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IoT-Driven Emotional Data Analytics for Medical Applications: Insights and Innovations

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Abstract

This study introduces the Internet of Things-based Emotional State Detection Model (IoT-ESDM), a comprehensive and intelligent emotional computing framework aimed at detecting and managing anxiety-related behavior in healthcare environments. The model leverages a multi-modal approach that combines facial expression analysis, physiological signal monitoring, and AI-driven classification to accurately identify emotional states in real time. Core components of the system include fuzzy color filtering, histogram analysis, and virtual face modeling, which work together to extract relevant emotional features from input data. These features are then analyzed to provide adaptive, personalized feedback to patients or caregivers, enhancing emotional well-being support. Experimental results demonstrate the superior performance of IoT-ESDM over existing emotion detection systems. The model achieved a feedback ratio of 97.54%, accessibility ratio of 95.3%, detection accuracy of 92.7%, and a classification accuracy of 98.13%. Additionally, it showed a quality assurance rate of 94.13%, contributed to a 29.1% reduction in anxiety levels, and yielded a health outcome ratio of 94.5%. These metrics validate the system's effectiveness in clinical and real-world applications. The success of IoT-ESDM highlights its potential as a powerful tool for emotion-aware AI interventions, paving the way for future advancements in mental health monitoring and personalized healthcare solutions.

Keywords:

Emotional State Detection;
Internet of Things;
Image Processing;
Data Analytics.

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1- Introduction

Emotional Intelligence (EI) refers to a person's ability to perceive, interpret, and regulate emotional states in themselves and others [1]. While once confined to psychology, EI is now becoming central in technology design, especially as Artificial Intelligence (AI) systems begin to simulate human behavior [2]. This shift in emotion-sensitive fields like healthcare is not just surface-level; it alters how machines perceive users and respond to complex human needs [3].

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When embedded in AI systems, EI supports richer, more adaptive interactions. It doesn't just help machines understand context, it helps them act on it [4]. In other words, AI embedded in EI contributes to technological development by enabling more efficient techniques and precise outcomes [5]. When emotionally enhanced, AI becomes a superior input-output mechanism for addressing complex societal issues [6]. Introducing emotional parameters into intelligent agents reduces the risk of social misinterpretation, improves understanding of human psychology, and facilitates more accurate emotional assessments over time [7]. By evaluating situations through observation, emotionally intelligent agents can recognize and interpret human behaviors [8].

The healthcare industry has risen dramatically in recent years, contributing significantly to revenues and jobs [9]. A few years ago, illnesses and anomalies were diagnosed through physical examinations in the hospital [10]. Traditionally, patients diagnosed with such conditions were required to undergo therapy while remaining in the hospital, leading to increased healthcare costs and stress, especially for those from rural and remote areas [11, 12]. However, emerging technologies, particularly the Internet of Things (IoT), are beginning to ease this burden [13]. IoT, embedded in everything from wearable sensors to ambient smart environments, is reshaping how patients are monitored and supported beyond clinical settings. Related frameworks, such as a ubiquitous personal health record (uPHR) framework [14], also support this shift by enabling integrated patient data management.

Emotion recognition technology remains the unresolved issue and is an essential technology that has been requested in several areas [15]. Detecting human emotions is possible using face picture, speech, form of the body [16]. The face picture is the most common source of emotion. In particular, face pictures are often utilized in detecting emotion [17]. Emotion identification is not a simple technique since it is important to extract suitable characteristics and recognize emotion [18].

As IoT systems become more pervasive in healthcare, there is growing interest in enhancing their responsiveness to human emotions and behaviors. This has led to the emergence of Emotional Intelligence with the Internet of Things (EmIoT), a concept based on the idea that IoT devices can be equipped with the emotional skills that enable individuals to succeed in life [19]. In this context, a "semi-immersive" environment refers to a user interface that blends elements of virtual and physical interaction without fully enclosing the user in a virtual reality system. It typically involves partial sensory engagement, such as screen-based simulations with real-time feedback. The term "EmIoT" (Emotional Internet of Things) is indeed an original term coined in this work. It represents the integration of emotional intelligence into IoT frameworks. When implemented effectively, the emotional responsiveness of such systems can lead to outcomes that are functionally and socially comparable to those of humans. Specifically, improvements in personal emotional intelligence can help individuals better utilize available resources and manage contextual challenges more effectively [20]. Feedback Ratio: The percentage of users who provide useful responses or reactions out of the total number of users interacting with the system. Quality Assurance: A systematic process to ensure that the developed model or system meets specified performance standards and delivers reliable results. The study is well-grounded in theory, drawing on concepts from Emotional Intelligence (EI) to understand and interpret human emotions effectively. It integrates Artificial Emotional Intelligence (AEI) to simulate and respond to emotional states through AI-driven techniques. The model applies these concepts to healthcare, aiming to monitor and manage anxiety-related behaviors. By referencing established EI and AEI frameworks, the work ensures theoretical robustness. This alignment strengthens its relevance for emotional analysis in medical applications.

The increasing use of technology to monitor physiological indicators has also enabled researchers to design and implement wearable applications that assess various aspects of health in real time [21]. In this context, maintaining mental well-being, alongside physical activity, is essential for achieving a more balanced and holistic lifestyle [22].

With the integration of AI, human emotions can be recognized, interpreted, and simulated in wearable computing devices and systems [23]. Although considerable progress has been made, continued innovation is necessary, as Artificial Emotional Intelligence (AEI) plays a pivotal role across various professional sectors [24]. AEI addresses the fundamental accessibility issues, particularly in underserved and remote regions worldwide. It assists the world's distant regions in achieving equal results and opportunities.

AEI has the potential to transform existing systems and introduce new paradigms of interaction and support. It has demonstrated efficiency in various domains [24]. In healthcare, it demonstrates a higher efficiency in supporting early diagnosis, such as cancer classification, by integrating emotional and physiological data. In business, it improves consumer engagement through real-time emotion-based feedback systems, and in automotive safety, it monitors the emotional state of drivers to promote safer travel conditions. Moreover, focused web crawler systems [25] can enhance these domains by improving access to relevant data sources and supporting the adaptability of emotion-aware systems.

Building on these advancements, this paper introduces a hybrid Internet of Things-based Emotional State Detection Model (IoT-ESDM) that aims to integrate emotional intelligence capabilities into IoT systems for more context-aware, personalized, and responsive user support. The proposed model combines biomedical sensor data with emotion analytics to monitor anxiety levels in semi-immersive environments. While the paper references studies from diverse fields like workplace stress, mental health monitoring, and educational engagement, it lacks a critical synthesis linking them to the design of IoT-ESDM. The authors should explain how these domains influenced the system's features, such as emotional detection parameters or user interaction methods. Clarifying these connections would show how prior research supports the model's structure and relevance. A more analytical comparison would strengthen the justification for the system design. This would also highlight the interdisciplinary value of IoT-ESDM.The system serves three primary functions:

- **i.** Understand users' needs by allowing them to express their current emotional status or set it as a predefined input, enabling the system to adapt its behavior and provide customized services.
- **ii.** Assess users' emotional states to understand their capabilities and available resources better, empowering them to manage situations independently.
- **iii.** Establish emotional attachment to enhance user engagement within the IoT environment.

This work introduces a comprehensive and efficient integrated framework—IoT-ESDM (Internet of Things-based Emotional State Detection Model) designed to assess emotional features and monitor anxiety-related disorders. The model functions by analyzing physiological signals such as heart rate, skin conductivity, and facial expressions, alongside emotional arousal levels, providing a multi-dimensional understanding of a user's emotional state. Operating within a semi-immersive environment, the framework creates an interactive setting where users can engage with the system while still being partially connected to the real world enabling realistic emotional interactions without the need for full virtual immersion. Beyond just detecting internal physiological changes, IoT-ESDM also evaluates external environmental factors (such as lighting, sound, and temperature) that may influence emotional well-being. By integrating personal contextual data like user history, preferences, and situational background the model ensures that emotional responses are interpreted within a meaningful, individualized framework. This holistic approach allows for more accurate identification of anxiety patterns and supports personalized healthcare interventions, making it valuable for applications in mental health monitoring, emotional well-being assessments, and therapeutic environments.

The key contribution of this work is:

- A novel IoT-based Emotional State Detection Model (IoT-ESDM) is developed to improve health outcomes by identifying and interpreting emotional data in real time.
- The proposed model employs a fuzzy color filter and histogram-based technique to extract and analyze facial expressions for emotion detection.
- Numerical experiments using the IoT-ESDM demonstrate its effectiveness in enhancing feedback quality and accessibility in medical applications, outperforming several widely used methods.

The entire research paper is structured as follows: Section I is an overview of emotional intelligence in medical applications. Section II describes the literature review, and Section III presents the proposed IoT-ESDM to reduce user anxiety levels and improve medical application accessibility. Section IV discusses the numerical results and evaluation. Finally, Section V concludes the research findings. Section 4 presents a critical discussion of the findings, addressing the framework's strengths and challenges, followed by a conclusion in Section 5.

2- Literature Review

This section reviews studies on emotional intelligence in workplace settings, mental health, and academic environments.

2-1- Employee Emotions Analysis

Alam et al. [26] examined the mediating role of employee motivation in the relationship between leadership and organizational behavior. The study highlighted the importance of emotional intelligence (EI) in leadership, showing that a leader's emotional intelligence positively influences employee behavior. Furthermore, employee motivation strengthened this relationship, emphasizing the value of emotionally intelligent leadership in fostering a supportive work environment.

Several studies have applied machine learning and deep learning techniques [27] for analysis and related text classification tasks, demonstrating the versatility of these approaches across domains. Machine Learning Technique for detecting emotional states and transitions was proposed by Sultana et al. [28]. A key indicator of health and well-being is the emotional condition of everyday life. This study emphasized the need for automated emotion tracking since emotional assessments are often self-reported and prone to inaccuracy. The model analyzed contextual data daily and identified relationships between background knowledge, emotional transformations, and stress transitions.

Wavelet Packet Transform (WPT) cochlear model (CM) for emotion recognition was introduced by Hamsa et al. [29] to determine the underlying feeling of the speaker by designing an artificial emotional intelligence system. They claimed that this representation is coupled with the random forest classification by WPT-CM, which shows superior performance over existing models across two languages and three different speech datasets. The model proved particularly effective under stressful and emotionally degraded speech conditions.

