Ekman & Friesen, 1978), to more advanced methods like Electroencephalography (EEG). However, these methods face limitations in real-time, non-intrusive emotion detection. AER overcomes these challenges using Machine Learning (ML) and Deep Learning (DL), enhancing consumer insights (Khare et al., 2024).

Image and video-based AER involves mainly seven steps of processing (Khare et al., 2024): (1) source (images/videos), (2) stimuli (scenarios), (3) input signals (raw data), (4) feature extraction (representative attributes), (5) feature selection (e.g., via Lasso regression), (6) classification (ML/DL), and (7) model evaluation (e.g., accuracy, recall, or specificity).[1] Automation mainly occurs in classification, where algorithms analyze large datasets to identify emotional patterns. The extracted features are then classified into emotional categories, such as basic emotions or emotional dimensions like valence, arousal, and dominance (Wang et al., 2022).

2.2 AER through facial expressions

Facial expression analysis detects emotional states through facial movements and configurations (Paul Ekman & Friesen, 1978), using tools like FACS to identify Action Units (AUs). Common facial expression datasets include JAFFE (Lyons et al., 1998) and AffectNet (Mollahosseini et al., 2017)[2].

Several commercial software programs, such as Noldus' FaceReader (2024), analyze over 500 facial points to classify eight emotions (joy, sadness, anger, surprise, fear, disgust, contempt, and neutral), along with arousal and valence levels (Lewinski et al., 2014). AFFDEX by Affectiva (2023) detects seven emotions: anger, disgust, fear, joy, sadness, surprise, and contempt (Stöckli et al., 2018), while Realeyes (2024) analyzes AUs and detects the seven properties smile, surprise, frown, disgust, fear, contempt, and empathy (McDuff et al., 2016). iMotions' Facial Expression Analysis software combines technologies from Affectiva and Realeyes, detecting 20 AUs and classifying into the seven emotions joy, anger,

[1] We will not dwell deeper on these techniques since we aim to provide a non-technical hitchhiker's guide to AER in marketing research.
[2] Wang et al. (2022) provide a facial expression datasets overview.

disgust, surprise, fear, sadness, and contempt (iMotions, 2025).

Other tools include Google's Cloud Vision API, which provides probabilities for emotions (joy, sadness, anger, surprise) (Google, 2025), and Microsoft Azure (2023) Face API, which detects multiple faces and generates continuous scores for emotions (Yazdani et al., 2024). However, Microsoft withdrew Face API from the market in 2023 due to concerns about accuracy and discrimination (Microsoft, 2023). Further widely used tools include OpenFace (Baltrušaitis et al., 2016), MorphCast (Morphcast Inc., 2025) , Face++ (Beijing Kuangshi Technology Co.,Ltd., 2017), Py-Feat (Cheong et al., 2023), and Deepface (Taigman et al., 2014). Most of these programs are constantly being optimized, expanding their applications across various industries.

2.3 AER through body gestures and image features

In addition to facial expression analysis, emotion can also be recognized through body gestures and image features. Body gestures, including hand movements and posture, help detect emotions by analyzing movement sequences (Noroozi et al., 2018). Image features, inspired by psychology and art theory, extract visual characteristics like color and brightness to identify emotions (Machajdik & Hanbury, 2010).

2.4 Recent AER Review Studies

The growing interest in AER has led to a series of recent reviews on the subject, summarized in Table 1. However, as highlighted in the table, not all reviews have followed the PRISMA 2020 guidelines. Additionally, there is a clear gap in recent reviews specifically focusing on applying AER in marketing research.

Table 1

Recent AER literature overview by main characteristics

Author	Modality				Context	PRISMA guidelines
	Text	*Speech*	*Visual*	*Physiological*		
Khare et al. (2024)	x	✓	✓	x	General	✓
Adyapady and Annappa (2023)	x	x	✓	x	General	x
Ba and Hu (2023)	x	x	x	✓	Education	✓
Kamble and Sengupta (2023)	x	x	x	✓	General	x
Singh and Goel (2022)	x	✓	x	x	General	✓
Hasnul et al. (2021)	x	x	x	✓	Healthcare	x
Zhang et al. (2020)	✓	✓	✓	✓	General	x
Bota et al. (2019)	x	x	x	✓	General	x
Present article	**x**	**x**	**✓**	**x**	**Marketing**	**✓**

The following section outlines the methodology employed in the present SLR, which sets out to close the identified gaps. From the 2,173 articles identified, 17 studies that employed image and video-based AER methods were ultimately included and analyzed to highlight fields of application.

