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Data Article

Physiological and behavioral data on active and traditional learning in engineering education

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ABSTRACT

This dataset comprises information gathered from an experiment designed to examine learning engagement and physiological responses in students exposed to different teaching methodologies. The dataset includes records from 50 engineering students, ensuring a diverse representation of participants. It contains survey responses capturing self-reported engagement, neurophysiological measurements such as electrodermal activity (EDA), heart rate (HR), and skin temperature (ST), along with observational records documenting behavioral interactions during the learning process. Participants were first exposed to a 15-minute video lecture introducing the One-Dimensional Cutting Stock Problem, its industrial applications, and heuristic algorithms such as Next Fit, First Fit, and First Fit Decreasing. In the active learning condition, students engaged in a hands-on problem-solving task, using a physical artifact made of bamboo and PVC to develop and optimize cutting plans for a predefined set of pieces, following a heuristic approach before searching for an optimal solution. The dataset is structured to facilitate analyses comparing active and traditional instructional methods. Given its multimodal nature, it can be reused in various educational

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and physiological research contexts, including investigations into cognitive load, emotional responses, and instructional design optimization.

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Specifications Table

Subject	Health Sciences, Medical Sciences & Pharmacology
Specific subject area	Learning engagement and physiological responses in students under different teaching methods, including HR, EDA, and ST data.
Type of data	Table (.csv format) Raw
Data collection	Physiological data were collected using the BioEvolution Neurometria V6, which records electrodermal activity (EDA), heart rate (HR), and skin temperature (ST) at 4 Hz. Non-invasive sensors were attached to students' fingers, capturing EDA signals processed via an encoder with a microprocessor. This system digitized and transmitted data via USB while maintaining signal integrity. The setup included automatic calibration, electrical isolation, and noise reduction to ensure accuracy. Data collection occurred in a controlled environment (23°C, no external noise). However, relative humidity was not monitored during data acquisition. Since environmental humidity can influence electrodermal responses, its exclusion is noted as a limitation in interpreting absolute EDA values. Participants completed a 15-minute instructional video followed by an active learning task lasting up to 15 minutes, with researcher observations and a questionnaire adapted from validated engagement scales.
Data source location	Institution: Production Department, São Paulo State University (Unesp). City: Guaratinguetá, São Paulo State. Country: Brazil. Latitude and Longitude: -22.802484882385883, -45.18960242194603
Data accessibility	Repository name: PhysioActiveLearning on Mendeley Data Data identification number: doi:10.17632/w9tcfhx9cn.1 Direct URL to data: https://data.mendeley.com/datasets/w9tcfhx9cn/1
Related research article	none.

1. Value of the Data

- Comprehensive Multimodal Dataset. This dataset combines physiological signals (HR, EDA, ST) [1], survey responses, and researcher observations, offering a rich source for studying learning engagement and physiological responses to different teaching methods. Researchers can analyze correlations between subjective engagement reports and objective physiological data, enhancing the understanding of cognitive and emotional responses in educational contexts.
- Reusable for Diverse Research Areas. The dataset can be used beyond education research, supporting studies in cognitive science, neuroscience, psychology, and human-computer interaction. It provides high-resolution physiological data that can be applied in stress analysis, attention studies, and biometric modeling for adaptive learning environments.
- The dataset follows a structured format (CSV/Excel) with clearly defined variables, facilitating easy integration into various analytical tools such as Matlab, Python, and R. It includes normalized scales and categorical values, ensuring consistency across different types of analyses.
- Data were collected in a temperature-controlled (23°C), noise-free environment, ensuring high-quality recordings. The experimental design allows researchers to confidently attribute variations in physiological responses to instructional methods rather than external environmental factors.

- This dataset enables comparisons between active and traditional learning methodologies, helping to evaluate their impact on student engagement and stress. Researchers can explore how different teaching approaches affect cognitive load and physiological reactions, providing empirical support for optimizing educational strategies.
- The dataset's rich physiological and survey-based attributes make it suitable for training machine learning models to predict student engagement levels [2]. It can also aid in developing adaptive learning systems that respond dynamically to student engagement and stress indicators [3].

