MULTIMODAL SYSTEMS FOR EMOTION ANALYSIS. INTEGRATION OF EKG, EEG AND EDA SIGNALS FOR MODELING AFFECTIVE STATES

Prof. PhD. Eng. Eusebiu CATANĂ – Université libre de Bruxelles;
Doctor Emanuel-Gabriel BOTNARIU, PhD Cand. - Titu Maiorescu University;
Lecturer PhD. Alina - Corina COSTACHE - Titu Maiorescu University.
https://doi.org/10.66793/titui19proceeding21

Abstract:

Emotions represent complex processes, integrated at the cognitive, neurophysiological and behavioral levels. Multimodal systems for affective analysis, based on the integration of EKG, EEG and EDA signals, offer a more complete perspective on the emotional state than traditional unimodal methods.

The electrocardiogram reflects autonomic activation, EEG captures cortical processes associated with valence, and EDA indicates the level of physiological activation. By fusing these signals, robust models for classifying emotions in real time can be built, with applications in mental health, neurofeedback, adaptive interfaces, social robotics and autonomous vehicles.

However, the use of these systems involves challenges related to signal synchronization, individual variability and the ethics of biometric data protection. In the future, integration with generative AI and the Internet of Bodies opens new directions for the analysis of emotions in natural contexts.

Keywords: *emotions, EKG, EEG, EDA, multimodal analysis, HRV, arousal, valence, affective computing, Internet of Bodies*

1. INTRODUCTION

The study of emotions occupies a central role in psychology, neuroscience and behavioral sciences, as emotions influence perception, decision-making and social interactions. Emotions are complex processes that include cognitive, physiological and behavioral components, integrated into an adaptive system that allows the body to respond effectively to internal and external stimuli (Scherer, 2009). These processes manifest not only at the subjective level, but also through measurable changes in neural activity, heart rate, and skin conductance, making their objective analysis possible by biometric means (Critchley & Garfinkel, 2017).

1.1. The scientific context of emotion research

Emotions play an essential role in regulating behavior and interpersonal communication, being involved in the evaluation of situations and the selection of adaptive responses (LeDoux, 2012). In social interactions, emotions facilitate the recognition of the other's intentions, the formation of empathy, and the maintenance of group cohesion (Keltner & Lerner, 2010). Therefore, understanding emotional mechanisms contributes both to explaining human behavior and to the development of more efficient human–machine interaction systems (Paraschiv, R, 2024).

1.2. The Need for Multimodal Analysis of Affective Data

Traditional methods for identifying emotions have frequently focused on a single observation channel - facial expression, heart rate or brain activity. However, unimodal systems can lead to limited interpretations, since emotions do not manifest uniformly in all physiological components (Calvo & D'Mello, 2010). For example, a facial expression can be voluntarily controlled, while heart rate and skin conductance more accurately reflect autonomic activation. Therefore, the multimodal approach - the simultaneous integration of ECG, EEG and EDA signals - allows for a more complete and robust assessment of affective states (Paraschiv, R, Cochior, D, Priescu, I, et all 2023).

1.3. Relevance and applicability of multimodal systems

Multimodal systems for analyzing emotions have extensive applications. In clinical psychology, they facilitate real-time monitoring of anxiety or depressive symptoms (Mendes, 2016). In human–computer interfaces (HCI), these systems allow the automatic adaptation of digital applications to the user's state, improving interaction and accessibility (Picard, 2010). In autonomous vehicles and IoT, emotional analysis can contribute to safety and personalization, detecting fatigue, stress or cognitive overload. Thus, the importance of these systems transcends the field of research, having significant practical potential (Paraschiv, R.V., Zamfirescu, V., 2025).

1.4. Defining the research objective and questions

The objective of this study is to create a biometric data fusion system that allows for the classification of emotions in real time, through the synchronized integration of ECG, EEG and EDA signals. This approach raises the following theoretical questions:

- How can the optimal synchronization of signals from different physiological sources be achieved?
- Which features extracted from ECG, EEG and EDA are most relevant for identifying emotions?
- To what extent do multimodal models outperform unimodal ones in affective detection?

These questions substantiate the direction of analysis and justify the relevance of using multimodal methods.

2. EMOTIONS AND THEORETICAL FOUNDATIONS OF PHYSIOLOGICAL RESPONSE

Understanding how emotions manifest in the body is the foundation of multimodal analysis. Emotions are not just subjective experiences, but integrated biological processes that involve the activation of the central and autonomic nervous systems, hormonal changes, and muscle and electrodermal responses (Scherer, 2009). Thus, the measurement of physiological signals such as ECG, EEG, and EDA allows the objectification of emotional response and the assessment of affective dynamics in real time.