3 Method

The review process includes three key stages following the PRISMA 2020 guidelines (Page et al., 2021): identifying, filtering, and including relevant articles. We considered AER applications beyond images and video stimuli, providing a comprehensive overview of its popularity, focusing on different modalities.

3.1 Search process

This SLR employed search criteria focusing on articles from 2019 to 2024 published in A or A+-ranked marketing journals (German Academic Association, 2024). This ranking highly correlates with other journal rankings worldwide (Hult et al., 2009). We additionally include other Top-tier journals like the *Journal of Retailing and Consumer Services*. Only empirical articles were considered. To ensure comprehensive coverage, a broad set of keywords was used to create search queries, including both single-line searches and searches with specific keywords enclosed in quotation marks (“”). The single-line search used the following logic: *("Emotion" OR "Emotions") AND ("Software" OR "Recognition" OR "Measurement" OR "Detection" OR "Automation") AND ("Video" OR "Text" OR "Speech" OR "Pictures" OR "Photo" OR "Facial expression" OR "Audio" OR "Voice" OR "Webcam" OR "Face").*

This aimed to identify studies on emotions and physical AER modalities like text, speech, or visuals. Additionally, specific software tools for AER were included to capture relevant articles referencing these programs, using the following logic as a specific keyword search:

“WordNet”; “text2emotion”; “Nemesysco - QA5 software”; “OpenEAR”; “Microsoft Face API”; “Azure Face API”; “OpenFace”; “Luxand FaceSDK”; “FaceReader”; “Evaluative Lexicon”; “MorphCast”; “EmoReact”; “Adobe Audition”; “iMotions”; “OpenCV”; “Deepface”.[3]

3.2 Identification

The identification process involved applying search criteria across multiple databases, including *EBSCO* (Business Source Premier), *JSTOR*, *Nature Portfolio*, *ProQuest*, *Sage*

[3] This set of software solutions resulted from a discussion with two renowned experts.

Journals, *Science Direct*, *Scopus*, *Springer*, and *Google Scholar*. A total of $N = 2{,}173$ articles were retrieved, and after removing duplicates ($N = 285$), the screening included $N = 1{,}888$ articles.

3.3 Screening

In the screening phase, articles were reviewed, and those without empirical AER methodologies using image, video, text, or speech were excluded, reducing the total from $N = 1{,}888$ articles to $N = 103$ articles. Among these, $N = 68$ articles employed AER via text, $N = 9$ via speech, and $N = 26$ via image or video. The remainder of this article focuses on AER based on image and video due to their previously highlighted relevance in marketing on digital platforms. As a result, $N = 77$ articles were excluded from further consideration, leaving $N = 26$ articles.