2. Background

Learning engagement and cognitive load play important roles in students' academic performance and overall educational experience. The ability to maintain focus and adapt to different instructional methods is influenced by both subjective perceptions of engagement and objective physiological responses, such as heart rate (HR), electrodermal activity (EDA), and skin temperature (ST). These physiological signals provide valuable insights into cognitive effort, emotional states, and stress levels during learning activities [4].

This dataset was collected to examine the relationship between different teaching methodologies (active and traditional) [5], students' physiological responses [6], and their perceived engagement levels [7]. By analyzing these interactions, we aim to identify patterns in learning engagement, potential cognitive overload, and the physiological impact of different instructional approaches.

Additionally, this dataset contributes to the development of predictive models for engagement and cognitive effort, supporting adaptive learning environments and instructional design improvements. The data are structured to be reusable for classification, analysis, and future research in neuroscience, cognitive psychology, and educational technology, enabling broader investigations into student engagement, stress adaptation, and performance in academic settings.

3. Data Description

The dataset includes information from an experiment examining learning engagement and physiological responses in students exposed to different teaching methods. The data were collected from 50 engineering students, ensuring a diverse sample for comparison. It contains survey responses, neurophysiological measurements (heart rate - HR, electrodermal activity - EDA, and skin temperature - ST), and researcher observation data.

The dataset is structured into different folders and files, as described:

3.1. Survey and observational records

The survey and observational data are organized into five main sections:

1. Demographic Information: Contains essential details about participants, including age, gender, height, weight, academic background, and course of study. These attributes help define the characteristics of the sample population.
2. Learning Experience and Preferences: Focuses on students' engagement in different teaching methodologies, recording their frequency of participation in active learning activities, preferred teaching method, and self-reported engagement levels in both traditional and active classes. The following questions were used to assess these aspects:
   - Regarding the frequency and preferred method, which active learning methods have you experienced and how often?
   - Which teaching method do you prefer?
   - In the learning experience you just completed, how would you describe your level of engagement in each teaching method?

Table 1
Survey data structure and contents.

Section	File
Demographic information	Demographic.csv
Learning preferences and engagement	Experience.csv
Emotional and stress responses	Stress.csv
Perceived learning responsibility	Responsibility.csv
Researcher evaluations	Researcher_Observations.csv

- Did you notice a difference in your concentration level between the two teaching approaches?

3. Stress and Emotional Responses: Explores the emotional and physiological effects of various teaching methods, particularly stress levels, engagement perception, and cognitive load. Participants provided responses using a Likert scale and open-ended comments regarding stress-related factors. The following questions were used to assess these aspects:
   - During the class sessions, did you experience any stress or anxiety?
   - If you answered yes to the previous question, can you identify a specific cause for this emotion?
   - How would you describe your level of engagement during the class sessions?
   - Which class format do you find more effective for your learning?
   - Do you have any suggestions for improving active learning sessions?
   - Do you have any concerns or comments about the use of EDA and heart rate variability (HRV) as measures of engagement or stress during classes?
4. Perceived Responsibility and Learning Role: Investigates how students perceive their role and responsibility in the learning process, drawing comparisons between traditional and active learning methodologies to understand how each approach influences their sense of accountability:
   - During traditional classes, I felt that the teacher was the central figure in the learning process.
   - During active classes, I felt that the students (including myself) were the central figures in the learning process.
   - I felt responsible for my own learning during traditional classes.
   - I felt responsible for my own learning during active classes.
   - The active teaching methodology increased my sense of responsibility for the success of my learning.
5. Researcher Observations: This section contains qualitative insights recorded by the researcher, documenting students' performance in problem-solving tasks. It evaluates their ability to apply heuristic strategies, such as First Fit Decrease (FFD) for Problem 1, and assess whether they reached the optimal solution for Problem 2. Additionally, the observations include student engagement levels during the task, as well as verbalizations expressed while reasoning through the problem.

The survey response data are stored in CSV files located in the Questionary folder. The main files and their contents are listed in Table 1.

Each file is linked through a unique student_ID attribute, enabling data correlation across different sections (Fig. 1). The 1:1 relationship indicates that each student has only one record (row) in each file.

