

Beyond Frequency Bands: Toward a Representation-Centric Paradigm for Next-Generation EEG-Based Emotion Recognition

Mahdi Jafari Asl^{1,2,3}, Sina Shamekhi^{1,2,3*} 

¹ Faculty of Biomedical Engineering, Sahand University of Technology, Sahand New Town, Tabriz, Iran

² Biomedical Engineering Research Center, Sahand University of Technology, Sahand New Town, Tabriz, Iran

³ Brain Mapping Laboratory, Faculty of Biomedical Engineering, Sahand University of Technology, Sahand New Town, Tabriz, Iran

*Corresponding Author: Sina Shamekhi

Received: 31 July 2026 / Accepted: 31 August 2026

Email: shamekhi@sut.ac.ir

Abstract

Electroencephalography (EEG)-based emotion recognition has become a key enabling technology for affective computing, Mental Health Assessment (MHA), Brain–Computer Interfaces (BCIs), and human–machine interaction (HMI). However, many existing systems continue to rely on predefined frequency bands and handcrafted spectral features, limiting their ability to capture the complexity of emotional brain dynamics and generalize across individuals and recording conditions. In this editorial, we advocate a shift toward a representation-centric paradigm in which adaptive signal conditioning, Self-Supervised Learning (SSL), multimodal integration, and physiological knowledge jointly support learning Neuro-Semantic EEG Representations (NSERs). Rather than replacing spectral information, this perspective embeds it within richer neural representations that preserve temporal dynamics, neurophysiological relevance, and semantic interpretability. We further propose a conceptual framework that positions these representations as the foundation for more robust, explainable, and transferable EEG-Based emotion recognition systems. Finally, we highlight key research priorities and translational opportunities that may accelerate the development of clinically relevant affective neurotechnologies.

Keywords: Electroencephalography -Based Emotion Recognition; Electroencephalography Processing; Neural Representation Learning; Self-Supervised Learning; Cross-Subject Generalization; Multimodal Learning; Neurophysiological Interpretability.

1. Introduction

Emotion recognition from Electroencephalography (EEG) has become an important interdisciplinary research area spanning biomedical engineering, affective computing, and artificial intelligence. By directly measuring neural electrical activity, EEG offers a unique window into the neurophysiological mechanisms underlying human emotions and has enabled applications in Brain–Computer Interfaces (BCIs), adaptive Human–Machine Interaction (HMI), Mental Health Monitoring (MHM), and neurotechnology. Despite these advances, a fundamental mismatch remains between the dynamic, distributed, and context-dependent nature of emotional brain activity and the representations employed by many existing EEG analysis pipelines. Although emotional responses emerge from complex neural interactions that vary across individuals and contexts, EEG signals are still frequently represented using predefined frequency bands or handcrafted spectral descriptors [1-6]. Traditional EEG-Based emotion recognition has largely relied on handcrafted features extracted from conventional EEG frequency bands, such as spectral power, differential entropy, coherence, hemispheric asymmetry, and other time–frequency descriptors [7-9]. Although these features have provided valuable insights into neural oscillations and affective states, relying on them as primary representations may limit current pipelines' ability to capture the temporal dynamics, spatial interactions, and inter-subject variability underlying emotional processing. Recent advances in Deep Learning (DL) and Representation Learning (RL) therefore motivate a shift from identifying informative handcrafted features to learning neural representations that preserve the dynamic, spatial, and physiologically meaningful organization of emotional brain activity [9, 10].

Publicly available benchmark datasets, including DEAP, SEED, DREAMER, and AMIGOS, have accelerated methodological development by enabling reproducible performance comparisons [9, 11-13]. However, substantial differences in experimental protocols, including stimuli, emotion annotations, acquisition systems, electrode configurations, preprocessing pipelines, and participant characteristics, can significantly influence learned

representations and reported performance. Consequently, strong performance on a single benchmark should not be considered evidence of robust or generalizable neural representations of emotion.