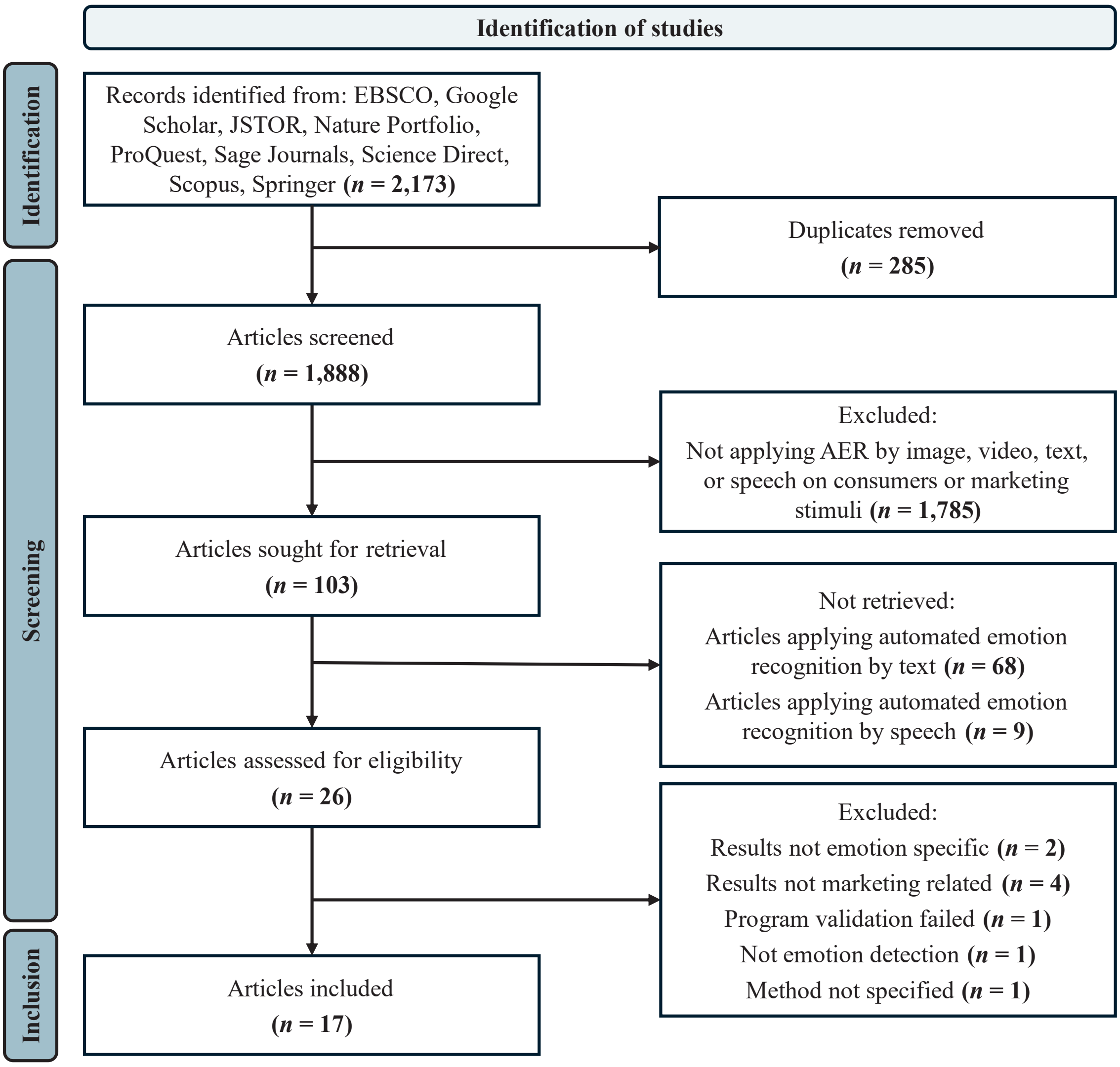
Figure 2 shows the resulting PRISMA flow diagram. An additional data repository in the Open Science Framework also includes detailed information on all the retrieved articles (Bohorquez Camacho et al., 2025). This includes articles drawing on AER methods not focused on here (e.g., AER from audio stimuli), which might guide other researchers in the future.

3.4 Included

Among the 26 articles assessed, $N = 9$ articles were excluded. Two articles (Dzyabura & Peres, 2021; Kanuri et al., 2024) used image and video-based AER software but did not focus on emotions. Four articles addressed emotions in non-marketing contexts (Hickman et al., 2022; Luo et al., 2024; Serra-Garcia & Gneezy, 2021; Y. Zhou et al., 2020). Studies, where software generated emotions (Friesen et al., 2019) or lacked transparent facial expression analysis methodology (e.g., Hamelin et al., 2020), were also excluded. Lastly, we excluded Zwebner and Schrift (2020) due to a lack of valid results.

Figure 2

PRISMA flow diagram



4 Results

4.1 Results overview

Table 2 summarizes the final articles. Researchers applied AER to analyze consumers' reactions and marketing stimuli (e.g., advertisements).

Table 2

Articles included by method and source of emotions

Emotion Recognition Method	Source of Emotions	Photo	Video	Sample Size	Journal
Noldus FaceReader					
Huang and Pricer (2024) (Study 4)	Consumer		✓	Study 4 (N = 66 consumers)	Int J Res Mark
Jiang et al. (2019)	Marketing stimuli		✓	N = 1,460 entrepreneurial projects videos	Acad of Manage J
Krause and Franke (2024) (Study 2 and 3)	Consumer		✓	Study 2 (N = 62 consumers); Study 3 (N = 132 consumers)	J Mark
Ladeira et al. (2023)	Consumer		✓	Study 2 (N = 91 consumers); Study 3 (N = 41 consumers)	J Retail Consum Serv
Google Cloud Vision API					
Li and Xie (2019)	Marketing stimuli	✓		Study 1 (N = 4,537 images); Study 2 (N = 1,660 images); Study 3 (N = 2,044 images)	J Mark Res
iMotions					
Hodges and Chen (2022) (Study 3)	Consumer		✓	Study 3 (N = 170 consumers)	J Consum Res
Smith and Rose (2020) (Study 1)	Consumer		✓	Study 1 (N = 113 consumers)	Int J Res Mark
Friedmann et al. (2024)	Consumer		✓	N = 74 consumers	J Retail Consum Serv
Microsoft Azure					
Lee (2021) (Study 1b and 1c)	Marketing stimuli	✓		Study 1b (N = 36,967 images); Study 1c (N = 61,519 images)	J Mark Res
Momtaz (2021)	Marketing stimuli	✓		N = 50 CEO profiles	Strategic Manage J
Yazdani et al. (2024) (Study 1)	Marketing stimuli	✓		N = 6,189 projects	J Acad Market Sci
Zhou et al. (2021)	Marketing stimuli		✓	Study 1 (N = 771 videos); Study 2 (N = 1,127 videos)	J Mark Res