Barreiro et al. [30] explored the Facet-Level Approach (FLA) as a predictor of employee engagement. The study analyzed how specific traits of emotional intelligence influenced engagement in a sample of 360 participants. Structural equation modeling revealed that facet-level EI analysis explained nearly twice the variance in engagement compared to general EI measures, highlighting the importance of granular emotional traits in organizational settings. Deep learning approaches have also been applied to recognition tasks [31]. Chowdary et al. [32] developed a deep learning-based facial emotion recognition (DL-FER) system using transfer learning. Several pre-trained networks—ResNet50, VGG19, Inception V3, and MobileNet—were fine-tuned for emotion classification. The study achieved an average accuracy of 96% on the CK+ dataset, demonstrating the effectiveness of deep learning in automated emotion recognition.

2-2- Human Mental Disorder Analysis

Trigueros et al. [33] highlighted the challenges faced by families and caregivers of individuals with mental disorders, particularly the emotional burden and self-stigmatization experienced by parents. Caring for a child or adolescent with a serious mental condition often places families in emotionally vulnerable positions, contributing to feelings of guilt and stress. The findings underscored the importance of developing interventions that specifically target the psychological strain of caregiving, particularly by addressing self-stigma and emotional fatigue among family members.

Zhang et al. [34] introduced the Health Knowledge Graph Builder (HKGB), a tool designed to assist clinicians by integrating diverse health data sources into extendable, disease-specific knowledge graphs as a foundation for knowledge-driven services and applications in mental healthcare. The study demonstrated how structured knowledge representation can support clinical decision-making and improve the accessibility of mental health services through intelligent information systems.

2-3- Evaluating Student Emotions

Navarro-Mateu et al. [35] investigated student stress using Structural Equation Modeling (SEM) and Qualitative Comparative Analysis (QCA). The study emphasized that stress negatively affects students' social well-being and academic performance. While no single factor was found to be solely responsible for high stress levels, combinations of factors explained approximately 35% of elevated stress cases. Notably, the interaction between high Emotional Associations (EA) and low self-efficacy emerged as the most influential combination in predicting high stress levels among students.

Shi et al. [36] explored the role of gratitude, empathy, and EI in developing professional competencies among medical students. Empathy is considered a vital trait for healthcare professionals, so the study examined how EI and gratitude contribute to cultivating empathy in future doctors. The findings suggest that these psychological attributes are foundational for building emotional competence, essential for effective patient care. Intervention programs designed to enhance professional skills should incorporate training in emotional intelligence and empathy [37-39] provide a comprehensive survey on integrating facial expression analysis both macro and micro with IoT platforms. They highlight advancements enabling real-time emotional monitoring in smart healthcare contexts and outline challenges and future directions for emotion-aware IoT systems. Emotion-Aware IoT in Personalized Healthcare An article from GNIOT [40] emphasizes how IoT devices such as wearables and smart sensors can interpret emotional states and deliver targeted interventions (e.g., stress prediction, notifications, mental health support), enhancing care personalization and remote monitoring. IoT Frameworks for Emotion Detection and Behavioral Influence Asar, Handosa, and Rashad [41] propose an IoT-based framework combining EEG and physiological data with deep learning (CNN, SVM, Decision Trees, etc.) for accurate, real-time emotion detection while ensuring GDPR and HIPAA privacy compliance. Their system achieves remarkable accuracy rates nearing 100%. Emotional intelligence is vital across the workplace, mental health, and academic settings. While existing methods offer valuable insights, they often lack real-time responsiveness and contextual integration with IoT systems. To address these gaps, the proposed IoT-ESDM model aims to deliver adaptive, emotion-aware support by combining biomedical sensing with emotion analytics

3- Internet of Things-Based Emotional State Detection Model (IOT-ESDM)

The development of emotionally intelligent systems is a growing focus in artificial intelligence (AI), particularly in applications requiring human-centered interaction. Traditional AI models emphasize rational decision-making, but integrating emotional intelligence is critical for improving personalization and responsiveness. The proposed Internet of Things-Based Emotional State Detection Model (IoT-ESDM) aims to bridge this gap by enabling real-time emotional state recognition using facial expression analysis within IoT-enabled environments.

The model captures frontal face images and analyzes them to detect emotional cues. In the pre-processing image phase, facial regions are isolated using fuzzy color filtering and histogram analysis techniques. These methods help extract key facial features, such as eyes, mouth, and brows, which are crucial for emotion classification. The system then applies a feature extraction algorithm, followed by classification using a trained functional classifier to determine the user's emotional state.

This approach allows the system to recognize emotions with high accuracy and minimal latency, making it suitable for real-time applications. Beyond facial recognition, the IoT-ESDM framework is designed to be extensible, enabling integration with other biomedical sensors to support emotion-aware applications in healthcare, virtual consultation, and context-sensitive business environments.

Figure 1 demonstrates the components of emotional intelligence within AI systems, particularly in the context of the IoT. It integrates data collection, external awareness, IoT connectivity, and ethical considerations. These elements enable real-time perception, reasoning, and action in dynamic environments, simulating human-like emotional understanding.

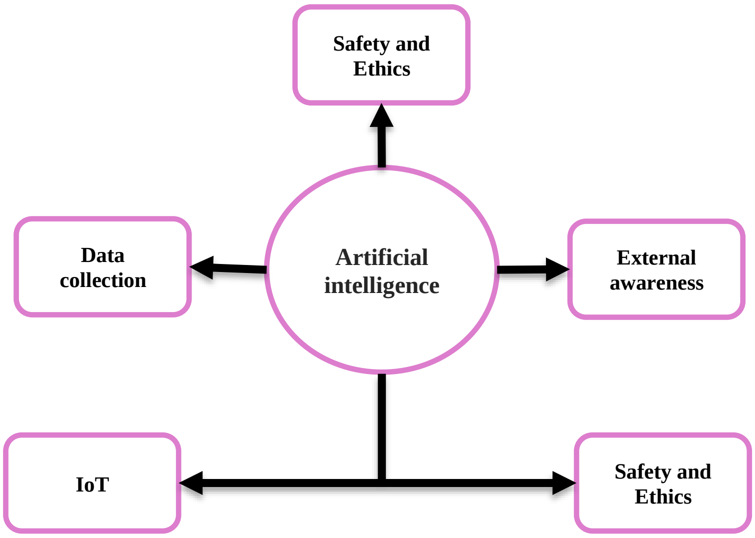

Figure 1. **Artificial intelligence-based Emotional intelligence**

EI agents are supported by technologies such as cloud computing, Big Data analytics, deep learning, and self-awareness models. These systems are designed to process structured sensor data and interpret users' unstructured emotions, such as facial expressions, speech patterns, or text inputs. EI is central to how humans think, feel, and respond. Bringing it into AI doesn't just improve interaction; it transforms machines from reactive tools into emotionally aware, socially intelligent agents. In digital healthcare, sentiment analysis has become a key tool for interpreting patients' emotions and feedback. AI-driven emotion detection offers an alternative to traditional assessments, especially in evaluating user responses to treatment plans, medications, and digital health services. Systems can analyze text from blogs, social media, and medical feedback forms to detect emotional tone, enabling proactive, patient-centered care.

The increase of user-generated content on the internet, through forums, chat systems, and personal blogs, has created a vast repository of emotional data. Emotion detection techniques now extend to phrase-level sentiment parsing, where emotional meaning is extracted from individual expressions to infer the overall sentiment of a document. This document-level emotional analysis supports a deeper understanding of user experience, human-computer interaction, and behavioral patterns. AI systems can provide more personalized, ethical, and emotionally aware responses by integrating multimodal emotion recognition (facial, physiological signals, and text-based sentiment). This is critical for healthcare, where human emotions significantly influence outcomes.

3-1- Emotion Detection

Figure 2 depicts the architecture of the emotion detection system, integrating multiple IoT-based health monitoring components. These include an Integrated Health Machine, a Smart Watch, and Intelligent Home Monitoring, all of which work together to collect real-time physiological and behavioral data. The internet handles all of the IoT and health data. Service data and basic information are stored in the Mobile Communication Network. This layered structure supports senior management, house management, co-operator management, booking management, and Statistical Data for Health records.

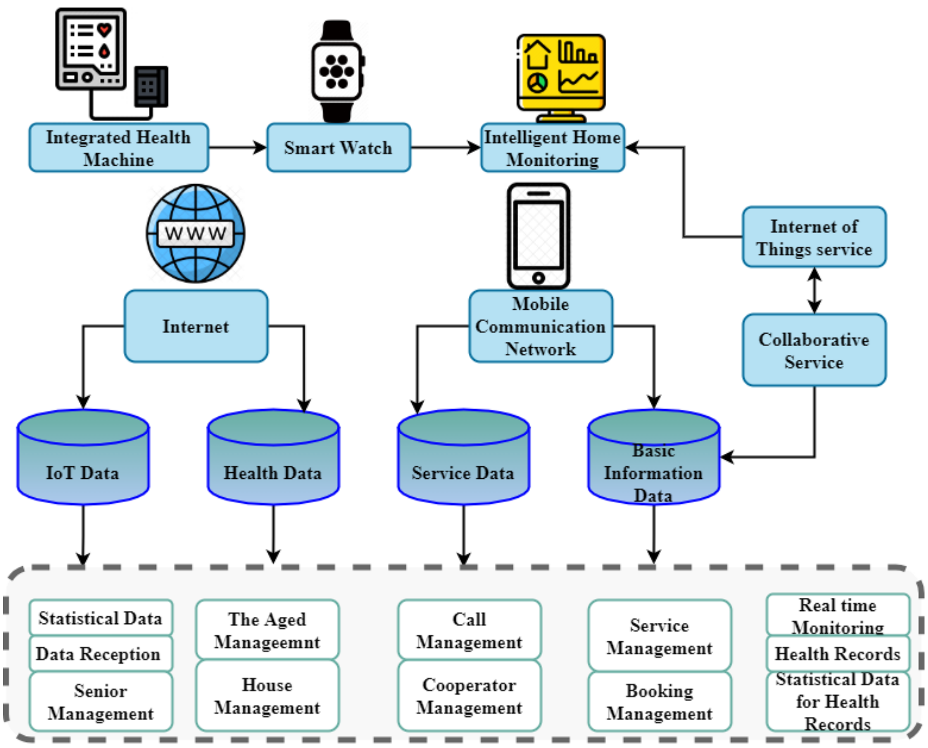

Figure 2. **Emotion Detection**

Emotion detection is built on understanding human needs, which can be categorized into five hierarchical levels: physiological, safety, social, demand, and self-realization. The first three are especially important for elderly populations. The system must prioritize health and safety monitoring for seniors, maintain normal bodily function indicators, and promote emotional connection with family members.