3.2. Physiological measurements

The physiological signals were recorded using BioEvolution Neurometria V6, a system capable of capturing real-time neurophysiological data. The following signals were collected:

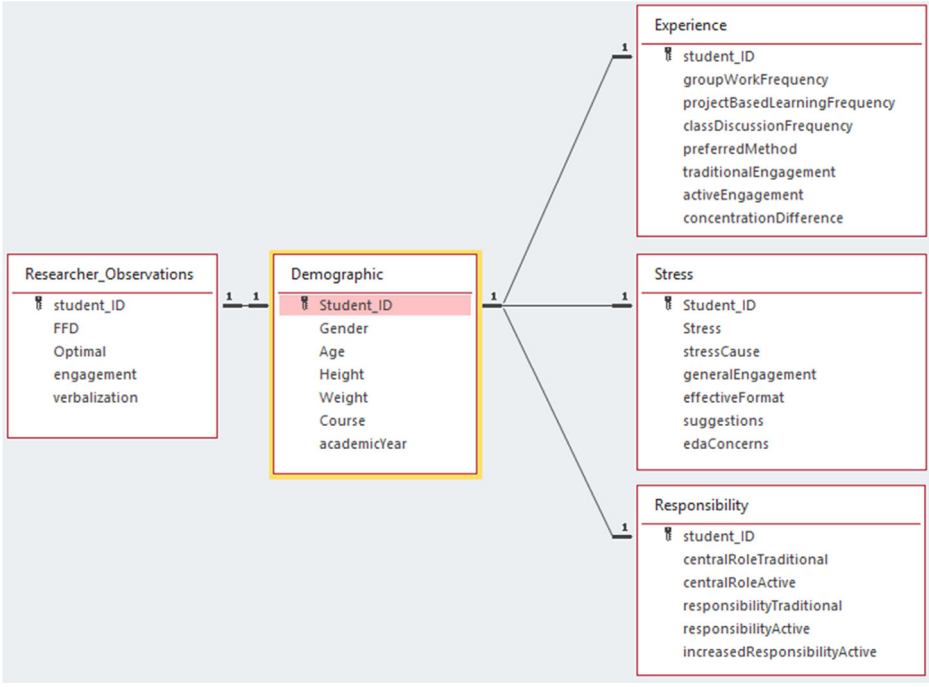


Fig. 1. Entity-relationship diagram of the survey dataset.

- EDA_Signal: Electrodermal activity (EDA) recorded at 4 Hz, measuring skin conductivity to assess phasic and tonic stress responses.
- HRV_Signal: Heart rate variability (HRV), used to analyze autonomic nervous system responses and physiological stress levels.
- Skin_Temperature: Measured at 4 Hz, providing insights into physiological reactions during learning activities.

Each student generated two CSV files, corresponding to the Active Learning condition and the Traditional Learning condition. The naming convention is:

- A_studentID.csv → Active Learning session
- T_studentID.csv → Traditional Learning session

Each file contains the following columns: Time (seconds), Heart Rate (HR), Electrodermal Activity (EDA), and Skin Temperature (ST).

The physiological data are organized into two main folders:

- Active/ → Stores physiological data from the Active Learning sessions.
- Traditional/ → Stores physiological data from the Traditional Learning sessions.

Fig. 2 illustrates the data structure of the physiological recordings.

4. Experimental Design, Materials and Methods

4.1. Experimental design

The experiment aimed to analyze learning engagement and physiological responses of students exposed to two different instructional methods: active learning and traditional lecture-based learning. Each participant attended two sessions, one for each method, while their heart

	A	B	C	D
1	Seconds	HR	EDA	ST
2	1	60	4,2	35,1
3	2	78	4,3	35,1
4	3	81	4,3	35,1
5	4	60	4,3	35,1

Fig. 2. Example of the organization of physiological data.

rate (HR), electrodermal activity (EDA), and skin temperature (ST) were recorded using non-invasive sensors.

Data collection followed a within-subject experimental design, ensuring that each participant experienced both teaching methodologies. All participants were first exposed to the video lecture and then completed the problem-solving activity. The experiment was conducted in a controlled environment, maintaining:

- Temperature: 23°C.
- External noise: None.
- Participants per session: One or two students per session.

A questionnaire was administered after the sessions to assess participants' engagement, stress perception, and learning preferences.