Emotion Recognition Method	Source of Emotions	Photo	Video	Sample Size	Journal
Chuah and Yu (2021)	Marketing stimuli	✓		N = 223 images	J Retail Consum Serv
Py-Feat					
Yu et al. (2024)	Marketing stimuli	✓		N = 1,028 images	J Retail Consum Serv
Face++					
Zhang et al. (2024)	Marketing stimuli	✓		N = 1,240 property listings	J Retail Consum Serv
Custom ML model					
Bharadwaj et al. (2022)	Marketing stimuli		✓	N = 99,451 sales pitches	J Mark
Matz et al. (2019)	Marketing stimuli	✓		Study 1 (N = 1,040 images); Study 2 (N = 60 images); Study 3 (N = 69 images)	J Consum Psychol

It becomes clear that studies using AER for facial expression analysis of consumers primarily relied on real-time video sources. Among other domains, AER was applied across diverse contexts, including social media (e.g. Lee, 2021), crowdfunding platforms (e.g. Jiang et al., 2019), live stream retail (Bharadwaj et al., 2022), video conferencing (Huang & Pricer, 2024), Initial Coin Offering (ICO) platforms (Momtaz, 2021), e-commerce (Krause & Franke, 2024), education (M. Zhou et al., 2021), and direct messaging (Smith & Rose, 2020). Research settings included lab (e.g., Krause & Franke, 2024) and field studies (e.g., Yazdani et al., 2024). As researchers implemented a broad range of AER tools, we discuss the main findings sorted by employed tools.

4.2 Noldus FaceReader

Krause and Franke (2024) used Noldus's FaceReader to track consumers during real-time product customization. Initially, participants experienced a positive emotional state, reflecting high expectations. However, once the process began, a shift towards a negative emotional state was observed, with participants showing frustration as the process turned out to be less enjoyable than anticipated, leading many to abandon the customization. Those who overcame this critical point exhibited a positive emotional state, confirming the value of self-designed products. The authors described this phenomenon as a "U-shaped valence curve" and suggested social feedback to reduce frustration.

Similarly, Huang and Pricer (2024) analyzed social appearance anxiety during video calls, focusing on the mediating role of anxiety and the moderating role of webcam mode. By tracking real-time facial expressions of fear, they found that participants with active webcams exhibited higher anxiety levels and were more likely to enroll in self-enhancement programs. This effect extended to various products, including self-image enhancement apps, gym memberships, facial retouching tools, non-invasive cosmetic procedures, educational services, and health products.

Likewise, Ladeira et al. (2023) analyzed how disorganized store displays could evoke emotions like surprise and influence consumer behavior. Contrary to traditional beliefs, they found that disorganization can evoke curiosity and surprise. Additionally, disorganized displays could trigger positive emotional responses, such as joy and arousal, thus increasing purchase intentions.

Moreover, Jiang et al. (2019) examined the impact of joy in entrepreneurial funding pitches on Kickstarter. They measured the duration of "peak displayed joy", which is positively correlated to funding success. However, an inverted U-shaped relationship emerged, with the highest funding amount achieved when joy emerged for about 2.5 seconds.

In contrast, prolonged peak joy level negatively affected the funding amount, suggesting that duration, rather than intensity, of joy may trigger a “too much of a good thing” phenomenon.

4.3 iMotions

Hodges and Chen (2022) used the iMotions program, combined with Affectiva's AFFDEX, to analyze how numerical ability and processing fluency influence consumer response to prices ending in .99. By analyzing real-time facial expressions, they found that consumers with higher numerical ability experienced less anxiety, processed price endings faster, and showed greater purchase intention for .99 pricing.