To accommodate declining muscle function and cognitive responsiveness in older people, the system interface should be simple, and manual communication should be minimized. Healthcare professionals also play a central role. They provide physical support, lifestyle counseling, and risk prevention guidance. The system enables them to monitor key health indicators like heart rate, respiration, body temperature, and blood pressure while gaining insights into daily habits and medical history. This comprehensive approach helps reduce the risk of sudden illness and supports proactive elderly care.

From a family perspective, it is essential to understand the health status of older adults quickly and easily, without requiring professional medical training. The proposed system enables elderly individuals and their healthcare providers to monitor vital data in real time through a user-friendly interface. Health professionals can assess a senior's current condition and provide timely guidance. If abnormal readings are detected, the system can automatically alert healthcare personnel. Family members can also remotely monitor the physical condition of their elderly relatives anytime, anywhere, via internet access. This real-time connection improves peace of mind and enhances support. The system is designed with high modularity for sustainability, ensuring it remains open for future maintenance, reuse, and expansion.

The full system includes hardware and software components, covering data collection, intelligent home healthcare, and application server layers. It integrates advanced sensor technologies, emotional computing, smart terminals, and internet connectivity to meet user needs based on prior intelligent service system models. Hardware comprises IoT sensors, an intelligent terminal, and integrated healthcare equipment. The devices capture the temperatures, moisture, and overall experience from the home environment and send them regularly. Smart gadgets (smartwatches, for example) can detect hypertension and respiratory rate and make an emergency call. RFID integration is used for secure authentication via password-enabled tags. In communal living spaces, an Integrated Health Machine is installed to collect data such as:

Circulatory rates, glucose levels, cholesterol levels, blood oxygenation, urination, thermal energy, the weight of the person, aspartate transaminase, and complete blood pressure. All data is transmitted to centralized servers via WiFi or cellular networks (2G/3G/4G) through a middleware interface. When elderly users initiate a service request, the system intelligently routes and allocates tasks to customer service agents. The network model can analyze this incoming data stream to support decision-making. Additionally, family members can access health and environmental data through a mobile application.

In case of emergency or data anomalies, the system can automatically trigger application alerts and SMS notifications for caregivers and family members, ensuring a rapid response.

Figure 3 presents the attention recognition framework using emotional AI, which was developed to detect an individual's focus level and identify distraction in real time. The system begins by processing video input to extract facial landmarks, identifying key features such as the eyes, brows, and mouth for further analysis.

These features are then passed to the Emotional AI Attention Feature Model, which selects the most relevant features based on visual analysis. The system sequentially processes key components to assess attention levels in real time, eliminating the need to analyze all 68 facial landmarks generated by OpenFace. Instead, it focuses on a subset of the most relevant features for distraction detection.

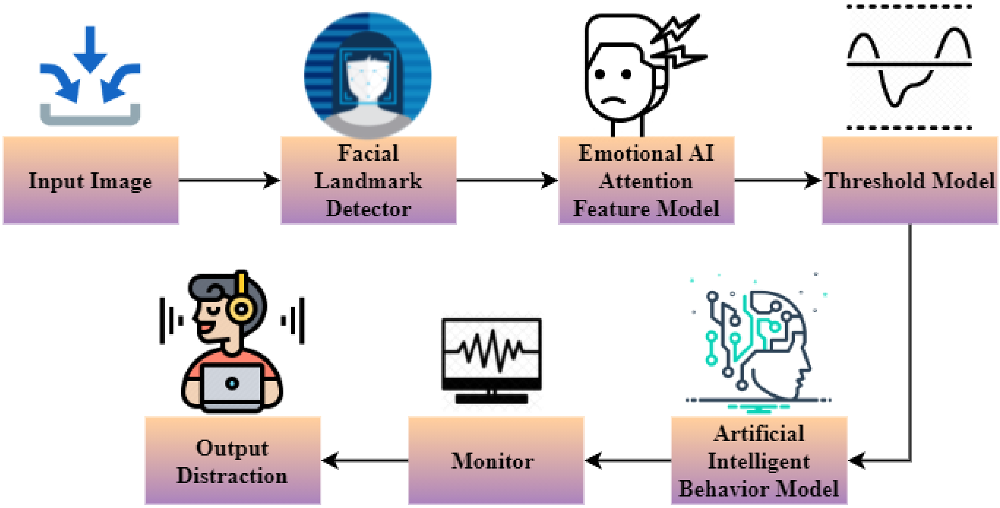

Figure 3. Proposed IoT-ESDM

Not all facial attributes are equally important. For example, in a classroom setting, only specific facial cues indicate a student's attention, such as eye movement, head pose, or lip activity. Our model isolates these essential cues to monitor behavioral shifts and assess distraction. One of the contributions of this research is the development of a feature selection framework that filters out irrelevant data and prioritizes high-impact facial landmarks. Instead of analyzing the full set of facial points, the model dynamically concentrates on a critical subset that effectively reflects attention levels.

- **i.** Head Pose Alignment: Using Euler angles (pitch, yaw, roll), the system estimates head orientation using a Perspective-n-Point (PnP) approach. Head direction changes, such as turning left, right, upward, or downward, are strongly associated with attention loss. A forward-facing head typically indicates focused attention, while frequent movement suggests distraction.
- **ii.** Eye Aspect Ratio (EAR): EAR measures eye openness and detects drowsiness. The model classifies the state as somnolence when the EAR drops below 0.25 for more than 5 seconds. Additionally, a high blink frequency can signal reduced cognitive engagement.
- **iii.** Eye Direction: Eye orientation is computed using 12 facial landmarks (6 per eye). The system segments the eye region, applies a binary threshold, and divides each eye into halves. The model determines gaze direction by calculating the distribution of white pixels in both halves. A sustained shift to the left or right indicates visual disengagement.
- **iv.** Lip Distance: The vertical separation between the upper and lower lips helps identify yawning and talking, signs of distraction. Yawning is flagged when lip distance exceeds 30 pixels for 3–5 seconds, while talking is detected when this condition persists across 20 or more consecutive frames.

By focusing on these selected features, the model enables efficient and accurate detection of real-time attention states, minimizing computational overhead while enhancing behavioral interpretation.

The extracted features are evaluated against a Threshold Model to determine acceptable focus levels for a given context. If the attention level falls below this threshold, the Artificial Intelligence Behavior Model interprets the deviation and triggers a response. This may include auditory or visual alerts sent via the Output Distraction Module or logged events for caregivers or support systems to review. The monitoring system captures and updates user state in real time, allowing continuous behavioral analysis.

i. Processing Phase

This phase marks the core processing step, where the system extracts emotional and behavioral information from facial images. The complete emotion detection pipeline is illustrated in Figure 3.

The facial area is first detected during pre-processing, followed by extracting specific facial components. This is achieved using a combination of fuzzy color filtering and histogram-based techniques, which are employed to isolate the facial region accurately. Skin color is not easy to identify since variations in skin color are conditioned by personality and lighting. However, a type filter should be used to remove the face region for the skin color.

A fuzzy color filter solves this problem. The fuzzy color filter is based on the fuzzy inference system. The ambiguous skin tones are shown as fuzzy sets in fuzzy rules. The construction of the fuzzy rule is shown as,

$$O_j: if\ Y_1 \sim N_{j1} and \dots \& Y_n \sim N_{jn} \quad \text{Then} \quad X_j(y) = b_j j = 1, \dots, K \tag{1}$$

As shown in Equation 1, a fuzzy rule has been represented. When the color is $Y_i \in O_j$and jth $N_{j1}, \dots, N_{jn}$ is the predecessor of a fuzzy set, $X_j(y)$ is the result of the jth rule, $Y = [Y_1, \dots, Y_n]^S$where ith is input, $\in E \subset O^{>}$is the vector for input, E is the vector set for the feature, and $b_{j,}$ is the parameter that follows, and means the weight for the rule j. In the following equations, the output of the fuzzy control system is derived:

$$\boldsymbol{X}(\boldsymbol{y}) = \frac{\sum_{j=1}^{k}\left\{\prod_{i=1}^{n} e^{-\frac{\left(D_i^j - Y_j\right)^2}{U_i^j}}\right\}}{\sum_{j=1}^{k}\prod_{i=1}^{n} e^{-\frac{\left(D_i^j - Y_j\right)^2}{U_i^j}}} \tag{2}$$

As Equation 2 outlines, the fuzzy rule system is inferred based on a set of defined membership functions. Each rule in the system is constructed using parameters, where D_i^j and U_i^j represent the lower and upper bounds (or spread) of the *i*th input variable in the *j*th rule, effectively defining the breadth and center of the corresponding membership function. Lastly, the final output of $\hat{X}(Y)$ is computed using a weighted aggregation of all activated fuzzy rules, following the standard fuzzy inference mechanism.

$$\hat{X}(Y) = \sigma v(X(y) - X_{min}) \tag{3}$$

As shown in Equation 3, the final output of the fuzzy color filter is defined. In this context, σ represents the grey image offset value, $U(y)$ denotes the unit step function, and X_{min} is the minimal value of $X(y)$. If $X(y)$is larger than X_{min}. Then, a coefficient α is introduced into the output. This allows for dynamic adjustment of the skin color filter's sensitivity by modifying the threshold parameter Y_{min}. The process of identifying fuzzy skin filters is described next.

When the photo is filtered using a fluffy skin filter, the image is converted to a grayscale representation, denoted as, $J_h \subset O^{n\times m}$ where each $w_{ji} \in J_h$corresponds to a pixel containing possible facial region information. To refine the localization of the facial area, the system computes: A horizontal histogram vector $R = [R_1, \dots, R_n]$ and a vertical histogram vector $Q = [Q_1, \dots, Q_n]$.

These histogram vectors are generated by summing the grey values of each pixel across the image's rows and columns. Specifically:

$$R_j = \sum_{i=1}^{m} w_{ji}$$
$$Q_i = \sum_{i=1}^{m} w_{ji} \tag{4}$$

where, R_j represents the horizontal histogram (row-wise sum) and Q_i represents the vertical histogram (column-wise sum). As expressed in Equation 4, this histogram-based analysis enhances the accuracy of facial region segmentation by identifying dominant distributions of pixel intensity in both axes. Using this method, the grayscale image is transformed into histogram vectors R and Q, from which the most significant segments, those with the highest cumulative values, are selected. These segments correspond to the width and height of the final facial bounding box.

