Enhancing Learning with Physiological Measures: A Systematic Review of Applications in Neuroeducation

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Abstract: This systematic review explores the integration of neuroscience and education, focusing on physiological monitoring technologies such as Electrodermal Activity (EDA), Heart Rate (HR), and Skin Temperature (ST). These metrics, facilitated by wearable devices and machine learning models, provide real-time insights into student engagement, emotional states, and academic performance. The analysis synthesizes findings from recent studies, highlighting the transformative potential of physiological measures in creating adaptive, student-centered learning environments. The review examines the use of physiological monitoring in education for stress assessment, motivation enhancement, and academic performance optimization, while also addressing challenges in reliability, ethics, and implementation. By identifying existing gaps, it proposes directions for future research to refine these tools and promote their widespread adoption in educational contexts. These advancements underscore the role of physiological insights in fostering emotional well-being and optimizing teaching practices, marking a significant step toward evidence-based, neuroeducation-informed strategies.

1 INTRODUCTION

The intersection of neuroscience and education offers a promising avenue for optimizing learning environments. Understanding physiological processes allows educators to tailor teaching methods to students' cognitive and emotional needs. Key metrics such as Electrodermal Activity (EDA), Heart Rate (HR), and Skin Temperature (ST) have emerged as critical tools for real-time insights into student engagement, stress, and emotional states. Leveraging these metrics, studies have highlighted the potential of physiological monitoring in enhancing teaching and learning practices. These dynamic measures hold the potential to enhance learning outcomes through a deeper understanding of student behavior and performance (Amaral & Fregni, 2021). Furthermore, Moura et al. (2022) highlight the imperative for educational and corporate strategies to address skill gaps and workforce demands, particularly within the context of Industry 4.0, which necessitates a blend of technical expertise, creativity, and collaboration.

Despite growing research, a comprehensive review of physiological monitoring in education is lacking. This study examines its applications, benefits, challenges, and reliability in adaptive learning. A systematic search in major databases identified peer-reviewed studies on EDA, HR, and ST as engagement indicators.

Relevant studies applying physiological monitoring in education were selected, while non-educational research was excluded. Extracted data

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included study design, sample characteristics, physiological measures, and key findings. A qualitative synthesis identified trends and gaps, with a methodological appraisal assessing data reliability.

This review critically evaluates physiological monitoring in education, highlighting its potential, limitations, and integration strategies.

1.1 Physiological Metrics in Education

EDA has been extensively studied as a reliable indicator of academic performance and engagement. For instance, Horvers et al. (2021) highlighted its efficacy in monitoring and predicting students' participation in academic tasks. Building on this, Abromavičius et al. (2023) demonstrated the utility of combining EDA, HR, and ST metrics to predict academic performance, emphasizing the importance of feature selection and advanced modeling techniques in educational research.

The application of neurophysiological metrics extends beyond engagement to address motivation and cognitive retention. Sánchez-Carracedo et al. (2021) demonstrated that neuroscience-based strategies can enhance students' motivation and attention, leading to improved conceptual retention. Similarly, Khan et al. (2019) examined the correlations between physiological responses, such as EDA and ST, and their impact during high-pressure academic tasks, providing evidence of their relevance in challenging learning environments.

1.2 Multimodal and Emotional Engagement Approaches

Research has increasingly explored the value of multimodal approaches in active learning scenarios. Villanueva et al. (2018) identified the potential of combining EDA with other modalities to enhance engagement and academic performance in active learning contexts. Meanwhile, Loderer et al. (2020) established a link between emotional engagement and improved outcomes in technology-based learning environments. These findings align with the work of Thammasan et al. (2020), who demonstrated the feasibility of monitoring physiological signals such as EDA and HR through wearable sensors, making these insights more accessible in real-time educational settings.