Sensors were attached to the participants' fingers, following the manufacturer's specifications. The sensors used for EDA recordings consisted of dry stainless steel electrodes affixed with Velcro straps to the distal phalanges of the index and middle fingers on the non-dominant hand. Participants remained seated and were instructed to minimize movement to avoid motion artifacts. The Neurometria V6 system does not support Ag/AgCl electrodes. These conditions were maintained to ensure signal consistency and minimize extraneous variability. Only one hand was used for sensor placement, specifically the hand with the participant's best motor control. The chosen hand was not used for any other tasks during the experiment to prevent movement artifacts and ensure accurate physiological data collection. Fig. 3 shows a participant with the sensors connected while performing the active task.

4.1.1. Instructional content

The instructional content covered in both learning conditions focused on the One-Dimensional Cutting Stock Problem, a classical optimization problem in Operations Research [8].

In the traditional video-based lecture, participants attended a 15-minute recorded class covering: a) Definition and context of the One-Dimensional Cutting Stock Problem; b) Applications in industries; c) Introduction to heuristic algorithms commonly used for this type of problem, including Next Fit, First Fit, Best Fit, and First Fit Decreasing (FFD); d) Comparisons between online and offline problem-solving approaches, illustrating how different scenarios influence decision-making strategies.

In the active learning condition, students participated in a hands-on problem-solving task using a physical artifact designed to simulate the cutting process. The artifact consisted of bamboo bars (each with a maximum length of 8.5 cm) and PVC tubes representing the pieces to be allocated. Students were required to develop a cutting plan for a predefined set of demanded pieces (see Table 2) while aiming to minimize material waste.

The activity was structured into two problem-solving challenges:

1. First Challenge: Students were instructed to follow the First Fit Decreasing (FFD) heuristic to create the initial cutting plan, using the 14 available bars. This solution, however, does not guarantee optimality.

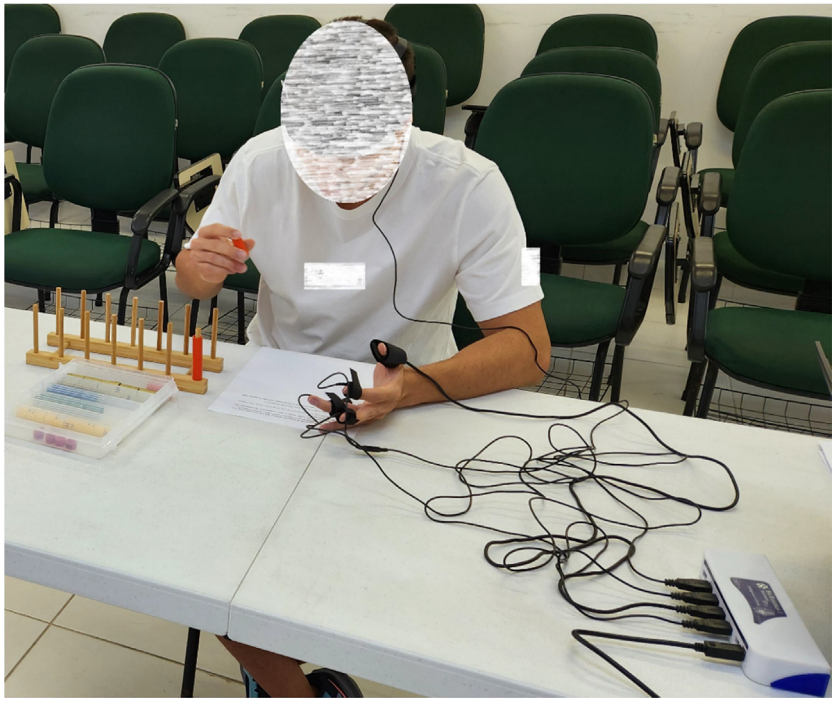


Fig. 3. Participant performing the active task.

Table 2
Demand for cutting stock problem.

Piece Length (cm)	Demand
3.5	4
3	15
2.5	5
2	10
1.5	10
1	4

2. Second Challenge: Regardless of whether the student correctly applied FFD, they were then tasked with rearranging the pieces to identify the optimal solution, which requires only 13 bars.