Unlike recent review articles that summarize advances in SSL, multimodal fusion, and foundation models for EEG analysis, this editorial offers an integrated conceptual perspective. We propose that these developments can be organized around a common goal: learning neural representations that preserve electrophysiological structure while supporting affective interpretation and generalization across individuals and contexts. From this perspective, self-supervised learning, multimodal alignment, foundation models, and physiological constraints represent complementary mechanisms for developing and validating such representations. This framework provides a conceptual basis for the next generation of EEG-Based emotion recognition without treating these methodologies as isolated research directions.

2. Beyond Accuracy: Generalization and Physiological Validity

The widespread use of benchmark datasets has shifted evaluation toward classification accuracy, often at the expense of cross-subject generalization, interpretability, and physiological validity. However, high accuracy alone does not guarantee generalizable or physiologically meaningful neural representations. Future EEG-Based affective computing should therefore prioritize cross-subject, cross-session, cross-dataset, and real-world validation [10].

3. Limitations of Current EEG-Based Emotion Recognition Approaches

Frequency-domain analysis has been fundamental in EEG research, with classical frequency bands and features such as band power, entropy, asymmetry, and coherence widely used for emotion recognition [1-3]. However, emotional states cannot be fully represented by isolated oscillatory components, as they arise from complex interactions among brain networks, temporal dynamics, and individual variability. Therefore, future EEG-Based affective neuroscience research should

move beyond conventional frequency representations by integrating spectral information with richer temporal, spatial, connectivity, and multimodal neural representations.

3.1. Inter-Subject Variability

Inter-individual variability remains a major challenge in EEG-Based affective modeling [2, 14]. Differences in brain structure, cognitive strategies, attention, fatigue, and psychological characteristics can lead to distinct neural responses to the same emotional stimulus. Therefore, achieving robust generalization across unseen individuals requires models that explicitly account for subject variability [10, 15].

3.2. Limited Temporal Modeling

Emotions are dynamic processes rather than static events, yet many EEG-Based approaches rely on predefined temporal windows and handcrafted features. Such representations often fail to capture the transient and long-range temporal dynamics that shape affective states [4, 15].

3.3. Cross-Dataset Generalization

Many EEG-Based affective intelligence models perform well on individual benchmark datasets but show limited generalization across datasets. Variations in acquisition hardware, electrode configurations, preprocessing pipelines, experimental protocols, and participant populations introduce domain shifts that hinder cross-dataset transfer. Therefore, future models should learn robust neurophysiological representations that generalize beyond dataset-specific characteristics [5, 10].

3.4. Interpretability Challenges

Although spectral features are physiologically interpretable, their link to complex emotions remains indirect. This challenge is further amplified by Deep Neural Networks (DNNs), whose abstract latent representations are often difficult to interpret. Consequently, high predictive accuracy does not necessarily reflect meaningful neurophysiological representations of emotion [1, 7].

4. Emerging EEG Processing Paradigms

To address these limitations, the field is gradually shifting toward more comprehensive representation-driven approaches.

4.1. Representation Learning

DL has enabled hierarchical RL from raw or minimally processed EEG signals [1, 14, 16]. While modern architectures such as convolutional, recurrent, attention-based, and hybrid architectures capture complex spatiotemporal patterns, greater complexity alone does not guarantee generalizability or physiological interpretability. Future progress depends on learning robust, transferable, and interpretable neural representations [6, 15].

4.2. Self-Supervised and Contrastive Learning

The limited availability of large-scale, well-annotated EEG datasets remains a major challenge [1, 17]. SSL offers a promising alternative by leveraging unlabeled data to learn transferable neural representations. Among SSL approaches, Contrastive Learning (CL) has attracted particular attention by encouraging consistent representations of different views of the same EEG signal while separating unrelated samples. However, these methods depend on diverse pretraining data, effective learning objectives, and rigorous cross-dataset validation [18, 19].