Integrating emotional and physiological metrics into pedagogical strategies has been shown to enrich learning experiences. For example, Eliot and Hirumi (2019) advocated for the inclusion of emotional engagement measures to enhance educational practices and foster more personalized learning environments. Similarly, Darvishi et al. (2022) highlighted the potential of neurophysiological measures to address individual cognitive and emotional needs, thereby improving overall educational practices.

Collectively, these studies underscore the critical role of physiological insights in advancing the field of neuroeducation. By leveraging neurophysiological data, educators can create adaptive, student-centered environments that promote both academic success and emotional well-being. This research highlights the intersection of neuroscience and education as a fertile ground for innovation, offering a robust framework to enhance traditional and technology-mediated learning.

2 PHYSIOLOGICAL MEASURES IN EDUCATION

2.1 Electrodermal Activity

EDA, a measure of sympathetic nervous system activity, offers valuable insights into emotional arousal and cognitive states by quantifying variations in skin conductance, typically measured in microsiemens (μS). This metric has gained prominence in education research for its ability to provide objective, real-time data on student engagement, stress, and emotional responses.

2.1.1 Advancements in EDA Measurement Techniques

Several studies have contributed to refining EDA measurement methodologies. Quintero et al. (2016b) introduced the TVSymp index, utilizing time-frequency spectral analysis to enhance the consistency of sympathetic activity assessments. Similarly, Quintero et al. (2016a) demonstrated the significance of low-frequency EDA components (0.045–0.15 Hz) in evaluating responses to cognitive and physical stressors.

Geršak and Drnovšek (2020) developed a simulator to improve the precision of metrological evaluations for EDA devices, advancing the reliability of EDA measurements. Additionally, Hernando-Gallego et al. (2017) proposed the SparsEDA algorithm, which improved computational efficiency and interpretability of EDA data.

Nourbakhsh et al. (2012) validated the relationship between EDA and cognitive load, highlighting spectral features' ability to differentiate task difficulties. These advancements have significantly enhanced the accuracy and utility of EDA measurements, making them more practical for educational and non-educational applications alike.

2.1.2 Applications in Stress and Emotional Analysis

EDA has been particularly useful in analyzing stress and emotional responses. Lui and Du (2018) developed a method for psychological stress detection based solely on EDA, achieving an 81.82% recognition rate using Fisher projection and linear discriminant analysis.

Sánchez-Reolid et al. (2020) combined EDA with other physiological signals, achieving up to 99.69% accuracy in stress detection using neural networks and Adaboost algorithms. Villarejo et al. (2012) created a wearable stress sensor based on galvanic skin response (GSR), demonstrating a 76.56% success rate. Malathi et al. (2018) extended the application of EDA to road safety, developing a device for real-time drowsiness detection in drivers.

Poh et al. (2010) validated wearable sensors for continuous EDA assessment, identifying consistent patterns of sympathetic modulation during daily activities. These studies underscore EDA's role in stress monitoring and its broader applicability in diverse contexts beyond education.

2.1.3 EDA in Educational Contexts

In educational environments, EDA has demonstrated significant potential for enhancing teaching and learning practices. Di Lascio et al. (2018) used wearable EDA sensors to distinguish engaged students from disengaged ones, achieving 81% recall using support vector machines (SVM).

Villanueva et al. (2019) explored EDA responses in academic mentoring settings, revealing the influence of identity on physiological responses. Reid et al. (2020) combined EDA data with behavioral analyses to identify key factors affecting academic performance, demonstrating the value of integrating physiological and qualitative data.

Pijeira-Díaz et al. (2018) employed EDA to detect moments of high and low engagement in classroom settings, offering insights into students' emotional and cognitive states. Villanueva et al. (2018) incorporated EDA into multimodal assessments during engineering activities, showing increased EDA levels during active, collaborative tasks.

Potter et al. (2019) highlighted EDA's ability to gauge student engagement across various teaching methodologies, emphasizing its utility for real-time feedback. These studies illustrate the versatility of EDA as a tool for assessing engagement, emotional states, and the effectiveness of educational interventions. Its integration into multimodal approaches has proven especially valuable in active and collaborative learning scenarios.

