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Enhancing User Experience for Real-Time Panic Attack Detection with Wearable Technology: A Human-Computer Interaction Approach with Machine Learning Integration

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ABSTRACT

Panic attacks are sudden and debilitating episodes of intense fear, often accompanied by physiological symptoms such as increased heart rate, irregular heart rhythms, and shortness of breath. Early detection and timely intervention can significantly improve the management of panic disorder. This paper presents a human-computer interaction (HCI) focused approach to real-time panic attack detection using wearable devices that monitor physiological signals. The system uses data such as heart rate (HR), heart rate variability (HRV), blood oxygen saturation (SpO2), and electrocardiogram (ECG) to predict panic attacks. A machine learning model, incorporating algorithms such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), is employed to analyze these signals and detect abnormal patterns indicative of a panic episode. The study prioritizes the user interface design and interaction experience, ensuring the system is user-friendly, discreet, and provides timely alerts and coping strategies. A six-month clinical trial with participants diagnosed with panic disorder demonstrated the feasibility of real-time monitoring and detection. Results show promising accuracy in detecting panic attacks, while user feedback indicated high satisfaction with the device's usability and effectiveness in real-world scenarios. This research contributes to the growing field of wearable technology in mental health by integrating machine learning with a focus on improving user experience.

1. Introduction

Panic disorder is a pervasive mental health condition characterized by recurrent and sudden panic attacks, which are intense episodes of fear and anxiety. These episodes manifest through a range of physiological symptoms, including increased heart rate, shortness of breath, dizziness, and chest pain, which can have a profound impact on daily life. Managing these attacks effectively is a challenge, as they often occur unpredictably and without warning. Traditional treatment methods, such as

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cognitive-behavioral therapy and pharmacotherapy, are effective in long-term management but do not offer real-time support during acute panic episodes. This gap in immediate intervention highlights the need for innovative solutions that can provide real-time detection and assistance.

Wearable technology has emerged as a promising avenue for real-time health monitoring, offering continuous tracking of physiological metrics such as heart rate (HR), heart rate variability (HRV), blood oxygen saturation (SpO2), and electrocardiogram (ECG). These signals are closely linked to the body's autonomic response during panic attacks, making them valuable indicators for early detection. In recent years, wearable devices have advanced significantly, enabling continuous data collection in everyday environments without intruding on the user's routine. This makes wearable technology a viable tool for detecting physiological changes that precede or accompany a panic attack, providing opportunities for timely intervention.

In this research, the primary focus is on integrating Human-Computer Interaction (HCI) principles to design an effective and user-friendly panic attack detection system using wearable technology. The core objective is to develop an intuitive interface that minimizes cognitive load and delivers clear, actionable alerts to users during high-stress situations. The system is designed to ensure that users receive timely notifications and coping mechanisms, such as breathing exercises or guided relaxation techniques, without overwhelming them. The interaction design plays a critical role in the success of the system, as users need to trust and engage with the device, particularly during moments of heightened anxiety.

To support real-time detection, machine learning models such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) are employed to analyze physiological signals and identify patterns that are indicative of a panic attack. While machine learning is essential for detecting these patterns, the emphasis of the research remains on creating a seamless and engaging user experience. By applying HCI principles, the system not only detects panic attacks but also ensures that users are supported with personalized and context-aware interactions, making the technology accessible and effective for individuals with panic disorder.

Through a six-month clinical trial, the system was evaluated with participants diagnosed with panic disorder. Continuous monitoring of their physiological data allowed us to assess the system's accuracy in detecting panic attacks and gather feedback on the overall user experience. The results demonstrate the potential of wearable technology to assist in the real-time management of panic disorder, highlighting the importance of user-centered design in mental health technologies. This research aims to bridge the gap between real-time physiological monitoring and effective, user-friendly interventions, offering a novel approach to managing panic attacks through wearable technology.