Friedmann et al. (2024) analyzed consumers' reactions to discriminatory brand advertisements in the real estate industry. They analyzed facial expressions linked to emotional arousal and stress. The results showed that discriminatory ads, particularly among socially discriminated groups, triggered stress, revealing both immediate emotional discomfort and long-term stress in affected consumers.

Similarly, Smith and Rose (2020) studied unconscious affective responses and the impact of emojis, specifically the smiling emoji “☺”, on consumer-service provider relationships. The results indicated that the emoji triggered emotional contagion, strengthening relationships. However, its influence on purchase intention was indirect, mediated by affective response, and limited to already well-established relationships.

4.4 Microsoft Azure Face API

Lee (2021) used Microsoft Azure’s Face API to show how emotionality in brand communications influences consumers' perceptions of brand status. The study assessed facial expressions in Twitter (now X) and Weibo posts, using an emotionality score that encompassed emotions like anger, contempt, disgust, fear, happiness, sadness, and surprise. The results showed that higher emotionality levels correlated with lower median prices, indicating a negative impact of textual and visual emotionality on brand status perception.

Similarly, Yazdani et al. (2024) examined how emotional (mis)alignment between facial expressions in cover images and project descriptions influences crowdfunding success on GoFundMe. Specifically, they measured happiness and sadness in images with FaceAPI and text tone with the Linguistic Inquiry and Word Count Software (Boyd et al., 2022). Misalignment (e.g., a happy face with negative text or vice versa) had a stronger positive impact on donations than alignment. Sad cover images reduced donations, but urgency appeals and non-adult beneficiaries mitigated this impact. Additionally, greater progress toward funding goals amplified the misalignment’s positive impact.

Zhou et al. (2021) analyzed online video consumption from a content-centric perspective on platforms like MasterClass and the YouTube channel Crash Course. They extracted emotions from instructors' faces and found that sentiment positively impacted consumer behavior, while emotions had complex, context-dependent effects. For instance, higher levels of sadness were associated with increased video completion rates, whereas happiness generally had a negative effect.

Chuah and Yu (2021) examined how emotional expressions in human-robot interactions affect user engagement, focusing on the robot Sophia's facial expressions. They analyzed Sophia's Instagram posts. The results showed that positive (vs. negative) emotions led to higher engagement and more positive comments.

Additionally, Momtaz (2021) developed "Emotion AI," an R-based tool using Microsoft Face API to detect positive and negative emotions in CEO photos during ICOs. The study examined how CEOs' emotional traits influenced firm valuation, focusing on underpricing behavior. Emotion AI categorizes emotions into positive (happiness) and negative (anger, fear, sadness, and surprise). The study drew on data from ICObench, CoinMarketCap, and social media and found that negative emotions impacted valuation through two mechanisms: (1) Conformity Mechanism—CEOs displaying more negative emotions were 17% more likely to accept underpriced ICOs. (2) Signaling Mechanism—investors demanded 15% higher discounts when CEOs showed more negative emotions. Positive emotions had no significant effects.

4.5 Google Cloud Vision API

Li and Xie (2019) explored how image content influences consumer engagement with social media posts from airline and sport utility vehicle brands. They analyzed posts on Twitter and Instagram, considering factors like the presence of images, human faces, and facial expressions. The results showed that on Twitter, images featuring human faces increased sharing, but happy faces reduced retweets.

4.6 Py-Feat

Yu et al. (2024) employed the Py-Feat package in Python, which quantifies facial expressions and muscle movements based on FACS (Paul Ekman & Friesen, 1978) to examine the impact of emotional expressions on user engagement with AI-generated virtual influencers, specifically focusing on Lil Miquela's Instagram posts. They found that happiness was the most engaging emotion, generating the highest user interaction. Surprise and anger also led to some level of engagement, but to a lesser extent. Sadness, however, had the weakest impact.

4.7 Face++

Zhang et al. (2024) used Face++, which identifies seven distinct facial expressions: happiness, surprise, sadness, anger, fear, disgust, and neutrality. They explored how the sellers' profile picture on peer-to-peer accommodation platforms affects buying intentions. They found that positive emotional expressions, such as happiness and surprise, led to higher purchase intentions. On the other hand, negative emotions like anger, fear, and disgust were linked to lower purchase intentions.

