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Electrodermal activity as an indicator of student engagement: a comparative study of traditional and active learning environments

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Abstract**– *Electrodermal Activity (EDA) has emerged as a valuable physiological measure in educational research, providing insights into emotional and cognitive engagement. This study investigates the variation in students' EDA responses under traditional lecture-based and active learning conditions. Data were collected from eight university students using electrodermal resistance sensors during instruction on the Single Minute Exchange of Die (SMED) methodology. Each participant engaged in both instructional modalities within a controlled environment. The EDA signals were analyzed using statistical techniques including paired t-tests and Mann-Whitney tests. Results indicated that most students exhibited significantly higher EDA levels during active learning sessions, suggesting increased arousal and engagement. However, individual differences, including potential non-responsiveness and gender-based variability, were also observed. These findings underscore the potential of EDA as a real-time, non-invasive tool for assessing instructional effectiveness and student engagement, offering implications for the design of adaptive and student-centered learning environments.***

Keywords—Electrodermal activity · Traditional teaching · Active learning · Neuroscience · Learning environments.

I. INTRODUCTION

Electrodermal Activity (EDA), also referred to as Galvanic Skin Response, has garnered research interest across multiple fields, including psychology, medicine, and, more recently, education [1], [2]. Despite its widespread application in monitoring emotional and cognitive states, a notable gap persists in understanding how EDA can be effectively utilized within educational contexts. Addressing this gap, the present study investigates whether students' electrodermal activity exhibits measurable differences when they are engaged in traditional versus active learning approaches.

EDA serves as a reliable physiological measure of arousal, responding to emotional, cognitive, or environmental stimuli [3], [4]. Recent advances have further demonstrated the capability of machine learning algorithms to predict emotional states from EDA signals alone [5], [6]. Within educational settings, EDA has been used to gauge students' engagement and emotional involvement [7]. For instance, studies have shown that active learning environments, as opposed to traditional instructional settings, tend to evoke higher EDA levels, indicating heightened engagement [8], [9].

Understanding fluctuations in EDA in response to different teaching methods can provide critical insights into student engagement. This is especially relevant as educational institutions increasingly prioritize more adaptable and interactive learning experiences [10]. In this study, we conducted a quantitative assessment involving eight university students who participated in both traditional and active learning environments. EDA data were gathered and subjected to various mathematical analyses and statistical tests, including paired t-tests and Mann-Whitney tests, using Minitab software.

The objective of this research is to compare students' EDA levels across distinct learning environments, specifically examining physiological responses during traditional and active learning sessions. Grounded in previous literature, we hypothesize that EDA levels will be higher during active learning sessions compared to traditional teaching approaches.

Beyond its academic contributions, this study holds practical implications. The results could potentially guide educational policies and pedagogical practices by promoting more interactive, student-centered teaching strategies. This practical dimension is further discussed in the conclusions, where we explore how real-time EDA monitoring might be integrated into educational technologies to provide immediate feedback and facilitate personalized learning.

This paper is structured as follows: Section II offers a comprehensive literature review, focusing on the role of EDA in educational research and the effectiveness of varying teaching methodologies. Section III details the materials and methods, including the experimental design, participant selection, and data collection and analysis procedures. Section IV presents and discusses the results, offering statistical insights into EDA variations between traditional and active learning contexts. Finally, Section V concludes the study, summarizing key findings, limitations, and future research directions.

II. THEORETICAL FRAMEWORK

EDA encompasses a range of electrical phenomena in human skin, including the psychogalvanic reflex and the galvanic skin response [11]. EDA measurements are generally categorized as either endosomatic or exosomatic [12].

Endosomatic measurements capture the naturally occurring electrical potential within the skin, while exosomatic measurements involve applying an external current, either alternating or direct to the skin. The relevance of EDA to educational contexts becomes evident when we consider its potential impact on student performance, a topic further explored below.

A study investigating the use of electrodermal activity (EDA) and temperature sensors to assess students' performance during real-time exams was conducted in [7]. Their findings indicated that increased exam difficulty correlated with heightened cognitive engagement, which, in turn, was reflected in elevated EDA levels. This relationship can be explained by heightened sweat secretion and reduced skin temperature, both of which indicate increased physiological arousal associated with cognitive effort.

Methodological considerations in electrodermal activity (EDA) research were examined in [13], synthesizing empirical evidence on the relationship between physiological arousal and learning processes. Their results highlighted considerable variation in the use of EDA within educational research, revealing that the associations between physiological arousal and learning outcomes were often inconsistent, suggesting an ongoing need for methodological standardization.

Building on these methodological insights, two distinct approaches to analyzing students' electrodermal activity (EDA) data were employed in [14]. First, they calculated interindividual differences in physiological activity by assessing each student's EDA confidence level. Second, they adjusted intervals to capture variations in these interindividual differences over time, revealing nuanced patterns in EDA responses among students.

In summary, the use of EDA in educational research frequently focuses on capturing detailed insights into the learning process. The application of electrodermal activity (EDA) in educational contexts primarily involves quantitative methods, such as correlation analyses, dataset comparisons, and multiple regression models, as emphasized in [15]. This methodological rigor and flexibility highlight the value of EDA as a tool for examining various dimensions of educational engagement and student performance.

