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RESEARCH PAPER

How to design adaptive systems to improve stress management using artificial intelligence

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Abstract

Biofeedback is a technique that relies on measuring bodily functions and providing feedback to the individual so that they can train and control those functions. Artificial intelligence has empowered these systems by making them context-aware, adapting models to users' physiological variations, and providing personalized feedback. However, incorporating AI techniques has opened up new challenges in designing, developing, and evaluating biofeedback systems. In this work, we conducted 25 semi-structured interviews with various specialists in medicine, psychology, human-computer interaction, and computer science to investigate what an AI-based system that considers differences in personal health data should look like. The results helped us answer 'How can we design AI-assisted systems that take into account differences in personal physiological and AI knowledge between individuals to avoid misinterpretations?' by defining six design considerations for biofeedback systems that use AI techniques trained with users' physiological signals. Finally, we discuss how these considerations could help researchers design systems for well-being.

Keywords:

Biofeedback; Sports; Design considerations; Heart-Rate Variability; Machine Learning; Physiological signals.

1 Introduction

Research on biofeedback systems has explored regulating physiological functions to maintain autonomic balance, such as stress management and relaxation training [1, 3, 8]. Biofeedback is considered a technique that enables individuals to learn to monitor their physiological activity to enhance their health and performance. This technique employs specialized instruments to measure various physiological activities, such as brain waves, heart function, breathing, muscle activity, and skin temperature. The gathered data is then provided to the user, facilitating self-awareness and thus enabling targeted improvement [9]. Biofeedback has extended its applications beyond clinical settings, thanks to advancements in biosensors and artificial intelligence (AI) techniques. This allows for unobtrusive and portable data collection, broadening the scope and enhancing the modalities of biofeedback. In addition, innovations in the design of these systems have improved the user experience in biofeedback-assisted learning and training, derived from the use of AI and the implementation of adaptive systems capable of adjusting themselves to users' needs, such as variations among individuals in their physiological signals, contextual variations to which users are exposed, or sensory preferences [6, 7]. Moreover, VR has been effectively used to represent stressful scenarios, providing a controlled environment for stress management and training. However, there are still open questions regarding what considerations are necessary to create technology that promotes physiological and mental well-being using AI techniques.

In this work, we look to answer, 'How can we design AI-assisted systems that take into account differences in personal physiological and AI knowledge between individuals to avoid misinterpretations?' by defining six design considerations obtained based on the analysis of 25 semi-structured interviews conducted for the design and development of an adaptive biofeedback system to reduce stress in American football players. This biofeedback system uses AI techniques to adjust the threshold heart rate variability (HRV) of the session, considering the individual characteristics of each football player. Finally, we conclude with reflections and limitations of our work.

2 Design of an adaptive Biofeedback System

2.1 Participants

Following a user-centered design approach to develop the biofeedback system prototype, we conducted 25 semi-structured interviews (mean = 57 min; sd = 10 min) over five months in Mexico. The objective of these interviews was to gather diverse insights from different stakeholders involved in the context of American football. We conducted 2 interviews with coaches, 13 interviews with American football players (mean age = 19.4 years; SD = 1.27 years) to understand the specific stressors they encounter during training and competition. The footballers had between 1 to 3 years of experience (mean= 2 years; SD = 0.81 years) and belonged to the youth branch of the university (Junior league). Additionally, we aimed to identify the aspects of physiological signals that should be considered to accurately detect stress. For this reason, we conducted 4 interviews with sports psychologists and 4 with clinicians who provided expert opinions on the physiological indicators of stress and the processes of biofeedback therapy. Lastly, 2 psychologists with experience in biofeedback

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sessions were interviewed to gain insights into how an adaptive biofeedback system and a model that adjusts HRV thresholds to individual sessions should be designed. The main topics varied by group, focusing on stress causes and management techniques with athletes and coaches, and on the variation of physiological signals and the customization of biofeedback systems with psychologists and clinicians.