2.1. Autonomic response and emotions

The autonomic nervous system plays a central role in the regulation of emotions, by mobilizing the physiological resources necessary to adapt to relevant stimuli. Activation of the sympathetic branch is associated with states of alertness, fear, or anger, while parasympathetic activation indicates relaxation and recovery (Critchley & Garfinkel, 2017).

The electrocardiogram (EKG) reflects these processes through heart rate (HR) variation and heart rate variability (HRV), sensitive indicators of emotion intensity and psychophysiological stress level.

2.2. Cortical activity and emotional processing

At the cerebral level, emotions are integrated through networks involving the amygdala, anterior cingulate cortex and prefrontal cortex (LeDoux, 2012). The electroencephalogram (EEG) allows the investigation of neuronal activity noninvasively by analyzing brain rhythms. For example, frontal EEG asymmetry is associated with emotional valence: left prefrontal activation is correlated with positive emotions, and right with negative emotions (Davidson, 2004). α, β and θ rhythms can thus provide clues about the affective state and cognitive processes associated with emotion.

2.3. Electrodermal response and affective intensity

Skin conductance (EDA), also known as electrodermal activity, is a direct indicator of the activation of the sweat glands controlled by the sympathetic system. Unlike facial expression, which can be voluntarily shaped, EDA accurately reflects the intensity of emotion, especially in situations of stress, fear or surprise (Boucsein, 2012). For this reason, EDA is frequently used in the detection of implicit emotional reactivity.

2.4. Why multimodal integration is necessary

Each physiological channel captures a different dimension of emotion:

- EEG → valence and cortical processing,
- ECG (HRV) → autonomic intensity and stress,
- EDA → level of activation (arousal).

While a single indicator can be ambiguous, combining them reduces uncertainty and increases the accuracy of emotion classification (Calvo & D’Mello, 2010). Multimodal systems are thus superior to unimodal ones because they model emotion as a dynamic and distributed phenomenon, not as a singular response.

3. BIOMETRIC SIGNALS FOR EMOTION ANALYSIS

Analyzing emotions through biometric signals allows for a deeper understanding of the dynamics of the affective response. Each type of physiological signal - electrocardiogram (EKG), electroencephalogram (EEG) and electrodermal activity (EDA) - provides complementary information about autonomic activation, cortical state and emotional intensity. The integration of these sources allows for a multimodal representation of emotional experience, essential for the automatic modeling of affective states (Calvo & D'Mello, 2010).

3.1. Electrocardiogram (EKG / HRV)

Heart rate is one of the most sensitive indicators of emotional activation. During high-intensity emotions - such as fear, anger or joy - the activity of the sympathetic nervous system increases, causing an acceleration of the heart rate. In contrast, emotions with positive valence, associated with relaxation and safety, involve a predominance of the parasympathetic system, reflected by a reduction in heart rate (Appelhans & Luecken, 2006).

A central parameter of cardiac analysis is heart rate variability (HRV), which expresses the dynamic balance between sympathetic and parasympathetic activation. A high HRV value suggests physiological flexibility and effective emotional regulation, while a low HRV is associated with stress, anxiety and difficulties in emotional control (Thayer, Åhs, Fredrikson, Sollers, & Wager, 2012).

The LF/HF ratio index, derived from the spectral analysis of HRV, is used to estimate the ratio between sympathetic (LF – low frequency) and parasympathetic (HF – high frequency) influences. These indicators provide a solid basis for quantifying the intensity of emotions and for training automatic classification models based on ECG.

3.2. Electroencephalogram (EEG)

Electrical brain activity reflects the processes of perception, attention, and affective appraisal involved in the experience of emotions (Davidson, 2004). Brain rhythms, especially the alpha (8–12 Hz), beta (13–30 Hz), theta (4–7 Hz), and gamma (>30 Hz) bands, are frequently analyzed in studies of affective neurophysiology. For example, decreased power in the alpha band in frontal regions is associated with reduced emotional appraisal (Knyazev, 2007).

A robust indicator of emotional valence is frontal EEG asymmetry. Left prefrontal activation is correlated with positive emotions and approach behaviors, while right prefrontal activation is associated with negative emotions and avoidance tendencies (Coan & Allen, 2004). This asymmetry serves as a bridge between neurophysiological data and psychological models of emotion.