A. Sensor technology and daily applications

EDA sensors are often embedded in wearable devices, such as wristbands, enabling continuous monitoring throughout daily activities. These wristbands use electrodes to detect changes in skin galvanic response and can transmit the collected data to smartphones via Bluetooth [2]. This portability and adaptability make EDA sensors highly suitable for real-time studies in educational psychology, as we will examine in further detail.

EDA has become an important tool for assessing emotional engagement and stress in educational settings, and its use extends across a wide range of experiments that incorporate physical, cognitive, and emotional components. For example, increased skin conductance was observed in students during mental arithmetic tasks, indicating heightened cognitive load [1]. Similarly, electrodermal activity (EDA) was combined with machine learning algorithms to predict emotional responses to audiovisual stimuli, demonstrating EDA's potential for real-time emotional assessment [5].

Further evidence of the utility of electrodermal activity (EDA) is provided in [16], which tracked twenty-four students over a three-week period and reported a generalized excitement rate of 81%. Notably, this study also demonstrated momentary engagement levels during student-professor interactions by employing a Support Vector Machine (SVM) classifier. Expanding on these findings, the reliability of electrodermal activity (EDA) signal processing in educational research was evaluated in [17], while students' psychophysiological responses during learning activities were investigated in [18].

In alignment with the application of electrodermal activity (EDA) in classroom settings, a method employing galvanic skin response (GSR) sensors to measure student engagement during various pedagogical approaches was introduced in [19]. Their findings indicated heightened engagement during varied instructional formats, such as lectures, film screenings, and group discussions, compared to traditional lecture-only formats. Similarly, galvanic skin response (GSR) was used in [20] to compare student engagement during lectures delivered in both remote and in-person settings, revealing higher GSR density in remote environments. This suggests a promising area for further exploration within remote and hybrid learning environments.

B. Neuroimaging and EDA

In [21], functional magnetic resonance imaging (fMRI) was utilized to examine brain region activity associated with auditory and language processing. Conducted among children aged 11-13, the study involved both passive listening (PL) and active response (AR) tasks. Using a General Linear Model approach alongside paired t-tests, researchers identified significant activation in areas such as the primary auditory cortex, bilateral superior temporal gyrus, and inferior frontal gyrus (IFG) for both tasks.

Similarly, the potential of functional near-infrared spectroscopy (fNIRS) in monitoring brain activity, particularly for distinguishing levels of student engagement, was demonstrated in [22]. This study assessed engagement by correlating questionnaire responses in virtual environments with data collected from the prefrontal cortex (PFC) of eighteen students while watching video lectures. EDA, as a research tool in education, thus offers a valuable means of exploring students' emotional responses to diverse teaching methods and instructional approaches [9].

C. Individual variability in stress responses

Stress manifests in diverse forms, emotional, cognitive, and motivational, varying based on everyone's neurological state. An experiment involving a group of students was conducted in [23] to analyze cognitive and emotional stress during task completion in a controlled laboratory environment. Their findings revealed notable differences in stress responses across individuals, with spatial modeling techniques applied to detect subtle variations in cognitive and emotional stress levels among participants.

In a related study, stress responses were examined in [8] among eighty-eight students aged 18 to 20, comparing engagement levels between active learning and traditional teaching settings. Engagement levels were assessed over five workshop sessions, providing further insights into the impact of varied teaching approaches on individual stress responses.

As educational institutions increasingly transition to flexible learning spaces, there is a growing emphasis on enhancing student engagement. Redesigned learning spaces were found to foster higher levels of engagement and more positive perceptions of the educational environment in [10]. The study also identified motivation as a key mediating factor, suggesting that flexibility in physical learning spaces can positively influence students' learning experiences.

D. *EDA applied in education*

EDA sensors offer valuable insights into students' emotional involvement, regardless of their engagement level in class. Table I presents an overview of the application of EDA devices in educational contexts, highlighting various stressors as reported by students. Across the studies reviewed, EDA was consistently used as a primary parameter for assessing engagement and emotional response.

TABLE I
EDA IN AN EDUCATIONAL ENVIRONMENT

References	Title	Students	Stressor	Results
[16]	Unobtrusive Assessment of Students' Emotional Engagement during Lectures Using Electrodermal Activity Sensors	Twenty-four students	General excitement Physiological synchrony Momentary engagement	During students' interaction with the professor, there was a large increase in general arousal and indication of momentary engagement by 81% of students using the Support Vector Machine classifier coupled with resources related to momentary engagement.
[7]	Exploring relationships between electrodermal activity, skin temperature and performance during engineering exams	Seventy-six students	Engagement	They suggest that performance is linked to students' physiological responses during the tests, thus revealing a connection between emotions and cognition via physiology.
[24]	Establishing a Link between Electrodermal Activity and Classroom Engagement	Four students, 4 men aged between 18 and 21 years	Engagement	The greater the intensity of EDA signals, the better the involvement of students in the learning environment.
[8]	A Multimodal Exploration of Engineering Students Emotions and Electrodermal Activity in Design Activities	Eighty-eight students aged between 18 and 20 years	Engagement	The EDA of students Increased when exposed to active learning compared to the traditional teaching method, i.e. student engagement increased when active learning activities were introduced in the workshops.
[25]	Electrodermal Activity Sensor for Classifying Calm/Distressful Conditions	Forty-five students, 25 men and 20 women aged 24 years on average	Calm and Anguish	89% overall accuracy was found while distinguishing a calm condition from a distressful condition.

