Towards Emotion-Aware VR: Preliminary Results of a Multimodal Biofeedback Approach for Sense of Presence

Jonas G. da Silva Junior[1,2]**, Meryck F. B. da Silva**[1,2,3]**, Melina Mottin**[1,2]
Carolina H. Andrade[1,2]**, Arlindo Rodrigues Galvão Filho**[1,2]

[1]Institute of Informatics – Federal University of Goiás (UFG)
Goiânia – GO – Brazil

[2]Advanced Knowledge Center for Immersive Technologies – AKCIT
Goiânia – GO – Brazil

[3]School of Medical and Life Sciences - PUC Goiás
Pontifical Catholic University of Goiás
Goiânia – GO – Brazil

`juniorgomes601@gmail.com, carolina@ufg.br`

Abstract. *This work-in-progress investigates the application of artificial intelligence (AI) and multimodal biofeedback for emotion recognition and objective validation of the sense of presence in virtual reality (VR). Using synchronized physiological signals, such as eye tracking, electrocardiogram (ECG), and galvanic skin response (GSR) from the VREED dataset, we trained models based on Russell's affective model. Preliminary results indicate that eye-tracking metrics are particularly effective in emotion prediction and also show strong potential for objectively assessing the users' subjective sense of presence. These models are being integrated into the SOFIA Framework as a foundation for adaptive and dynamic virtual environments. Although this stage of the project does not yet include olfactory experiments, the findings provide the basis for future integration of scent delivery to further enhance realism and user immersion. Future work will also explore real-time validation tests, integrate EEG data for deeper analysis, and expand the repertoire of olfactory stimuli.*

1. Introduction

Virtual Reality has evolved to deliver increasingly immersive experiences by integrating multiple sensory modalities. However, olfaction remains often overlooked, despite its proven impact on emotional memory, affective engagement, and sense of presence Niedenthal et al. (2023); Slater et al. (2022). Niedenthal et al. Niedenthal et al. (2023) emphasize that active bodily interaction is essential for compelling virtual experiences, aligning with Slater's concepts of Place Illusion and Plausibility Slater et al. (2022). Yet, a critical gap persists in adaptively integrating olfactory stimuli in response to users' emotional states and presence.

This study addresses this gap by exploring artificial intelligence (AI) applied to multimodal biofeedback—eye tracking, galvanic skin response, and electrocardiogram. These signals provide real-time, objective measures of users' emotional and cognitive

states, directly linked to presence in VR. Eye tracking reflects visual attention and engagement; GSR captures emotional arousal via skin conductance; ECG offers heart rate variability metrics related to stress. Combined, these signals enable continuous and objective evaluation of presence, complementing traditional questionnaires. Computational analysis of these biofeedbacks can accurately capture the emotional and sensory impact of olfactory stimuli, enabling dynamic and personalized VR adaptations to enhance realism and immersion Kim et al. (2020); Ahmad et al. (2023).

1.1. Justification

The combined use of biofeedback and AI can enhance immersive experiences by dynamically adjusting stimuli based on users' emotional responses and perceived presence Riva et al. (2019). Current presence assessments rely mainly on subjective questionnaires, which lack real-time data and are prone to bias. In contrast, physiological biofeedback provides continuous, objective indicators of attention, emotional engagement, and immersion. Despite this potential, few systems integrate physiological data with subjective assessments to evaluate presence comprehensively, highlighting the need for integrated approaches, especially in enhancing olfactory VR experiences where immersion and sensory congruence are key Niedenthal et al. (2023); Slater et al. (2022).

1.2. Main Goals

The main objective of this study is to develop and validate computational models based on AI that can objectively and in real time assess users sense of presence and emotional states through the analysis of multimodal biofeedback signals, including eye tracking, GSR and ECG. More specifically, the study aims to investigate whether olfactory stimuli enhance the perceived sense of presence in virtual reality environments (VRE). By adopting this integrated approach, the research seeks to optimize the immersiveness and personalization of olfactory virtual experiences, while empirically validating the impact of scent on the subjective sensation of "being there" through objective physiological data.

2. Literature Review

Biofeedback signals like eye tracking, GSR, and ECG are effective not only for emotion recognition but also for real-time assessment of presence in VR Adhanom et al. (2023); Ahmad et al. (2023). Eye tracking measures visual attention and immersion; GSR indicates emotional arousal intensity; ECG provides heart rate variability associated with emotional engagement and stress, all closely tied to presence.

