IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 11 December 2024, accepted 3 February 2025, date of publication 13 February 2025, date of current version 24 February 2025.
Digital Object Identifier 10.1109/ACCESS.2025.3540034

SURVEY

Identification of Anomalous Behavior Through the Observation of an Individual's Emotional Variation: A Systematic Review

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This work was supported in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior-Brazil (CAPES) under Grant 001, in part by the Fundação de Amparo a Ciência e Tecnologia do Estado de Pernambuco (FACEPE), and in part by the Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq)-Brazilian Agencies.

ABSTRACT Emotion recognition plays a critical role in understanding how individuals perceive and interact with the world by accurately inferring emotions from various sources, such as physical signals and physiological responses. Anomalous emotion recognition, in particular, focuses on identifying emotions that deviate significantly from expected patterns in specific contexts or individuals, including abrupt emotional shifts, inconsistencies across different emotional signals, or persistent, atypical emotional patterns. The importance of recognizing anomalous emotions has grown, particularly in intelligent systems designed for mental health monitoring and crime prevention, where early detection can enhance context-sensitive interventions. This study presents a systematic review that investigates the link between emotional variations and anomalous behaviors across diverse settings. By examining the relationship between emotional shifts and deviant behaviors, the study sheds light on the challenges of detecting emotional anomalies and assesses the efficacy of various recognition methods. A thorough analysis of 102 relevant studies highlights the potential and limitations of current approaches, emphasizing the need for more diverse datasets, improved algorithm robustness, and broader applications to enhance performance in real-world scenarios.

INDEX TERMS Emotional variations, anomalous behaviors, early detection, systematic literature review, mental health, machine learning, deep learning.

I. INTRODUCTION

Emotions play a crucial role and are essential in how individuals understand and perceive the world around them. The process of recognizing emotions is dynamic and important for the development of intelligent agents that can interact with individuals in complex situations [1]. Accurate interpretation of emotional signals originating from multiple modalities, such as visual expressions, physiological signals and vocal tones is essential to ensure meaningful communication, both in human-to-human and in human-to-machine interactions [2], [3].

The associate editor coordinating the review of this manuscript and approving it for publication was Tallha Akram.

Anomalous emotion recognition technologies have demonstrated significant potential in various fields, particularly in security and mental health. In security systems, for example, the detection of atypical emotional states, such as excessive anger or extreme fear, can help predict potentially dangerous behaviors, enabling real-time preventive interventions [4]. This type of emotional monitoring in public environments can significantly contribute to crowd management and enhance safety at large events by estimating abnormal behavioral dynamics [5].

Surface electromyography (sEMG), applied to the recognition of facial expressions related to emotions, has become an essential tool for emotional assessment, particularly in the mental health field. The detection of anomalous emotions through sEMG enables continuous monitoring and provides real-time feedback, allowing for personalized therapeutic interventions [6]. In cases such as dementia treatment, identifying deviant emotional patterns makes it possible to immediately alert caregivers, facilitating early intervention [7].

The monitoring of affective states using wearable devices and non-intrusive sensors allows for the early detection of stress and burnout, enabling preventive intervention against psychosocial hazards [8]. The use of emotional data to personalize clinical treatments, helps tailor care to the specific needs of patients. This approach is particularly useful for children with Autism Spectrum Disorder (ASD), where recognizing atypical emotions can assist in the development of effective and targeted interventions [9].

Emotion detection methods analyze text and complex signals. Khare et al. (2024) classify them into three groups: questionnaires, physical signs, and physiological signs, as shown in Fig. 1. Each group uses different techniques. Questionnaires collect subjective data. In contrast, methods that analyze physical signs and use EEG or ECG offer objective, detailed insights into emotional responses [10].

Following the categorization of emotional sensing techniques, shown in Fig. 1, hybrid methods have enhanced the integration of various modalities by combining mathematical models, neural networks, and machine learning techniques. Techniques like the Stationary Wavelet Transform (SWT) and Particle Swarm Optimization (PSO) are included, enabling the extraction of key features from physiological signals, facial expressions, and audio data, which can lead to a more accurate classification. For example, combining SWT with PSO achieves an accuracy of over 99% [11]. Furthermore, hybrid methods are flexible and can adapt to different situations, broadening their use in areas such as human-computer interaction and sentiment analysis.

From an affective computing perspective, these hybrid methods have not only increased the capacity to process emotional data but have also improved the identification and understanding of anomalous behaviors. By enabling the automated recognition of diverse socio-psychological aspects, and facial, auditory, physiological, and textual characteristics, they lead to more accurate predictions and help prevent adverse incidents [12], [13].

The detection of anomalous emotions can be applied to various contexts, such as human-computer interaction, medical interventions, and advanced driver assistance systems (ADAS). In these scenarios, the identification of emotions that fall outside typical patterns, such as extreme stress, anger, or distraction, is essential to anticipate risky behaviors and implement proactive interventions, significantly enhancing the impact of these technologies in critical areas, such as safety, health, and mobility [14].

Therfore, the main contribution of this study lies in its focus on identifying anomalous emotions. By specifically targeting emotions that deviate from typical patterns, this study advances the field by providing a deeper understanding of how these atypical emotional states can be detected and analyzed in various contexts. This approach not only enhances detection accuracy but also opens new avenues for applications in mental health monitoring, security, and adaptive human-computer interactions.

The aim of this study is to build on this focus and conduct a systematic literature review that analyzes emotion detection methods in recent years, the theoretical advancements of predictive intelligent data model applications, and highlights the importance of studies that identify patterns automatically in different datasets across various sectors.

This study follows the Kitchenham systematic review guidelines, which cover three stages: planning, conducting and documenting. There were 104 relevant studies that met specific criteria and were analyzed. Using the PICOC method, the effectiveness of emotional observation methods was addressed. Furthermore, the study looked for the most effective detection methods.

To assess study quality, the review applied both general and specific criteria. It assigned greater weight to specific criteria, that were directly linked to its objectives. This approach allowed for a thorough and critical evaluation of methods and results.

This study is organized as follows: Section II lays out the theoretical groundwork for the review; Section III outlines the methodology, covering research questions, string definitions, inclusion and exclusion criteria, quality assessment, and execution; Section IV analyzes the selected studies; Section V discusses emerging trends and challenges; and Section VI summarizes the conclusions, highlighting implications and suggesting future research directions.

II. BACKGROUND

In recent decades, the analysis of emotions has advanced, due to more data and improved machine learning, including deep learning [10], [11]. These advancements have made it possible study of complex emotions that relate to unusual behaviors. This has led to new solutions in digital security, mental health, and public safety [12], [15].

Early studies in the early 2000 utilized physiological monitoring to capture emotional responses. Wilhelm et al. initiated this movement, integrating mobile devices with physiological sensors, such as ECG and GSR, to monitor mood changes in psychiatric patients in real-world settings [16]. During this period she established a foundation for using physiological data in understanding emotional states.

In the 2010, the field evolved by incorporating machine learning and a multimodal approach. In 2013, researchers such as Esubalew et al. and Henriques et al. began exploring techniques such as virtual reality, eye tracking, and electrodermal activity to map more complex emotional reactions, particularly in conditions such as autism [9], [17].