III. MATERIALS AND METHODS

This study employed a quantitative experimental design to gather EDA data from eight university students exposed to both traditional teaching and active learning environments. EDA data were measured and analyzed using an Electrodermal Resistance sensor, as illustrated in Fig. 1, which shows the sensor used for data collection. This device was selected for its reliability in capturing accurate EDA measurements, ensuring data validity throughout the study.

The protocol aimed to monitor and compare physiological responses across different instructional methods, providing insight into the students' engagement and emotional involvement in varied learning environments.

Fig. 1 Electrodermal Resistance Sensor

The students' electrodermal activity data were captured and visualized in real-time using neuroimaging techniques based on Functional Magnetic Resonance (fMR) technology. This was achieved by non-invasive sensors attached to the students' hands, allowing for continuous monitoring. The sensors transmitted signals to an encoding unit (microprocessor), which digitized, encoded, and then relayed the data to a computer via USB cable.

This setup ensured maximum freedom of movement for participants while preserving signal fidelity and providing electrical isolation for safe operation. Additionally, it enabled graphical analysis and assessment of the acquired signals using various mathematical algorithms, including Fast Fourier Transform (FFT), Median Frequency (MF), and Root Mean Square (RMS). To further support data processing, the LAPACK Math Kernel Library (BLAS) was used in conjunction with an advanced scientific computing system compatible with Matlab, LabVIEW, Omatrix, and Scilab.

The sensors were automatically calibrated by the software, enhancing measurement precision. Power was supplied through the computer's USB port, which, along with a battery module, ensured the system remained isolated from the electrical network, thereby preventing any risk of electric shock to participants.

A. Participants

EDA data were collected from a sample of eight university students, equally divided between male and female participants. All students were in the sixth to eighth semesters of their undergraduate studies, aged between 20 and 23. Before participation, each student reviewed and signed an Informed Consent Form (ICF), approved by an ethics committee for human-subject research. The experiment involved exposure to two instructional methods: traditional lectures and active learning sessions. The content for both methods focused on the Single Minute Exchange of Die (SMED) technique.

SMED is a lean manufacturing method developed to minimize production downtime during transitions involving design, product, or raw material changes. Originally formulated by Shingo at Toyo Kogyo’s Mazda plant in the 1950s, SMED aims to optimize ‘internal’ and ‘external’ setup operations to reduce machine downtime. The technique has since been widely adopted across industries to streamline processes and reduce changeover times [26].

To ensure consistency and minimize variability, the measurements were conducted with the same students and instructor in a controlled environment set at 23ºC. This control was implemented to enhance the reliability of the data. Each student completed the Informed Consent for Registry before the experiment began.

B. Data collection

For data collection, an isolator was connected to the notebook's USB port, using a six-channel cabinet with a proprietary fastening system for electrode connections. The isolator specifications included an input signal range from 0 to +500 mV, channel input values of DC 5 Volts at 0.01 A, and a 14-bit ADC output. Sampling rates were set at 2048 Hz for three channels and 256 Hz for the remaining three, with noise levels below 1 RMS µV (frequency range 1-64 Hz). Input impedance exceeded 10^10 Ohms, with a CMRR (typical) greater than 130 dB, ensuring 1500V of safety isolation and a ±2% accuracy (both initial and post self-calibration). The equipment operated at a 60 Hz frequency to power the sensors, as depicted in Fig. 2.

Fig. 2 Cabinet with channels for connecting the sensors

The Electrodermal Resistance sensor, with an accuracy of ±5% and a sensitivity of ±0.2 µS, was attached to each participant’s index and middle fingers using a double wire configuration with two metal discs, as shown in Fig. 3. This setup was designed to optimize signal reception from the skin, allowing precise measurement of electrodermal responses during the experimental sessions.

Fig. 3 Electrodermal Resistance sensor connection

Each measurement session spanned one hour per student, divided into two 30-minute segments: one involving a traditional lecture format and the other incorporating an active learning approach, both taught by a PhD professor specializing in SMED. During data collection, the Electrodermal Resistance sensor was initially placed on Student A, with data transmitted in real-time to a computer through a case equipped with sensor ports.

For the traditional class segment, the professor presented the SMED topic using slides, lasting 30 minutes. Following this, the active learning session also lasted 30 minutes and began with a brief introduction to SMED. Each student then engaged in a sequence of three hands-on activities, focusing on the assembly process for various devices. First, each participant assembled device 1 on the assembly base; after completing this task, they moved on to device 2, and finally, they assembled device 3 on the base. These assembly activities, illustrated in Fig. 4, were structured to simulate realworld applications of SMED principles, facilitating experiential learning through active participation.