3.3. Electrodermal Activity (EDA / GSR)

Skin conductance, also known as galvanic skin response (GSR), measures the activity of sweat glands, which are controlled by the sympathetic nervous system. Increased skin conductance reflects increased physiological activation (arousal) and is considered a direct indicator of implicit emotional response (Boucsein, 2012).

In affective experiments, the peak of the electrodermal response often coincides with the moment of emotion onset, which allows for the identification of rapid reactions, even in the absence of conscious expression. However, EDA cannot distinguish the valence of the emotion - positive or negative - but only its intensity, which is why it is recommended to combine this signal with other physiological sources (Critchley & Garfinkel, 2017).

Limitations of EDA include high individual variability and the influence of external factors (temperature, hydration, movement). Despite these, EDA remains one of the most widely used methods in research on implicit and uncontrolled emotional responses.

4. CAPTURE, PREPROCESSING AND FEATURE EXTRACTION

Processing physiological signals for emotion classification involves a series of rigorous methodological steps, which include signal capture, artifact removal, preprocessing and extraction of relevant features. The quality of these operations determines, to a large extent, the performance of multimodal systems, since biometric signals are, by nature, sensitive to contextual variations and external interference (Hajihashemi & Pantic, 2018).

4.1. Instruments and capture devices

ECG, EEG and EDA signals can be collected by:

- professional medical systems, used in psychophysiological laboratories (e.g. Biopac, BrainVision),
- wearable sensors, such as smart bracelets, mobile EEG headsets or sensors integrated into smart textiles,
- IoT devices, used for monitoring in the real environment.

The current trend is towards miniaturization and mobility, which allows the analysis of emotions in natural, not just experimental contexts (Peake, Kerr & Sullivan, 2018). However, this mobility often comes at the cost of a noisier signal.

4.2. Artifacts and noise sources

Physiological signals are affected by numerous artifacts, and their management is essential to avoid classification errors.

- In EEG, artifacts can come from muscle movements (EMG), blinking, breathing or electromagnetic interference (Urigüen & Garcia-Zapirain, 2015).
- In ECG, noise can result from body movements, poor electrode contact or intense muscle activity.
- In EDA, perspiration, temperature and skin movement influence conductance.

Correct management of these artifacts is a prerequisite for obtaining an interpretable signal.

4.3. Preprocessing techniques

Preprocessing aims to stabilize the signal and extract relevant information. Among the most used techniques are:

- Filtering (low-pass, high-pass, band-pass) to eliminate unwanted frequency noise,
- Signal normalization to reduce inter-individual variations,
- Temporal segmentation, by dividing the signal into time windows adapted to affective dynamics (e.g. 2–10 seconds) (Mollahosseini, Hasani & Mahoor, 2017).

A faulty preprocessing can lead to inconsistent results, even if the algorithm used for classification is advanced.

4.4. Feature Extraction

Feature extraction is the stage in which the raw signal is transformed into meaningful indicators, usable by classification models:

Domain	Examples of Characteristics	Application
Time	HR, HRV, EDA amplitude, instantaneous EEG variation	Capturing the evolution of the signal
Frequency	Spectral analysis (PSD), EEG bands (α, β, θ, γ), HRV components	Detecting rhythmic patterns
Time–Frequency	Fourier Transform (FFT), wavelet transform, spectrograms	Identifying dynamic changes

Time-frequency methods are preferred in emotion analysis, as they capture not only the value of the signal, but also the way it evolves over time, reflecting the dynamic nature of the emotional process (Daubechies, 1990).

Partial conclusion

The quality of multimodal analyses directly depends on the precision of signal capture, the rigor of preprocessing and the relevance of the extracted features. A well-designed processing chain considerably increases the performance of automatic emotion recognition systems.

5. MULTIMODAL DATA FUSION

Multimodal fusion is the stage in which physiological signals collected from different sources – such as ECG, EEG and EDA – are integrated into a single emotion classification model. This approach is based on the hypothesis that emotions are distributed processes, manifesting themselves simultaneously in several systems of the body, and the use of a single biometric channel may provide an incomplete picture (Calvo & D'Mello, 2010). By combining channels, interpretation errors are minimized and the accuracy of identifying affective states is improved (Paraschiv, R.V., 2025).

5.1. Information fusion concepts

Data fusion can be achieved at three main levels:

Early fusion

- Raw signals are combined before preprocessing. This strategy allows deep models to learn common representations, but is sensitive to differences in resolution and noise between data sources (Baltrusaitis, Ahuja & Morency, 2019).