Algorithm 1. Segmentation for an image

Information: $\boldsymbol{Z} = [\boldsymbol{Z}_1, \dots, \boldsymbol{Z}_d]$: histogram input
$\boldsymbol{C}$: minimal depth of segment
$\boldsymbol{O}$: different region segmentation
Outcome: The highest segment in the specified histogram $\boldsymbol{Z}$
edge$\boldsymbol{e}_{\boldsymbol{begin}}$=false
for $\boldsymbol{j = 1}$ to $\boldsymbol{d}$ do
$\widehat{\boldsymbol{Z}}_j = \prod_{l=-o}^{-1}\boldsymbol{\gamma}(\boldsymbol{z}_{j+l} - \boldsymbol{f}_{j+l}^1)\prod_{l=1}^{o}\boldsymbol{v}(\boldsymbol{z}_{j+l} - \boldsymbol{f}_{j+l}^1) - \prod_{l=-o}^{-1}\boldsymbol{v}(\boldsymbol{z}_{j+l} - \boldsymbol{f}_{j+l}^2)\prod_{l=1}^{o}\boldsymbol{\gamma}(\boldsymbol{z}_{j+l} - \boldsymbol{f}_{j+l}^2)$
Where
$\boldsymbol{e}_j^1 = \{\boldsymbol{o}\ -\boldsymbol{o} \le \boldsymbol{j} \le -\boldsymbol{1}\ \boldsymbol{c}\ \boldsymbol{0} \le \boldsymbol{j} \le \boldsymbol{o}, \boldsymbol{e}_j^2 = \{\boldsymbol{c}\ -\boldsymbol{o} \le \boldsymbol{j} \le -\boldsymbol{1}\ \boldsymbol{o}\ \boldsymbol{0} \le \boldsymbol{j} \le \boldsymbol{o}$
If $\widehat{\boldsymbol{Z}}_j = \boldsymbol{1}$ and edge$\boldsymbol{e}_{\boldsymbol{begin}}$= false then
temp=j
edge$\boldsymbol{e}_{\boldsymbol{begin}}$=true
endif
if$\widehat{\boldsymbol{Z}}_j = -\boldsymbol{1}$ and edge$\boldsymbol{e}_{\boldsymbol{begin}}$=true then
$(\boldsymbol{temp}, \boldsymbol{j})$ is the current segment
edge$\boldsymbol{e}_{\boldsymbol{begin}}$=false
endif
end

As detailed in Algorithm 1, this process allows for identifying the facial area by locating the largest continuous ranges within the horizontal and vertical histograms. This yields a more specific and reliable facial region extraction, forming the basis for subsequent attention and emotion analysis.

In this work, the proposed method offers a novel frontal face photo algorithm to detect emotions. The algorithm consists of three stages: pre-processing the image, extracting face characteristics, and identifying the mood. While the initial image processing techniques follow methods previously established in earlier work, this paper introduces a refined approach to feature extraction that enhances both efficiency and accuracy. The new method segments the face into three characteristic regions: eye, mouth, and auxiliary. These regions are selected for their high correlation with emotional expression.

As shown in Figure 4(a), eight features are extracted from the eye region. These include four geometric features related to eye and eyebrow positioning, and four shape-based features that describe eye form characteristics. These shape features are compared with a predefined template, illustrated in Figure 4(b), to determine eye-form deviations that may indicate specific emotions.

The mouth region, illustrated in Figure 4(c), captures key indicators such as mouth width and height. As shown in Table 1, this region includes two geometric features and six shape-based features, which are further visualized in Figure 4(d). These features are vital for detecting expressions such as smiling, speaking, or yawning.

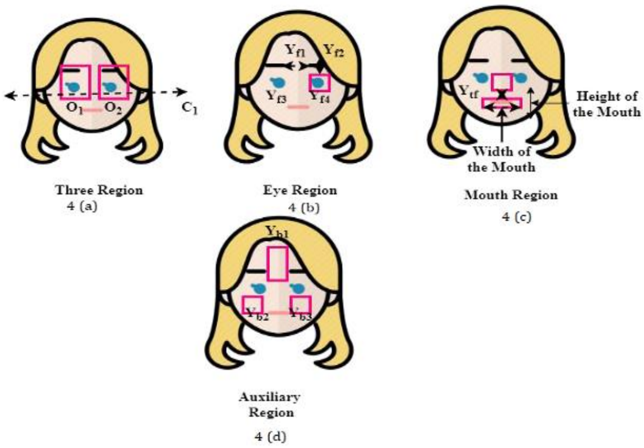

Figure 4. **Facial Expression Prediction**

The auxiliary region includes additional facial areas that support the interpretation of the eye and mouth regions. This region contributes three features, complementing other regions' geometric and structural cues. To improve the efficiency of feature localization and reduce computational load, a Virtual Face Model (VFM) is employed. VFM defines facial components' approximate position and length based on normalized face geometry. When the facial region is extracted, components are localized using VFM-guided histogram analysis, narrowing the search space and improving detection speed.

This method accurately identifies the eye, mouth, and auxiliary components across diverse face types. All features are normalized relative to the facial image width, which ensures consistency across images of varying size and scale. Furthermore, a new template-matching method is proposed to avoid high computational complexity when comparing facial features. This method enables rapid and scalable emotion classification by aligning extracted features with a reference template derived from training data.

Algorithm 1 outlines the step-by-step procedure for facial region segmentation, feature extraction, and emotion identification. Figures 4(a)–4(d) visually support the feature localization process and demonstrate the feature-template comparison technique.

Table 1 presents the facial expression landmarks used to identify emotional states and assess potential distraction across key facial regions. The features are categorized into three primary regions: the eye region, the mouth region, and the auxiliary region, each contributing to emotion classification through geometric and structural analysis.

In the eye region, features Y_{f1} to Y_{f4} are extracted, representing distances between the eyebrows, eyes, and nose. For the mouth region, features Y_{n1}, Y_{n2} and Y_{tf} are used, with Y_{tf} denoting the template-matching error between the extracted mouth region and a predefined reference template. In the auxiliary region, wrinkle-based features $Y_{b1}\ to\ Y_{b3}$ are measured to provide additional emotional cues. These extracted features serve as inputs to the facial image segmentation and behavior detection pipeline, which is outlined in Algorithm 1.

Table 1. Facial Expression Landmarks

Features	Description
In the eye region, the following parameters are extracted:	
Y_{f1}	Distance between two eyebrows
Y_{f2}	Distance between the eye and eyebrow
Y_{f3}	Distance between nose and left eye.
Y_{f4}	Distance between nose and right eye
The mouth region	
Y_{n1}	Width of mouth
Y_{n2}	Distance between nose and mouth
Y_{tf}	The error between the mouth and the template
The auxiliary region includes wrinkle-based features.	
Y_{b1}	Wrinkles between eyes
Y_{b2}	Wrinkles between the left side of the face
Y_{b3}	Wrinkles between the right side of the face

Algorithm 1 performs facial image segmentation for real-time detection of human emotional states, identifying attentiveness or distraction from video streams. The system tracks behavioral cues such as speech, yawning, drowsiness, and potential indicators of attention-deficit behavior, using facial alignment and landmark deviation. The algorithm begins by applying standard facial alignment techniques, extracting facial landmarks from each frame. These facial landmarks detect deviations from a neutral or baseline configuration. Any sustained divergence in landmark alignment is interpreted as behavioral change, signaling either attention loss or cognitive engagement.

One of the key strengths of this method is that it operates without the need for manual annotation or supervised training. The system bypasses computationally intensive calculations typically found in deep learning-based systems using predefined reference models and selected landmark points. As a result, the overall configuration is significantly faster and more efficient than many state-of-the-art solutions. Traditional facial expression comparison methods are computationally expensive and unsuitable for real-time monitoring. Our method introduces an optimized template matching approach for comparing facial features to address this.

Let Y_g, Y_Z, and Y_q be pixels in pictures in width, height, and number. The similarity score T can be determined:

$$T = |Y_z - S_z| + |Y_g - S_g| + \left|\frac{Y_Z}{Y_g} - \frac{S_z}{S_g}\right| + |Y_q - S_q| \quad (5)$$

As defined in Equation 5, similarity has been described, where the width, height, and pixel numbers in the template are S_z, S_g, and S_q.

In pattern recognition tasks, such as fingerprint identification, precise patterns are matched against a known database. However, emotional recognition presents a greater challenge, involving imprecise, overlapping, and often ambiguous patterns. A facial expression may not correspond to a single, clearly defined emotional class, making classification difficult.

A fuzzy classifier is introduced into the emotion recognition system to address this uncertainty. Unlike rigid rule-based classifiers, the fuzzy classification approach is well-suited to handling ambiguous or soft boundaries between emotional states. A fuzzy classifier uses a set of fuzzy rules, allowing it to process input vectors with uncertainty and assign degrees of membership to possible emotional categories. This makes it a powerful solution for resolving ambiguity in real-world emotion detection.

$$O_j: if Y_1 is N_{j1} and \dots and Y_n is N_{jn} \quad \text{then} \quad X_j(y) = b_j y_1 + \cdots + b_{jn} y_n + a_j K \quad (6)$$

As shown in Equation 6, this expression defines the jth fuzzy rule used in the fuzzy classification system. In this context: $N_{j1}, \dots, N_{jn}$ are the fuzzy sets or linguistic terms (e.g., "low", "medium", "high") associated with each input in the jth rule antecedent. $Y = [Y_1, \dots, Y_n]^S \in E \subset O^{>}$ is the feature input vector, where each Yi represents an input variable such as a facial feature or metric derived from the image.

$$X(y) = \frac{\sum_{j=1}^{k} g_j(y) a_j}{\sum_{j=1}^{k} g_j(y)}$$
$$g_j(y) = \prod_{i=1}^{n} \tau N_{ji}(Y_j) \quad (7)$$