Fig. 4 Device assembly 1, 2, and 3

It is important to note that the time taken to complete each assembly activity was recorded to compare the internal setup times for each device, specifically focusing on tasks that could only be performed when the computer was idle. After completing the active learning session for one student, the sensor was removed and placed on the next participant. This process was repeated for each of the eight students in the study. Each student participated in both a traditional lecture using slides and a subsequent active learning session on the SMED topic, each lasting 30 minutes. During both sessions, EDA data were collected via the Electrodermal Resistance sensor for later analysis.

The EDA data collected from each student were then visualized in graphs, illustrating the distribution of EDA values over time. EDA, measured in microsiemens (μS), typically ranges between 1 to 20 μS in humans, with variations reflecting cognitive arousal levels [27]. While EDA values fluctuate, they generally change by only a few tens of microsiemens [3]. It is further noted in [28] that electrodermal activity (EDA) levels exhibit slight variations, with pulses showing amplitudes of only a few microsiemens.

C. *Data analysis*

EDA data were analyzed using Minitab software. The Anderson-Darling Test was performed initially to assess data normality, as this test effectively compares the empirical cumulative distribution of EDA data [29]. Results indicated an asymmetric data distribution, confirming non-normality.

Subsequently, a paired t-test was applied to determine whether there were statistically significant differences between the mean EDA levels for the traditional and active learning methods. The paired t-test was chosen for its suitability in comparing means between two related groups. However, for ordinal or non-normally distributed data, standard tests for mean comparison are inappropriate, as noted in [30]. In these cases, the Mann-Whitney test, a non-parametric alternative, was used, especially relevant for Student G's data, which retained the null hypothesis (H0) in the paired t-test with a P-value exceeding the 0.05 significance threshold.

The Mann-Whitney test was also utilized to examine overall trends between the traditional and active learning methods, especially when both sets of data exhibited similar distribution shapes. It has been highlighted in [31] that approximately 10% of students may be non-responders in electrodermal activity (EDA) measurements, potentially increasing data variability by up to 25%.

These methodologies provide the basis for the data collection and analysis that follows. It is important to recognize certain study limitations, notably the sample size, which may affect the generalizability and statistical power of the results.

IV. Results and Discussion

A. *EDA results*

Table II presents the EDA data for each of the eight participating students, measured over the course of one hour. The data were recorded in two distinct 30-minute intervals: the first during a traditional lecture format and the second during an active learning session, both centered on the SMED topic. This division allowed for a direct comparison of EDA levels across different instructional methods, providing insight into physiological responses linked to engagement and arousal in each setting.

TABLE II
EDA Measurements of Students

EDA	Student A	Student B	Student C	Student D	Student E	Student F	Student G	Student H
Traditional Maximum	5.6 μS	6.6 μS	3.1 μS	5.5 μS	4.1 μS	6.4 μS	7.0 μS	6.0 μS
Traditional Minimum	3.4 μS	5.3 μS	1.3 μS	4.4 μS	2.2 μS	5.3 μS	6.6 μS	4.3 μS
Active Maximum	6.5 μS	6.6 μS	6.1 μS	5.6 μS	5.4 μS	6.4 μS	7.1 μS	7.0 μS
Active Minimum	4.6 μS	5.5 μS	1.2 μS	4.7 μS	3.4 μS	5.5 μS	6.6 μS	2.4 μS
Traditional Mean	4.2 μS	6.0 μS	1.7 μS	4.7 μS	2.8 μS	6.0 μS	6.8 μS	4.8 μS
Active Mean	5.7 μS	5.9 μS	4.6 μS	4.9 μS	4.4 μS	5.8 μS	6.8 μS	5.9 μS
Paired Difference	-1.5 μS	0.1 μS	-2.9 μS	-0.2 μS	-1.6 μS	0.1 μS	0.0 μS	-1.0 μS
Traditional Median	4.2 μS	6.1 μS	1.5 μS	4.6 μS	2.8 μS	6.0 μS	6.8 μS	4.8 μS
Active Median	5.8 μS	5.9 μS	4.8 μS	4.8 μS	4.4 μS	5.8 μS	6.8 μS	6.1 μS
Median Difference	-1.5 μS	0.2 μS	-3.2 μS	-0.2 μS	-1.7 μS	0.2 μS	0.0 μS	-1.2 μS
Paired t-test	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Accept H0	Reject H0
Mann-Whitney	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0
Teaching Method	Active	Traditional	Active	Active	Active	Traditional	Traditional	Active