2.2 Data Collection

We conducted remote, one-on-one semi-structured interviews lasting 45 minutes to one hour. The interviews began with questions on which physiological signals best represent stress in athletes, how these variations are considered in feeding an AI model, and how physiological parameters can be adjusted based on performance. We focused on understanding the flow of a traditional biofeedback session to adapt AI techniques for assigning personalized HRV thresholds. The interviewer then shared her screen to present the first prototype, noting participants' initial reactions and asking about specific components. Insights from these interviews guided subsequent design sessions to better align the interface and prototype with biofeedback therapy practices.

2.3 Data Analysis

The interviews were transcribed and analyzed following grounded theory techniques, including the use of open and axial coding [10]. The obtained codes were grouped and organized in an affinity diagram (Figure. 1), which illustrates the key components identified during the analysis. The categories include, diversity of physiological data, encompassing variability in data, demographic diversity, and diversity in physiological signals; Intuitive user interface, ensuring ease of understanding, alignment with clinical models, and clear risk thresholds; Usage of adaptive thresholds, such as assigning thresholds based on HR, HRV, and GSR, adapting sensory stimuli, and employing adaptive algorithms. Additional categories include validation and verification of AI models, user participation, and monitoring and updating AI models. This diagram was integral to the design sessions, guiding the development of the adaptive prototype and highlighting important considerations for designing AI-assisted systems that accommodate differences in personal physiological signals.

3 Results

3.1 Findings and Considerations

The coding of these interviews and expert opinions helped us to identify and design the requirements of an adaptive biofeedback VR videogame. We grouped these requirements into six different design considerations that need to be taken into account during the design and implementation of biofeedback adaptive systems. We next describe each of them (Table 1).

3.2 Adaptive System Design

Based on these considerations, an adaptive biofeedback VR video game was designed, dividing the measured HRV into a scale of 5 stress levels following clinical frameworks in the literature [12]. The video game uses a modification of the visual elements of the video game interface (i.e., timer, crowd sound, coach prompts) to represent the different stress levels (Fig. 2a). In addition to the visual elements shown in the interface, the box breathing exercise, for relaxation, is also shown. For this, we implemented the metaphor of the fogged glasses to imitate how the user should perform the breathing exercises. A binary stress detection model [13] and a set of 15 fuzzy logic rules were used to assign the thresholds.

The main adaptive component that includes artificial intelligence techniques is a tachometer that indicates the HRV detected at the moment; it is constituted by 3 elements: (Figure 2b.1) A dashed line with the assigned threshold for the player; (Figure 2b.2) A light trail that glows when the participant is within the threshold; (Figure 2b.3) The tachometer needle that is manipulated by the HRV obtained in real-time.