4.3. Neuro-Semantic Representations

We define NSER as a conceptual and evaluative framework for EEG representations that jointly consider three objectives: (i) preservation of essential electrophysiological dynamics, (ii) alignment with interpretable neurophysiological and affective concepts, and (iii) transferability across subjects, sessions, and related affective tasks. These objectives have been addressed individually in previous work through self-supervised and CL, physiological constraints, semantic or cross-modal alignment, and domain-invariant learning. Thus, NSER does not claim these properties as individually novel; rather, it emphasizes their joint consideration as criteria for meaningful and transferable EEG representations.

In practice, NSER-oriented models could combine these existing strategies within a multi-objective framework while validation would extend beyond classification accuracy to assess neural-information preservation, semantic or physiological interpretability, and cross-subject/session/task transfer. NSER is therefore proposed as an organizing framework for integrating and evaluating these complementary objectives, rather than as a new standalone learning algorithm.

4.4. Multimodal Integration

Multimodal integration has become a promising direction in emotion recognition, combining EEG with complementary modalities such as facial expressions, speech, and peripheral physiological signals [3]. However, future progress depends on learning aligned multimodal representations rather than simply fusing heterogeneous data. Representation alignment, cross-modal learning, and physiologically informed fusion may provide more robust and interpretable solutions than conventional feature concatenation [20, 21].

Figure 1 illustrates the conceptual perspective discussed in this editorial: a shift from feature-centric EEG analysis to representation-centric learning (RCL). Unlike conventional pipelines that rely on handcrafted descriptors, the proposed perspective emphasizes learned representations that integrate physiological relevance and semantic interpretability. Through adaptive processing, physiological constraints, and cross-modal alignment, these

representations aim to support robust and transferable emotion understanding across subjects, datasets, and affective tasks.

5. Toward a Representation-Centric Approach for EEG-Based Emotion Recognition

The central transition proposed in this perspective study is a move from feature extraction toward RCL. Rather than manually defining EEG characteristics, future models should learn hierarchical representations while incorporating neurophysiological constraints and interpretable structures. The goal is not to replace physiological knowledge with deep neural networks, but to develop representations that preserve temporal, spatial, oscillatory, and connectivity-related properties of the EEG while capturing their relationships with emotional states. Achieving this vision requires integration of advanced architectures, SSL, and physiological approaches.

We envision this transition as an integrated framework in which adaptive signal conditioning, learned neural representations, neuro-semantic alignment, and emotion inference are jointly optimized rather than treated as isolated stages. Such a framework may enable artifact-robust and subject-aware representations that preserve electrophysiological information while establishing meaningful links between neural activity and affective