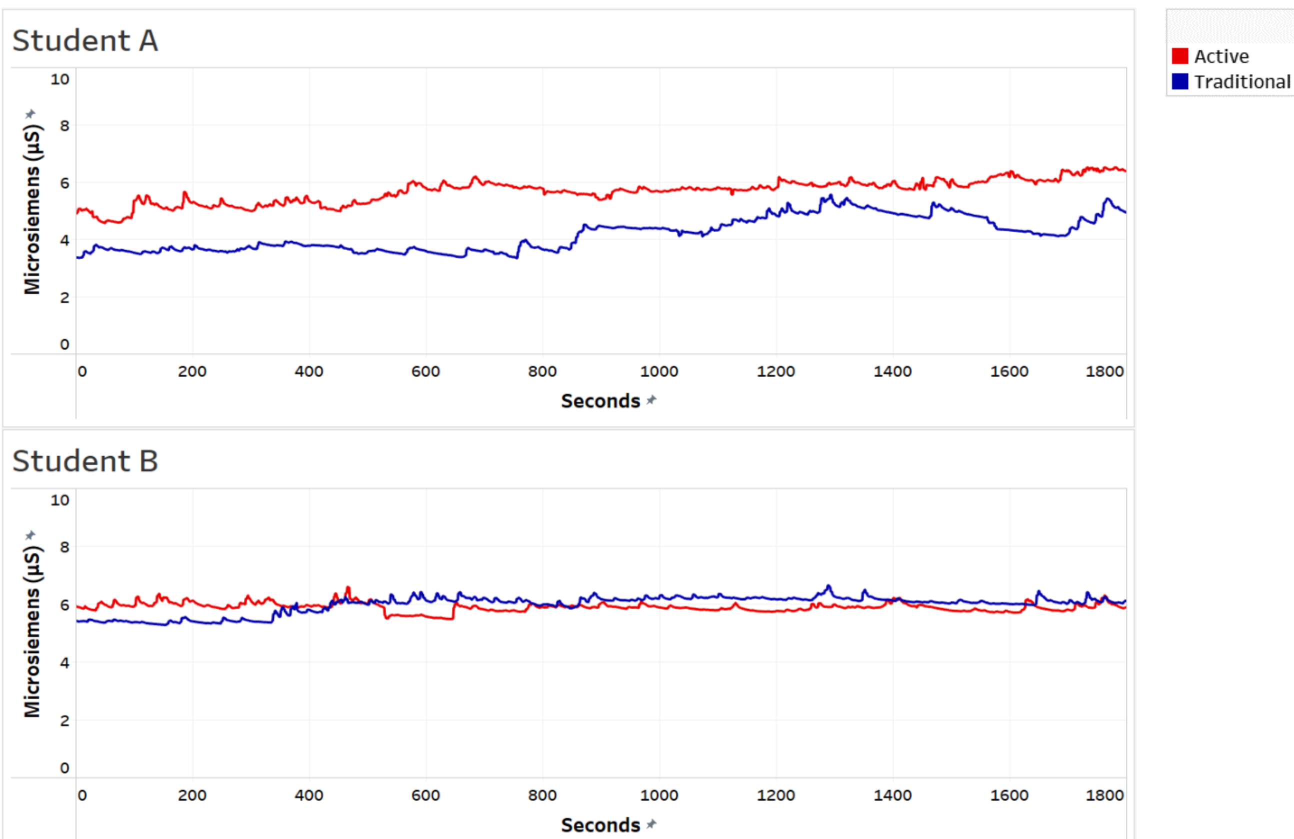
The analysis highlights significant differences in EDA responses between students in active learning sessions compared to traditional lecture-based sessions. Specifically, students A, C, D, E, and H displayed higher mean and median EDA values during active learning, indicating increased physiological arousal associated with this more interactive method. Conversely, students B, F, and G exhibited higher mean and median EDA values during traditional learning sessions.