Feature-level fusion

- Features extracted from each signal (e.g. HRV for ECG, frontal asymmetry for EEG, tonic-phasic amplitude for EDA) are concatenated into a multimodal vector used for classification (Hajihashemi & Pantic, 2018).

Late fusion

- Separate classifiers analyze each channel independently, and the results are combined using voting, averaging, or Bayesian methods. This approach is robust and flexible, but may lose the fine-grained relationships between signals (Zhang et al., 2020).

5.2. Algorithmic techniques and models

Machine Learning methods were initially used in multimodal fusion, in particular:

- Support Vector Machines (SVM) - efficient for classification on small to medium feature vectors.
- Random Forest - stable under noisy and nonlinear data conditions.

With the advancement of Deep Learning, the dominant methods have become:

- Convolutional Neural Networks (CNN) - for analyzing EEG and ECG spectrograms.
- LSTM and GRU networks - for temporal modeling of affective variations (Mollahosseini, Hasani & Mahoor, 2017).
- Multimodal Transformer architectures – capable of learning relationships between signals through attention mechanisms (Tsai et al., 2019).

More recently, hybrid networks are being developed, combining CNN for spatial feature extraction, LSTM for temporal dynamics and Transformer modules for inter-modular integration - representing the cutting edge direction in real-time emotion analysis (Paraschiv, R.V., 2025).

5.3. Temporal synchronization of physiological signals

A major challenge in multimodal fusion is the difference in latency between signals.

- EDA responds slowly (2–5 seconds delay),
- HR/HRV reacts in ~1 second,
- EEG responds almost instantaneously (<100 ms).

To avoid desynchronization of the recorded emotion, the following are used:

- sliding windows adapted to the duration of the affective response,
- temporal alignment based on the stimulus-event,
- sequential LSTM models that absorb dynamic variations.

Thus, temporal synchronization allows for the coherent interpretation of physiological activation and significantly increases the accuracy of real-time systems.

Partial conclusion

Multimodal fusion is not just a technical step, but a reflection of the integrative nature of emotions. By correlating cardiac, cerebral and electrodermal signals, automated systems can capture both the intensity and valence of emotion, overcoming the limits of unimodal analyses and providing a solid basis for interactive and clinical applications.

6. CLASSIFICATION OF AFFECTIVE STATES IN REAL TIME

Classification of affective states in real time involves the continuous interpretation of biometric signals and their transformation into emotional labels or coordinated in an affective space. This process requires models capable of analyzing dynamic data, identifying coherent neural and physiological patterns, and responding rapidly to the emotional changes of the individual. Consequently, classifying emotions is not only a technical problem, but also a conceptual one - depending on how emotions are defined and represented theoretically (Scherer, 2009).

6.1. Modeling in Valence–Arousal Space and/or Discrete Emotions

There are two dominant strategies for representing emotions:

Categorical modeling (Ekman, 1999)

Emotions are classified into discrete categories (e.g. fear, anger, joy). This approach is intuitive, but may lose the nuances of affective transitions.

Dimensional modeling (Russell, 1980)

Emotions are represented in a two-dimensional space:
- valence (positive–negative),
- arousal (low–high).

This approach is more suitable for real-time analysis, as it captures the continuous dynamics of emotion and does not require rigid classification.

In practice, multimodal models can simultaneously use both paradigms: the Valence–Arousal dimensions for continuous monitoring and discrete labels for semantic interpretation.

6.2. Performance and metrics

The performance of classification models is evaluated through standardized metrics (Goodfellow, Bengio & Courville, 2016):

Metric	**Description**	**Interpretation**
Accuracy	The total percentage of correct classifications	General, but sensitive to data imbalance
Precision	The proportion of correct classifications out of all predicted for a class	Relevance of the prediction
Recall	The proportion of correctly detected actual instances	Sensitivity to the omission rate
F1-score	The harmonic mean between precision and recall	A robust measure for comparison

In controlled (laboratory) contexts, multimodal models frequently achieve >90% accuracy, but in real-world situations with high variability, performance drops to 65–80%, indicating the need for contextual calibration (Zafeiriou, Papaioannou & Nicolaou, 2017).

6.3. Comparing unimodal vs multimodal classification

System Type	Data Source	Advantages	Limitations
Unimodal	EKG, EEG, or EDA alone	Easy to implement	Sensitive to artifacts, loss of information
Multimodal	Combination of EKG + EEG + EDA	High accuracy and robustness	Requires synchronization and computational resources

Research shows that multimodal models consistently outperform unimodal models because they can compensate for signal fluctuations and integrate both the intensity and valence of emotion (Mollahosseini, Hasani & Mahoor, 2017). For example, EEG provides information about valence, while EDA and HRV are sensitive to arousal - together, they describe the entire affective state, not just an isolated aspect.