2.1.4 Implications for Pedagogical Strategies

The application of EDA in education provides a non-invasive and objective method for monitoring students' physiological responses. By bypassing the biases often associated with self-reported measures (Caruelle et al., 2019), EDA enables educators to tailor pedagogical strategies more effectively. From real-time feedback to long-term performance monitoring, EDA contributes to a nuanced understanding of student engagement and learning outcomes.

The growing body of research on EDA highlights its relevance in neuroeducation, offering robust methods for measuring engagement and emotional states. By integrating these insights into teaching practices, educators can create adaptive, data-driven environments that enhance both academic performance and emotional well-being.

2.2 Heart Rate

HR serve as indicators of physiological arousal and stress, providing valuable insights into students' engagement and emotional states. Schneider et al. (2020) explored HR synchronization among collaborators during programming tasks, revealing positive correlations between synchronization and task performance. This study highlights the potential of HR metrics as objective measures of collaboration quality and engagement in group activities.

Similarly, Ghannam et al. (2020) emphasized the role of HR monitoring in neuroengineering education, demonstrating how wearable technologies can enhance learning experiences by offering real-time physiological feedback.

2.2.1 Applications in Active Learning and Physical Engagement

Research has also focused on the role of HR in active learning contexts. Darnell and Krieg (2019) analyzed HR fluctuations during active learning sessions, identifying strong correlations between physiological engagement and academic interaction. Their findings underscore the importance of HR monitoring as a tool for assessing and optimizing engagement in dynamic educational settings.

Wang and Liu (2019) extended this research to physical education, utilizing wearable devices to monitor HR and provide real-time feedback. Their findings revealed significant differences in engagement levels among participants, showcasing the potential of wearable technology in fostering personalized education strategies and enhancing student participation.

2.2.2 Consistency and Contextual Analysis of HR and HRV

The consistency of HR and and Heart Rate Variability (HRV) measures has also been a topic of investigation. Quintero and Bolkhovsky (2019) examined these metrics under controlled conditions, identifying low HRV indices as reliable markers of physiological engagement. Their research highlights the utility of HRV as a robust measure for evaluating focus and stress levels in educational settings. Additionally, Gao et al. (2020) combined HR data with environmental variables to predict student engagement in diverse classroom environments. Their work demonstrates the value of integrating physiological and contextual data to improve teaching methods and outcomes.

Collectively, these studies establish HR and HRV as essential tools for understanding and enhancing educational outcomes. By integrating these measures into classroom practices, educators and researchers can gain a deeper understanding of physiological engagement, allowing for more targeted and effective interventions that enhance both academic performance and emotional well-being.

2.3 Skin Temperature

ST is a subtle but impactful physiological indicator, reflecting the body’s thermoregulation processes, which are influenced by emotional and environmental factors.

Studies such as Pérez et al. (2018) have demonstrated significant correlations between ST and academic performance, particularly under stress. This research highlights the relevance of ST as a non-invasive marker for understanding students’ emotional and cognitive states during high-pressure academic activities. However, Terriault et al. (2021) identified challenges in real-time ST monitoring during educational activities, particularly due to external environmental factors that can affect measurement accuracy.

2.3.1 Wearable Technology and Real-Time Monitoring

The development of wearable technology has advanced the continuous monitoring of ST, facilitating its application in educational settings. Yoon et al. (2016) emphasized the utility of wearable sensors, demonstrating their effectiveness for real-time stress detection and intervention. Their findings showcase the potential of wearable patches for long-term ST monitoring, enabling educators to better understand students' physiological responses in diverse learning environments. Additionally, Pérez et al. (2018) explored the application of wearable devices in assessing stress levels among students, finding significant correlations between ST and academic performance during high-stress tasks.