By 2014, studies focused on detecting emotional stress in specific situations. Gao et al. applied NIR cameras

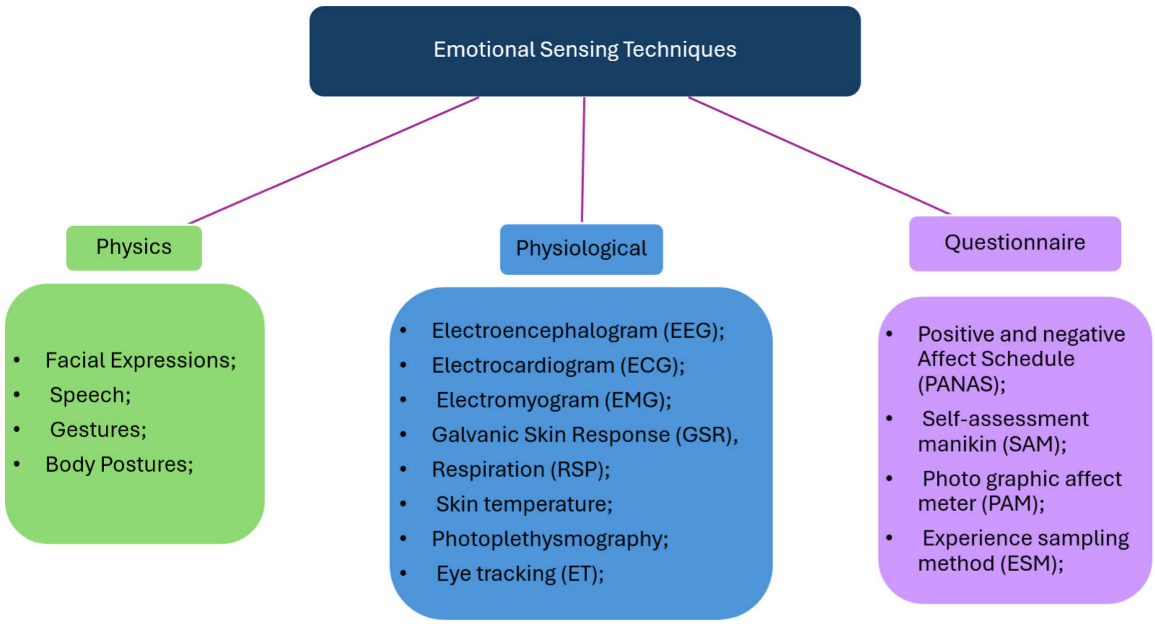

FIGURE 1. **Emotional sensing techniques.**

for facial analysis to enhance driver safety, while Bacchini et al. developed emotion-capturing technologies in customer service settings [18], [19]. These advances paved the way for multimodal recognition, integrating facial, vocal, and physiological data.

The use of deep learning intensified from 2015 onwards, with Zhu et al. employing techniques like LSTM for emotion recognition based on EEG, achieving 97% accuracy a major milestone in using neural networks to identify complex emotional patterns [4]. Khalil et al., in the same period, applied CNNs and RNNs to real-time speech emotion recognition, expanding the scope of deep learning applications in dynamic environments [1], [3].

During 2020, the focus on multimodal fusion technologies and IoT allowed for real-time monitoring with a high level of precision. Saxena et al. reviewed the state of the art in deep learning for emotion detection, highlighting the importance of multimodal integration [11]. Similarly, Chen et al. proposed a multimodal fusion model based on Deep Learning for facial expression recognition (FER) in the emotional monitoring of drivers [14]. Additionally, The integration of human annotations with multimodal data was employed to analyze children's behavior in educational games, revealing cognitive and affective variations [20]. While, Ahmed et al. investigated the multimodal approach combining CNNs and Random Forest for identifying affective states and depression using wearable sensors [15]. Singothu and Bolem demonstrated that combining facial, physiological, and vocal signals can improve the diagnosis of mental health conditions [21]. While Chhirolya and Dubey used image processing to detect unusual crowd behaviors [13].

Hao et al. created a framework that used 3D and Graph Convolutional Neural Networks to detect unusual behaviors. This enhanced real-time detection in mental health settings [22]. These methods highlight the effectiveness of EEG and computer vision in detecting emotions and anomalous behaviors. In the context of public safety, hybrid neural networks, which combine CNN and ResNet layers, have been successfully used to detect anomalous human behaviors in crowded scenes, as demonstrated by the work of Karki et al. Their study highlighted the superior performance of hybrid models compared to traditional architectures, achieving 97.19% accuracy in classifying anomalous behaviors [23].

Recent studies show EEG is effective in recognizing emotions. It detects brain activity and subtle emotional changes directly. Singothu and Bolem conducted a review using machine learning methods like LSTM, RF, and SVM for emotion detection. They highlighted LSTM's accuracy, which reached 97% [24].

The study by Khare et al. (2024), in a systematic review, emphasized the importance of datasets like OMG-Emotion, which are essential for evaluating the impact of affective behavior in narrative interactions and are fundamental for developing intelligent systems capable of oper-ating in complex environments [21].

In summary, the analysis of emotional anomalies has advanced significantly and shows promise in areas such as digital security, mental health, and crowd safety. The use of technologies such as deep learning, multimodal analysis, and IoT systems has improved the detection of subtle emotional changes. These changes can signal potential risks or unusual behaviors. As the field grows, these technologies are expected to lead to more innovations, solving current problems and opening new opportunities.

III. METHODOLOGY

With the goal of conducting a comprehensive analysis, this study adhered to the guidelines proposed by Kitchenham et al. [25] for conducting a systematic literature review. In this context, the goal is to evaluate and synthesize the use of techniques to identify anomalous behaviors through the observation of emotional variation in individuals. This process, depicted in Fig. 2, consists of three essential steps: Planning, Conducting, and Documentation [25].

In the Planning stage (Stage A), the goals are to find the review's needs, set specific research questions, and check the protocol. Next, in the Conducting stage (Stage B), the focus turns to gathering relevant studies, and also involves picking key studies, checking their quality, and extracting important data. Finally, in the Documentation stage (Stage C), the main goal is to present findings clearly and concisely, in order to provide a full view of the discoveries.

A. RESEARCH QUESTIONS

When forming research questions, it is important to aim for specificity. They should cover all relevant studies to be able to guide the investigation properly. The PICOC method, recommended by Kitchenham and Charters, is important because it focuses on the essentials of each study and helps with question creation and data analysis. The PICOC structure is as follows:

- **Population:** Individuals from different backgrounds and settings.
- **Intervention:** Techniques for studying emotional changes. For example, observing facial expressions, body language, and heart rate. These techniques can spot abnormal behaviors linked to mental health, crime, or security.
- **Comparison:** It compares normal and abnormal behaviors.
- **Outcome:** This study aims to find methods for spotting abnormal behaviors. It also looks at study details like understanding measures, processes, publication info, and researchers.
- **Context:** Studies in settings like clinics, communities, institutions, or security.

After applying the PICOC method, specific research questions were set for this review. The main one was: "How effective is emotional observation to spotting abnormal behavior early in mental health, crime prevention, and security?" Also, secondary questions were created to organize information. Examples include:

- **RQ1:** Does emotional observation reveal mental health issues?
- **RQ2:**How does spotting emotional changes impact crime and cybersecurity?
- **RQ3:**Which methods are best for spotting abnormal behavior through observation?
- **RQ4:**What emotional signs are key for early cybercrime detection?
- **RQ5:**Where can relevant data on emotional observation for cybercrime prevention be found?
- **RQ6:**How can observation techniques boost digital security and prevent cyber crimes?
- **RQ7:**What techniques are used in emotional anomaly detection systems?
- **RQ8:**What performance metrics are used in emotional anomaly detection?