As depicted in Equation 7, the output of the fuzzy rule has been inferred. Where the $\boldsymbol{g_j(y)}$ are an $\boldsymbol{i}$th rule firing force and the $\tau N_{ji}(Y_j)$ is the $\boldsymbol{j}$th rule $\boldsymbol{i}$th feature membership degree. The membership role must be defined as,

$$\tau N_{ji} = e^{-\frac{\left(D_i^j - Y_j\right)^2}{U_i^j}} \tag{8}$$

Equation 8 shows that the membership function has been introduced. The center of D_i^j and the breadth of $\boldsymbol{i}$th of the rule is U_i^j where $\boldsymbol{i}$is the center. The result $X(y)$ can be written as the following matrix equation for computational convenience:

$$\begin{aligned} &G = \left[c_1(y)\ \vdots\ c_j(y)\ \vdots\ C_k(y)\right], \\ &A = \left\{a_1\ \vdots\ a_j\ \vdots\ a_k\ \right\} \\ &C_j(y) = \frac{g_j(y)}{\sum_{i=1}^{k} g_j(g'y)} \end{aligned} \tag{9}$$

As suggested in Equation 9, the fuzzy classifier output is reformulated for computational efficiency. Since most pattern recognition systems require crisp (hard) class labels, the fuzzy classifier employs the following mapping equation to transform a soft mark $X(y)$ to a hard mark $X_d(y)$:

$$X_d(y) = arg_g min\{|h - X(y)|\}, h \in \{1, \dots, m\} \tag{10}$$

Algorithm 2. **Fuzzy Classifier Detecting Algorithm**

For $\boldsymbol{j} \in \{\boldsymbol{1}, \boldsymbol{2}, \dots, \boldsymbol{m}\}$ do

$\boldsymbol{Z} \leftarrow$ Compute the difference in the information collection

Improve the following LMI constraints for the LMI system,

$\boldsymbol{U_j > 0}$

$\boldsymbol{U_j > \beta Z}$

for$\boldsymbol{y} \in \boldsymbol{D_j}$ do

Improve the following LMI constraint to the LMI system,

$\boldsymbol{[\beta\ *\ U_j y - P_j\ \beta\ ] > 0}$

end

$\boldsymbol{O_j, U_j} \leftarrow$resolving the LMI-optimized Problem

$\boldsymbol{d_j \leftarrow U_j^{-1} O_j}$

end

for $\boldsymbol{j} \in \{\boldsymbol{1}, \boldsymbol{2}, \dots, \boldsymbol{m}\}$do

for $\boldsymbol{y} \in$E do

$\boldsymbol{G_j(y) \leftarrow f^{-(y-d_j)^S U_j^S U_j (y-d_j)}}$

end

end

for $\boldsymbol{y} \in$E do

calculate the required outcome $\boldsymbol{X_c \leftarrow j}$

improve the upcoming LMI constraint to the LMI system,

$\boldsymbol{[\beta\ *\ X_c - G^S(By + A)\ J\ ] > 0}$

end

B, A ← resolving the LMI optimization problem through IoT-ESDM

As evaluated in Equation 10, the mapping function has been computed. While m is the class number and h is the class index, m indicates the class number. Finally, determine u_j and d_j in the preceding part and B and A in the subsequent part to construct fuzzy emotional recognition classification.

System parameters can't be easily identified in the classifier since the classifier is built with 19 inputs and at least five criteria. It utilized the approach of optimizing LMI (linear matrix inequality) in this work. The LMI optimization process is shown in Algorithm 2. The parameters in the next portion are determined once membership functions are identified in the preceding part. In earlier research, the specific descriptions are given [28-30].

Algorithm 2 demonstrated the detection of user emotion using a fuzzy classifier. In the system and control theory, several significant issues may be quantitatively addressed by reformulating them as convex optimization problems using linear matrix inequality constraints (LMIs). There are four main phases in the process of emotional detection. Utilize a fuzzy filtering technique to extract the face area from a histogram, apply a color filter, and perform face component extraction using VFM and histogram analysis methods. Step 2: To extract face features from a face vector, repeat steps 3 and 4. It identifies the vector extracted by the fuzzy classifier in the fourth step of this process. Classifier, step 5: Uncertainty test. Facial features may be correctly recovered from stages 1 and 2 of the process.

3-2- Warning Service

The proposed framework (Figure 5) enables the collection of static and dynamic data from trainees to maintain an updated, real-time model. This model prioritizes critical behavioral features for personalized monitoring, adaptive feedback, and early warning services.

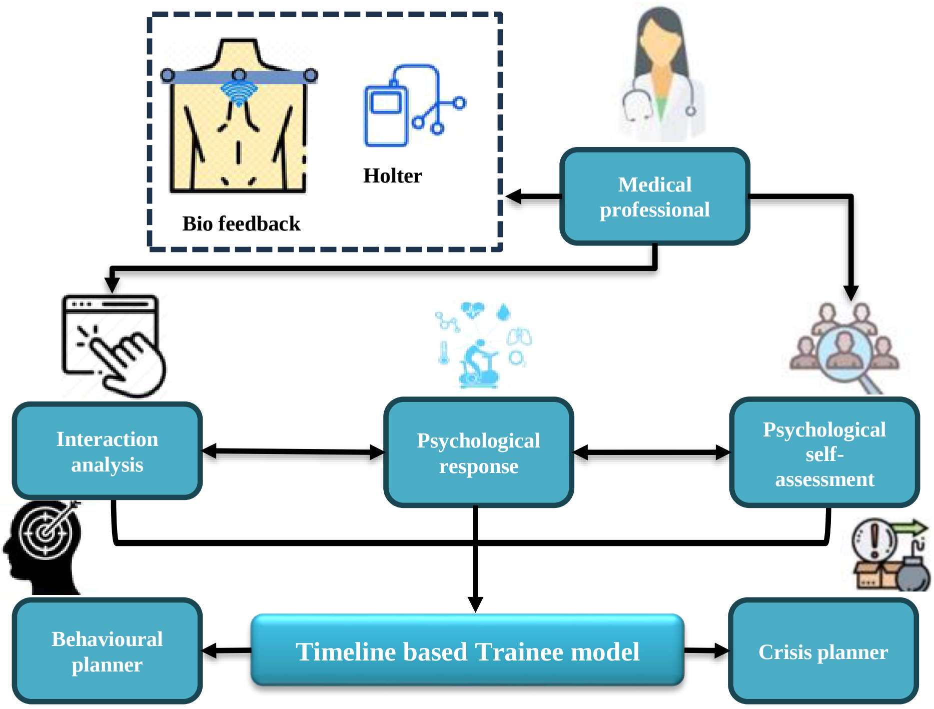

Figure 5. Timeline-based trainee model integrating biofeedback, self-assessment, and interaction data for adaptive behavioral and crisis planning

The system integrates biofeedback, Holter monitoring, and psychological self-assessments, all overseen by a medical professional, to monitor a trainee's physiological and emotional responses throughout the training process. Trainee behavior is assessed through three primary feedback streams: interaction analysis, physiological response, and psychological self-assessment, which feed into a timeline-based behavioral model.

Interaction analysis captures decisions, actions, and communication with group members. This process is partially automated using systems like Pandora and is further enriched through manual annotations made by coaches. Physiological response involves the real-time monitoring of neurophysiological signals, including heart rate variability, stress markers, and anxiety indicators. Meanwhile, psychological self-assessment allows trainees to report their perceived stress or anxiety, which is then compared to baseline values to track emotional adaptation throughout the training session.

These data streams are integrated into two core modules within the model: a behavioral planner and a crisis planner, which support adaptive intervention and real-time performance evaluation. A more detailed view of the model architecture is shown in Figure 5. The system captures interactions between trainees and their environment, including decisions, emotional reactions, and communication with peers or coaches. Some data, such as interface actions or physiological signals, is collected automatically by systems like Pandora, while a coach adds manual annotations during live sessions. These annotations enhance the granularity of feedback during and after training, especially in debriefing phases.

Standardized self-report tools are employed to assess trainee psychological states (e.g., stress and anxiety inventories). For instance, initial levels of leader anxiety are compared against baseline values and tracked over time to assess the effectiveness of training interventions. The model aims to quantify how training affects emotional regulation and self-efficacy, especially under decision-making pressure.

Key physiological indicators monitored within the system include heart rate variability, which is used to detect emotional arousal at decision points; blood pressure, as an indicator of vascular resistance and cardiac stress; ECG rhythms of the atria and ventricles to analyze cardiac cycles; and body temperature, measured through thermal sensors to identify signs of physical stress. These indicators provide real-time insights into the trainee's physiological state, allowing timely intervention and more accurate emotional state assessment. These physiological signals are continuously fed into the timeline-based trainee model, enabling the Behavioral Planner to dynamically adjust the timing, content, and delivery of stimuli. If sudden heart rate or blood pressure spikes occur at critical moments, the system may suggest alternative instructional methods or trigger an alert for review.

The system also integrates data mining techniques such as segmentation, correlation analysis, and association rule learning to uncover meaningful patterns in trainee behavior. For instance, if a specific heart rate pattern (event A) frequently coincides with increased hesitation or delayed decisions (event B), the model can learn to anticipate cognitive overload and trigger appropriate support mechanisms. Examining association rules allows the system to determine that if a transaction contains event B, event A is also likely to occur. This relationship can be included in the transaction. This can be characterized as the value of the assistance.

$$Support_{(B\to A)} = \frac{T_{(B)} \cap T_{(A)}}{T_{all}} \tag{11}$$

As shown in Equation 11, a support value has been formulated. The trust in intelligent, emotional service for older adults can be characterized as follows.

$$Confidence_{(B\to A)} = \frac{T_{(B)} \cap T_{(A)}}{T_{(B)}} \tag{12}$$

As calculated in Equation 12, an IoT-based emotional intelligence service in medical applications has been described. When some events are detected and their laws excavated, rules of the association are established. These rules can be used to provide emotional intelligence services.

3-3- Anxiety Recognition

Two occurrences, B and A, have a combined probability as $\mathrm{Q(B\cap A)}$, whereas their conditions are as $\mathrm{Q(A)}$. Depending on the occurrence of the fixed event A, the probability here shows the occurrence of B. This relationship is possible in Bayes' theorem.

$$\mathrm{Q(A)} = \frac{\mathrm{Q(B\cap A)}}{\mathrm{Q(A)}} \tag{13}$$

The Bayes theorem has been demonstrated as computed in Equation 13. The Bayes theorem offers a combined distribution, probability ratio of several distinct variables, and conditional probabilities. A related $\mathrm{Q(\theta)}$ hypothesis in Equation 14 is supplied in a given dataset for each Y variable in the Bayesian network:

$$\mathrm{Q(Y)} = \frac{\mathrm{Q(\theta)}}{\mathrm{Q(Y)}}\mathrm{Q(\theta)} \tag{14}$$

As inferred in Equation 14, the Bayesian network has been deliberated. The connection between these two probabilities is referred to as the probability ratio.