2. Related Work

Wearable technology has become a significant area of research in the healthcare domain, particularly for real-time monitoring of physiological states. Early efforts in this field focused on the use of wearables for fitness tracking and general health metrics, such as heart rate, step count, and sleep patterns. As wearable devices evolved, they expanded into more specialized areas of health monitoring, including mental health, where physiological signals are closely linked to emotional states. These advancements have led to the exploration of wearable devices for anxiety and stress management, particularly through the monitoring of heart rate variability (HRV), which reflects autonomic nervous system activity and is often used as a stress indicator. [1]

In mental health applications, real-time monitoring of physiological data like HR and HRV has shown promise in detecting changes in emotional and physiological states related to anxiety and panic attacks. Research in this area typically relies on continuous monitoring of these metrics to detect deviations from baseline, which could indicate an oncoming panic attack. Machine learning algorithms have been increasingly integrated into these systems to improve accuracy in detecting panic episodes. These algorithms, such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), are trained to recognize complex patterns in physiological data that may be indicative of panic attacks. This has allowed for more precise detection compared to traditional methods. [2-3]

One major focus of recent studies is the development of interventions triggered by real-time detection. Wearable devices, equipped with sensors to capture physiological changes, provide immediate feedback to users when a panic episode is detected. The feedback mechanisms often include prompts for calming techniques such as deep breathing exercises, mindfulness activities, or other cognitive-behavioral interventions. These interventions are typically delivered through notifications, haptic feedback, or auditory signals designed to guide the user through managing the panic attack. The integration of these features aims to empower users by providing them with tools to control their symptoms in real-time, rather than relying solely on long-term therapeutic approaches. [4-5]

Human-Computer Interaction (HCI) plays a pivotal role in ensuring the success of these wearable systems. The design of the user interface and interaction experience is critical, especially in high-stress situations like a panic attack. Studies emphasize the need for interfaces that are simple, intuitive, and non-intrusive, as users are likely to have reduced cognitive capacity during a panic episode. Additionally, the importance of personalization in these systems has been highlighted, as individuals may respond differently to various interventions. Personalized feedback and adaptive interfaces, which adjust to the user’s preferences and physiological responses, are key areas of exploration in HCI for mental health. [6-7]

There has also been significant research on user acceptance and adherence to wearable devices in mental health applications. Usability and comfort are essential to ensuring that users continuously engage with the system over time. Wearables need to be discreet and non-disruptive to daily activities while offering consistent and accurate monitoring. Users have expressed a preference for systems that offer seamless integration into their routines, with minimal interaction required unless necessary. The ability of a system to predict panic attacks and provide timely, actionable alerts without overwhelming the user is central to the success of such technologies. [8-9]

Recent developments in wearables also explore multi-modal approaches, where data from multiple sensors—such as heart rate, skin conductance, and movement—are combined to increase the reliability of panic attack detection. While single-sensor systems have been successful, multi-sensor approaches allow for richer datasets that can improve the performance of machine learning models.[10] However, these approaches come with challenges, such as balancing power consumption and ensuring real-time data processing without compromising the user’s experience. [11-12]

Overall, the convergence of wearable technology, machine learning, and HCI has led to significant advancements in the real-time management of mental health conditions like panic disorder. This body of work provides a foundation for the continued development of systems that not only detect panic attacks but also deliver meaningful, user-friendly interventions.

3. Methodology

This section outlines the design and implementation of the panic attack detection system using wearable technology, focusing on Human-Computer Interaction (HCI) and machine learning integration. The methodology ensures the system is user-friendly, adaptive to individual users, and effective in real-time detection and intervention.

A. Participants and Data Collection

A total of **100 participants** diagnosed with panic disorder were recruited for the study. The participants, aged 18 to 60, were diverse in terms of gender and background. Each participant was provided with a wearable device capable of collecting physiological data, including heart rate (HR), heart rate variability (HRV), blood oxygen saturation (SpO2), and electrocardiogram (ECG). Data was collected over a **six-month period**, during which participants wore the device during their daily activities.