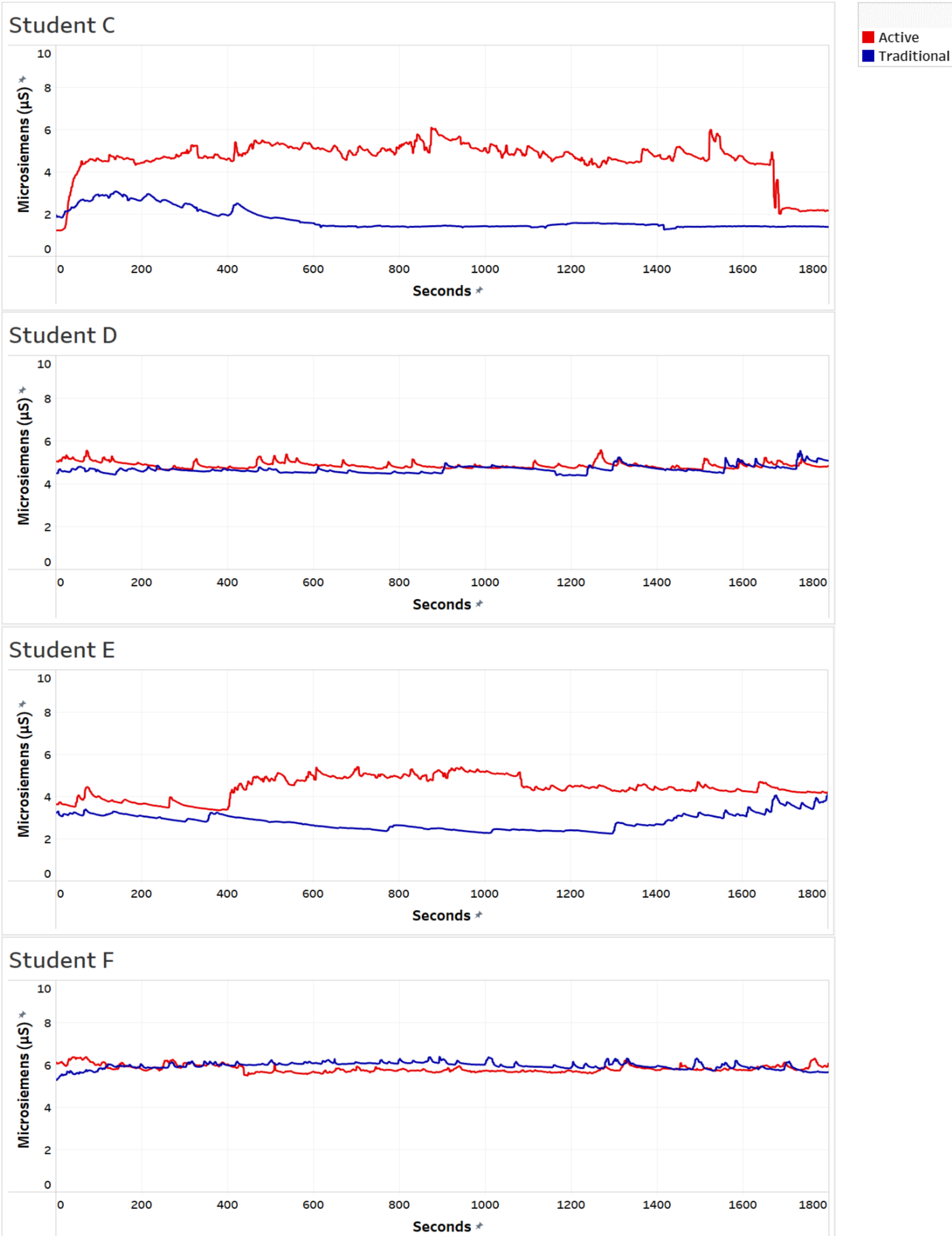
The paired t-test results confirmed that the mean differences in EDA levels were statistically significant for students A, C, E, and H, suggesting that these individuals experienced a marked increase in engagement and arousal during active learning. For the remaining students, the higher mean EDA levels during traditional teaching indicate a contrasting pattern of response to instructional methods.

The Mann-Whitney test also revealed significant median differences for students A, C, E, and H, while the median differences for students B, D, F, and G were not statistically significant. Notably, Student G demonstrated an interesting result: the null hypothesis (H0) was accepted in the paired t-test but rejected in the Mann-Whitney test. This discrepancy may stem from Student G's potential non-responsiveness to EDA measurements, a phenomenon documented to affect around 10% of students [31].

A power analysis was performed, with approximately 1,800 data points collected per student. The paired t-test achieved a statistical power of 1 for each participant, confirming that the data quantity was sufficient to establish the significance of observed differences in EDA responses.

Although the study's sample size is relatively small, a confidence interval for the proportion (P) of students with elevated EDA during active learning (IC = $0.4735 \leq P \leq 0.9968$) suggests that most students are likely to experience heightened EDA in response to active learning techniques. These findings strongly support the notion that EDA responses are significantly heightened for students A, C, D, E, and H during active learning sessions, whereas students B and F show greater EDA responses in traditional settings. This differentiation in EDA responses is visually represented in Fig. 5.




Student C
Student D
Student E
Student F
Microsiemens (µS)
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Traditional