3-4- Emotion Distraction

Algorithm 3 describes the suggested artificial emotional intelligence algorithm for distraction detection. The first stage is to detect the necessary points at which all the needed points for distracting the subject are recognized at any time $\boldsymbol{s}$ or in any frame $\boldsymbol{E}$ based on the suggested Emotional AI feature Model (Lt).

Algorithm 3 has been utilized to identify the emotional distraction of the user. Step 1 initializes the images, such as N_K, W_K, A_g. These images enter the while loop function for user emotion, whether distracted or not distracted. Step 2, the while loop checks the conditions, such as identifying the position K_s. Step 3: choose the wanted feature model, and Step 4: calculate the AI feature model NK_s. Step 5 is now equivalent to the regular threshold over timeB_s, W_K. Step 6: Take the if-else condition and if $\gamma B_s > o$ If the value exceeds zero, our output indicates the user is distracted; otherwise, we loop back to step 1 and step 2. At this phase, extra calculations are avoided; they are relatively quick. The next stage is to calculate and then determine the fundamental features of the Emotional AI model N_{ks}. The next stage is the calculation with the help of a suggested threshold model. W_k of the difference between the standard threshold values for each $J_i \in K$. The number of accessible points of reference $J_i$is here n at all times s.

$$\gamma B_s = \sqrt{\frac{\sum_{j=0}^{m}(J_i - W_K)^2}{m}} \tag{15}$$

Algorithm 3. Identification of Emotion Distraction

```
Process IDENTIFICATION DISTRACTION (image, N_K,W_K,A_g)
    While the image≠null do
    K_s ←identifyposition(image)
    NK_s ←Choosewantedposition Necessary For Feature Model(K_s,NK_s)
    B_s ←Calculate AI Feature Model NK_s
      B_s ←Equate with regular threshold over timeB_s,W_K
    If γB_s > o then
       Report Distraction
    else
        Continue
    end if
  end while
end process
```

The present value for γB_s and changing the model attribute (ML) is compared with the time restrictions of the behavioral model (B_s), which is chosen to divert from the behavioral model or not. A warning can be generated for a distracting occurrence. The results of distraction detection and departure attribute values are preserved for further processing following distraction and attention detection. The stored data is employed to depict the results statistically. The process continues until no frame is left in the camera module.

Figure 6 illustrates the process flow diagram for user emotion detection in medical applications. The behavioral response, including the impact of time constraints and decision-making, is guided by the behavior model outlined in Algorithm 3. When distraction is detected, a warning signal is triggered. Subsequently, the results of distraction detection, along with corresponding attribute values, are stored for further analysis and statistical evaluation. This process continues until all frames within the input video stream have been processed. The system calculates periods of user attention and inattentiveness for each frame, enabling a continuous assessment of emotional engagement over time.

By extending this approach, the IoT-ESDM framework enhances the ability to monitor user or patient engagement, resulting in improved feedback delivery, system accessibility, detection accuracy, classification performance, anxiety rate monitoring, and overall health outcomes.

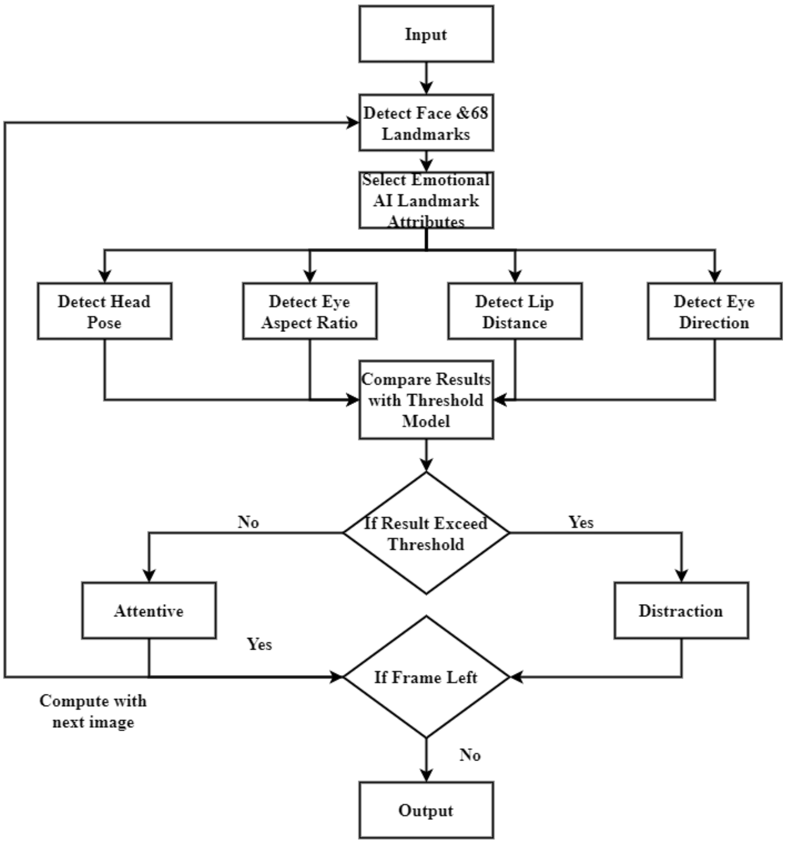

Figure 6. **Process Flow Diagram of Emotion Detection**

4- Results and Discussion

This section addresses the challenge of recognizing and forecasting specific human behaviors using facial cues, such as distraction and attention loss. The proposed algorithm detects changes in visual attention by analyzing selected facial landmarks. Since not all landmarks directly relate to behavioral shifts, the model focuses on key facial features that most accurately characterize distraction. Once changes in these features are identified, the Emotional AI model compares them against predefined thresholds to evaluate behavioral variation. Over time, these changes are assessed to determine the user's attention level, and a secondary threshold model is employed to confirm the presence of attention deficiency.

A comparative analysis was conducted to evaluate the performance of the proposed model against several existing methods, including MLT, Wavelet Packet Transform (WPT), cochlear model (CM), Facet-level approach (FLA), and Health Knowledge Graph Builder (HKGB). The evaluation was performed using a dataset of 100 users, and the results are visualized with the X-axis representing individual users across performance metrics such as detection accuracy, attention span estimation, and classification reliability [38].

4-1- Feedback Ratio

The application layer encompasses multiple user-facing components such as websites, management systems, mobile applications, and micro-web platforms. It facilitates the administration of web pages, IoT integration, skill development, program coordination, and healthcare information management. These immersive interfaces provide users with interactive environments, allowing them to navigate virtual spaces while receiving audiovisual cues based on their surroundings and daily routines.

A key function of the application layer is to capture and interpret patient feedback, which is a vital indicator of the effectiveness and quality of healthcare services. Feedback from patients offers valuable insight into what aspects of care are performing well and highlights areas requiring improvement. This process enhances the patient experience and supports healthcare providers in refining service delivery.

For physicians, patient feedback is essential for understanding patient satisfaction and identifying improvement opportunities. Well-structured questionnaires are a crucial tool for systematically collecting this feedback.

The application layer interfaces with IoT technologies and employs visualization tools to deliver real-time feedback, particularly for home care services, bridging gaps between traditional healthcare systems and modern service models. The 3D bar chart compares the feedback ratio (%) for five models—IoT-ESDM, HK-GB, FLA, WPT-CM, and MLT—across varying numbers of users (from 10 to 100). As the number of users increases, IoT-ESDM consistently achieves the highest feedback ratio, indicating superior performance in user interaction or satisfaction. The other models show comparatively lower and more fluctuating feedback percentages. The steep rise of IoT-ESDM bars highlights its scalability and effectiveness. Overall, IoT-ESDM outperforms all other techniques in handling user feedback efficiently. Moreover, the system enables dynamic alignment between patient demand and service supply, promoting efficiency and responsiveness. As shown in Figure 7, the framework achieves a patient feedback response rate of 97.54%, demonstrating high engagement and reliability in outcome assessment.

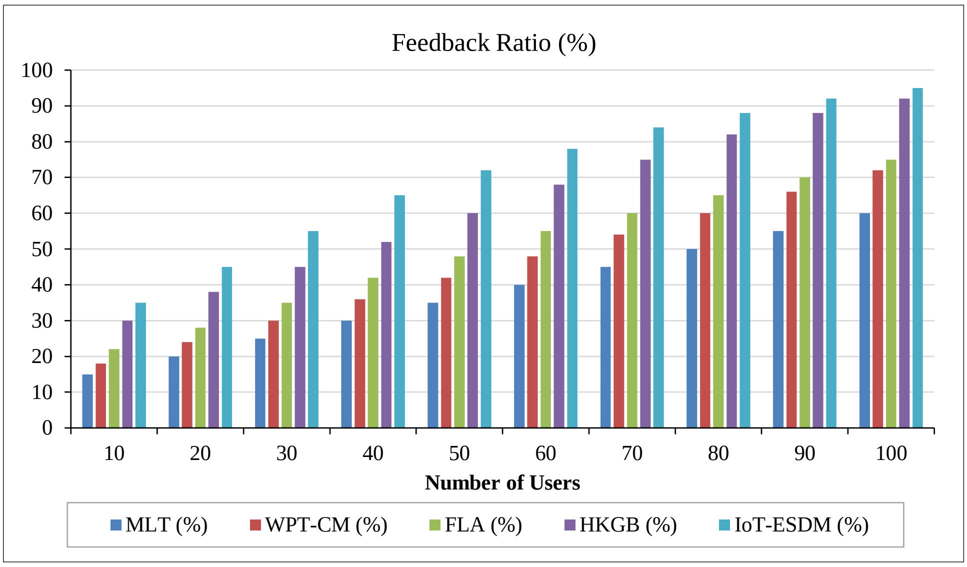

Figure 7. Feedback Ratio

4-2- Accessibility Ratio

Ensuring accessibility for all patients, including those with visual impairments or disabilities, is a critical objective of modern healthcare systems. The proposed framework supports this goal by incorporating IoT-enabled atmospheric monitoring and life-support systems designed to enhance the health and well-being of older adults and individuals with special needs. These systems provide web-based access and mobile application interfaces that support remote healthcare management, real-time communication, and assistive diagnostics. The chart illustrates that IoT-ESDM achieves the highest accessibility rate (%) across all user levels compared to other models. This indicates its superior reliability and user access performance under varying user loads.