A database search strategy was developed to find articles. It focused on the main terms and their synonyms from the research questions. This search revealed various studies on abnormal behavior. A quantitative analysis was performed using publication counts, citations, venues, metrics, and key findings. Additionally, a qualitative review was carried out to detail important aspects of each approach.

B. DEFINITION OF SEARCH STRINGS

To devise the article search strategy for the databases, key terms from the research questions were used, incorporating their synonymous and alternative equivalents [25]. After the search, methods that explore the detection of abnormal behaviors in individuals were identified.

Subsequently, a thorough examination was conducted, focusing on quantitative measures such as the annual publication count, article citations, publication sources, identified metrics, and key contributions. Additionally, a further qualitative analysis was performed, providing comprehensive insights into the crucial elements of each approach. Therefore, the search string used in this study was as follows:

("anomalous behavior" OR "unusual behavior" OR "abnormal behavior" OR "deviant behavior" OR "emotional variation" OR "emotional fluctuations" OR "variation in emotions" OR "emotional patterns" OR "detection" OR "recognition" OR "observational techniques")
AND
("cybercrime prevention" OR "prevention strategies" OR "digital security" OR "cybersecurity measures" OR "individual observation" OR "behavioral observation" OR "individual monitoring" OR "emotional monitoring")

The logical operators (AND and OR) were used to refine the search, and data were collected from five recognized digital libraries: IEEE Digital Library, ACM Digital Library, Science Direct, ISI Web of Science, and Scopus, as listed in Table 1.

This process involves analysis of the metadata, abstracts, and titles of each article, ensuring the inclusion of those that explicitly mention the relevant keywords. However, it is important to note that this approach may result initially in an extensive set of articles, as it also includes those that mention

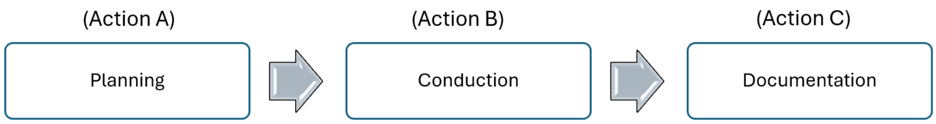

FIGURE 2. RSL process.

some of the keywords in their abstracts, even if they are not directly related to the topic.

The search results from each database were then imported into the Rayyan platform (https://www.rayyan.ai/) for the next phase of review and selection.

TABLE 1. Digital sources.

Sources	Studies	Percentage
IEEE Digital Library	257	39,97%
ACM Digital Library	128	19,90%
ScienceDirect	153	23,79%
ISI Web of Science	21	3,27%
Scopus	84	13,06%
Total	643	100,00%
Duplicates	47	7,30%

The analysis of the search process results revealed that a total of 643 studies were identified in the selected digital libraries. The IEEE Digital Library contributed the highest percentage of studies, representing 39.97% of the total. Following that, the Science Direct Digital Library and ACM Digital Library contributed 23.79% and 19.90%, respectively. The Scopus accounted for 13.06%, while the ISI Web of Science had the smallest percentage of studies, at 3.27%.

C. INCLUSION AND EXCLUSION CRITERIA

Defining criteria is essential for a good Systematic Literature Review (SLR) [25]. It ensures that only relevant, high-quality studies are included. The goal is to filter out studies that do not meet the research objectives. Even after refining search terms, criteria can further filter articles. Material included was peer-reviewed and focused on using behavioral analysis for mental health, crime prevention, and security enhancement (Criterion I1). Studies referenced by authors were also added, found through snowball searches (Criterion I2). Exclusion criteria were used to narrow the selection. Articles without access or with only abstracts were excluded (Criterion E1).

The inclusion criteria established were:

C1 - Peer-reviewed articles from journals, conferences, and workshops that addressed the main research question: "What is the effectiveness of identifying anomalous behavior through the observation of individual emotional variation for the early detection of mental health issues, crime prevention, and security enhancement?"

C2 - Relevant studies cited by the authors of the articles found during the direct search.

Exclusion criteria were also established:

E1 - Duplicate articles.

E2 - Articles that did not apply to the main research question.

E3 - Articles written in languages other than English.

E4 - Studies that were not available in full.

E5 - Articles that did not meet any of the quality criteria specified in this review to maintain adherence to the research topic.

These criteria were crucial. They ensured that only relevant, high-quality studies were considered, guaranteeing strong and trustworthy results.

D. QUALITY ASSESSMENT

Evaluating the quality of studies is crucial. The success of the Systematic Literature Review (SLR) depends, among various factors, on the quality of the selected studies. How-ever, there is no consensus on the definition of a high-quality study. Nevertheless, the quality of the primary studies chosen is fundamental for achieving reliable results (Kitchenham & Charters, 2007). In this context, the SLR utilized part of the approach used by Duarte et al., with Souza et al. (being considered when applying exclusion criterion E6. Accordingly, a set of general and specific criteria (Table 2) was used, with general contributions G made up of four items and specific contributions S comprising seven items, each with a maximum score of 1. This setup calculated a weighted average, with S weighted 3 times more than G, because the specific contributions of a study are significantly more important than its general contributions (see Equation (1)).

$$\text{Score} = 0.25\left(\frac{G1+G2+G3+G4}{4}\right) + 0.75\left(\frac{S1+S2+S3+S4+S5+S6+S7}{7}\right) \quad (1)$$

To ensure the relevance and quality of the studies included in this review, they were classified into three levels of quality based on their overall scores:

- **High Quality:** Studies that achieved a score between 0.75 and 1.00, indicating superior adherence to both general and specific criteria.
- **Medium Quality:** Studies that achieved a score between 0.50 and 0.74, reflecting satisfactory but not excellent fulfillment of the criteria.

- **Low Quality:** Studies that achieved a score below 0.50, suggesting minimal compliance with the established criteria.

Detailed Criteria for Evaluation: Table 2 outlines the specific criteria used to evaluate the studies. Table 2 is instrumental in determining the overall score for each study, as described above. It is important to note that this criterion does not evaluate the quality of the article itself but only the alignment of its contributions with the goals of this study. Articles with an overall score of 0.75 or higher were selected for inclusion in the review.

This strict quality assessment ensures the reliability of the chosen studies. It helps in accurately investigating the links between emotions and strange behaviors. The goal is to find key patterns.

E. CONDUCTION

This study was carried out through a systematic search conducted in various digital libraries, initially identifying 643 potential studies. These were subsequently imported into the Rayyan tool, which offers advanced features for systematic review through both collaborative and individual filters. Through the rigorous application of inclusion and exclusion criteria, involving detailed analysis of titles, keywords, and abstracts, it was possible to refine this initial selection to 143 studies that were considered relevant to the theme under investigation. The selection process is described in detail in Figure 3.

Fig. 3 clearly demonstrates how the selection and exclusion of studies were conducted on each of the platforms used. After the initial filtering, a rigorous quality assessment was applied to the remaining 143 studies, resulting in 37 of them being excluded for not meeting the established quality criteria. The final 102 studies were then included in the subsequent detailed analysis. The synthesis of data extracted from these final studies is discussed in the next section of the document.

IV. ANALYSIS OF STUDIES

Data analysis begins with the fundamental extraction step, in which a systematic process is implemented to gather relevant information from the selected studies. The primary objective is to ensure both the accuracy and relevance of the data obtained. This data typically includes article titles, author names, publication dates, and research locations. The subsequent stages are outlined as follows. After extraction, the next phase is the consolidation of results. In this stage, the extracted data is carefully organized and standardized to ensure uniformity and eliminate any inconsistencies. This process is necessary to enable robust statistical analysis and meaningful comparisons, establishing a solid foundation for further investigations.