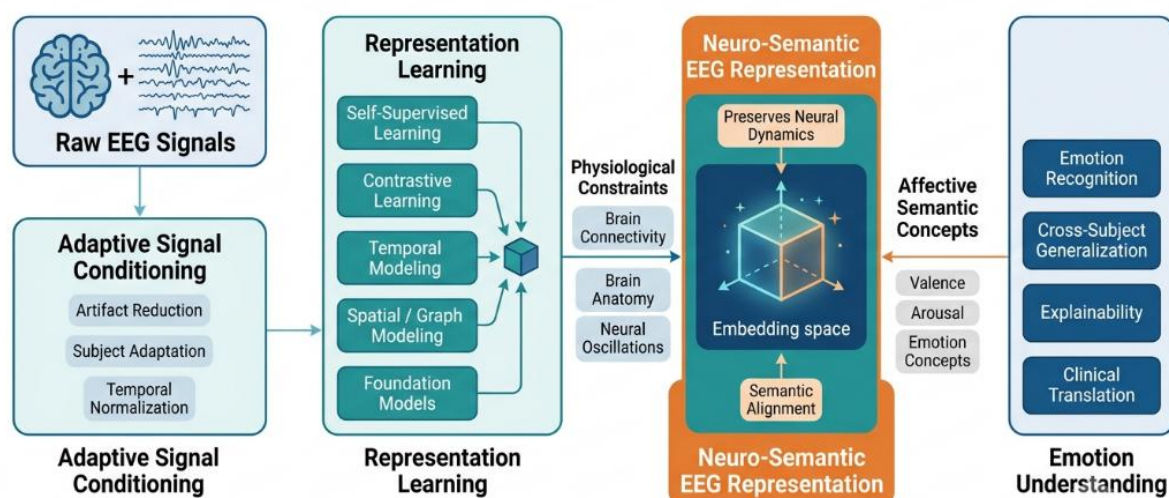


Figure 1. From Engineered Features to NSER: A Representation-Centric Approach for Next-Generation EEG-Based Emotion Recognition

concepts. These representations can subsequently support classification, regression, and continuous affect estimation.

Within it, frequency information remains valuable but becomes one component of a richer representation integrating temporal dynamics, spatial connectivity, and affective meaning. This transition may improve generalization, enhance modeling of emotional dynamics, and increase interpretability by connecting learned representations with neurophysiological mechanisms. Emerging directions, including diverse EEG pretraining, foundation models, long-sequence and State-Space Models (SSM), and cross-modal learning, may further accelerate this transition toward robust and physiologically grounded Neuro-AI.

Three complementary priorities emerge from this representation-centric perspective: (1) developing neural representations that preserve electrophysiological structure while supporting affective interpretation, (2) improving their generalization through adaptive processing, self-supervised and multimodal learning, and physiological constraints, and (3) validating them beyond classification accuracy through physiological validity, interpretability, robustness, and transferability. Together, these priorities provide a practical conceptual roadmap for developing more generalizable and meaningful EEG-Based ERSs.

5.1. Clinical Translation and Biomedical Applications

Beyond methodological advances, representation-centric EEG learning (RCEL) may enhance the clinical translation of ERSs. More robust and interpretable neural representations could improve reliability in real-world healthcare settings, where individual variability, recording differences, and clinical heterogeneity remain major challenges. These advances may support future applications in MHM, neuropsychiatric assessment, and personalized healthcare.

5.1.1. Mental Health Assessment

Objective: MHA is a promising application of this framework. Existing EEG-Based studies have largely emphasized diagnostic performance, while the neurophysiological basis underlying model

predictions is often less explicitly characterized. This gap can limit clinical confidence, motivating representation learning that links predictions to interpretable neurophysiological mechanisms rather than relying solely on black-box outputs.

5.1.2. Neurorehabilitation

Neurorehabilitation may also benefit from RCEL. Adaptive neural representations could support continuous monitoring of emotional and cognitive recovery in patients with stroke, traumatic brain injury, or neurodegenerative disorders. Such biomarkers may facilitate personalized rehabilitation and improve robustness across longitudinal assessments and diverse patient populations.

5.1.3. Brain–Computer Interfaces

BCIs represent another promising application of RCEL. By learning invariant neural representations, future affective BCIs may improve subject-independent decoding, long-term adaptation, and HMI. Integrating neuro-semantic representations with multimodal foundation models may further enable context-aware BCIs with richer emotional understanding. Collectively, these examples highlight the translational potential of the RCEL beyond algorithmic innovation. By promoting physiologically grounded, interpretable, and transferable neural representations, this framework provides a foundation for clinically deployable EEG technologies across mental health, neurorehabilitation, and BCIs.

6. Challenges and Open Research Questions

Despite RCL's promise, several challenges must be addressed before this approach can achieve broad scientific and clinical impact. Key priorities include computational scalability, the availability of large and diverse EEG datasets, robustness across subjects and recording conditions, reproducibility, interpretability, and clinical translation. Overcoming these challenges will be essential for realizing reliable and trustworthy EEG-Based ERSs.

6.1. Computational Scalability

Although RCL offers clear advantages, it also increases computational demands. Foundation models, self-supervised pretraining, and multimodal learning require substantial computational resources, highlighting the need for lightweight and efficient architectures for real-world EEG applications.