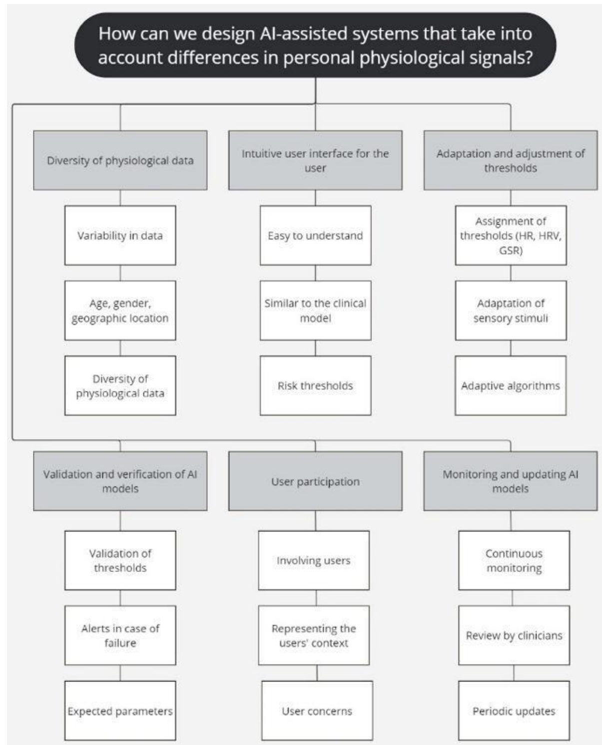

Figure 1 Affinity Diagram

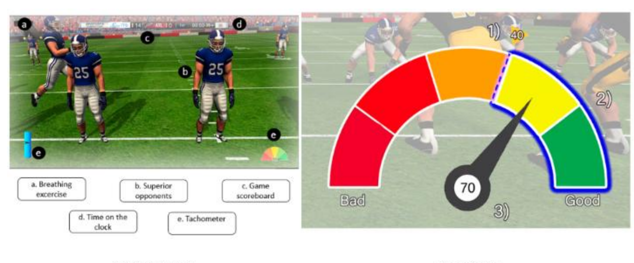

Figure 2 Visual elements and functionality

Table 1. Design considerations

Considerations	Rationale	Representative Quote	Representation
Incorporation of multiple data sources and data diversity	Integration of multiple data sources, such as electronic medical records, wearable device data, genomic data, lifestyle, and behavioral data, to get a more complete and accurate picture of an individual's health. This helps capture a wider range of interpersonal variations. In addition to collecting and using health datasets that adequately represent the diversity of the population in terms of age, gender, ethnicity, geographic location, etc.	"...if you want to make a general system that adapts the thresholds, they would have to take into account different databases to have different levels, for example, the one that always has low pressure, the one that is at the standard or the one that always has high pressure..." Psychologist of biofeedback [#2] "...various physiological databases that bring together a variety of profiles must be taken into account so that the AI model can differentiate between them..." Clinician [#1].	The adaptive model uses a public database containing 17 records from different individuals characterizing physiological signals including ECG, EMG (right trapezius), GSR (galvanic skin resistance) measured at the hand and foot, and respiration.
Intuitive user interface	Codesign intuitive and accessible user interfaces that present information in a clear and easy-to-understand manner for people with different levels of data literacy. This may include simple graphics, clear explanatory text, and options to expand on details or request additional explanations	"... for the user to understand and improve their internal state, they must first understand what they are seeing on screen [referring to their physiological signals], is it right or is it wrong...". Psychologist of biofeedback [#1].	The adaptive biofeedback VR videogame incorporates visual and auditory elements that make it possible to identify the internal state in which the athlete is (score, clock, sound of the crowd, size of the players). In addition to incorporating a tachometer that directly shows the state in which he/she is.
Customization and adaptation	Use customized data modeling techniques that account for intrapersonal and interpersonal variations. This may involve the use of machine learning algorithms that adapt and adjust based on each individual's specific data, rather than applying a one-size-fits-all approach. In addition to enabling customization and tailoring of the interface and recommendations based on individual user preferences and needs, including their level of data literacy. This may involve the ability to adjust the level of detail, or the amount of information presented.	"...just as you were saying a moment ago, the model should be able to adjust the threshold depending on how the user is that day so that each time it adapts to the user's needs..." Sports clinician [#1] "The clinician must have an interface to be able to modify the parameters if necessary". Biofeedback psychologist [#2].	After stress detection, the videogame defines the threshold at which the athlete will perform the session. This threshold is defined through a set of rules implemented in fuzzy logic. Finally, the AI model defines the personalized HRV threshold.
Validation and verification of AI models	Conduct ongoing validation and verification of AI models using diverse and representative data sets. This helps ensure that results are relevant and accurate for a wide variety of people, rather than biased toward a specific demographic group. In addition to incorporating clinical expertise and professional judgment in the interpretation of AI results. AI models can provide valuable information, but healthcare professionals must evaluate and contextualize these results within the appropriate clinical framework.	"...in my opinion, it is always going to be necessary to have a specialist validate this type of system from time to time...." Clinician [#2] "...it would be very good for the doctor to have a platform to check the patient's progress, how to follow up and see that the system is giving the patient the right dose..." Clinician [#1]	The adaptive VR videogame incorporates a platform where the therapist can see the athlete's signals in real-time. These signals map in different colors (red: signal at a dangerous threshold, green: signal at an expected threshold, blue: signal at an optimal threshold).
User participation	Actively involve users in the process of developing and evaluating AI models, allowing them to express their needs, preferences, and concerns. This helps ensure that the results are relevant and useful from the patient's perspective.	"... the first option I like [referring to another possible solution], but the virtual reality simulator I think would help us more because it is the closest to real practice..." American football players [#8] "[following up on what his teammate said] I think the same thing because when we can't attend practice, the virtual reality system could be used at home" American football player [#9].	The entire adaptive VR videogame design involved the users. The design incorporates the most relevant stressors encountered in a football game. In addition, it incorporates relaxation techniques normally used in a game (box breathing). Also to simulate as close as possible to a football game (sounds, crowd, uniforms).