Partial conclusion

Real-time emotion classification is possible thanks to the development of multimodal models, which capture the physiological complexity of the affective response. Although the performance of these systems is promising, their optimization requires improving signal synchronization, diversifying databases, and integrating situational context into the interpretative process.

7. APPLICATIONS AND IMPLICATIONS

Multimodal emotion analysis systems offer significant opportunities in various fields, due to their ability to capture affective responses in real time and integrate subtle neurophysiological dimensions of emotion. At the same time, their use involves major ethical challenges, especially in situations where biometric data can be exploited without consent or in surveillance contexts. Therefore, practical applications must be balanced with rigorous measures of protection and social responsibility (Paraschiv, R.V., Zamfirescu, V., 2025).

7.1. Applications in mental health and neurofeedback

In clinical psychology, multimodal systems can support the assessment and intervention in emotional disorders such as anxiety, depression or affective regulation disorders. Parameters such as HRV and frontal EEG activity are already used as biomarkers of affective state, providing objective information about the level of stress, tension or mood (Thayer et al., 2012).

Also, in neurofeedback, users can learn to self-regulate their emotional state in real time based on the information reflected in EEG or HRV, which facilitates the development of sustainable emotion management strategies (Hammond, 2011).

7.2. Affective Interfaces (Affective Computing) and Adaptive Technologies

The concept of Affective Computing aims to develop systems capable of recognizing and responding to users' emotions, in order to create more natural and efficient interactions (Picard, 2010). Multimodal systems can adapt:
- the tone and communication style of a virtual assistant,
- the difficulty of an adaptive educational program,
- the content of an interactive therapeutic application.

This leads to empathetic interfaces, which react to the user's state, not just to explicit inputs.

7.3. Autonomous vehicles, social robotics, adaptive e-learning

In autonomous vehicles, emotion detection can contribute to safety, identifying driver fatigue, overload or stress and activating preventive mechanisms (Duan et al., 2021).

In social robotics, robots capable of interpreting emotions become more effective partners in assisting the elderly or in behavioral therapy (Breazeal, 2014).

In adaptive e-learning, multimodal systems can adjust the pace, difficulty, and style of teaching according to the emotional and cognitive state of the student, improving engagement and retention of information (D'Mello & Graesser, 2015).

7.4. Risks, ethics, and biometric data protection

Despite the benefits, automated emotion analysis raises important ethical issues:

- the risk of affective surveillance - constant involuntary monitoring of emotions,
- algorithmic bias - systematic errors associated with cultural or biological diversity (Buolamwini & Gebru, 2018),
- the vulnerability of biometric data, which are irreversible and unique to the individual.

Therefore, it is necessary to implement rigorous protocols of consent, anonymization and algorithmic transparency, as well as clear regulation of how affective data is collected and used.

8. CONCLUSIONS

Multimodal systems open up new perspectives for understanding and interacting with human emotion, but their responsible exploitation depends on a careful balance between technological innovation and the protection of the dignity and autonomy of the individual.

The study of the integration of ECG, EEG and EDA signals in the analysis of emotions highlights the complexity of affective processes and the need to approach them from an integrative perspective. Emotions are not manifested only in facial expressions or isolated physiological responses, but constitute distributed processes, involving the simultaneous activation of the central nervous system, the autonomic system and behavioral systems. Thus, multimodal systems represent an essential methodological advance over classical unimodal approaches, as they allow the capture of both the valence of emotion (via EEG) and the physiological intensity (via HRV and EDA), offering a more complete representation of the affective state.

Compared to traditional models based solely on facial expressions or self-reports, multimodal systems demonstrate superior accuracy, contextual robustness, and better adaptability in real, dynamic situations. However, their development requires solving challenges related to signal synchronization, cultural diversity, contextual interpretation, and biometric data protection.

In the future, research directions are directed towards:

- integration with advanced generative artificial intelligence models, capable of reconstructing and predicting emotional states in real time,
- development of affective ecologies within the Internet of Bodies (IoB), where body-connected devices will allow for the monitoring of emotions in the everyday environment,
- and the extension of multimodal systems towards personalized applications in mental health, social robotics, and adaptive human–machine interfaces.