Participants were asked to log any panic attacks manually via a connected mobile application. These logs were used to label panic episodes in the physiological data. Non-panic periods served as control data for machine learning models. All data was securely stored on a cloud server for further processing.

B. Physiological Metrics Used

Heart Rate (HR): HR increases during panic attacks due to heightened anxiety. Continuous monitoring provided a baseline for each participant’s normal HR and tracked deviations during panic episodes.

Heart Rate Variability (HRV): HRV, the variability in time between consecutive heartbeats, is a key indicator of autonomic nervous system activity. Low HRV is associated with stress and panic episodes, making it an important metric for detection.

Blood Oxygen Saturation (SpO2): Panic attacks can affect breathing patterns, which in turn may alter SpO2 levels. The wearable device measured SpO2 to help detect changes in respiration.

Electrocardiogram (ECG): Irregular heart rhythms or arrhythmias may occur during panic attacks. The wearable captured ECG data when abnormal HR patterns were detected or when the user manually triggered the feature during an attack.

C. Human-Computer Interaction (HCI) Design

TThe HCI design emphasized simplicity, usability, and real-time support, with the goal of reducing cognitive load during high-stress situations. The following components were central to the system's design:

1. **Alert and Notification System:**
   - **Haptic Feedback:** The system uses gentle vibrations to alert users when abnormal physiological patterns indicative of a panic attack are detected. The vibration strength is adjustable to suit user preferences.
   - **Auditory Cues:** The system provides soft, non-intrusive sound alerts, such as a chime, to notify users of potential panic episodes. The volume and type of sound can be customized by the user.
   - **Visual Notifications:** The wearable screen displays clear, concise notifications in large, easy-to-read text. The interface uses calming colors (blue, green) to reduce anxiety upon receiving an alert.
2. **Dynamic User Interface (UI):**The interface dynamically adapts to the user's interaction and environment to provide a seamless experience during panic events.
   - **Calming Interventions:** The system uses gentle vibrations to alert users when abnormal physiological patterns indicative of a panic attack are detected. The vibration strength is adjustable to suit user preferences.
   - **Simplified Response Options:**If the user does not respond to initial alerts, the system automatically reduces notifications, focusing on passive monitoring until the user engages. This helps to avoid overwhelming the user with multiple alerts during high-stress moments.
3. **User-Defined Panic Attack Thresholds:**To cater to individual differences in physiological responses, users are given control over certain parameters of the system:
   - **Customizable Sensitivity:** Users can adjust the sensitivity of the system's detection algorithm. This allows individuals with varying levels of baseline anxiety or stress to modify the system to suit their unique needs.
   - **Event Threshold Adjustment:** Users can manually adjust the HR, HRV, or SpO2 thresholds at which the system should alert them, tailoring it to their comfort level and ensuring that they are not overwhelmed by false positives.
4. **Context-Aware Interaction:**The system is designed to adapt its responses based on the user's context, such as location, activity, or time of day:
   - **Location Awareness:** The system uses GPS to recognize when the user is in potentially stressful environments (e.g., a crowded place or a known anxiety trigger). In such cases, it offers discreet notifications, such as vibration-only alerts, to avoid drawing unnecessary attention.
   - **Activity Sensitivity:** If the user is engaged in physical activity (e.g., exercising), the system adjusts its thresholds to avoid false alarms due to elevated HR from exercise. The system temporarily adapts to a higher HR baseline during such activities.

- **Time of Day Adaptation:** The system adjusts the style of alerts based on the time of day. For example, it uses dimmed lighting and softer sounds during nighttime to prevent sleep disruption if an alert is triggered.

