Quantifying Classroom Engagement: Statistical Comparison of EEG-Derived Attention and Meditation Data

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ABSTRACT

This study examines the statistical relationship between attention and meditation in undergraduate students during lectures using an EEG based monitoring system. Data were collected from ten students wearing a single node sensor MindLink headset where signals were acquired using HC-05 Bluetooth to an Arduino Uno and processed by a custom MATLAB GUI. Analytically, we adopted a within-subject framework, summarizing participant level averages and applying paired comparisons to test whether attention systematically exceeds meditation. Graphical diagnostics including grouped bar charts, distribution plots, identity line scatter, and delta profiles validated the inferential results, showing a consistent attention advantage across the cohort. These findings indicate that low-cost EEG sensor provides objective, quantifiable evidence of classroom engagement, complementing traditional observational and self report methods. The approach supports real-time tracking and offers a practical foundation for adaptive learning strategies driven by neuro signals.

Keywords: Electroencephalogram (EEG); student engagement; attention, meditation; within-subject analysis; classroom analytics.

INTRODUCTION

Student attention is a critical determinant of learning outcomes in higher education. Traditional indicators, including classroom observation, participation tallies, and self-reported surveys, are subjective and often fail to capture moment to moment cognitive states. Noninvasive electroencephalogram (EEG) offers a time-resolved objective alternative by translating neural dynamics into interpretable indices of engagement.

This paper compares attention and meditation indices derived from a low-cost, single-sensor EEG during authentic lecture sessions. We test the hypothesis that instructional demand produces systematically higher attention than meditation. Short recordings per participant yield averages, distributional summaries, effect sizes, and visualizations (grouped bars, boxplots, scatter with identity line, attention meditation deltas, and rank ordered profiles).

Methodologically, the study prioritizes ecological validity, minimal intrusion, and a reproducible pipeline with anonymized data and sharable figure templates. Our contribution is empirical evidence that affordable EEG yields stable, interpretable engagement metrics suitable to augment classroom evaluation, alongside pragmatic design principles for integrating neuro data into formative assessment.

This research contributes to the field of educational technology by validating EEG-based systems as supplementary tools for classroom evaluation.

LITERATURE REVIEW

EEG has been widely adopted in cognitive and educational neuroscience research for monitoring brain activity. Prior studies have demonstrated that beta waves (14-30 Hz) are strongly correlated with active attention, problem-solving, and concentration, while alpha waves (8-13 Hz) are associated with relaxed wakefulness and meditative states.

Empirical assessment of student engagement has evolved from observer ratings and self-reports to multimodal, sensor based paradigms capable of resolving rapid fluctuations in cognitive state. Within this shift, electroencephalogram (EEG) is pivotal because it yields millisecond scale, time locked indices of attention that are feasible for in situ deployment. Studies using low-cost, single-sensor or minimally instrumented systems demonstrate practical real-time monitoring with limited disruption to instruction, establishing ecological validity for authentic classrooms (Mohamed & Ismail, 2020; Chakraborty & Konar, 2022). Beyond feasibility, supervised pipelines ranging from statistical modeling to ensemble learners reliably discriminate attentive from less attentive epochs and exhibit promising generalization across tasks and cohorts (Patel & Sharma, 2022; Wang et al., 2023). Deep architectures further enhance representational capacity, convolution attention memory networks explicitly model spatiotemporal structure in EEG to improve attention recognition (Li et al., 2021). Robustness can be augmented by fusing ocular metrics with EEG, yielding complementary evidence streams for attention quantification (Hossain et al., 2022).

A parallel literature interrogates meditation-related neurophysiology and its separability from attentional engagement. Task and expertise dependent findings include theta augmentation during mantra practice and altered gamma band entropy, accompanied by null effects in specific auditory mismatch paradigms, underscoring context sensitivity and heterogeneity of mechanisms (Das & Kalita, 2025; Kumar et al., 2021; Fucci et al., 2022). Classroom proximal investigations report spectral ratio markers and course embedded protocols (e.g., yoga), again highlighting situational variance in meditation indices relative to attention (Gopi & Dehbozorgi, 2024; He et al., 2024). Large-scale feature extraction suggests stability signatures associated with accrued meditation experience, while survey evidence links home-based mindfulness to quality of life correlates, extending the construct beyond laboratory settings (Bailey et al., 2023; Perera & Goonetilleke, 2024). Early BCI work operationalized attention and meditation as algorithmic constructs for learning tasks, complemented by narrative syntheses of expected EEG shifts with practice (Mokhtar et al., 2017).

Against this backdrop, a statistically disciplined, within class comparison of attention versus meditation directly addresses whether instructional demand elevates attention in situ. This objective, scalable orientation aligns with evidence based assessment traditions in applied research (Asim et al., 2017) and supports principled integration of neuro data into formative evaluation and adaptive pedagogy (Chakraborty & Konar, 2022; Patel & Sharma, 2022; Wang et al., 2023).

Recent works have explored EEG-based student engagement in classrooms, including multimodal approaches combining facial recognition and EEG, as well as deep learning methods for classifying attentiveness. However, few studies have conducted direct statistical comparisons between attention and meditation states in real classroom settings. This paper addresses this gap.