These directions emphasize the transformative potential of multimodal systems in understanding and supporting human affective experience, provided that clear ethical frameworks and rigorous protection of personal data are implemented.

6. BIBLIOGRAPHY

1. Appelhans, B. M., & Luecken, L. J. (2006). Heart rate variability as an index of regulated emotional responding. Review of General Psychology, 10(3), 229–240. https://doi.org/10.1037/1089-2680.10.3.229
2. Baltrusaitis, T., Ahuja, C., & Morency, L. P. (2019). Multimodal machine learning: A survey and taxonomy. IEEE Transactions on Pattern Analysis and Machine Intelligence, 41(2), 423–443. https://doi.org/10.1109/TPAMI.2018.2798607
3. Boucsein, W. (2012). Electrodermal activity (2nd ed.). Springer.
4. Breazeal, C. (2014). Social robotics. MIT Press.
5. Calvo, R. A., & D'Mello, S. (2010). Affect detection: An interdisciplinary review. IEEE Transactions on Affective Computing, 1(1), 18–37. https://doi.org/10.1109/T-AFFC.2010.1
6. Coan, J. A., & Allen, J. J. (2004). Frontal EEG asymmetry as a moderator of emotional response. Psychological Science, 15(6), 403–406.
7. Critchley, H. D., & Garfinkel, S. N. (2017). Interoception and emotion. Current Opinion in Psychology, 17, 7–14.
8. D’Mello, S., & Graesser, A. (2015). Feeling, thinking, and computing with affect-aware learning technologies. International Journal of Artificial Intelligence in Education, 26, 1–38.
9. Daubechies, I. (1990). The wavelet transform, time–frequency localization and signal analysis. IEEE Transactions on Information Theory, 36(5), 961–1005.
10. Davidson, R. J. (2004). What does the prefrontal cortex "do" in affect? Biological Psychiatry, 54(6), 502–514.
11. Duan, Y., et al. (2021). Driver emotional state monitoring for autonomous driving safety. IEEE Transactions on Intelligent Vehicles, 6(4), 682–695.
12. Hammond, D.C. (2011). What is neurofeedback? Journal of Neurotherapy, 15(1), 1–12.
13. Keltner, D., & Lerner, J.S. (2010). emotion In S. T. Fiske, D. Gilbert, & G. Lindzey (Eds.), Handbook of Social Psychology (5th ed., pp. 317–352). Wiley.
14. Knyazev, G. G. (2007). Motivation, emotion, and alpha oscillations. Biological Psychology, 74(1), 1–19.
15. LeDoux, J. (2012). The emotional brain. Simon & Schuster.
16. Mollahosseini, A., Hasani, B., & Mahoor, M. H. (2017). AffectNet: A database for facial expression and emotion recognition. IEEE Transactions on Affective Computing, 10(1), 18–31.
17. Paraschiv, R, (2024), Current Models in Psychological Research, University Publishing, 978-606-28-1834-0;
18. Paraschiv, R, Cochior, D, Priescu, I,et all (2023), Investigating Unique EEG Patterns Related to Depression, Advances In Digital Health And Medical Bioengineering, Vol 2, EHB-2023, Volume 110, Page 336-347, DOI 10.1007/978-3-031-62520-6_38
19. Paraschiv, R.V., (2025), Experimental Psychology. Theories, methods and applications”, University Press, ISBN 978-606-28-2035-0;
20. Paraschiv, R.V., Zamfirescu, V., (2025), Introduction to modern psychometry, TREI Publishing House, Bucharest;
21. Peake, J. M., Kerr, G., & Sullivan, J. P. (2018). A critical review of consumer wearables. Journal of Science and Medicine in Sport, 21(6), 578–589.
22. Picard, R. W. (2010). Affective computing. MIT Press.
23. Thayer, J. F., Åhs, F., Fredrikson, M., Sollers, J. J., & Wager, T. D. (2012). A meta-analysis of heart rate variability and neuroimaging studies. NeuroImage, 59(4), 351–366.
24. Tsai, Y.H., et al. (2019). Multimodal transformer for unaligned multimodal language sequences. ACL Conference Proceedings, 6558–6569.
25. Urigüen, J. A., & Garcia-Zapirain, B. (2015). EEG artifact removal—State of the art and guidelines. Journal of Neural Engineering, 12(3), 1–23.
26. Zafeiriou, S., Papaioannou, A., & Nicolaou, M. A. (ion Computing, 66, 3–9.
27. Zhang, Z., et al. (2020). Decision fusion strategies for multimodal emotion recognition. Information Fusion, 63, 69–80.