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Designing an Emotion Recognition and Visualization Feedback System for High-Pressure Workplace Users

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ABSTRACT
This paper presents a user-centered feedback system that leverages artificial intelligence (AI) for emotion recognition and visualization, specifically designed for users in high-pressure workplaces. The system integrates multimodal emotion detection and a tree-shaped visual metaphor to help users understand and reflect on their emotional states in real time. By combining affective computing, interactive design, and empirical evaluation, the study highlights how AI can enhance emotional self-awareness (ESA) sustainably and engagingly.

KEYWORDS
Emotional self-awareness; AI emotion recognition; Workplace stress; Emotion visualization; User-centered design

1 Introduction

Modern workplaces expose employees to continuous psychological demands that can lead to chronic stress, fatigue, and emotional imbalance. When sustained, these conditions undermine well-being, decision-making, and productivity [1]. Although organizations have begun to emphasize emotional health through workshops, counseling programs, and wellness platforms, many employees find existing approaches inconvenient or ineffective in providing timely and personalized feedback. Emotional self-awareness (ESA), the ability to recognize, understand, and interpret one's emotions, plays a central role in maintaining psychological resilience [2]. However, methods for cultivating ESA often depend on deliberate self-reflection, which may not align with the pace and pressure of contemporary work environments.

Conventional ESA tools such as journaling or mood-tracking applications encourage self-monitoring but typically provide delayed insights. Their effectiveness relies heavily on consistent user engagement, which tends to diminish over time. As a result, users rarely receive the kind of immediate emotional feedback necessary to regulate stress dynamically. In contrast, artificial intelligence (AI) and affective computing offer a new paradigm in which systems can interpret emotions from behavioral and physiological cues in real time. This technological shift enables more interactive and adaptive support for users who struggle to maintain awareness of their emotional states during demanding tasks.

Based on these developments, this research introduces an approach that links AI-driven emotion recognition with a visual feedback tool, referred to here as the Emotion Tree. The system interprets facial expressions and voice tones to detect emotions automatically and then maps these states onto an evolving tree interface. Leaf color and shape indicate users' daily emotional variations, with green representing positive states, withered tones representing negative states, and transitional colors representing mixed moods. The aim is not only to visualize emotions but also to foster self-reflection through an intuitive and aesthetically engaging experience (Ghandeharioun et al., 2019). By merging emotional intelligence with interactive design, this study seeks to explore how AI-driven visualization can enhance awareness and emotional regulation among high-pressure workplace users.

2 Literature review

2.1 Tools for emotional self-awareness

Over the past decade, researchers have developed diverse methods to support emotional self-awareness. Common approaches include mood journals and check-in applications [3], structured questionnaires [4], counseling-based feedback systems [5], and wearable sensors that track physiological signals [6]. These tools encourage reflection but often rely on self-reporting, which introduces bias and inconsistency. Users may underreport negative emotions or abandon tracking altogether, resulting in fragmented emotional records and limited long-term benefits [7].

2.2 Complexity of emotional data

Emotions are multifaceted, dynamic, and influenced by situational context. Capturing them through static or single-modality approaches frequently oversimplifies human experience. Mauss and Robinson [8] argue that emotional processes evolve across time and are shaped by cognitive, social, and physiological factors. Systems that fail to accommodate this complexity often produce feedback that feels disconnected from lived experience. For high-pressure environments, where emotions fluctuate rapidly, this lack of adaptivity reduces the usefulness of existing ESA tools.

2.3 Visualization as a reflective approach

Visualization has emerged as a promising strategy to make emotional data more accessible and meaningful. By translating invisible emotional processes into visual representations, users can reflect more easily on their experiences. Prior research has explored emotion heatmaps, animated avatars, and abstract symbols as vehicles for emotional reflection. For instance, Cernea [9] created "emotion-prints" that respond dynamically to user interaction, while Qin [10] proposed HeartBees, a visualization of collective emotional states. Such interfaces encourage curiosity and awareness but often remain limited by device constraints or lack of interactivity. Most importantly, few studies explore how visual representation can foster long-term emotional reflection and behavioral change.