For each study, the following data were extracted:

- **Article Title:** Accurate identification of the study.
- **Names of Authors:** Record of the main contributors.
- **Year of Publication:** Indication of the period when the study was conducted.
- **Country of Origin:** Geographical location of the study.
- **Keywords:** Key terms associated with the study's content.
- **Number of Citations:** Quantification of the academic impact of the article.
- **Data Source/Research Mechanism:** Description of the database or data collection method.
- **Suggested Applications:** Practical uses of the study in the field of expertise.
- **Tracking Challenges:** Obstacles encountered in the data tracking process.
- **Identification of Emotional Anomalies in Individuals:** Types of emotional irregularities detected.
- **Applied Learning Techniques:** Machine learning or statistical methods used.
- **Type of Tracking:** Method of monitoring or tracking employed.
- **Evaluation Bases:** Criteria or benchmarks used for assessing the results.
- **Evaluation Metrics:** Quantitative or qualitative indicators used to measure the study's effectiveness.

To visually represent the extracted data and analyze the distribution and impact of the studies, several graphs were constructed. These visualizations provide immediate comprehension of the trends and patterns within the data, facilitating a deeper understanding of the research landscape. The graphical analysis encompasses various dimensions of the dataset, including temporal distribution, geographic diversity, and individual contributions, each offering unique insights into the scope and focus of the research field.

By analyzing the graph that displays the number of publications over time, shown in Fig. 4, we can observe the evolution of interest and advancements in the field.

The graph displays a sharp rise in published articles, notably surging after 2021 and peaking in 2023. This signals a growing interest. The increase could be due to advancing technology and more available data. Matching studies to their respective countries shows where this research is being focused. It also highlights leading regions. Fig. 5 gives a global overview.

The graph shows the US and UK leading in publications, with 26 and 21 articles, respectively. India and Austria also contribute significantly. The global spread reflects varied research perspectives and highlights the potential for international collaborations and wide-reaching scientific research.

Building upon the geographic origins of significant research contributions, it is important to explore the dissemination channels for these studies. Studies that were accepted have been published in both conference proceedings and journals. Table 3 shows the top publications. Fig. 6 then compares these types, revealing popular channels and communication trends.

TABLE 2. Quality assessment.

General Criteria (G = 25%)	Specific Criteria (S = 75%)
G1: Problem Definition and Contextualization (1) Explicit definition and motivation (1,0) (2) Clear definition (0,5) (3) Without definition (0,0)	**S1: Correlation between emotional variation and anomalous behavior** (1) Formalized assessment (1,0) (2) Some informal evidence (0,5) (3) Ad-hoc method (0,0)
G2: Literature review (1) Empirical and methodological analysis (1,0) (2) Generalized analysis (0,5) (3) No appropriate methods (0,0)	**S2: Impact on the detection of anomalous behaviors** (1) Formalized experimental method (1,0) (2) Some informal evidence (0,5) (3) Ad-hoc method (0,0)
G3: Methodology (1) Explicitly correlating contributions to results (1,0) (2) No clear correlation (0,5) (3) Without description (0,0)	**S3: Effectiveness of detection techniques** (1) Formalized metrics (1,0) (2) Some informal definitions (0,5) (3) Definition not justified (0,0)
G4: Analysis and Discussion (1) Formalized empirical assessment (1,0) (2) Some informal evidence (0,5) (3) Validation not justified (0,0)	**S4: Emotional Indicators and early detection** (1) Formalized use of another device (1,0) (2) Some informal definitions (0,5) (3) Definition not justified (0,0)

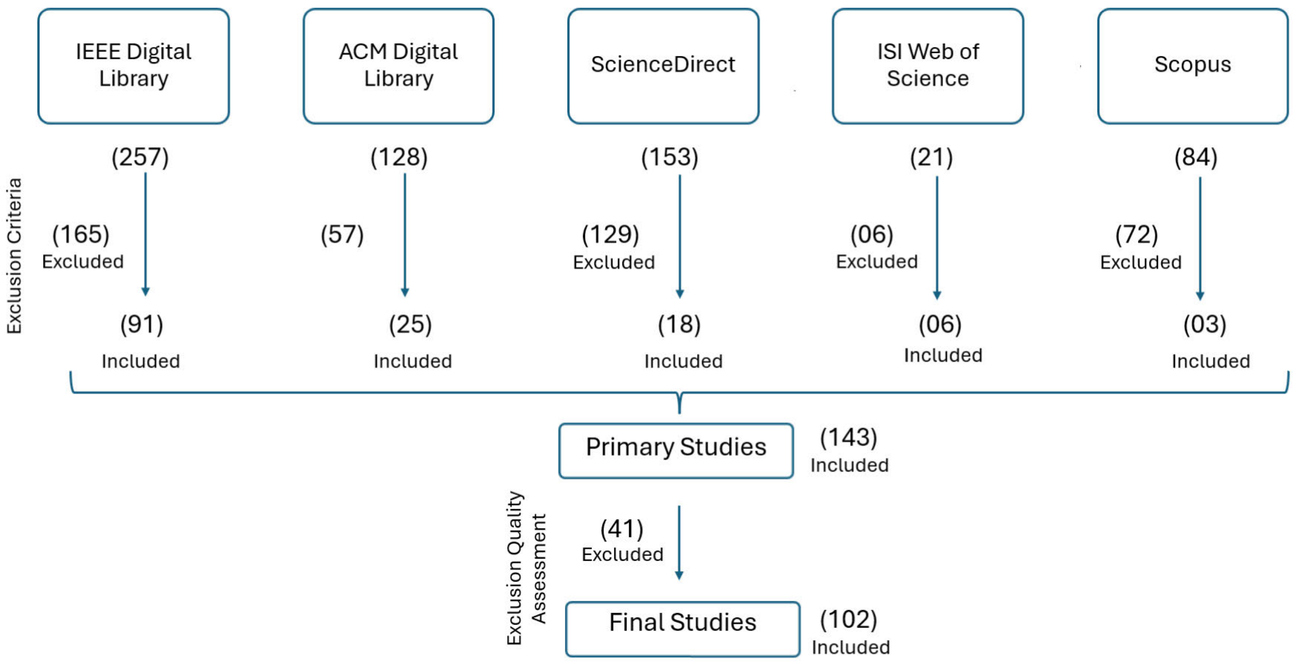

FIGURE 3. Study selection and evaluation process.

The graph presented highlights that "Conference Papers" dominate with a total of 65 publications, surpassing "Journal Articles," which account for 38. This dominance suggests that conferences are a preferred platform for the initial dissemination of research.

Complementing this, Table 3 reveals the most frequent publication venues, with "Deviant Behavior" leading with four publications, followed by "IEEE Access" with three. Other significant entries, including various publications from the IEEE and international conferences, are present with two publications each. This suggests a preference for specialized forums across a broad spectrum of conferences and journals, highlighting a predilection for well-established and recognized platforms within the scientific community.

The selected articles were analyzed based on the keywords used, to gain a broad understanding of the current state of relevant studies in the field. The authors proposed the terms used under the "Keywords" sections. Table 4 summarizes the most frequent keywords, highlighting the main themes and techniques addressed.