6.2. Limited Large-Scale EEG Datasets

Unlike computer vision and Natural Language Processing (NLP), EEG research still lacks large, standardized, and diverse datasets. Heterogeneity in data acquisition and annotation remains a major barrier to scalable and generalizable DL. Establishing collaborative benchmark datasets will be essential for developing future EEG foundation models.

6.3. Generalization and Robustness

Robust generalization across subjects, recording sessions, devices, and experimental methods remains a major challenge. Future RL should promote invariance to subject- and session-specific variability while preserving meaningful neurophysiological information through domain-invariant or adversarial objectives and physiological constraints, with validation based on cross-subject, cross-session, and cross-device transfer.

6.4. Interpretability

Learned representations should not only improve predictive performance but also remain neurophysiologically interpretable. Explaining the relationship between neural representations and emotional states will be essential for scientific credibility and clinical translation.

6.5. Clinical Translation

The translation of advanced EEG representations into clinical practice requires improved validation across diverse patient populations, real-world conditions, and regulatory contexts. Beyond algorithmic performance, clinical applicability and usability should become essential criteria for evaluating future EEG-Based systems.

6.6. Reproducibility

Reproducibility remains essential for advancing EEG-Based affective neuroscience research. Future studies should prioritize standardized protocols, public benchmarks, and open-source implementations to enable reliable comparison across RL approaches. Ultimately, progress will depend not only on algorithmic innovation but also on scalable, interpretable, reproducible, and clinically applicable frameworks.

7. Conclusion

Frequency-band analysis has provided valuable neurophysiological insights in EEG-Based emotion recognition; however, affective brain dynamics extend beyond predefined spectral descriptors. Future research should therefore address three concrete priorities. First, EEG representations should jointly capture temporal, spectral, and spatial information while explicitly relating learned features to identifiable neurophysiological and affective variables. Second, representation-learning frameworks should address inter-subject, inter-session, and cross-dataset variability through self-supervised, contrastive, and multimodal learning, with generalization assessed on unseen subjects, sessions, and datasets. Third, these representations should be validated under diverse and real-world conditions, with emphasis on reproducibility, robustness, and clinically meaningful outcomes rather than within-dataset accuracy alone. Together, these priorities provide a practical path from feature-based EEG analysis toward physiologically grounded, interpretable, and generalizable representations for affective and biomedical applications.

References

- 1- Asl Mahdi Jafari and Shamekhi Sina, "Channel-Reduced Hybrid Deep Neural Networks for High-Accuracy EEG-Based Emotion Recognition." *Frontiers in Biomedical Technologies*, Vol. 0 (No. 0), 07/18 (2026).
- 2- M. J. Asl, S. Shamekhi, and F. Shalchizadeh, "Region-Specific Eeg Channel-Based Emotion Detection Using Bi-Directional Deep Neural Networks." in *2025 32nd National and 10th International Iranian Conference on Biomedical Engineering (ICBME)*, (2025), pp. 323–28.