2.3.2 Multimodal Approaches Combining Skin Temperature

Combining ST with other physiological measures has further enhanced its predictive power in understanding emotional and cognitive states. Rodríguez-Arce et al. (2020) demonstrated that integrating ST with metrics such as HR and EDA can accurately predict stress and anxiety levels in academic settings. This multimodal approach provides a more comprehensive understanding of how physiological signals interact, offering insights into student behavior and well-being. These findings underscore the critical role of ST as an indicator of emotional and physiological states, with practical implications for creating adaptive and supportive learning environments. By leveraging advances in wearable technology and combining ST with other physiological measures, educators can develop strategies that address students' emotional needs, enhance academic performance, and foster a more inclusive and responsive educational experience.

3 METHODOLOGICAL ADVANCEMENTS

3.1 Wearable Technology

The integration of wearable devices, such as the Empatica E4, has revolutionized physiological monitoring in educational contexts by enabling unobtrusive and real-time data collection. These devices capture multimodal metrics, including EDA, HR, and ST, making them highly applicable for classroom environments.

3.1.1 Physiological Monitoring and Data Collection

Research by Rodic-Trmcic et al. (2016) emphasized the role of wearable solutions in assessing physiological arousal and engagement within classroom settings. Their findings highlighted the utility of Skin Conductance Response (SCR) and HR data for monitoring stress and underscored the importance of mobile assessment systems in delivering continuous feedback to improve educational quality. Building on this, Lu et al. (2017) proposed a framework leveraging widely available wearable devices to monitor basic student actions and infer engagement levels through sensors such as accelerometers and HR monitors. This framework demonstrated how wearable technology can capture both physiological and behavioral data to enhance the understanding of student dynamics.

The study by Domínguez-Jiménez et al. (2020) advanced the application of wearable devices by integrating GSR and Photoplethysmogram (PPG) signals for emotion recognition, achieving a precision rate of up to 100%. Pérez et al. (2018) also highlighted the practical utility of wearable sensors for real-time stress monitoring among students, demonstrating their capacity to support adaptive educational strategies. Similarly, Yoon et al. (2016) contributed to the development of flexible wearable patches capable of continuously monitoring EDA, HR, and ST, providing a robust solution for long-term use in educational settings.

3.1.2 Adaptive Interventions and Personalized Education

Rodríguez-Arce et al. (2020) demonstrated the reliability of wearable devices in accurately predicting stress and anxiety levels, particularly in high-pressure academic environments. Their findings underscored the robustness of wearable technology in measuring physiological responses critical for student well-being. Gao et al. (2020) extended this research by integrating wearable devices with environmental data to enhance engagement predictions. This approach not only provided more comprehensive insights but also offered actionable data to educators for tailoring interventions to individual student needs. These methodological advancements illustrate the transformative potential of wearable technology in modern education. By enabling continuous, precise, and real-time monitoring of physiological and contextual data, these devices are paving the way for a more adaptive, personalized, and effective educational experience.

3.2 Machine Learning Integration

Machine learning (ML) techniques have revolutionized the analysis of physiological data, enabling the development of predictive models for student engagement and academic performance. For example, Pérez et al. (2018) demonstrated how combining ML algorithms with multimodal physiological data could effectively detect stress, highlighting the potential of these techniques in educational settings. Similarly, Cain and Lee (2016) applied ML methods to Makerspace activities, identifying moments of high engagement by correlating them with peaks in EDA and HR data. Kanna et al. (2018) showcased a practical integration of wearable sensors in engineering education, allowing students to analyze their own physiological data, such as ECG signals, while learning signal processing techniques.

3.2.1 Machine Learning for Student Performance Prediction

Supervised learning techniques have proven particularly effective in predicting student performance. Rastrollo-Guerrero et al. (2020) demonstrated the utility of Support Vector Machines (SVM), achieving high accuracy in performance prediction. Simjanoska et al. (2014) expanded this application by using ML algorithms to develop adaptive e-Learning strategies, ensuring targeted learning outcomes while reducing random guessing. Ensemble methods, such as RealAdaBoost combined with J48, were shown by Imran et al. (2019) to improve model precision, achieving a classification accuracy of 95.78%. Walsh and Mahesh (2017) integrated behavioral and traditional academic data to predict outcomes early, enabling timely interventions that significantly improved learning experiences.