"Emotion recognition" and "Feature extraction" appear most often, with 26 and 24 mentions. This emphasis shows a clear focus on emotional analysis and improving machine learning. "Monitoring" and "Deep learning" are

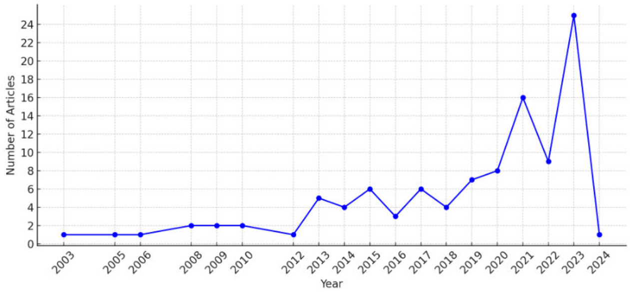

FIGURE 4. Number of articles distributed by year.

TABLE 3. Publication frequency.

Publication	Frequency
Deviant Behavior	4
IEEE Access	3
IEEE Transactions on Neural Systems and Rehabi...	2
IEEE Transactions on Affective Computing	2
2023 International Conference on Network, Mult...	2
Journal of Affective Disorders	2
2013 Humaine Association Conference on Affecti...	2
2019 4th International Conference on Recent Tr...	1
2013 Seventh International Conference on Image...	1
2020 3rd International Conference on Intellige...	1

Percentage relative to the total number of mentions in the studies.

TABLE 4. Most common keywords.

Keyword	Frequency
Emotion recognition	26
Feature extraction	24
Monitoring	21
Deep learning	15
Biomedical monitoring	10
Training	9
Stress	9
Real-time systems	8
Machine learning	8
Support vector machines	8

Percentage relative to the total number of mentions in the studies.

also key themes. They highlight the need for real-time checks and advanced AI. "Biomedical monitoring," "Machine learning," and "Support vector machines" highlight the use of advanced tech in data analysis. This implies notable progress in research and future applications.

Citation trends show academic impact and guide future health research. Table 5 displays the most cited articles, showcasing key advances and applications. These studies shape academic debate and spur technological growth. Their importance extends beyond academia and can help foster healthcare innovation.

Analysis of the data reveals a notable distribution of citations among the catalogued articles. The study entitled "Facial stress detection while driving" garnered 233 citations, reflecting interest in emotional recognition for vehicle safety (see Table 5). Emotional states were classified using NIR cameras and computational analysis. The impact of virtual reality on autistic adolescents' facial expression reactions received 185 citations. Emotional responses were analyzed using eye tracking and physiological monitoring. Mood monitoring in psychiatric patients' real-life contexts earned 154 citations. Speech capture and behavioral analysis through mobile devices provided targeted treatment insights. These studies highlighted interdisciplinary approaches and applied research in emotional recognition technologies.

Similar to the keywords the keywords, the techniques mentioned in the accepted articles were analyzed to understand the environments where advances in detecting emotional anomalies in individuals are being developed. Table 6 shows the frequencies recorded for each technique.

The Table 6 summarizes techniques from the selected articles and shows a clear preference for advanced machine learning and signal processing methods. The Convolutional Neural Network (CNN) leads, with 96 mentions (16.13%), highlighting its key role in computer vision and pattern recognition. Following this, are: Random Forest with 73 mentions (12.27%) and Recurrent Neural Network (RNN) with 47 mentions (7.90%). These techniques excel in tabular and sequential data analysis, respectively. Other notable techniques include Support Vector Machine (SVM) with 46 mentions (7.73%), Autoencoders with 33 mentions (5.55%), and iForest with 40 mentions (6.72%). These methods are vital for detecting anomalies and reducing data dimensions, key in information security and data analysis. Techniques for processing physiological signals also stand out. EMG Signal had 37 mentions (6.22%), Galvanic Skin Response 33 (5.55%), and Electroencephalogram (EEG) 22 (3.70%). This trend underscores a growing interest in biofeedback and neuroscience. Overall, the results showcase the evolution of research methodologies.

After examining the techniques used in the selected studies, the metrics used to measure the performance of the models were analyzed. Table 7 presents the most cited metrics from the reviewed articles, providing a clear view of the criteria considered most critical. These metrics not only reflect the rigor of model evaluation, but also highlight the specific demands and challenges of the research domain.

The results indicate a strong emphasis on Accuracy, which appears most frequently, underscoring its role as a fundamental measure of overall model performance. F1-Score, Precision, and Recall also feature prominently, highlighting the importance of balancing true positives and minimizing errors in classification tasks. Metrics such as AUC-ROC and Specificity are indicative of the need to assess model performance in binary classification, particularly in imbalanced datasets. The presence of Sensitivity, Confusion Matrix, and error-based metrics like MSE and RMSE further illustrate the comprehensive approach taken by researchers to ensure robust and reliable model evaluation.

After highlighting the most commonly used metrics, the analysis focused on the main emotional anomalies identified by the reviewed studies. The following Table 8 presents the main emotional anomalies detected, as well as their respective

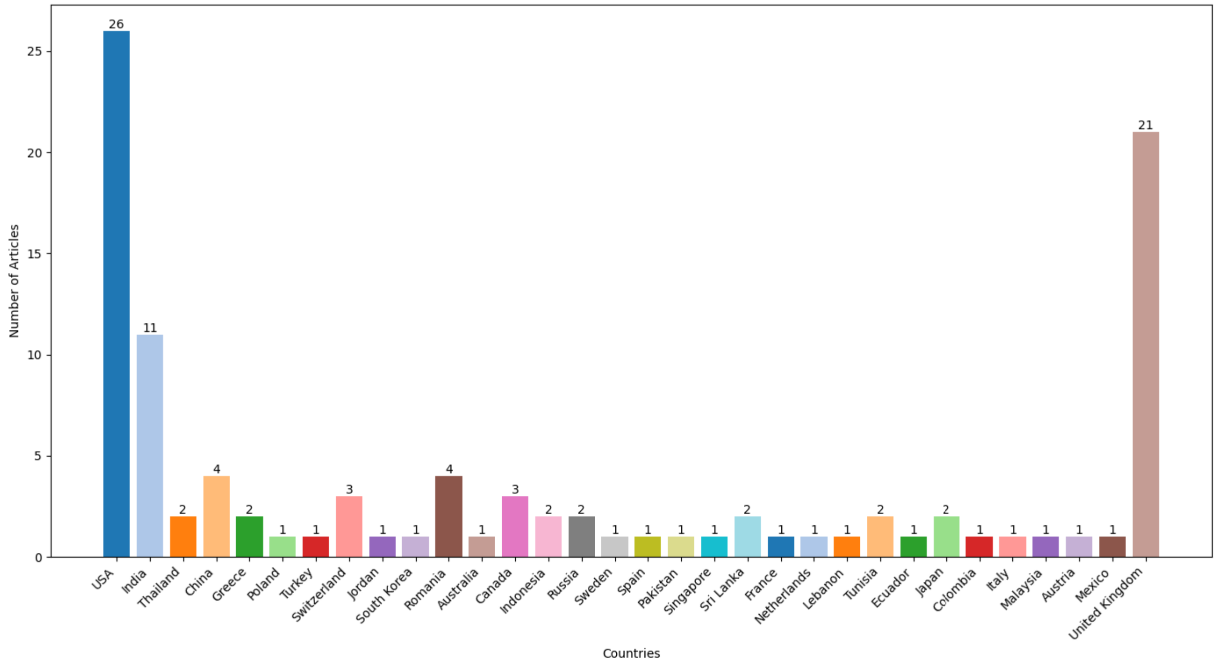

FIGURE 5. Number of Articles distributed by year.