5. **Intervention and Response System:**
   - **Quick Access to Coping Mechanisms:** After receiving an alert, users can initiate stress-reduction exercises, such as guided breathing or mindfulness, with a single tap. Large buttons and simple instructions make the system easy to navigate during moments of stress.
   - **Minimal Cognitive Load:** The system is designed to require minimal user interaction. Once an alert is triggered, the user can quickly activate an intervention or dismiss the notification with one touch. The interface prioritizes simplicity, avoiding complicated navigation during critical moments.
6. **Personalized Feedback and Interaction:**
   - **Learning from User Patterns:** The system adapts to individual users over time, learning their typical physiological patterns and adjusting alert thresholds to minimize false positives.
   - **Preemptive Alerts:**If the system detects early signs of abnormal physiological patterns but before a full panic attack, it sends preemptive notifications to the user, encouraging them to engage in a calming activity
7. **Post-Attack Reflection:**
   - **Post-Event Summaries:** After a panic attack, the system provides a summary of the event, including physiological data and any user interventions. This allows the user to reflect on the event and identify potential triggers.

D. Human-Computer Interaction (HCI) Design: The system employed machine learning models to detect panic attacks based on the physiological data collected by the wearable devices. Two models were used:

- **Support Vector Machine (SVM):**The SVM was employed to classify physiological data into “panic” or “non-panic” states. The model was trained using HR, HRV, SpO2, and ECG data and was selected for its robustness in handling high-dimensional data.
- **Convolutional Neural Networks (CNN):**The CNN was used to analyze the time-series data collected from the wearable devices, learning patterns in the temporal data that could predict panic attacks. CNNs are well-suited for detecting sequential dependencies in physiological signals.

4. Results

The performance of the wearable-based panic attack detection system was evaluated using both quantitative metrics for machine learning model accuracy and qualitative feedback from participants on the Human-Computer Interaction (HCI) aspects. The results are categorized into the following sections: machine learning model performance, user engagement and feedback, false positive analysis, and system usability.

A. Machine Learning Model Performance

The system employed two machine learning models—Support Vector Machine (SVM) and Convolutional Neural Networks (CNN)—to detect panic attacks based on physiological data. The models were trained and tested on data collected from participants over the first four months of the trial, with the final two months reserved for evaluation. The performance of the models was evaluated using standard classification metrics such as accuracy, precision, recall, F1 score, and false positive rate.

The SVM model achieved an accuracy of **85%** and an F1 score of **0.83**, while the CNN model demonstrated a slightly better performance, achieving an accuracy of **88%** and an F1 score of **0.86**. Both models demonstrated satisfactory performance in distinguishing between panic and non-panic episodes, with the CNN model showing superior results due to its ability to capture temporal dependencies in the physiological signals.

Accuracy: The CNN model was able to correctly classify **88%** of the data, which indicates a high level of precision in detecting true panic events and minimizing the misclassification of normal physiological states as panic attacks. The SVM model's accuracy was slightly lower, at **85%**, but still within an acceptable range for real-time applications.

Precision: Precision for the SVM model was **82%**, meaning that 82% of the detected panic episodes were true positives. The CNN model achieved a precision of **85%**, reflecting a slightly better capability to reduce false positives and ensure that the system alerted users primarily during actual panic episodes.

Recall (Sensitivity): The SVM model's recall was **80%**, while the CNN model achieved a recall of **83%**, indicating that both models were able to capture a significant portion of actual panic events from the data. A recall of this level is important in the context of panic detection, as missing actual panic attacks (false negatives) could undermine user trust in the system.

F1 Score: The F1 score, which balances precision and recall, was **0.83** for the SVM model and **0.86** for the CNN model, further demonstrating the robustness of the CNN in capturing and classifying panic episodes with minimal errors.

False Positive Rate: A key concern in panic attack detection systems is the false positive rate, as frequent false alarms could cause unnecessary stress and reduce user trust. The false positive rate for the SVM model was **12%**, while the CNN model achieved a lower rate of **10%**, indicating that the CNN model was more effective at minimizing unnecessary alerts. This relatively low false positive rate suggests that the system can provide reliable and timely alerts without overwhelming the user with false alarms.