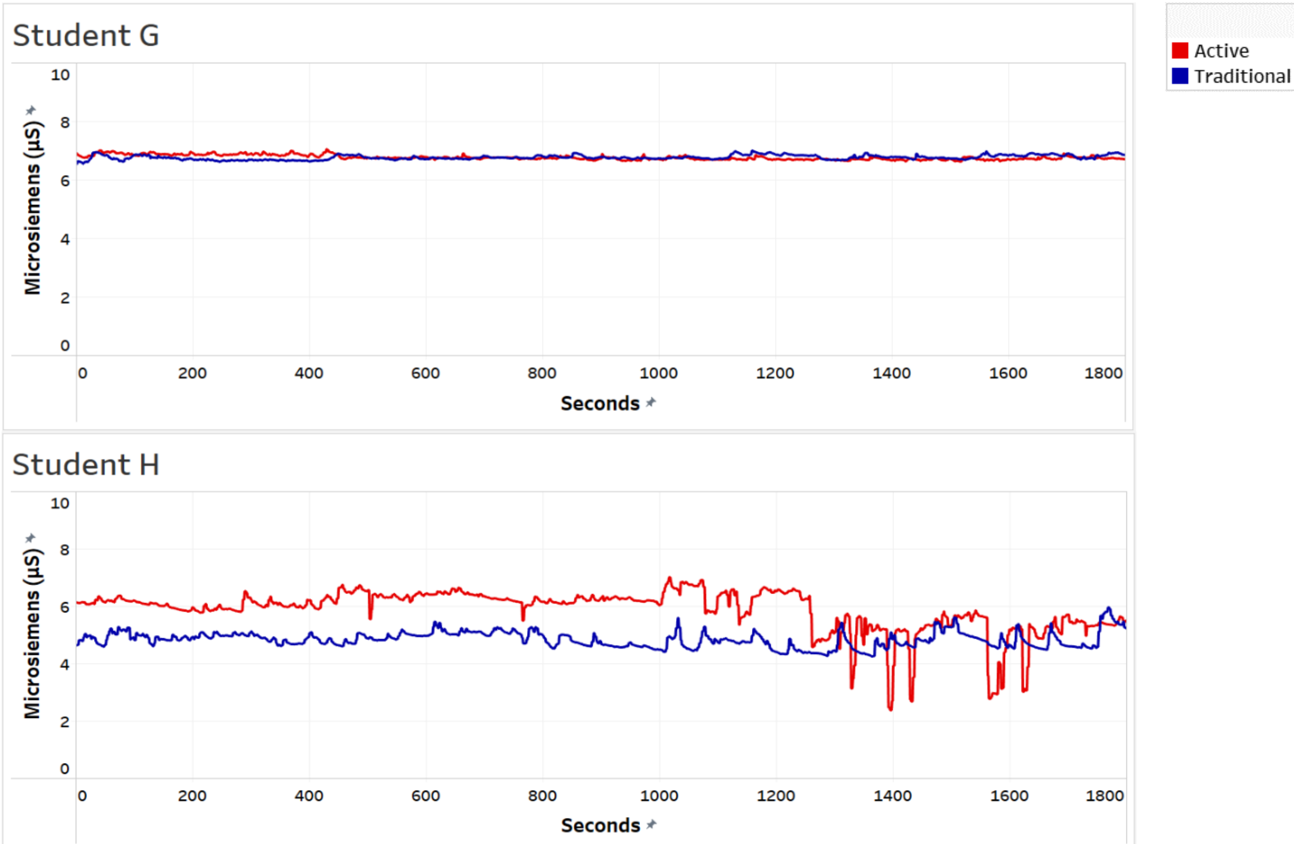

Fig. 5. EDA of students A, B, C, D, E, F, G, and H

The similarity in EDA data for Student G across both instructional methods suggests minimal variation in physiological response, supporting the observed non-responsiveness in their EDA data. It is also relevant to consider gender differences among participants: students A, C, E, and G are female, whereas students B, D, F, and H are male. Although females generally demonstrate higher baseline cutaneous conductance levels, research suggests that males tend to exhibit greater reactivity in skin conductance [3]. This gender-based trend could provide additional context for the observed variations in EDA responses across different learning methods, potentially influencing the degree of physiological arousal in each instructional setting.

B. *Discussion of results*

The data indicate a general trend of increased physiological engagement in active learning environments for most participants. However, individual variability, particularly observed in Students B, F, and G, suggests that engagement responses are influenced by personal or contextual factors beyond the instructional format. These results underscore the importance of tailoring pedagogical strategies to account for learner-specific differences.

In particular, Student G exhibited consistently stable EDA readings across both instructional conditions, suggesting a persistent physiological non-responsiveness to EDA measurement. This pattern may reflect an inherent individual trait, warranting further investigation into the factors that contribute to such responses.

Student G's case illustrates the complexity of interpreting EDA data. While stable values may indicate physiological non-responsiveness, they could also reflect individual differences in cognitive or emotional processing. To better understand these divergences, future research should incorporate complementary data sources, such as self-reported engagement, behavioral observations, or facial expression analysis, to provide a more comprehensive view of learner engagement.

The heightened EDA responses in students A, C, E, and H indicate unique patterns within this subset, which may suggest underlying differences in electrodermal reactivity that deserve additional investigation. Furthermore, gender differences among participants provide additional context for EDA variations. Female students A, C, E, and G, who exhibited strong EDA responses, contrast with male students B, D, F, and H, who demonstrated higher EDA reactivity in traditional learning contexts. This aligns with existing findings that females typically show higher baseline cutaneous conductance, while males tend to exhibit greater reactivity in response to stimuli [3].

This gender-related trend adds nuance to the interpretation of EDA responses, suggesting that both gender and instructional environment jointly influence physiological engagement. Graphical representations of continuous and comparative EDA data effectively illustrate temporal patterns and emphasize individual differences, offering critical insights into the dynamics of student engagement.

The observed interindividual variability in electrodermal responses indicates that engagement is likely shaped by factors beyond instructional modality, such as personality traits or situational influences. Future research would benefit from the inclusion of standardized psychological assessments, such as personality inventories or cognitive style measures, to clarify whether observed differences stem from intrinsic non-responsiveness or context-dependent variations in arousal.

Statistical analyses, including paired t-tests and Mann-Whitney tests conducted using Minitab, demonstrate significantly higher EDA means and medians during active learning sessions compared to traditional ones. With 62.5% of participants showing increased EDA levels under active learning conditions, the findings support the hypothesis that instructional format has a measurable effect on physiological engagement.