The Circumplex Model of Affect Russell (1980) has been widely used in studies of presence and emotion, providing a structured way to connect physiological data with affective dimensions. Recent research also emphasizes the user's active role in sensory perception, particularly olfaction, showing that coherent olfactory stimuli significantly enhance presence in VR Niedenthal et al. (2023); Slater et al. (2022); Archer et al. (2022); Yildirim et al. (2025). Integrating biofeedback with sensory stimuli underscores the need for adaptive systems that maximize emotional immersion and the physical sensation of presence in virtual environments.

3. Theoretical Background

Biofeedback integration in VR is a powerful approach for assessing emotional states and attention objectively Adhanom et al. (2023). Eye tracking correlates strongly with cognitive and emotional states Adhanom et al. (2023), while GSR and ECG provide physiological indicators of arousal and stress Kim et al. (2020); Ahmad et al. (2023). Advanced machine learning algorithms, like deep neural networks, enable accurate real-time emotional classification using these signals Ahmad et al. (2023).

Building on this framework, Russell's Circumplex Model of Affect Russell (1980) is particularly useful because it organizes emotions along two fundamental dimensions: *valence* and *arousal*. In psychology, *valence* refers to the intrinsic attractiveness or aversiveness of an event, object, or situation—ranging from positive (pleasant) to negative (unpleasant) emotional states—while arousal denotes the intensity of emotional activation. Together, these dimensions facilitate computational interpretation and adaptive responses in real time.

4. Proposed Methodology

This study builds upon computational models previously developed and trained using the VREED dataset Tabbaa et al. (2021), which provides synchronized measurements of eye tracking, GSR, and ECG, collected during immersive experiences in 360-degree VR videos. These models have already demonstrated effectiveness in predicting emotional states and levels of presence through multimodal analysis of users physiological signals.

In this phase of the project, the goal is to conduct empirical validation of the previously obtained results by collecting our own data in practical experiments with real users. For this purpose, we will employ the infrastructure of the Sensorial Olfactory Framework Immersive with AI (SOFIA) project, which enables dynamic integration of olfactory stimuli into virtual environments, synchronized with visual and sensory interactions.

Experiments will be conducted using proprietary devices for real-time physiological biofeedback acquisition. For eye-tracking data collection, the Apple Vision Pro device will be used, taking advantage of its high precision in capturing eye movements and metrics related to visual attention. Galvanic skin response will be recorded using specialized devices for skin conductance monitoring, widely used to assess levels of emotional arousal. Heart rate variability data (ECG) will be obtained via smartwatches, which allow for non-invasive and continuous measurement of emotional states and stress levels.

In each experimental session, users will be exposed to virtual scenarios specifically designed to stimulate sensory perception, including olfactory stimuli congruent with the presented visual content. Immediately after each session, participants will complete the Igroup Presence Questionnaire (IPQ) to obtain a subjective measure of the experienced sense of presence.

The collected physiological data will undergo the same preprocessing protocol adopted during the initial model training (missing value imputation, normalization, and relevant feature extraction). Subsequently, the data will be used to evaluate and validate the predictive capacity of the models previously trained with the VREED dataset, verifying whether the physiological metrics captured by our own devices are consistent with the earlier results.

Finally, the validated models will be integrated into the SOFIA Framework, enabling dynamic adaptation of olfactory stimuli and real-time adjustments within the virtual environment, aiming to maximize the sense of presence and emotional immersion. Results will be analyzed using quantitative metrics such as accuracy and F1-score, and will be interpreted through the SHAP technique (SHapley Additive exPlanations) Lundberg and Lee (2017), ensuring transparency and interpretability of the conclusions drawn.

4.1. Comparative Performance of Models

The evaluation of five classifiers — K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Logistic Regression, SGDClassifier, and Multilayer Perceptron (MLP) — on the test set (188 samples, 47 per class, corresponding to the four affective categories: high-valence/high-arousal, high-valence/low-arousal, low-valence/high-arousal, and low-valence/low-arousal) revealed significant performance differences. revealed significant performance differences. Table 1 summarizes the results, with Accuracy and F1-score consistently reported as percentages, while MCC is shown as a unitless coefficient.