Monitoring and updating AI models	Establishing mechanisms to continuously monitor and update AI models as patient health conditions change, and new data become available. This ensures that results remain relevant and useful over time.	"...yes, again, it would be good to have this platform where the doctor can follow the physiological signals of the user and can update the parameters as needed or even see how this model has performed, that is very important…" Psychologist of biofeedback [#1].	The adaptive VR videogame incorporates a platform where the therapist can see the progress of the athlete, the signals in time, and the threshold assigned by the system, among other variables. This platform allows the therapist to modify the assigned parameters, modify the set of rules if necessary, and start, pause, or stop the session if necessary.

3.2.1 Threshold adaptation of physiological signals using AI techniques

The tachometer component uses a database for training [5, 14]. The data provided already include stress labels and have been used in multiple studies for stress detection [2, 4, 11]. For stress values in the stress column >= 0.5 are labeled as 1, i.e., "stress." For values <0.5, the data are annotated as 0, i.e., "no stress." TPOT library[1], which is an automated machine learning tool that optimizes model selection and hyperparameters. TPOT is initialized to train with a five-fold cross-validation based on 80% of the data and then tests the trained model on 20% of the data. In our case, TPOT was initialized with a population size of 100, and the number of generations was set to 400. This means that TPOT [13] will train 100 models for each generation it iterates.
Finally, TPOT builds a K nearest neighbor channel achieving an F1 score of 0.8103 on the validation set and 0.8060 with cross-validation during training. We chose the F1 score as our primary evaluation metric because it provides a balanced measure of precision and recall, which is particularly important in our context to ensure that both false positives (misclassifying non-stress as stress) and false negatives (failing to detect actual stress) are minimized effectively. If the detection submodule detects that the user is stressed, the threshold definition submodule will calculate the HRV that the user will have to maintain during the session.

The threshold definition submodule uses the scikit-fuzzy library. To select the HRV threshold we developed a Mamdani Fuzzy logic system that maps the HRV to one of the 5 levels of the tachometer (relaxed – green, calm – yellow, neutral – orange, tense – red, stressed – bright red)

4 Conclusions and Future Work

This article addresses the critical question: How can we design AI-assisted systems that consider differences in personal physiological and AI knowledge between individuals to avoid misinterpretations? Additionally, we explore how to ensure that AI output remains relevant despite significant interpersonal variations in personal health data and other relevant factors. Through interviews conducted during the design and development of an adaptive biofeedback system, we gathered insights from American football players, coaches, and experts in medicine, psychology, and biofeedback psychology. Our findings indicate that AI-driven biofeedback systems aimed at improving well-being must accommodate individual user differences, offer intuitive interfaces, adapt models to each user's characteristics, and incorporate continuous monitoring and updates. Involving end-users, clinicians, psychologists, and specialists throughout the design, development, evaluation, and validation process is crucial. Key conclusions include the necessity of adaptive design principles and the importance of stakeholder involvement at every stage. Future work should address performance and liability challenges, such as determining when the AI biofeedback system can operate independently without physician oversight and understanding the legal and ethical implications related to data privacy and user consent.

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