This contrast between theoretical instruction and hands-on problem-solving was designed to assess differences in engagement, cognitive effort, and physiological responses between the two learning methodologies. By integrating heuristic problem-solving techniques with a practical optimization task, students were encouraged to critically evaluate their approaches and refine their strategies based on real-time feedback.

4.2. Participants

Sample Size: 50 engineering students of the 50 participants, 38 were male and 12 were female, with a mean age of 21.4 years (SD = 2.3), ranging from 18 to 26 years. This demographic

profile is relevant to interpreting the physiological and behavioral data collected during the sessions.

Inclusion Criteria: Enrollment in an engineering course, voluntary participation, and agreement to wear physiological sensors.

Exclusion Criteria: Pre-existing medical conditions that could affect physiological responses (e.g., cardiovascular diseases, skin conditions affecting EDA measurements).

Participants were briefed on the experimental procedures and signed an informed consent form approved by an Ethics Committee.

4.3. Data collection process

4.3.1. Physiological data acquisition

Physiological signals were recorded using BioEvolution Neurometria V6, a real-time neurophysiological monitoring system. The system captured data at 4 Hz sampling frequency, although the 4 Hz sampling rate is adequate for detecting general trends in skin conductance level (SCL), it is below the minimum recommended threshold for analyzing phasic skin conductance responses (SCR), which ideally requires at least 10 Hz (Boucsein et al., 2012). Therefore, only tonic components of the electrodermal activity were considered in our analyses, and the inability to resolve discrete SCRs is acknowledged as a methodological limitation.

Similarly, heart rate variability (HRV) was derived from heart rate signals sampled at 4 Hz. This relatively low temporal resolution restricts the calculation of high-fidelity HRV parameters, especially those requiring high-resolution interbeat intervals. As such, our analysis focused exclusively on basic time-domain features, and the absence of frequency-domain or nonlinear HRV indices is a recognized constraint of the current setup. Recording:

- EDA: Skin conductivity variations indicating stress and cognitive effort.
- HRV: Heart rate variability, assessing autonomic nervous system responses. Heart rate was estimated from photoplethysmographic (PPG) signals using the Neurometria V6 system. The device internally computes interbeat intervals via proprietary firmware algorithms, which were then used to derive time-domain HRV metrics. The raw PPG signal was not accessible for custom HRV processing.
- Skin Temperature: Peripheral temperature changes linked to emotional and cognitive states. Skin temperature was measured on the dorsal side of the ring finger's middle phalanx using a built-in thermistor. While the sensor provided continuous readings, it was not a fast-response resistance thermometer, thus limiting its ability to capture rapid temperature shifts.

The system applied automatic calibration, electrical isolation, and a 60 Hz filter to minimize artifacts

4.3.2. Survey and observational data

After sessions, participants completed a questionnaire assessing:

- Engagement Levels: Likert-scale self-reports on perceived engagement and cognitive effort.
- Stress Perception: Self-reported stress levels and qualitative feedback.
- Learning Preferences: Preferred instructional method and concentration differences.

Additionally, the researcher recorded observations on students' performance in problem-solving tasks, focusing on heuristic strategies (First Fit Decrease - FFD) and optimal solutions.

Limitations

Due to the characteristics of the equipment and the methodology used, it was not feasible for the researcher to conduct the experiment with more than two students simultaneously. The limitation primarily stems from the need to ensure accurate physiological data collection, as the sensors require individualized calibration and minimal interference from external factors.

Ethics Statement

This research was approved by the Human Research Ethics Committee of the Teresa D'Ávila University Center - UNIFATEA (approval opinion: 6899985) in accordance with CNS Resolution No. 510 of 2016, Article 19. All participants consented to the inclusion of their data in the study by signing the Free and Informed Consent Form.

CRediT Author Statement

José Roberto Dale Luche: Conceptualization, Methodology, Software, Writing - Review & Editing. **Claudia Regina de Freitas:** Validation, Writing - Original Draft. **Blaha Gregory Correia dos Santos Goussain:** Formal analysis, Visualization. **Messias Borges Silva:** Project administration

Data Availability

PhysioActiveLearning (Original data) (Mendeley Data)

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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