3.2.2 Leveraging Diverse Machine Learning Techniques

Various ML algorithms have been applied to enhance prediction models across educational settings. Pavani et al. (2017) highlighted Decision Tree (DT) algorithms, such as C4.5, for their accessibility and effectiveness in predicting academic performance.

Shanthini et al. (2018) demonstrated the potential of ensemble methods, including AdaBoost and Bagging, achieving accuracy rates of 97.6%. Yan and Liu (2020) validated the superiority of stacking models, which combine algorithms like Random

Forests (RF), SVM, and AdaBoost, to improve predictive accuracy

Ofori et al. (2020) incorporated socio-economic factors into their ML models, revealing significant impacts on academic outcomes, while Naicker et al. (2020) compared Linear SVM (LSVM) with other algorithms to identify its effectiveness across diverse student demographics.

3.2.3 Early Identification and Adaptive Learning Systems

ML has also been employed for early identification of at-risk students. Wakelam et al. (2019) applied RF and K-Nearest Neighbors (KNN) algorithms in small-class settings to predict academic challenges, achieving high reliability. Hussain et al. (2018) demonstrated ML integration in real-time learning systems, enabling continuous feedback and adaptive interventions. Polyzou and Karypis (2023) emphasized the use of Gradient Boosting and RF models for early warning systems, while Pang et al. (2017) achieved high accuracy in graduation predictions by incorporating psychopedagogical variables into SVM-based models.

Gray and Perkins (2019) successfully identified at-risk students by the third week of a semester using ML models with a 97% accuracy rate, and Zabriskie et al. (2019) employed RF models to develop early-warning systems in physics courses, leveraging institutional and classroom data.

3.2.4 Machine Learning in Physiological Data Analysis

Integrating ML with physiological data has opened new possibilities for adaptive education. Gao et al. (2020) combined ML techniques with wearable technology to analyze multimodal physiological data, improving engagement predictions in diverse learning environments.

Yoon et al. (2016) highlighted the feasibility of ML models for continuous data stream analysis, allowing educators to tailor strategies based on real-time feedback. Pérez et al. (2018) emphasized the effectiveness of ML in optimizing stress detection, enabling adaptive interventions to support student well-being. These advancements underscore the role of ML in leveraging physiological insights to create personalized and effective educational experiences, making adaptive learning environments more feasible and impactful.

4 IMPLICATIONS FOR NEUROEDUCATION

The integration of physiological measures into neuroeducation has opened new possibilities for understanding and enhancing individual learning processes. By addressing both cognitive and emotional dimensions, educators can create inclusive and adaptive learning environments that cater to diverse student needs.

Abromavičius et al. (2023) emphasized the practical implications of using physiological data to manage stress and enhance academic outcomes, particularly in high-pressure contexts. Similarly, Schneider et al. (2020) explored physiological synchronization metrics as indicators of effective teamwork in collaborative learning environments, highlighting their potential to improve group dynamics and performance.

Table 1 provides a comprehensive summary of empirical findings from 17 key studies that investigated the application of physiological measures, including EDA, HR, and ST, in educational contexts. These studies span diverse experimental settings, from traditional classrooms to e-learning environments, and highlight the potential of these metrics for monitoring engagement, stress, and emotional states. The table synthesizes data on participants, experimental conditions, and significant outcomes, offering valuable insights into the practical applications and limitations of physiological monitoring technologies.