Further analysis through confidence intervals estimated that approximately 87.5% of students demonstrated increased EDA in response to active learning methodologies. This result underscores a strong tendency for dynamic instructional techniques to elicit higher levels of physiological engagement among students.

In summary, while the small sample size limits the generalizability of this study, the findings emphasize the potential of EDA as a tool for advancing educational practices. The results highlight EDA's utility in capturing psychophysiological responses that correlate with engagement, suggesting its applicability as a metric in educational research aimed at optimizing learning environments.

C. Summary of main findings and links with the literature

This study's findings provide insights into the role of EDA in educational research, underscoring its alignment with existing literature on physiological responses in learning environments. Statistical analyses indicated that 62.5% of students exposed to active learning methods showed significant increases in EDA. This observation is consistent with findings in [16], which reported elevated general arousal and engagement levels in participants exposed to interactive learning activities. Similarly, correlations between physiological responses and student performance in exam settings were identified in [7], emphasizing electrodermal activity's (EDA) potential to reflect both cognitive and emotional engagement.

Supporting this, [24] found that higher electrodermal activity (EDA) intensity correlated with improved student engagement. This finding was further validated in [8], which reported increased EDA levels when students participated in active learning classes compared to traditional lectures. These studies collectively reinforce the notion that active learning methodologies evoke heightened physiological responses indicative of engagement and cognitive involvement.

The consistent EDA data from Student G across both instructional formats introduces an intriguing element for future research on non-responsive EDA patterns. The study also identified notably distinct EDA responses in students A, C, E, and H, reflecting findings in [10], which link interactive learning spaces to enhanced student engagement and more positive learning perceptions.

While the current graphical representations provided useful insights into individual trends, future versions of this study would benefit from more advanced visualizations, such as boxplots, EDA heatmaps, or time-series clustering. These techniques could enhance pattern recognition and facilitate comparative analysis across participants, offering a more intuitive understanding of engagement dynamics over time.

In conclusion, this study substantiates EDA's value as a metric in educational contexts, extending its application beyond clinical or psychological fields and highlighting new possibilities for tailoring teaching methods based on physiological responses. This research not only addresses an important gap in literature but also proposes a promising direction for future work, exploring how EDA-informed approaches might optimize student engagement through customized educational practices.

V. CONCLUSION

This study successfully achieved its general objective of comparing the EDA of students across different learning environments, as well as specific objectives related to examining EDA fluctuations over time in various educational settings. The analysis, supported by continuum graphs and EDA comparisons, revealed significantly higher EDA responses in classes utilizing active learning methods, underscoring the impact of instructional design on physiological engagement.

In terms of methodology, statistical analyses using Minitab software, including paired t-tests and Mann-Whitney tests, were well-suited for comparing the means of correlated samples and assessing independent sample distributions. These analyses indicated higher EDA means and medians during active learning sessions than traditional lectures, supporting the hypothesis that students' physiological responses vary with instructional methods.

These findings hold broader implications for educational practice, as they offer empirical support for the efficacy of active learning over traditional methods in stimulating student engagement and emotional arousal, as measured by EDA. This evidence provides a scientific foundation for educators and policymakers seeking to implement more interactive, student-centered teaching approaches.

Nonetheless, the study's limitations must be acknowledged. The sample size, limited to eight university students, restricts the generalizability of the findings. This small sample size may reduce the statistical power, potentially masking significant differences and increasing the likelihood of Type II errors. Future studies with larger sample sizes are essential to confirm and build upon these results.

While this study offers valuable preliminary insights, its small sample size limits the external validity and generalizability of the results. Future research should involve larger and more diverse populations to increase statistical power and allow for subgroup analyses based on individual factors such as prior knowledge, learning preferences, and academic background.

Expanding future investigations to include multiple instructors and a wider range of disciplines, such as Operations Research, Project Management, and Systems Simulation, would provide a broader understanding of how different teaching approaches influence EDA responses across educational contexts. This could advance knowledge on the physiological impact of instructional design and inform the development of optimized, evidence-based teaching strategies.

The integration of EDA monitoring into adaptive learning systems also presents a promising application. Real-time engagement data could enable instructional content and pacing to be dynamically adjusted to individual learners, enhancing personalization. In addition, EDA-informed analytics may help educators detect early signs of disengagement and tailor interventions accordingly.

Despite the methodological rigor, the limited sample of eight participants remains a critical constraint. Although appropriate for exploratory analysis, this restricts the generalizability of the findings. Replicating the study with larger and more varied samples is essential to validate the results and assess their applicability across broader educational settings.

To extend these initial findings, future research should: (i) increase sample size and diversity to improve external validity; (ii) triangulate EDA data with complementary sources such as facial expression analysis, behavioral tracking, or self-report measures; (iii) explore diverse instructional settings and hybrid learning environments; and (iv) investigate the integration of EDA into adaptive educational technologies responsive to students' real-time engagement.

Such efforts will support the development of personalized, evidence-based learning frameworks grounded in real-time physiological feedback.

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