- 3- F. Shalchizadeh, S. Shamekhi, and M. J. Asl, "Binary Discrete Emotion Detection with Peripheral and Fp1-Fp2 EEG Signals on PEEFS Dataset." in *2025 32nd National and 10th International Iranian Conference on Biomedical Engineering (ICBME)*, (2025), pp. 258–62.
- 4- Alexander Craik, Yongtian He, and Jose L Contreras-Vidal, "Deep learning for electroencephalogram (EEG) classification tasks: a review." *Journal of neural engineering*, Vol. 16 (No. 3), p. 031001, (2019).
- 5- Kübra Erat, Elif Bilge Şahin, Furkan Doğan, Nur Merdanoğlu, Ahmet Akcakaya, and Pinar Onay Durdu, "Emotion recognition with EEG-Based brain-computer interfaces: a systematic literature review." *Multimedia Tools and Applications*, Vol. 83 (No. 33), pp. 79647–94, (2024).
- 6- Priyadarsini Samal and Mohammad Farukh Hashmi, "Role of machine learning and deep learning techniques in EEG-Based BCI emotion recognition system: a review." *Artificial Intelligence Review*, Vol. 57 (No. 3), p. 50, (2024).
- 7- M. J. Asl and S. H. M. Rabie, "Deep Learning Approaches for Alzheimer's Disease Diagnosis: a Comprehensive Review." in *2025 32nd National and 10th International Iranian Conference on Biomedical Engineering (ICBME)*, (2025), pp. 1049–54.
- 8- Z. Zehtabi, L. M. Fanid, P. Salehpoor, and M. J. Asl, "Modeling Attention Performance Across Female Reproductive Aging Using Logistic Regression." in *2025 32nd National and 10th International Iranian Conference on Biomedical Engineering (ICBME)*, (2025), pp. 1–5.
- 9- Wei-Long Zheng and Bao-Liang Lu, "Investigating critical frequency bands and channels for EEG-Based emotion recognition with deep neural networks." *IEEE Transactions on autonomous mental development*, Vol. 7 (No. 3), pp. 162–75, (2015).
- 10- Andrea Apicella et al., "Toward cross-subject and cross-session generalization in EEG-Based emotion recognition: Systematic review, taxonomy, and methods." *Neurocomputing*, Vol. 604p. 128354, (2024).
- 11- Stamos Katsigiannis and Naeem Ramzan, "DREAMER: A database for emotion recognition through EEG and ECG signals from wireless low-cost off-the-shelf devices." *IEEE journal of biomedical and health informatics*, Vol. 22 (No. 1), pp. 98–107, (2017).
- 12- Sander Koelstra et al., "Deap: A database for emotion analysis; using physiological signals." *IEEE transactions on affective computing*, Vol. 3 (No. 1), pp. 18–31, (2011).
- 13- J. A. Miranda-Correa, M. K. Abadi, N. Sebe, and I. Patras, "AMIGOS: A Dataset for Affect, Personality and Mood Research on Individuals and Groups." *IEEE transactions on affective computing*, Vol. 12 (No. 2), pp. 479–93, (2021).
- 14- Tongtian Yue et al., "BrainGPT: Unleashing the potential of EEG generalist foundation model by autoregressive pre-training." *arXiv preprint arXiv:2410.19779*, (2024).
- 15- Xin Zhou and Xiaojing Peng, "Multi-scale spatiotemporal representation learning for EEG-Based emotion recognition." *IEEE Transactions on Affective Computing*, Vol. 16, no. 4, pp. 3266-3278, (2025).
- 16- Alec Radford et al., "Learning transferable visual models from natural language supervision." in *International conference on machine learning*, (2021): PmLR, pp. 8748–63.
- 17- Navid Mohammadi Foumani, Geoffrey Mackellar, Soheila Ghane, Saad Irtza, Nam Nguyen, and Mahsa Salehi, "Eeg2rep: enhancing self-supervised eeg representation through informative masked inputs." in *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, (2024), pp. 5544–55.
- 18- Dingkun Liu et al., "EEG Foundation Models: Progresses, Benchmarking, and Open Problems." *arXiv preprint arXiv:2601.17883*, (2026).
- 19- Gayal Kuruppu, Neeraj Wagh, Vaclav Kremen, and Yogatheesan Varatharajah, "EEG foundation models: a critical review of current progress and future directions." *Journal of neural engineering*, Vol. 23 (No. 2), p. 021001, (2026).
- 20- Rajasekhar Pillalamarri and Udhayakumar Shanmugam, "A review on EEG-Based multimodal learning for emotion recognition." *Artificial Intelligence Review*, Vol. 58 (No. 5), p. 131, (2025).
- 21- Gustave Udahemuka, Karim Djouani, and Anish M Kurien, "Multimodal emotion recognition using visual, vocal and physiological signals: a review." *Applied Sciences*, Vol. 14 (No. 17), p. 8071, (2024).