B. User Engagement and Feedback

The integration of SHAP and LIME into the dyslexia screening model provides a deeper understanding of the decision-making processes underpinning the model's predictions. These tools help clarify how each feature influences the model's output, contributing to transparent, trustworthy AI applications in educational and clinical settings.

User Satisfaction: 85% of participants reported overall satisfaction with the system, citing the simplicity and clarity of the user interface as key strengths. The system's unobtrusive nature was particularly appreciated, as most users preferred that the wearable device seamlessly integrate into their daily routines without drawing excessive attention to their condition.

Perceived Accuracy: Participants were asked to rate the accuracy of the system on a scale from 1 to 5, with **5 being highly accurate**. The average score was **4.2**, indicating that users generally trusted the system's ability to detect panic attacks. This is consistent with the high precision and recall values of the machine learning models. Some users mentioned occasional false alarms, but these were largely perceived as tolerable given the system's overall reliability.

Intervention Usefulness: 78% of users found the immediate intervention options (e.g., guided breathing, mindfulness prompts) to be helpful during panic episodes. The ability to access coping mechanisms with minimal effort, particularly through a single touch, was highlighted as a key strength. Users reported that the system's quick response helped them regain control during stressful moments.

Customization and Personalization: 70% of users appreciated the customizable nature of the system, particularly the ability to adjust sensitivity thresholds for panic attack detection. Several participants noted that this flexibility helped them tailor the system to their unique physiological responses, reducing false positives and making the system more responsive to their needs.

C. False Positive Analysis

While the overall false positive rate was relatively low, false alarms were reported by **18%** of participants. The analysis of these cases revealed that most false positives occurred during periods of heightened physical activity, such as exercising or walking up stairs, where HR and HRV naturally increase. Although the system had a built-in adjustment for activity level, some users engaged in activities that closely mimicked the physiological response of a panic attack. To mitigate this issue, future iterations of the system could include more sophisticated activity tracking or context-aware algorithms to better differentiate between physical exertion and panic episodes.

Users reported that false positives were not particularly disruptive due to the system's gentle notification style (vibration and visual cues). However, a few users expressed concern over the potential for anxiety escalation during false alarms. As a result, further refinement of the system's activity adjustment and multi-sensor integration may be beneficial in reducing such occurrences.

D. System Usability

The system's usability was evaluated using the **System Usability Scale (SUS)**, which is a widely used tool to assess the ease of use and overall user experience. The average SUS score was **82 out of 100**, indicating a high level of usability. Key factors contributing to the system's usability included the simplicity of the UI, the minimal cognitive load required to interact with the system, and the clear, non-intrusive design of the notifications.

UI Simplicity and Clarity: Users praised the large, easily accessible buttons and the minimalistic design, which reduced the complexity of interacting with the system during high-stress moments. The color scheme (soothing blues and greens) was well-received, with participants reporting that the interface contributed to a calming effect during panic episodes.

Ease of Accessing Interventions: Users found the one-tap access to interventions, such as breathing exercises, to be intuitive and helpful. The fact that the system required minimal interaction during panic episodes was a significant advantage, allowing users to focus on regaining control rather than navigating complex menus.

Dynamic User Interface: The system's ability to adjust the UI based on context (e.g., dimming alerts at night, reducing visual and auditory distractions during public settings) was particularly appreciated by users. **88%** of participants mentioned that they felt the system's notifications were timely and appropriately discreet, especially in social environments where they preferred not to draw attention to their condition.

5. Conclusion

This research presents the design, implementation, and evaluation of a wearable technology-based system for the real-time detection and management of panic attacks. By integrating physiological data collection through wearable devices with machine learning algorithms, such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), the system demonstrated a high level of accuracy in detecting panic episodes while minimizing false positives. The focus on Human-Computer Interaction (HCI) ensured that the system was not only technically robust but also user-friendly, providing a seamless experience for individuals during high-stress situations.