Table 1. Performance comparison of classifiers on the test set (188 samples).

Model	Accuracy (%)	F1-score (%)	MCC
K-Nearest Neighbors (k=5)	65.0	65.0	0.53
Logistic Regression	63.3	63.0	0.51
Support Vector Machine (RBF kernel)	70.7	71.0	0.61
SGDClassifier	53.2	53.0	0.48
Multilayer Perceptron (MLP)	87.2	87.0	0.83

The results demonstrate that the MLP neural network achieved the best performance, with 87.2% accuracy, 87.0% F1-score, and an MCC of 0.83. The MLP architecture consisted of three dense layers with 256, 128, and 64 neurons, applying batch normalization and 30% dropout. This configuration enabled robust nonlinear pattern recognition among the 64 physiological variables. In contrast, the SGDClassifier showed the lowest performance, while SVM with RBF kernel presented competitive results compared to classical models like Logistic Regression and KNN.

4.2. Attribute Importance Analysis (SHAP)

To interpret the models' decisions, we applied SHAP (SHapley Additive exPlanations)Lundberg and Lee (2017), an Explainable Artificial Intelligence (XAI) technique. SHAP enables the decomposition of model predictions into feature contributions and can be combined with different AI models to increase their interpretability. The analysis revealed that eye-tracking data were the most relevant for emotional prediction. Variables such as the variability of microsaccade peak velocity (SD_Microsac_Peak_Vel), the number of microsaccades (Num_of_Microsac), and the maximum saccade amplitude (Max_Saccade_Length) emerged as the most impactful predictive features. In contrast, ECG and GSR signals showed complementary importance. Parameters such as the mean and minimum RR intervals (Mean_RR, Min_RR) and the mean skin conductance level (Mean_GSR) had lower average influence on predictions but were useful for distinguishing specific classes, particularly at the extremes of emotional arousal. For example, microsaccades played a key role in distinguishing low arousal and negative valence states,

while the amplitude of voluntary saccades was more influential for detecting high-arousal and positive-valence emotions.

These findings support the hypothesis that oculomotor behavior is directly linked to the users' level of attention and engagement—factors fundamental to constructing a strong sense of presence in VR experiences. Meanwhile, autonomic signals reflect physiological changes associated with affective states such as arousal and relaxation, providing an additional layer of emotional information that complements the general interpretation of the users' state. The results obtained, particularly with the MLP model, demonstrate high predictive accuracy, suggesting its potential for affective monitoring in immersive environments. However, the feasibility of deploying this model in real-time applications depends on the computational resources available. While the present study validates the predictive capacity of the model offline, assessing its performance in real-time scenarios remains a direction for future work.

4.3. Hypothesis Validation

The results reinforce the central hypothesis: the use of AI with multimodal biofeedback not only accurately classifies emotional states but also provides a foundation to quantify and enhance, in practice, the sense of presence. The superiority of the MLP model and the clear dominance of eye-tracking signals suggest that sensory immersion and visual engagement are pillars for adaptive olfactory virtual reality systems.

5. Discussion

The integrated use of multimodal biofeedback with AI can significantly enhance the quality of immersive experiences by dynamically adjusting sensory stimuli based on users emotional states Riva et al. (2019). The lack of systems that fully explore this approach justifies the development of this research.

Our findings are consistent with previous studies Adhanom et al. (2023); Ahmad et al. (2023); Kim et al. (2020), reaffirming that physiological metrics captured through biofeedback, especially eye tracking, are extremely valuable for emotional prediction in VR. The integration of these models into the SOFIA framework enables the exploration of "enactive olfaction," where olfactory stimuli proactively adapt to the user's emotional states, thereby enhancing the sensory and emotional coherence of the virtual environment Niedenthal et al. (2023); Slater et al. (2022).

Furthermore, our models provide valuable insights into the most relevant physiological variables, facilitating the future personalization of immersive virtual experiences. This capability may have a significant impact on therapeutic, educational, and digital wellness applications Steed et al. (2023); Lopes and Falk (2024); Pratviel et al. (2024).

6. Conclusion and Future Work

This study demonstrates the potential of AI-driven models to classify emotional states using multimodal biofeedback, highlighting the relevance of oculomotor behavior and GSR in predicting presence and engagement in VR. The integration of these models into the SOFIA framework represents an important step toward adaptive and responsive immersive environments.