4.8 Further Custom Models

Bharadwaj et al. (2022) developed a framework to detect salespeople's faces and analyze six basic emotions (happiness, sadness, surprise, anger, fear, and disgust) to assess their impact on sales performance. The results showed that when a salesperson's face was visible, sales increased by 0.34%. However, emotional expressions generally had a negative effect on sales, with happiness reducing sales the most. Furthermore, Matz et al. (2019) applied a custom ML algorithm to estimate the emotionality and personality traits of images. They found that image preference could be predicted based on personality alignment between consumers and images, influencing brand attitudes and purchase intentions.

5 Discussion and conclusion

This SLR explored how AER image and video-based methods are applied in marketing research, highlighting several advantages over traditional techniques, such as real-time measurement (Hodges & Chen, 2022), scalability, cost-effectiveness (M. Zhou et al., 2021), and unobtrusive data collection (Krause & Franke, 2024), offering less constrained data and complementing traditional methodologies.

AER has proven versatile in contexts like social media (Lee, 2021), e-commerce (Krause & Franke, 2024), and online platforms (Jiang et al., 2019). Key tools for AER in marketing research, include Noldus' FaceReader, iMotions' Facial Expression Analysis, Google's Cloud Vision API, Face++, Py-Feat and Microsoft Azure Face API.

However, the use of AER, particularly facial recognition-based programs, which dominated the studies in this review, raises important challenges. These programs primarily rely on Ekman and Friesen's (1978) basic emotions theory, which suggests that specific facial expressions are innate, universally shared across cultures, and directly reflect internal emotional states.

Academics such as Barrett et al. (2019) have challenged these assumptions, arguing that facial expressions primarily serve as social tools rather than direct indicators of internal emotions. A smile, for example, can convey happiness, discomfort, or even malice, depending on the context. Accordingly, Bharadwaj et al. (2022) and Li et al. (2019) found that happy faces in marketing stimuli could negatively impact consumer reactions. Combining facial expression recognition with other AER methods could enhance the accuracy of internal emotion predictions.

Apart from theoretical challenges, also cultural variations and other contextual factors (Yuki et al., 2007) can affect the accuracy of the results. This had led to the discontinuation of facial AER programs such as the Face API by Microsoft Azure, which acknowledged that the program was causing issues related to discrimination, stereotypes, and unfair denial of services (Microsoft, 2023). Ethical and privacy concerns, legal and regulatory challenges, interpretation and validity concerns (Microsoft, 2023), and high dependency on training data (Luo et al., 2024) further complicate the widespread adoption of AER. For instance, one of the biggest challenges with unobtrusive AER methods, whether through facial expressions, speech, or text, is recognizing sarcasm.

Fortunately, there are ways to mitigate these issues and maximize the potential of AER. One approach is to use AER tools as decision support, not relying solely on their results but having close human supervision. Another way is using a multimodal approach, combining AER tools with other sources like text analysis and skin conductance measures. Additionally, increasing accuracy can be achieved by considering diverse cultural environments and contexts. This can be accomplished by diversifying the dataset to provide more inclusive data or by specializing tools for specific regions and cultures. Finally, it is also crucial to consider consumer consent and transparency when using this tool, providing clear communication and aligning with laws such as the General Data Protection Regulation.

Managerial implications

AER has transformative potential in marketing research, offering easy application in quantitative studies and providing valuable product and campaign optimization insights. Similarly, this technology can also be beneficial for governmental decision-making. For instance, the EU's Horizon2020 program investigates AER through facial expressions in fields such as healthcare, security, and improvements in AI systems (European Data Protection Supervisor, 2021). China has been one of the leading countries in implementing AER, benefiting public safety with large-scale monitoring in public spaces, education and healthcare (Kostka et al., 2021). The entertainment industry also benefits, with companies like imentiv (2024) offering AER solutions to optimize casting, scripts, and analysis. These are just a few examples of how AER can be implemented.

Limitations and future research

It is essential to highlight that this review focused on studies published in English between 2019 and 2024. Additionally, while this study primarily focuses on marketing, applying AER in healthcare and education could provide valuable complementary insights.

Additionally, due to the rapid evolution of AER technologies, it is crucial that future research addresses these advancements and evaluates emerging methodologies, ensuring that the analysis remains up-to-date and relevant. With the ongoing growth of AER, marketing has the opportunity to leverage innovative advancements that not only predict but also profoundly understand consumer motivations and behaviors to create personalized and meaningful experiences.

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