2.4 AI and affective computing

AI-driven emotion recognition offers new opportunities for developing responsive ESA systems. Using multimodal inputs such as facial micro expressions, voice tone, and speech patterns, AI models can identify emotions with increasing precision. Ghandeharioun [11] demonstrated the potential of integrating AI into wellness applications, showing that real-time recognition fosters user engagement and self-understanding. Yet, much of the existing research has focused on improving algorithmic accuracy rather than on designing meaningful user experiences. The challenge, therefore, lies in combining technical precision with empathic and human-centered feedback that encourages active self-reflection.

2.5 Research gap

Although affective computing has advanced in technical accuracy, many studies still focus more on algorithmic optimization than on user experience. Many researchers focus on improving recognition accuracy and multimodal data fusion [12], yet they pay little attention to how emotional feedback is communicated to users in a way that encourages understanding or self-reflection. As a result, many AI-based systems act mainly as diagnostic tools, giving emotion labels with little context or explanation. This limits their impact on emotional self-awareness and long-term behavioral change.

In addition, visualization-oriented studies often highlight aesthetic novelty instead of usability and sustained engagement. Interactive designs that initially attract attention frequently fail to maintain users' interest once the novelty fades. There is a lack of empirical evidence on how visualization can be used as an ongoing reflective tool to support emotional regulation in daily life. Similarly, most emotional tracking systems rely on specialized sensors or high user effort, making them difficult to integrate into ordinary workplace routines. These limitations reduce the practicality and inclusiveness of emotional self-awareness technologies.

The gap identified in this research lies in the absence of a lightweight, user-centered system that combines AI-based emotion recognition with intuitive, real-time visual feedback. Such a system should not only detect emotional states but also help users interpret and reflect on them in a visually meaningful and accessible way. The Emotion Tree system proposed in this study addresses this need by merging accurate emotional recognition with interactive design principles. Rather than treating emotion as data to be measured, this system views it as a dynamic experience to be understood, making emotional awareness a more engaging and sustainable part of daily work life.

3 Research questions and objectives

3.1 Research questions

(1) How can AI-based emotion recognition enhance workplace users' awareness of stress-related emotions?
(2) How does tree-shaped visualization encourage users to reflect continuously on their emotions?
(3) What measurable improvements in ESA can be observed when comparing this system to traditional methods?

3.2 Research objectives

(1) To integrate video-based multimodal emotion recognition (facial expression and speech).
(2) To design an interactive visualization system using a "Emotion Tree" model.
(3) To evaluate the system's effectiveness in enhancing emotional self-awareness.

The objectives are meant to show how new technology can be shaped around the needs and experiences of people, rather than just focusing on technical progress. By focusing on how users perceive, interpret, and respond to emotional feedback, the study seeks to demonstrate that AI technology can enhance human reflection rather than replace it. Through a balance between recognition accuracy and empathetic visualization, the proposed system intends to help users understand their emotions in a more engaging and sustainable way.

4 Methodology

4.1 User research

This study begins with a combination of online surveys and semi-structured interviews that target employees working in high-pressure sectors such as information technology, finance, and education. These methods are designed to explore participants' emotional experiences, coping strategies, and expectations for digital emotional support. The insights gathered from this stage will guide the system's design requirements and ensure that the proposed solution aligns with users' real-world needs rather than theoretical assumptions.

4.2 AI Emotion recognition

The AI component of the system analyzes both video and audio input to infer users' emotional states. Facial expressions are processed using convolutional neural networks (CNNs), while speech-related features such as pitch, tone, and rhythm are analyzed through recurrent neural networks (RNNs). Extracted data are categorized into emotion labels such as happiness, stress, calmness, or fatigue. These classifications are then mapped to visual changes within the system interface. The goal is to achieve an optimal balance between accuracy and responsiveness, enabling smooth updates that reflect users' changing emotions in real time.