The application layer, including IoT infrastructure and user interfaces, leverages IT and visualization technologies to deliver rapid feedback on home care needs. Core functions include two-way data transmission over Internet Protocol (IP) networks, facilitating seamless control between users, devices, and healthcare services. In this ecosystem, patients and their families can place service orders online, which are fulfilled through coordinated, door-to-door service delivery. Post-service reviews can be submitted through the management platform or mobile application, enabling a feedback-driven service model. As shown in Figure 8, the system achieves a high accessibility ratio of 95.3%, indicating that most users, regardless of age, ability, or technological literacy, can successfully engage with the platform. This performance surpasses other models, emphasizing the inclusivity and usability of the IoT-ESDM framework.

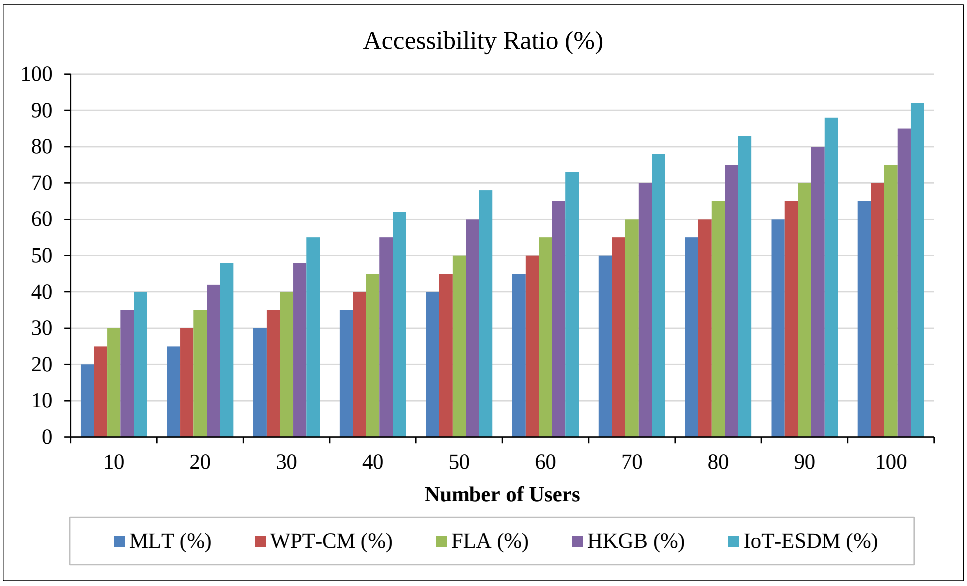

Figure 8. Accessibility Ratio (%)

Additionally, the integration of affective computing allows the system to interpret and simulate emotional states, fostering empathetic interactions between patients and digital assistants. Trained AI agents can assess whether reported symptoms require immediate medical attention or a consultation with a physician, offering a preliminary triage layer. This emotional intelligence layer provides patients with a sense of human-like empathy, whether used at home or in clinical settings, ultimately reducing the burden on healthcare professionals and improving the quality of care.

4-3- Detection Ratio

The proposed IoT-ESDM model continuously monitors input images to detect real-time attentive and distracted behavior. This distraction detection approach has wide applicability, particularly in medical settings, where recognizing a patient's level of attention can aid in improving diagnosis, treatment adherence, and care outcomes.

Performance evaluations of the proposed system demonstrate its ability to recognize behavioral deviations across multiple levels of scrutiny. The model can identify subtle changes in facial expressions that diverge from baseline significance thresholds. Even under supervised classification of real-time image streams, the algorithm successfully detects distraction-related anomalies. This capability is especially valuable in healthcare, where early detection of symptoms often leads to better outcomes, particularly in conditions like cancer, where timely diagnosis significantly increases the chances of survival. Delayed detection, by contrast, can lead to more complex treatments, poorer prognoses, and increased costs.

The overall emotion detection process in the IoT-ESDM framework involves a structured sequence of steps. First, histogram analysis combined with fuzzy filtering is applied to extract the facial region from the input image. Next, a Virtual Face Model (VFM) and histogram analysis apply a color filter, allowing precise isolation of key facial components. Following this, the system extracts a face feature vector, which is then classified using a fuzzy classifier. Finally, a fuzzy classification test determines the user’s emotional state. Notably, the first two steps ensure accurate extraction of facial components, serving as the foundation for reliable and consistent emotion recognition.

As shown in Figure 9, the face image analysis algorithm achieved a detection accuracy of 92.7%, demonstrating strong performance in identifying emotional and attentional states. This precision supports its use in preventive healthcare, where early detection enables timely interventions, lifestyle changes, or surveillance, even before symptoms appear. The IoT-ESDM system promotes proactive health management and improves patient outcomes by continuously monitoring subtle behavioral cues.

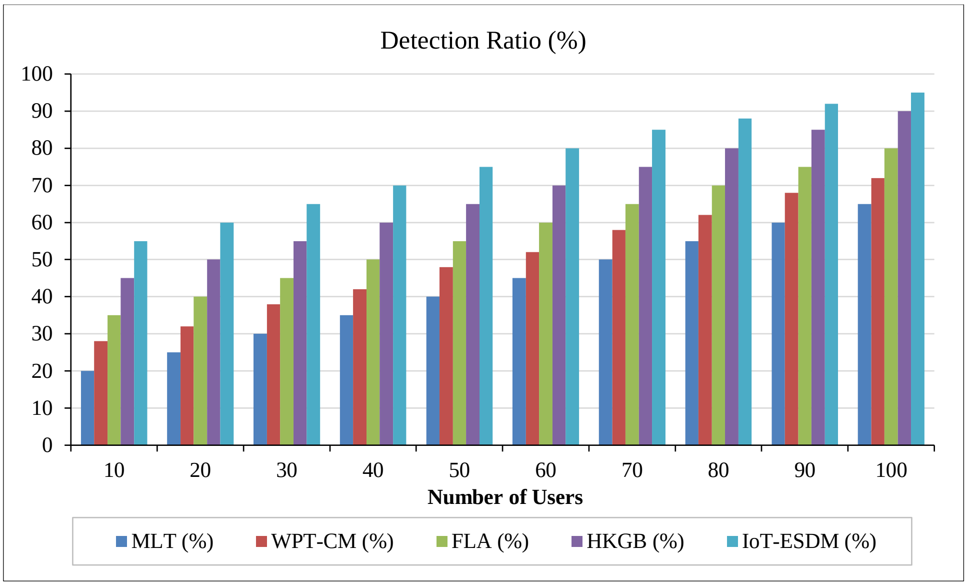

Figure 9. Detection Ratio (%)

4-4- Classification Accuracy Ratio

The proposed approach employs facial landmarks for alignment and utilizes these features for real-time distraction detection. Model-defined thresholds are applied to determine deviations in attention levels, enabling the system to analyze video streams without requiring manual intervention or motion-based classification techniques. Unlike traditional methods, the proposed technique does not require additional training data or classification layers.

The method integrates calibration curves and utilizes an emotion AI-based model as a classifier and threshold evaluator. This combination results in a detection precision of 96.76%, verifying the model's reliability in identifying real user behavior. Distraction detection accuracy is computed as shown in Equation (16), by calculating the ratio between the number of frames where the model identifies distraction and the actual number of distracted frames:

$$Accuracy = \frac{Total\ number\ of\ images\ where\ subject\ is\ found\ distracted\ by\ model}{Actual\ Distracted\ images} \tag{16}$$

Experimental results demonstrate that the classification accuracy of the proposed method reaches 95.3%, outperforming several existing techniques. Figure 10 illustrates the average eye aspect ratio (EAR) across video frames, highlighting attention and fatigue level fluctuations, particularly during increased blinking frequency and eye closure events. Accurate detection is critical in medical contexts, as clinicians rely on test results to select appropriate treatments, often basing up to 70% of medical decisions on diagnostic findings. As such, the accuracy and precision of AI-driven classification tools directly impact healthcare quality, making robust emotion and attention detection systems vital for improving patient monitoring and care outcomes.

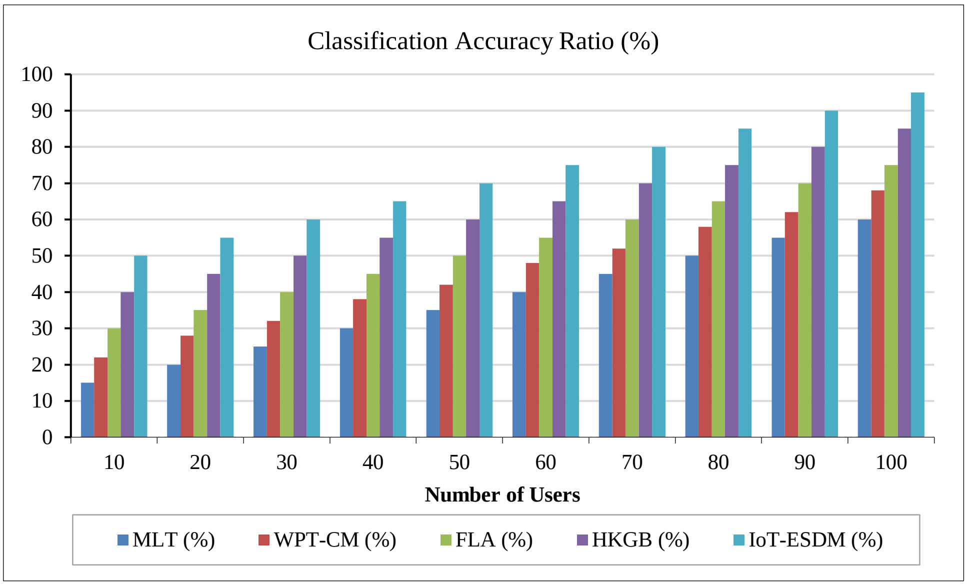

Figure 10. Classification Accuracy Ratio (%)

4-5- Quality Assurance Ratio (%)

Quality assurance ensures systems consistently deliver safe, effective, and timely care. The proposed IoT-ESDM framework integrates assistive technologies and intelligent monitoring to uphold high service standards across clinical and home care environments. The chart reveals that IoT-ESDM achieves the highest classification accuracy ratio (%) across all user groups. This indicates its strong capability in correctly identifying emotional states compared to other methods.