The studies summarized in Table 1 underscore the versatility and efficacy of physiological measures in enhancing educational practices. Key findings reveal that EDA consistently emerges as a reliable indicator of student engagement, as demonstrated by Di Lascio et al. (2018) and Villanueva et al. (2019), with engagement detection accuracies reaching up to 81% using advanced machine learning models. Similarly, HR and ST have been validated as complementary measures, particularly in stress-inducing academic environments, with studies such as Pérez et al. (2018) showcasing their predictive value in estimating stress levels with high precision.

One notable trend across the studies is the increasing reliance on multimodal approaches that integrate EDA, HR, and ST to achieve more robust insights. For instance, Rodríguez-Arce et al. (2020) demonstrated a stress detection accuracy of 90% by combining these metrics, highlighting the synergistic potential of multimodal data in understanding complex physiological responses during academic tasks.

Table 1: Studies on EDA, HR, and ST in education: participants, conditions, and key findings.

References	Title	Participants	Stressor	Results
Abromavičius et al. (2023)	Prediction of exam scores using a multi-sensor approach for wearable exam stress dataset with uniform preprocessing	10 undergraduate students	Exam stress during three examinations	Physiological signals, including EDA, HR, and ST, revealed high predictive potential for exam scores with accuracy, AUROC, and F1-score reaching 0.9, 0.89, and 0.87, respectively. A uniform preprocessing enhanced the robustness of signal analysis.
Al-Awani (2016)	A Combined Approach to Improve Supervised E-Learning using Multi-Sensor Student Engagement Analysis	20 students	E-learning sessions	Correlation analysis of EDA, pulse rate, and facial expressions indicated significant potential for measuring engagement. Findings suggest integration of multi-sensor data to dynamically adjust educational content.
Cain & Lee (2016)	Measuring electrodermal activity to capture engagement in an afterschool maker program	2 youth participants	Practical activities in a makerspace	Analysis of EDA data indicated higher engagement during interactive activities, such as presenting progress, and varied engagement during individual tasks.
Darnell & Krieg (2019)	Student Engagement Assessed Using Heart Rate Shows No Reset Following Active Learning Sessions in Lectures	15 students	Lecture-based active learning sessions	HR increased during active learning but returned to baseline immediately afterward. Demonstrated HR's limitations in reflecting sustained engagement post-activity.
Di Lascio et al. (2018)	Unobtrusive Assessment of Students' Emotional Engagement during Lectures Using Electrodermal Activity Sensors	24 students and 9 professors in 41 lectures	Emotional engagement during lectures	EDA sensors identified disengaged students with 81% accuracy using SVM, highlighting the potential of EDA for educational feedback.
Gao et al. (2020)	n-Gage: Predicting In-Class Emotional, Behavioral, and Cognitive Engagement in the Wild	23 students (13 females and 10 males) and 6 teachers (4 females and 2 males)	Classroom engagement tasks	Multidimensional engagement prediction (emotional, behavioral, and cognitive) using EDA, HRV, and ST achieved MAE of 0.788 and RMSE of 0.975. Highlighted the utility of wearable sensors for real-time engagement monitoring.
Jamal & Kamioka (2019)	Emotions Detection Scheme Using Facial Skin Temperature and Heart Rate Variability	20 subjects (10 females and 10 males)	Visual and auditory stimuli	Emotion detection (joy, fear, sadness, and relaxation) using HRV and facial skin temperature achieved 88.75% accuracy with an ANN-based classifier. Demonstrated the reliability of HRV and facial skin temperature for emotion recognition without physical interaction.
Khan et al. (2019)	Exploring relationships between electrodermal activity, skin temperature, and performance during engineering exams	76 engineering students	Exam difficulty and cognitive tasks	Weak but significant correlations observed between EDA, ST, and exam difficulty index (e.g., r=0.13 for EDA; r=0.08 for ST). Regression models indicated moderate significance in relationships among variables.
Lu et al. (2017)	A Framework for Learning Analytics Using Commodity Wearable Devices	24 participants (11 female and 13 male)	Academic stress and physical activity	Developed the LEARNSense framework integrating EDA, HR, and ST data for analyzing student engagement. Achieved F1 scores of 0.9 for classifying engagement states. Demonstrated feasibility of wearable sensors for real-time analytics.