TABLE 5. Articles with most citations.

Ref	Title	Citations	Year
[18]	Detecting emotional stress from facial expressions for driving safety	233	2014
[9]	Understanding How Adolescents with Autism Respond to Facial Expressions in VR Environments	185	2013
[106]	Ecologically valid long-term mood monitoring of individuals with psychiatric disorders	154	2014
[16]	Continuous electronic data capture of physiological and functional measures in advanced age home dwellers	112	2022
[55]	CNN-Based Health Model for Regular Health Factor Monitoring of ICU Patients	103	2020
[97]	Shared longitudinal predictors of physical peer and relational victimization among adolescents	99	2021
[27]	Defining Digital Self-Harm - Proceedings of the ACM on Human-Computer Interaction	98	2017
[96]	Customer deviance: A framework, prevention strategies, and opportunities for future research	80	2018
[51]	Anomaly-Based Insider Threat Detection Using Deep Autoencoders	75	2019
[88]	What girls need: recommendations for preventing cyberbullying among young women	62	2020

Percentage relative to the total number of mentions in the studies.

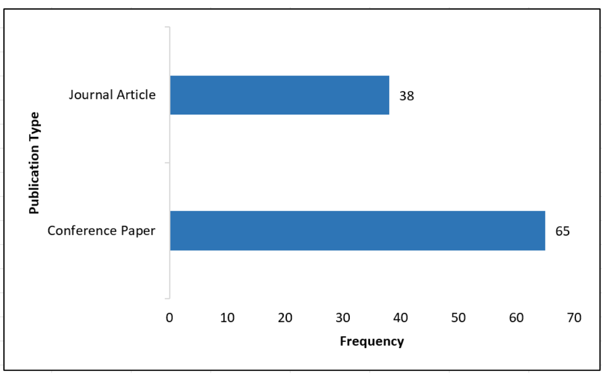

FIGURE 6. Frequency by publication type.

frequencies and percentages in relation to the total number of occurrences observed. This data reveals the most common emotional factors. It also highlights areas that need further research.

The results show that Intense Sadness was the most common emotional anomaly, accounting for 29.16% of the ocurrences. Anxiety, Anger, and Stress are also frequent, each contributing significantly to the overall emotional anomalies observed, with percentages of 16.67%, 15.83%, and 15.83% respectively. Aggressiveness follows with 8.33%, indicating its relevance in the contexts studied. Agitation, Panic, and Euphoria are less common, yet still important, highlighting the complexity and diversity of emotional states that require attention.

After identifying the main emotional anomalies in the selected studies, an analysis of the databases used was carried out. The following Table 9 presents the most frequently used databases in the reviewed articles, along with their frequency of use, type (public or private), and feature extraction methods.

The Table 9 presents a variety of features extracted from different databases, highlighting the predominance of

TABLE 6. Frequency of techniques.

Technique	Frequency
CNN (Convolutional Neural Network)	96
Random Forest	73
RNN (Recurrent Neural Network)	47
SVM (Support Vector Machine)	46
Eye Tracking	44
iForest (Isolation Forest)	40
DNN (Deep Neural Network)	38
EMG Signal	37
Autoencoders	33
GSR (Galvanic Skin Response)	33
Isolation Forest	29
LSTM (Long Short-Term Memory)	27
ECG (Electrocardiogram)	26
Data Mining	22
EEG (Electroencephalogram)	22
ANN (Artificial Neural Network)	22
PCA (Principal Component Analysis)	19
OCSVM (One-Class Support Vector Machine)	12
ELM (Extreme Learning Machine)	12
CAE (Convolutional Autoencoder)	10
LOF (Local Outlier Factor)	8

Percentage relative to the total number of mentions in the studies.

TABLE 7. Frequency of main metrics.

Metric	Frequency	Percentage (%)
Accuracy	55	43.31%
F1-Score	21	16.54%
Precision	19	14.91%
Recall	15	11.81%
AUC-ROC	4	3.15%
Specificity	4	3.15%
Sensitivity	3	2.36%
Confusion Matrix	2	1.57%
MSE	2	1.57%
RMSE	2	1.57%

Percentage relative to the total number of mentions in the studies.

TABLE 8. Frequency of emotional anomalies.

Anomaly	Frequency	Percentage (%)
Intense Sadness	35	29.16%
Anxiety	20	16.67%
Anger	19	15.83%
Stress	19	15.83%
Aggressiveness	10	8.33%
Agitation	6	5.00%
Panic	2	1.67%
Euphoria	2	1.67%

Percentage relative to the total number of mentions in the studies.

public sources such as JAFFE, AffectNet, and UCF101. The accessibility and wide acceptance of these databases in the scientific community are underscored by their frequency of use. The extracted features range from facial expressions and multimodal data to physiological signals and behavioral data, reflecting the diversity of methodological approaches adopted. Although less frequent, private databases provide access to more sensitive or specific information, essential for studies requiring restricted or confidential data. This diversity of features highlights the complexity involved in the analysis of emotions and behaviors, reinforcing the importance of careful selection of data sources to meet the specific objectives of each study.

In addition to the datasets reviewed, additional datasets have been incorporated, that are considered crucial for advancing research in emotion recognition, as reviewed by Kharea et al. (2023) in a study conducted by researchers at the University of Southern Denmark and the University of Southern Queensland. The following Table 10 complements these datasets, which are categorized by their accessibility, data types, and their specific applications within the research community.

The integration of these datasets provides a solid foundation for optimizing methodologies and validating models with a more diversified data set.

The following Table 11 presents the most frequently identified areas of application from the analyzed studies. Just as the predominance of public databases facilitates the replication of studies, identifying the main application areas helps to understand where technologies are being most often explored, revealing trends and priority focuses.

Behavioral Analysis, though less frequent, still holds significant relevance, particularly in contexts such as security and healthcare. The areas of Dementia Care and Robotics, despite appearing less often, indicate the application of advanced technologies in specific contexts, such as supporting patients with neurodegenerative conditions and developing autonomous systems. These results highlight the diversity of technological applications and the importance of adapting approaches to the specific needs of each field.

A. COST/BENEFIT ANALYSIS

The selection of appropriate tools and approaches is crucial and should be based on a careful balance between computational cost and the benefits obtained in terms of precision, robustness, and real-time applicability. Advanced techniques such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Deep Neural Networks (DNNs) stand out for their high precision and robustness, being especially effective in tasks involving complex patterns, such as facial recognition and physiological signal analysis. However, these techniques come with high computational costs, requiring specialized hardware such as GPUs and TPUs, as well as large volumes of data, which can limit their applicability in resource-constrained environments.

Techniques like SVMs and Random Forests offer a favor-able balance between cost and benefit, with lower processing demands that maintain precision across various applications, particularly in scenarios that require quick responses and operational simplicity. The following Table 12 summarizes the cost/benefit analysis of the main techniques.

It is evident that the analysis of physiological signals, such as EEG, ECG, and GSR, stands out for its high robustness, especially in controlled environments, although real-time

TABLE 9. Frequency of databases used.