The system's performance, as reflected in its **88% accuracy** and low **10% false positive rate** (CNN model), indicates that wearable technology can serve as a reliable tool for detecting panic attacks in real time. The real-world usability of the system was further validated through user feedback, with **85%** of participants expressing satisfaction with its functionality, design, and ease of use. Key strengths of the system include the dynamic and customizable user interface, which adapts to the user's physiological state and context, as well as the personalized thresholds that empower users to adjust the system based on their unique needs.

The user-defined panic thresholds and context-aware interaction mechanisms were particularly effective in ensuring that the system remained unobtrusive and supportive during both panic and non-panic states. Furthermore, the system's minimal cognitive load and easy access to interventions, such as guided breathing exercises, provided users with real-time assistance, contributing to a sense of control during panic episodes.

The results indicate that the combination of machine learning and thoughtfully designed HCI can significantly enhance the management of panic disorder. However, while the system demonstrated strong performance, a few areas, particularly the management of false positives during physical activity, warrant further exploration to refine the system's accuracy.

6. Future Work

Despite the success of the system, several areas for improvement and future research were identified. One important area is the refinement of the system's ability to handle false positives. Although the false positive rate was relatively low, some users reported instances of false alarms during periods of physical activity. Future iterations of the system should incorporate more advanced activity recognition algorithms to differentiate between physical exertion and panic attacks. This could involve integrating additional sensors, such as accelerometers and gyroscopes, to provide more accurate insights into the user's movement patterns and physiological state.

Expanding the system's use of multi-sensor data is another area for future work. While the current system relied on heart rate, heart rate variability, blood oxygen saturation, and electrocardiogram data, the addition of metrics such as skin temperature and galvanic skin response (GSR) could further improve detection accuracy. These additional metrics could provide a more comprehensive understanding of the user's physiological response to stress and anxiety, leading to better overall performance.

An important enhancement would be the development of adaptive machine learning models that continue to learn and evolve as the user's physiological patterns change over time. Panic disorder is not static, and users' responses to stress can vary significantly over weeks or months. By incorporating online learning or user-in-the-loop models, the system could adapt to these changes, ensuring that it remains effective in the long term. Future models could also involve more user interaction in refining detection thresholds, allowing for more personalized detection without requiring complete retraining of the system.

User customization is another area where improvements can be made. While the current system allows users to adjust panic attack detection sensitivity, future versions could offer more granular control over specific features, such as customizing alert styles, selecting preferred interventions, or adjusting the system's behavior based on the user's location or activity. Providing more control to users will further enhance the system's relevance and effectiveness in meeting individual needs.

Future studies should also involve larger and more diverse sample sizes, along with longer trial periods, to better evaluate the system's performance across different demographic groups. This would help ensure the system's robustness and generalizability, making it a viable tool for a broader population. Additionally, longitudinal studies would allow for the examination of the system's long-term effects on managing panic disorder and how user interaction with the system evolves over time.

Integration with healthcare platforms is another promising area for future development. The ability to share physiological data with healthcare providers or mental health professionals could enhance personalized care and treatment plans. Future versions of the system could include secure data sharing mechanisms that allow clinicians to remotely monitor patient progress and provide feedback, further expanding the system's utility in clinical settings.

Lastly, future work should explore the incorporation of behavioral and environmental data alongside physiological metrics. Data such as sleep patterns, activity levels, and social engagement could provide additional context for understanding the user's mental health and allow the system to offer more comprehensive support. Incorporating real-time feedback for behavioral modification, such as suggesting stress-reducing activities before a panic episode fully develops, could help users build long-term coping strategies and reduce the frequency of panic attacks.

In conclusion, while the current system has demonstrated its effectiveness, future work should focus on refining detection accuracy, enhancing personalization, and integrating additional data sources to improve its long-term utility in managing panic disorder. These enhancements will contribute to making wearable technology a powerful tool in both personal mental health management and clinical treatment settings.

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