4.3 Visualization and interaction design

High-fidelity prototypes will be created using Figma and Unity. The Emotion Tree visualization serves as a central metaphor for emotional states. As emotions fluctuate, the tree's leaves vary in color, size, and density. Positive emotions promote growth and vibrant colors, while prolonged stress causes the leaves to appear dull or withered. Users can interact by observing daily changes or reviewing their emotional history. This design encourages self-reflection without requiring users to manually input data. It also relies on natural metaphors of growth and change to create a more empathetic connection between users and their emotions.

4.4 Experimental evaluation

To evaluate system effectiveness, participants will be divided into two groups.

- The experimental group will use the AI-based visualization system daily.
- The control group will use traditional journaling for emotional reflection.

Both groups will complete standardized ESA questionnaires before and after the intervention (Mazefsky et al., 2021). Quantitative data will be analyzed using paired t-tests and ANOVA to detect significant changes in self-awareness levels. Qualitative data will be collected through post-experiment interviews to capture user perceptions and feedback. The evaluation will focus on engagement, ease of use, emotional insight, and overall satisfaction.

4.5 Ethical considerations

All participants will provide informed consent before participating in the study. Data privacy will be protected through anonymization and secure digital storage. Video and audio recordings will be used only for emotion recognition analysis and will not be shared with third parties. Ethical review approval will be obtained prior to data collection to ensure full compliance with institutional and academic standards.

5 Expected contributions

This research is expected to make both theoretical and practical contributions. On the theoretical side, this work adds to the conversation in affective computing by pointing out how reflection and visual methods can play a role in supporting emotional self-awareness. While much of the existing literature focuses on recognition accuracy, this study highlights how interaction design and visualization can transform emotion detection into a process that encourages understanding and self-growth. It contributes to the ongoing conversation about how AI technologies can support, rather than replace, human emotional intelligence.

From a practical perspective, the Emotion Tree system introduces a scalable and accessible model that can be integrated into workplace wellness programs, mobile applications, or digital counseling tools. The system brings together AI emotion recognition and simple visual feedback so that employees can keep track of their feelings on a daily basis without needing to put in much extra effort. It provides real-time insights that can help users recognize patterns of stress or fatigue early and take proactive steps to manage them.

The findings of this study can also inform designers, developers, and mental health practitioners about the potential of merging data-driven systems with emotionally meaningful interfaces. This integration may guide the creation of future tools that are not only efficient but also empathetic and psychologically supportive. In summary, this work seeks to demonstrate that emotional technology can be humanized through thoughtful design, creating a bridge between artificial intelligence and emotional well-being in the modern workplace.

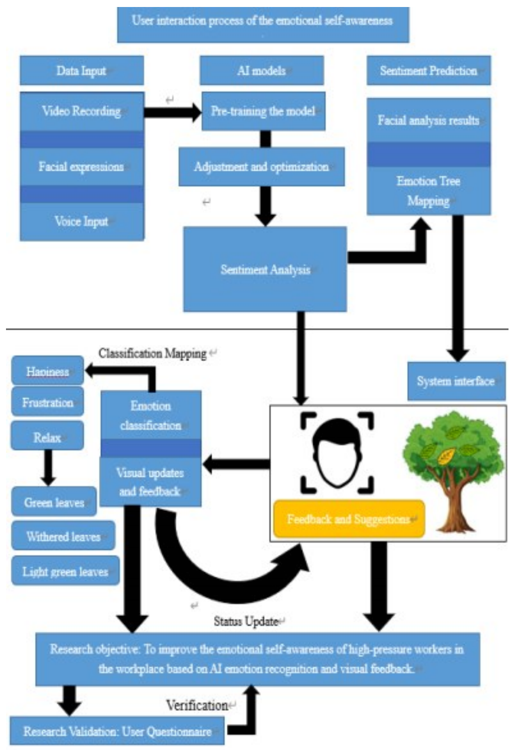

Figure 1

6 Technical route

This study collects emotional data through video and voice input, analyzes and classifies it using AI models, visualizes the results through the "Emotion Tree" feedback system, and verifies the effectiveness via user questionnaires to enhance emotional self-awareness in the workplace.

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