Our findings reaffirm the value of physiological signals, particularly eye tracking and GSR, not only in emotional prediction but also as objective indicators for validating users' sense of presence within immersive experiences. By correlating biofeedback data with subjective reports, the system gains a robust mechanism to assess and enhance immersion quality, ensuring a more coherent and emotionally resonant VR experience.

Ongoing work focuses on implementing these models in real-time systems and validating their effectiveness through user experiments. Although the present stage does not yet include olfactory input, the results provide a foundation for integrating adaptive scent delivery in future phases of the project. These future experiments will assess emotional responsiveness and the influence of scent on perceived presence by correlating physiological signals—such as eye movements and GSR variations—with subjective measures of engagement and realism.

Future directions also include incorporating electroencephalographic (EEG) data to enhance emotional modeling, expanding the repertoire of olfactory stimuli to enrich personalization, and deepening the analysis of GSR dynamics during emotional transitions. This integrative approach holds significant promise for creating adaptive, emotionally engaging VR experiences, with impactful applications in digital health, education, therapy, and entertainment.

References

Adhanom, I. B., MacNeilage, P., and Folmer, E. (2023). Eye tracking in virtual reality: A broad review of applications and challenges. *Virtual Reality*, 27(2):1481–1505.

Ahmad, Z., Rabbani, S., Zafar, M. R., Ishaque, S., Krishnan, S., and Khan, N. (2023). Multilevel stress assessment from ecg in a virtual reality environment using multimodal fusion. *IEEE Sensors Journal*, 23(23):29559–29570.

Archer, N. S., Bluff, A., Eddy, A., Nikhil, C. K., Hazell, N., Frank, D., and Johnston, A. (2022). Odour enhances the sense of presence in a virtual reality environment. *PLoS ONE*, 17(3):1–20.

Kim, J., Park, J., and Park, J. (2020). Development of a statistical model to classify driving stress levels using galvanic skin responses. *Human Factors and Ergonomics in Manufacturing & Service Industries*, 30(5):321–328.

Lopes, M. K. S. and Falk, T. H. (2024). Audio-visual-olfactory immersive digital nature exposure for stress and anxiety reduction: A systematic review on systems, outcomes, and challenges. *Frontiers in Virtual Reality*, 5.

Lundberg, S. M. and Lee, S.-I. (2017). A unified approach to interpreting model predictions. In *Advances in Neural Information Processing Systems (NeurIPS)*, volume 30, pages 4765–4774.

Niedenthal, S., Fredborg, W., Lunden, P., Ehrndal, M., and Olofsson, J. K. (2023). A graspable olfactory display for virtual reality. *International Journal of Human-Computer Studies*, 169:102928.

Pratviel, Y., Bouny, P., and Deschodt-Arsac, V. (2024). Immersion in a relaxing virtual reality environment is associated with similar effects on stress and anxiety as heart rate variability biofeedback. *Frontiers in Virtual Reality*, 5.

Riva, G., Wiederhold, B. K., and Mantovani, F. (2019). Neuroscience of virtual reality: From virtual exposure to embodied medicine. *Cyberpsychology, Behavior, and Social Networking*, 22(1):82–96.

Russell, J. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, 39:1161–1178.

Slater, M., Banakou, D., Beacco, A., Gallego, J., Macia-Varela, F., and Oliva, R. (2022). A separate reality: An update on place illusion and plausibility in virtual reality. *Frontiers in Virtual Reality*, 3:914392.

Steed, A., Archer, D., Izzouzi, L., Numan, N., Shapiro, K., Swapp, D., Lammiman, D., and Lindeman, R. W. (2023). Immersive competence and immersive literacy: Exploring how users learn about immersive experiences. *Frontiers in Virtual Reality*, 4.

Tabbaa, L., Searle, R., Bafti, S. M., Hossain, M. M., Intarasisrisawat, J., Glancy, M., and Ang, C. S. (2021). Vreed: Virtual reality emotion recognition dataset using eye tracking and physiological measures. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 5(4):1–20. Article 178.

Yildirim, M., Globa, A., Gocer, O., and Brambilla, A. (2025). Digital smell technologies for the built environment: Evaluating human responses to multisensory stimuli in immersive virtual reality. *Building and Environment*, 271:112608.