Central to this assurance process is IoT-enabled sensors, which monitor environmental conditions (e.g., air quality), physiological signals, and behavioral cues in real time. These inputs allow the system to detect anomalies, such as poor air conditions or signs of patient distress, and generate timely alerts, enabling rapid intervention. This continuous feedback loop enhances patient care reliability, safety, and responsiveness. The system also supports ambient assisted living (AAL) applications, helping older adults and vulnerable individuals maintain independence while proactively addressing any deviation from safe conditions. Features like real-time service reviews, automated alerts, and threshold-based diagnostics allow healthcare providers to maintain consistent service quality and compliance with care protocols.

As shown in Figure 11, the proposed model achieves a quality assurance ratio of 94.13%, outperforming traditional methods. This high score reflects the system's effectiveness in consistently detecting care-related risks and maintaining service reliability across different use cases. The IoT-ESDM model contributes to healthcare quality assurance by providing real-time monitoring, automatic issue detection, and immediate feedback mechanisms score components for improving patient outcomes and reducing system-level errors.

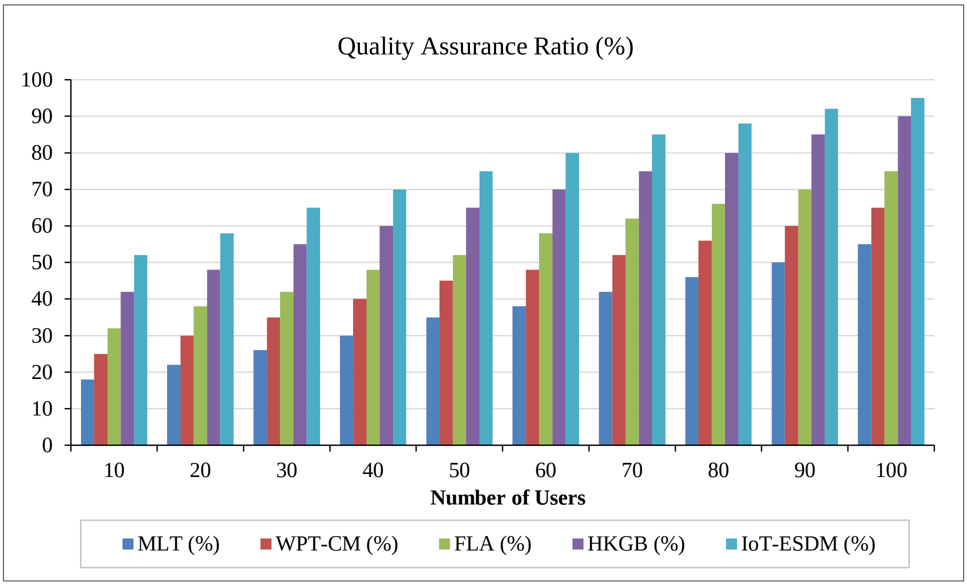

Figure 11. Quality Assurance Ratio (%)

4-6- Anxiety Rate (%)

Anxiety is a critical factor in assessing user comfort and emotional stability, especially in technology-assisted healthcare environments. It is typically categorized into two types: trait anxiety, which reflects a person's predisposition to respond with anxiety across situations, and state anxiety, which arises in response to specific, immediate stressors.

The proposed IoT-ESDM framework is designed to mitigate both forms by continuously monitoring physiological and environmental indicators, including heart rate variability, eye movement (ocular events), and ambient conditions such as temperature and humidity. These data streams are processed in real time to assess emotional states and adjust system responses accordingly, providing users with a more supportive and adaptive environment. This feedback-driven mechanism effectively reduces anxiety through environmental regulation and personalized interactions, whether implemented in home settings or clinical care. The system actively recognizes potential stress signals and simulates emotionally intelligent responses, helping users feel supported and safe.

As shown in Table 2, the IoT-ESDM model achieves consistently lower anxiety rates across all user samples when compared with traditional models such as MLT, WPT-CM, FLA, and HKGB. Notably, for a sample size of 100 users, IoT-ESDM records an anxiety rate of 29.1%, significantly lower than the 47.8% to 66.1% range observed in other methods. This outcome validates the model's effectiveness in minimizing psychological stress, making it well-suited for emotionally sensitive applications in digital healthcare.

Table 2. Comparison of anxiety rates (%) across different methods and user groups

Number of Users	MLT	WPT-CM	FLA	HKGB	IoT-ESDM
10	55.3	66.1	43.8	51.3	35.2
20	56.1	65.8	44.2	53.5	35.4
30	56.3	65.6	45.3	53.9	34.5
40	56.8	65.1	45.6	54.1	34.6
50	57.3	64.3	45.7	55.2	33.8
60	57.5	64.1	46.5	55.6	31.6
70	57.6	62.8	47.2	54.3	31.8
80	57.9	62.4	48.5	54.8	31.9
90	48.2	62.0	48.8	52.8	30.7
100	47.8	61.5	49.3	51.6	29.1

4-7- Health Outcome Ratio

Health outcomes are influenced by how effectively individuals engage with feedback systems that monitor behavior, provide motivation, and encourage consistent self-management. As shown in Figure 12, the proposed IoT-ESDM framework integrates behavior, motivation, engagement, and information in a continuous loop, ultimately improving clinical and lifestyle outcomes.

Wearable devices and IoT-enabled sensors play a vital role in this process. They allow for real-time physiological and behavioral data monitoring, delivering personalized feedback that can prompt early interventions, which is particularly useful for managing chronic conditions and supporting elderly patients. Elements such as gamification, activity tracking, and peer-based challenges can further motivate users to stay engaged and improve their health-related behaviors.

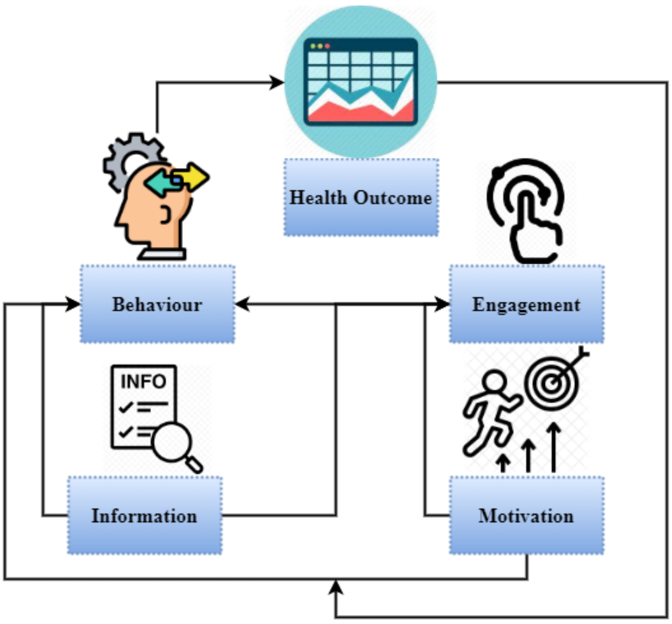

Figure 12. Health Outcome Ratio

The IoT-ESDM model leverages these principles by providing timely, individualized insights, empowering users to take an active role in their well-being. It also enhances data interpretation through emotional analytics and threshold-based classification, making it more responsive than conventional models.

As presented in Table 3, the IoT-ESDM method consistently achieves the highest health outcome ratios across all user groups. For example, at 100 users, it records a health outcome ratio of 94.5%, significantly outperforming MLT (65.2%), WPT-CM (51.3%), FLA (68.3%), and HKGB (65.6%). This demonstrates the system's effectiveness in translating behavioral engagement into measurable clinical improvements.

Table 3. Health Outcome Ratio (%) comparison across models

Number of Users	MLT	WPT-CM	FLA	HKGB	IoT-ESDM
10	45.3	31.4	56.4	32.4	76.2
20	47.5	35.6	59.2	36.5	78.4
30	49.4	39.4	63.5	38.5	79.8
40	54.1	44.8	69.4	42.3	81.9
50	59.6	38.2	57.6	49.8	83.5
60	62.8	42.3	59.4	51.1	85.8
70	66.9	48.5	61.2	54.4	88.6
80	69.3	53.1	63.4	58.6	92.1
90	62.7	55.5	62.1	62.3	93.4
100	65.2	51.3	68.3	65.6	94.5

5- Conclusion

This research introduces IoT-ESDM, an intelligent emotional computing framework designed to detect and manage anxiety-related behavior through IoT-enabled sensors, facial analysis, and threshold-based emotion classification. The system provides personalized, context-aware support in healthcare settings by combining real-time physiological monitoring with adaptive emotional modeling. The framework serves as a robust foundation for mobile health (mHealth) applications, enabling the collection of behavioral and biometric data while enhancing user engagement, satisfaction, and loyalty. Its use of commercially available components ensures cost-effective deployment without compromising performance. Integrating human input with automated detection achieves an overall accuracy of 90%, validating the system's reliability and responsiveness.

Experimental results further confirm the effectiveness of IoT-ESDM, which outperforms existing models across key performance metrics: a feedback ratio of 97.54%, accessibility ratio of 95.3%, detection accuracy of 92.7%, classification accuracy of 98.13%, quality assurance score of 94.13%, and a notably low anxiety rate of 29.1%. The system also achieves a health outcome ratio of 94.5%, underscoring its impact on emotional regulation and well-being. These findings establish IoT-ESDM as a high-performing, user-centered emotional health solution. Future work will explore integrating electrooculogram (EOG) signals and developing semi-immersive, portable environments to deepen emotional immersion and expand usability across domains.

6- Declarations

6-1- Author Contributions

Conceptualization, S.P. and B.S.; methodology, D.A.; validation, D.A. and S.M.; formal analysis, M.V.; investigation, D.A. and S.P.; resources, K.S.M.A. and S.P.; data curation, D.A. and S.P.; writing—original draft preparation, K.S.M.A. and S.M.; writing—review and editing, M.V. and B.S.; visualization, M.V. and B.S.; supervision, D.A. and S.P.; project administration, D.A and S.P. All authors have read and agreed to the published version of the manuscript

6-2- Data Availability Statement

The data presented in this study are available in the article.

6-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6-4- Institutional Review Board Statement

Not applicable.

6-5- Informed Consent Statement

Not applicable.

6-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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