Ref	Database	Frequency	Status	Feature Extraction	Type
[74], [14], [50], [74]	JAFFE Dataset	4	Public	Facial expression features	Image
[89], [84], [95]	Video Recordings	3	Variable	Video features	Video
[29], [57]	AffectNet	2	Public	Facial expression features	Image
[81], [48]	Smartphone Sensors	2	Private	Sensor data	Sensors
[22]	UCF101	2	Public	Video features	Video
[87]	Korean Children Youth Panel Survey	1	Private	Survey responses, socio-emotional factors	Survey, Socio-emotional
[64]	Chi-Mei Mood Disorder Database	1	Private	Psychological assessment and physiological data	Physiological, Psychological
[65]	Bio Vid Emo DB	1	Private	Physiological signals	Physiological
[22]	UCF-Crime	1	Public	Video features	Video
[22]	Sport-1M	1	Public	Video features	Video
[22]	Kinetics	1	Public	Video features	Video
[101]	Structured Questionnaires	1	Private	Survey and questionnaire responses	Survey, Questionnaire
[66]	FER-2013	1	Public	Facial expression features	Image
[69]	UCSD Dataset	1	Public	Multimodal features	Multimodal
[69]	Hajj Dataset	1	Public	Behavioral and environmental features	Behavioral, Environmental
[69]	UMN Dataset	1	Public	Physiological and environmental features	Physiological, Environmental
[70]	Geolife Dataset	1	Public	GPS and mobility patterns	GPS, Mobility
[107]	HMDB	1	Public	Video features	Video
[19]	EmoReact	1	Public	Multimodal features	Multimodal
[78]	Twitter	1	Public	Text features	Text
[79]	BEHAVE Database	1	Public	Behavioral and interaction features from videos	Behavioral
[79]	CAVIAR Database	1	Public	Video features related to human behavior	Behavioral
[82]	USC-IEMOCAP	1	Public	Audio and text features	Audio, Text
[19]	PhysioNet	1	Public	Physiological signals	Physiological
[59]	Dataset Type II - Cheating	1	Private	Video or behavioral features	Behavioral
[61]	DEAP Dataset	1	Public	Physiological signals and EEG data	EEG, Physiological
[38]	Sina Weibo	1	Private	Text features	Text
[82]	SWELL-KW Dataset	1	Public	Physiological signals and behavioral features	Physiological, Behavioral
[8]	WESAD Dataset	1	Public	Physiological features	Physiological
[31]	CHB-MIT Dataset	1	Public	EEG features	EEG
[31]	Bird et al. Dataset	1	Public	Varies according to the study	Variable
[32]	CMU-CareMedia Dataset	1	Public	Multimodal features	Multimodal
[21]	PUCV-VTF Face Database	1	Private	Facial features	Image
[21]	RGB-D-T	1	Private	Depth and RGB features	Image
[21]	UCH-TTF	1	Private	Physiological and behavioral features	Physiological, Behavioral
[21]	JUFIR-F1	1	Private	Physiological and behavioral features	Physiological, Behavioral
[37]	eHealth Monitoring Open Data Project	1	Public	Health monitoring signals	Health
[40]	USC CreativeIT Database	1	Public	Multimodal features	Multimodal
[30]	Facebook	1	Private	Text and social network analysis features	Text, Social Network
[14]	Oulu-CASIA	1	Public	Facial expression features	Image
[14]	CMU Multi-PIE	1	Public	Facial features	Image
[46]	WADI Dataset	1	Public	Network traffic and anomaly detection features	Network Traffic
[47]	SWaT Dataset	1	Public	Network traffic and anomaly detection features	Network Traffic
[53]	DMOZ Dataset	1	Public	Web directory and metadata features	Web, Metadata
[18]	Set1	1	Private	Video or behavioral features	Behavioral
[18]	Set2	1	Private	Video or behavioral features	Behavioral
[23]	BEHAVE Dataset	1	Public	Behavioral and interaction features from videos	Behavioral
[59]	Dataset Type I – Non-Cheating	1	Private	Video or behavioral features	Behavioral
[105]	Program Data "All of Us"	1	Private	Health and genetic data	Health, Genetics

Percentage relative to the total number of mentions in the studies.

application is moderate and may require fine adjustments to adapt it to different contexts. In contrast, techniques like PCA and OCSVM have low computational demands, making them ideal for outlier detection and dimensionality reduction, which makes them suitable for implementation in resource-limited environments.

Furthermore, the selection of datasets plays a crucial role in the performance of models. Public datasets, such as JAFFE

TABLE 10. Additional emotion recognition datasets.

Ref	Database	Type	Status	Feature Extraction
[10]	AMIGOS	AV (Audio and Video)	Public	EEG, ECG, GSR, Emotional states
[10]	ASCERTAIN	AV (Audio and Video)	Public	ECG, GSR, Emotional states
[10]	DREAMER	AV (Audio and Video)	Public	EEG, ECG, Emotional states
[10]	WESAD	AV (Audio and Video)	Public	ECG, Physiological features
[10]	MAHNOB-HCI	AV (Audio and Video)	Public	ECG, GSR, Emotional states
[10]	SEED	AV (Audio and Video)	Public	EEG, Emotional states (Positive/Negative)
[10]	BioVid Emo DB	AV (Audio and Video)	Public	Physiological signals, Discrete emotions
[10]	SWELL	AV (Audio and Video)	Public	ECG, Stress, Emotional states
[10]	eSEE-d	Video	Public	Eye-Tracking, Discrete emotions

Datasets recommended by Khare et al. (2023) as crucial for future research in emotion recognition.

TABLE 11. Application areas and their frequency.

Application Area	Frequency
Emotion Recognition	37
Healthcare	34
Robotics	19
Autism and EEG	19
Anomaly Detection	18
Dementia and Care	12
Transportation	6
Cybersecurity	5
Behavioral Analysis	5
Biotechnology	1

Percentage relative to the total number of mentions in the studies.

and AffectNet, are widely accessible and frequently used in the scientific community, providing a solid foundation for study replication. Private datasets, despite their high cost, can offer more specialized data that can significantly enhance the robustness of models. The diversity of data offered by multimodal datasets is an important differentiator, although it adds complexity to implementation and processing.

Regarding application areas, sectors such as healthcare and security demand highly robust and precise approaches, with high computational costs, that deliver results of great value. Conversely, areas like transportation and cybersecu-rity require a balance between cost and applicability, with demands ranging from moderate to high in terms of both precision and robustness.

B. SCIENTIFIC LANDSCAPE FROM OBSTACLES ADDRESSED

Analysis of obstacles to research in the reviewed studies showed a strong overlap with challenges from previous studies. Table 13 describes the most frequently mentioned obstacles from the analysis.

The obstacles identified highlight data Integration as one of the most critical challenges, reflecting the difficulties in cohesively combining multiple data modalities. Real-time processing is another sensitive issue, requiring the ability to handle large volumes of data efficiently and with low latency, to ensure the system's robustness and responsiveness. Additionally, data accuracy and variability underscore the need to ensure not only the quality but also the consistency of the data used in model training and validation, to mitigate the impacts of contextual and individual variations.

Challenges related to contextual variations add a layer of complexity to emotional detection systems, as each context, whether cultural, social, or situational introduces unique factors that directly influence the expression and interpretation of emotions. This requires that such systems be not only technically accurate but also highly adaptable to different scenarios. The ability to recognize and adjust to emotional nuances in diverse contexts is essential to avoid misinterpretations and ensure effective and contextualized application.

In addition to addressing technical issues such as data integration, real-time processing, and data variability, models must be capable of dynamically adapting to the specificities of each situation, ensuring precise and appropriate responses in multifaceted environments. Such adaptability is fundamental to the success of emotion detection systems in practical applications, guaranteeing that their responses accurately reflect the inherent complexities of each environment and individual.