Table 1: Studies on EDA, HR, and ST in education: participants, conditions, and key findings (cont.).

References	Title	Participants	Stressor	Results
Nourbakhsh et al. (2012)	Using galvanic skin response for cognitive load measurement in arithmetic and reading tasks	25 participants (13 for arithmetic tasks, 12 for reading tasks)	Reading and arithmetic tasks of varying difficulty	Spectral features of GSR demonstrated high significance in cognitive load measurement after normalization, highlighting the potential of spectral analysis for complex cognitive tasks.
Pérez et al. (2018)	Evaluation of Commercial-Off-The-Shelf Wrist Wearables to Estimate Stress on Students	12 first-year university students	Stress-inducing laboratory tasks and classroom activities	Protocol validated the efficacy of COTS wearables in capturing HR, HRV, and ST for stress analysis in educational settings. Machine learning models demonstrated high accuracy in estimating stress levels during academic tasks.
Pijeira-Díaz et al. (2018)	Profiling sympathetic arousal in a physics course how active are students	24 high school students	Advanced physics course and final exam	Arousal measured via EDA positively correlated with academic performance (r = 0.66). Low arousal states were predominant during lectures, while activation significantly increased during the exam.
Quintero & Bolkhovsky (2019)	Machine learning models for the identification of cognitive tasks using autonomic reactions from heart rate variability and electrodermal activity	16 participants (8 male, 8 female)	Cognitive tasks including vigilance and memory	EDA and HRV indices enabled identification of cognitive tasks with classification accuracy up to 66% using machine learning models like KNN and SVM.
Rodríguez-Arce et al. (2020)	Towards an Anxiety and Stress Recognition System for Academic Environments	21 university students	Academic stress tasks and self-reported anxiety	Stress detection achieved 90% accuracy using k-NN on HR, skin temperature, and oximetry signals. Anxiety recognition attained 95% accuracy with SVM using GSR data.
Schneider et al. (2020)	Unpacking the relationship between existing and new measures of physiological synchrony and collaborative learning: a mixed methods study	42 pairs of participants (84 individuals)	Collaborative tasks involving programming robots	Physiological synchrony (measured via EDA) correlated with learning gains (r = 0.35) and collaboration quality (r = 0.3). Developed a novel measure using EDA cycles that improved correlations with collaboration quality (r = 0.57).
Terriault et al. (2021)	Use of electrodermal wristbands to measure students' cognitive engagement in the classroom	8 participants (7 students and 1 professor)	Classes, workshops, and exams	EDA data from Empatica E4 wristbands revealed engagement patterns, but external factors, such as physical activity and room temperature, complicated data consistency.
Thammasan et al. (2020)	A Usability Study of Physiological Measurement in School Using Wearable Sensors	86 adolescents in schools	Daily academic activities	Demonstrated feasibility of EDA and HR measurements in school settings. Addressed challenges in data quality and preprocessing, highlighting limitations of generic signal processing tools.

Additionally, machine learning applications, as seen in studies like Gao et al. (2020), have further enhanced the predictive power of these measures, enabling real-time engagement and emotional monitoring with high accuracy. Despite these promising outcomes, the findings also highlight significant challenges. External factors, such as environmental conditions and physical activity, can affect the reliability of HR and ST measurements, as noted by Terriault et al. (2021). Similarly, the limited sample sizes in certain studies, such as Cain and Lee (2016), restrict the generalizability of results, emphasizing the need for larger-scale investigations. Moreover, ethical considerations surrounding the use of wearable devices in educational settings require further exploration to ensure student privacy and data security.

In conclusion, the evidence presented in Table 1 underscores the transformative potential of physiological measures for creating adaptive and student-centered educational environments. By addressing current limitations and leveraging advancements in wearable technologies and machine learning, future research can pave the way for more inclusive and effective educational practices.