V. TRENDS AND CHALLENGES

The field of detecting emotional changes and linking them to unusual behaviors is advancing quickly. This progress is fueled by improvements in machine learning, artificial intelligence, and computing power. A notable trend is the use of various data types, which include physiological signals, facial recognition, and textual analysis. This approach, as highlighted by Gupta et al., boosts accuracy in identifying complex emotions [11].

Securing diverse and high-quality datasets for emotion detection models is a critical challenge. These models need to be effective across different groups and contexts, as human emotions are strongly influenced by cultural and situational factors, making accurate readings difficult. Therefore, developing models capable of interpreting emotional signals within this broader context is essential to improving their accuracy and reliability.

TABLE 12. Cost/Benefit analysis of techniques.

Technique	Computational Cost	Benefit in Accuracy	Real-Time Applicability
CNN (Convolutional Neural Network)	High	High	Limited
RNN (Recurrent Neural Network)	High	High	Limited
DNN (Deep Neural Network)	High	High	Limited
SVM (Support Vector Machine)	Moderate	Moderate	Good
Random Forest	Moderate	Moderate	Good
PCA (Principal Component Analysis)	Low	Sufficient	Excellent
OCSVM (One-Class Support Vector Machine)	Low	Sufficient	Excellent
EEG, ECG, GSR (Signal Analysis)	Moderate	High	Moderate
iForest (Isolation Forest)	Moderate	Moderate	Good
Autoencoders	Moderate	High	Limited
LSTM (Long Short-Term Memory)	High	High	Limited
ELM (Extreme Learning Machine)	Moderate	Moderate	Good
CAE (Convolutional Autoencoder)	High	High	Limited
LOF (Local Outlier Factor)	Low	Sufficient	Good

TABLE 13. Commonly identified obstacles.

No	Obstacles	Frequency	Percentage
1	Data Integration	12	30.13%
2	Real-Time Processing	10	25.64%
3	Affects Accuracy	6	17.09%
4	Data Variability	5	13.29%
5	Data Collection	4	11.39%

Percentage relative to the total number of mentions in the studies.

To understand and strategically address the complexities associated with trends and challenges in emotional anomaly detection, it is essential to conduct a structured analysis of the strengths, weaknesses, opportunities, and threats (SWOT) of existing approaches. The SWOT analysis presented below provides a comprehensive and critical perspective, allowing for the identification of not only the advances achieved but also the gaps and promising pathways [108].

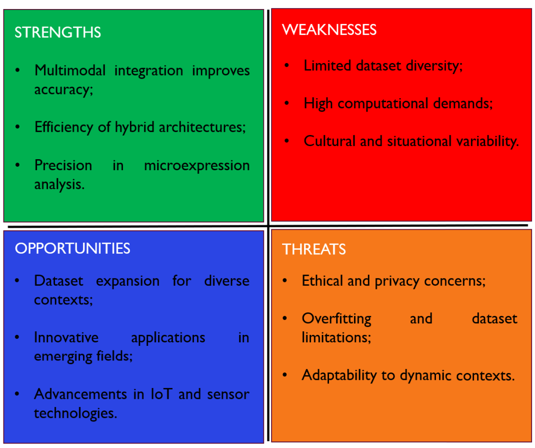

FIGURE 7. SWOT matrix for detecting emotional anomalies.

The SWOT analysis highlights the multifaceted nature of this field, emphasizing both the strengths of current approaches and the challenges that persist. Overcoming weaknesses and threats, such as limited datasets and the adaptability of systems in dynamic environments, requires strategic and innovative advancements. At the same time, the strengths and opportunities provide a solid foundation for exploring and refining existing methodologies.

An innovative approach to addressing these challenges is the combination of autoencoders with deep neural networks, such as CNNs and RNNs. Autoencoders, by learning latent representations, capture subtle patterns that often escape traditional models. When integrated with CNNs, which are effective in facial recognition, and RNNs, used for temporal modeling of auditory and physiological data, these models become highly efficient in multimodal emotion analysis.

The inclusion of facial microexpression analysis, which can vary significantly depending on the context, is an important complement to this integration of hybrid models. These microexpressions capture subtle and rapid emotional variations, requiring systems to quickly adjust their predictions to maintain accuracy in dynamic environments. They play an essential role in detecting anomalous emotions, especially in high-stakes contexts such as public safety and mental health. The ability to identify these variations in real-time, combined with the fusion of facial, auditory, and physiological data, significantly enhances the robustness and sensitivity of these systems.

The adaptability of these models to dynamic and unpredictable environments is essential to ensure their effectiveness in practical applications. Systems capable of adjusting to contextual and emotional changes quickly and accurately are vital for the success of technologies applied in complex scenarios, such as large public events and real-time monitoring.

VI. CONCLUSION

This systematic review thoroughly examined the methodologies and approaches used for the detection of emotional anomalies across various applications. In response to RQ7, the analysis revealed the predominant use of advanced machine learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which have proven effective in identifying emotional irregularities in real-time scenarios. However, despite their robustness, these methods face significant challenges, such as data integration issues and real-time processing limitations.

The review also highlighted the urgent need for more diverse and comprehensive datasets capable of reflecting the complexity and variability of human emotions across different cultural, social, and situational contexts. As posed in RQ5, the reliance on restricted and limited datasets compromises the generalizability of models, underscoring a critical gap that future research must address. Furthermore, the review identified a promising intersection between emotional anomaly detection and emerging application areas such as public safety, robotics, mental health, and digital security, which could substantially benefit from these technologies.

In robotics, multimodal fusion techniques have improved human-robot interaction, enabling machines to interpret and respond to emotional signals more accurately and promoting their use in complex real-world environments. In the context of RQ1 likewise in healthcare and autism research, for example, these methodologies have provided deeper insights into neurodivergent behaviors and emotional patterns, paving the way for more effective diagnostic and therapeutic tools. With respect to RQs 2 and 6, emerging fields such as cybersecurity and public safety also present significant opportunities where emotion detection can improve situational awareness, risk assessment, and decision-making in high-risk contexts. Expanding these practical applications to other areas, such as adaptive learning in education, marketing, and personalized healthcare, can further maximize the impact of these technologies.

About RQ3, multimodal fusion techniques and deep learning-based approaches have shown considerable potential in the detection of anomalous emotional behaviors, facilitating a more comprehensive and integrated analysis of multimodal signals. As for RQ4, key emotional indicators associated with the early identification of high-risk behaviors encompass variations in facial expressions, physiological signals, and vocal tone modulation, which have been increasingly recognized as relevant markers of atypical emotional states in critical environments.

Although recent advances have been remarkable, challenges related to emotional variability and contexts continue to exist. The evaluation of emotional anomaly detection systems, as outlined in RQ8, primarily relies on performance metrics such as accuracy, precision, recall, and F1-score. However, inconsistencies in benchmarking practices and dataset limitations hinder cross-study comparability, emphasizing the need for standardized assessment frameworks. The ethical implications of emotion detection, including privacy concerns, data security, and informed consent, represent critical areas for future exploration. Ensuring ethical usage of these technologies is paramount to fostering public trust and preventing misuse in sensitive domains. Furthermore, the continuous improvement of algorithms to better deal with the richness and fluidity of human emotions, and the creation of frameworks that allow real-time adaptation to diverse and dynamic scenarios, are essential to addressing the complexity of these challenges.

In summary, this review not only outlines the current state of emotional anomaly detection but also provides clear directions for future research in the field. Increasing data diversity, strengthening the robustness of algorithms, and expanding the practical applications of these technologies are imperative to ensure their effectiveness in real-world contexts and maximize their impact in critical areas such as security and healthcare.

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