4.1 Practical Applications of Physiological Insights in Education

The use of physiological data has also been applied to tailor pedagogical approaches. Villanueva et al. (2019) demonstrated how the intersection of identity and physiological metrics in academic mentoring can address diverse student needs, fostering a more inclusive learning experience.

Lee et al. (2020) exemplified the use of EDA to differentiate between public speaking and foreign language anxiety, showcasing its utility in addressing distinct stress contexts. Katmada et al. (2015) proposed a biofeedback system that integrates EDA, HR, and ST, highlighting its effectiveness in reducing anxiety through gamified educational tools. Furthermore, Jamal and Kamioka (2019) introduced an emotion detection framework using facial ST and HRV, achieving high accuracy without requiring physical interaction, thereby expanding the scope of non-invasive monitoring methods.

4.2 Building Emotionally Supportive and Adaptive Learning Environments

Physiological monitoring has proven instrumental in promoting emotional engagement, which is critical for deeper learning experiences. Loderer et al. (2020) demonstrated that emotional engagement, as measured through physiological data, fosters stronger connections to educational material and promotes long-term retention. Reid et al. (2020) highlighted the value of real-time feedback in identifying stress points during learning activities, enabling timely and effective interventions by educators to alleviate stress and maintain focus. The combination of physiological metrics has shown promise in creating supportive frameworks that improve resilience and academic outcomes, especially in high-stress environments. Rodríguez-Arce et al. (2020) explored the integration of EDA, HR, and ST in designing frameworks that support students' emotional well-being while fostering academic success.

Eliot and Hirumi (2019) emphasized that incorporating emotional and physiological metrics into pedagogy enhances inclusivity and responsiveness to individual learner needs, paving the way for more equitable educational practices. These advancements collectively underscore the transformative potential of physiological monitoring in advancing neuroeducation. By leveraging insights from metrics such as EDA, HR, and ST, educators can develop data-driven strategies to personalize learning and address students' emotional and cognitive challenges. The application of biofeedback systems, emotion detection frameworks, and real-time stress monitoring tools highlights the profound impact of integrating physiological insights into modern educational practices, ultimately promoting student success and well-being.

5 CHALLENGES AND FUTURE DIRECTIONS

The integration of physiological measures into education presents significant opportunities, yet it also faces notable challenges. Technical reliability remains a key concern, particularly for wearable devices measuring EDA, HR, and ST. External variables, such as environmental conditions and physical activity, can affect data accuracy, as highlighted by studies that emphasize the need for robust preprocessing techniques and adaptive algorithms. Moreover, variability in sensor quality and calibration across devices further complicates widespread adoption.

The collection of physiological data in educational settings, especially with minors, raises significant ethical and privacy concerns. Effective data governance and security are critical. Future research must standardize methodologies, enhance sensor accuracy, and refine machine learning models to reduce bias in diverse environments. Large-scale, longitudinal studies are needed for broader validation. Overcoming these challenges is key to achieving sustainable educational innovations.

6 CONCLUSIONS

This review underscores the transformative potential of physiological measures in advancing neuroeducation. By leveraging metrics such as EDA, HR, and ST, educators can gain real-time insights into student engagement, stress, and emotional states, enabling adaptive and personalized learning experiences. The integration of wearable technologies and machine learning models enhances the feasibility of implementing these approaches in diverse educational contexts.

Despite the promising applications, challenges related to technical reliability, ethical considerations, and scalability remain significant. However, ongoing advancements in wearable technologies, multimodal data analysis, and standardized frameworks offer pathways to address these barriers. Future research must prioritize inclusivity, ethical transparency, and empirical validation to ensure the widespread adoption of these tools.

In conclusion, physiological monitoring represents a critical innovation in fostering emotionally supportive, data-driven, and effective educational environments. By bridging neuroscience and pedagogy, this approach has the potential to revolutionize how educators understand and respond to the cognitive and emotional needs of learners.

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