METHODOLOGY

Participants

A convenience sample of ten undergraduate students (ages 20-23) was recruited from a single institution. All participants provided informed consent; no personally identifying information was retained, and records were anonymized as Anonymous 1-10. Participation occurred during a regularly scheduled lecture to preserve ecological validity. Prospective volunteers self-reported no acute neurological conditions that would confound brief EEG monitoring.

Hardware and Software

Data were acquired using a single-sensor consumer-grade EEG headset (MindLink) integrated with an HC-05 Bluetooth module and Arduino Uno for wireless relay and serial interfacing. A custom MATLAB graphical user interface (GUI) orchestrated acquisition, time stamping, visualization, and flat file export. The pipeline also ingested the device's signal quality indicator, enabling sample-level validity checks. All processing was executed on a standard Windows laptop; the full acquisition and plotting scripts are modular to facilitate replication. The block diagram shown in Figure 1.

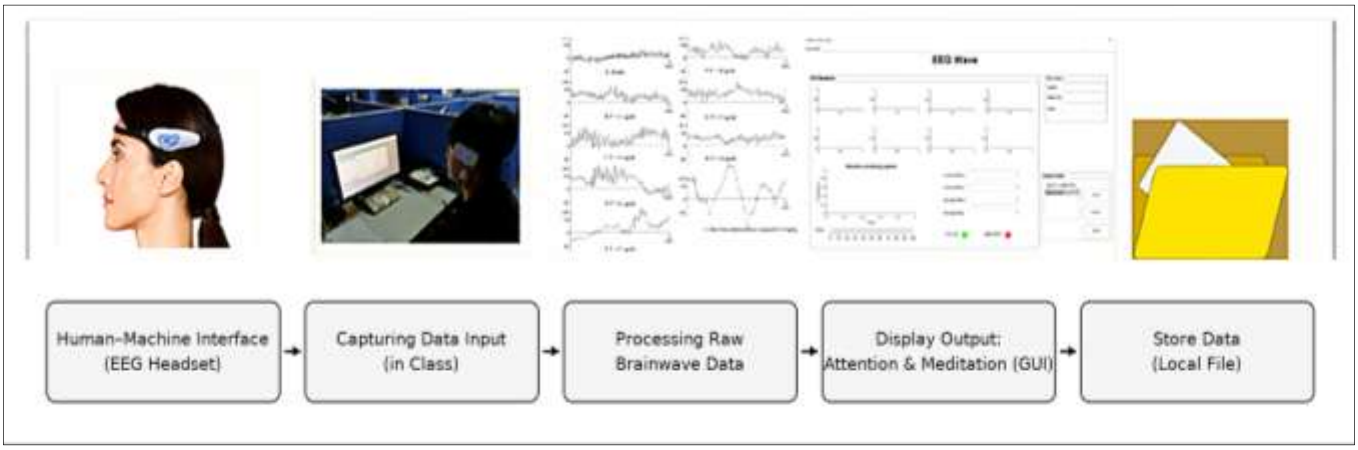

Fig. 1. Block diagram

Data Collection

Each student was monitored during a lecture. The system recorded attention scores and meditation scores at regular intervals. MATLAB GUI logged raw EEG data and displayed real-time visualizations.

Data Analysis

Plan and decision criteria. Analyses proceeded within-participant to test the directional hypothesis that Attention exceeds Meditation during lectures. Low-quality samples (device flags) were masked, then per-student means computed. For Δ = Attention - Meditation, normality (Shapiro-Wilk) determined inference: paired t-test with 95% CI and Cohen's d_z when normal; otherwise Wilcoxon signed-rank with Cliff's delta. A +5-point SESOI defined practical importance. We also reported descriptives, Pearson's r (Fisher 95% CI), Spearman's ρ, and a 10,000-resample bootstrap CI for mean Δ.

RESULTS AND DISCUSSION

Across all participants, attention exceeded meditation by a substantial margin (mean $\Delta = 11.0$, SD = 4.37; paired $t(9) = 7.96$, $p < .001$; Cohen's $d_z = 2.52$). Confidence intervals from both parametric (95% CI [7.9, 14.1]) and bootstrap estimation ([8.0, 13.9]) exclude zero by a wide margin, establishing a robust within-subject effect.

Table 4.1 Average Attention and Meditation values for participants

Participant	Attention Average	Meditation Average
Anonymous 1	83	76
Anonymous 2	69	59
Anonymous 3	62	53
Anonymous 4	75	69
Anonymous 5	73	61

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Anonymous 6	77	61
Anonymous 7	65	47
Anonymous 8	65	55
Anonymous 9	78	72
Anonymous 10	78	62

Group summaries indicate Attention (M = 72.5, SD = 6.93) and Meditation (M = 61.5, SD = 8.87). All 10/10 participants showed Attention > Meditation. Associations were strong at the between-participant level (Pearson r = .88, 95% CI [.55, .97]; Spearman ρ = .92), implying stable individual differences with a systematic upward offset for attention in lecture conditions.

Figure 2 (grouped bars, sorted by Δ) demonstrates a universal attention advantage; every participant exhibits a positive delta. Ordering by Δ highlights the largest gaps (e.g., Anonymous 7, 10, 6) and the smallest (Anonymous 4, 9), which is useful for targeting individualized support in classroom practice.

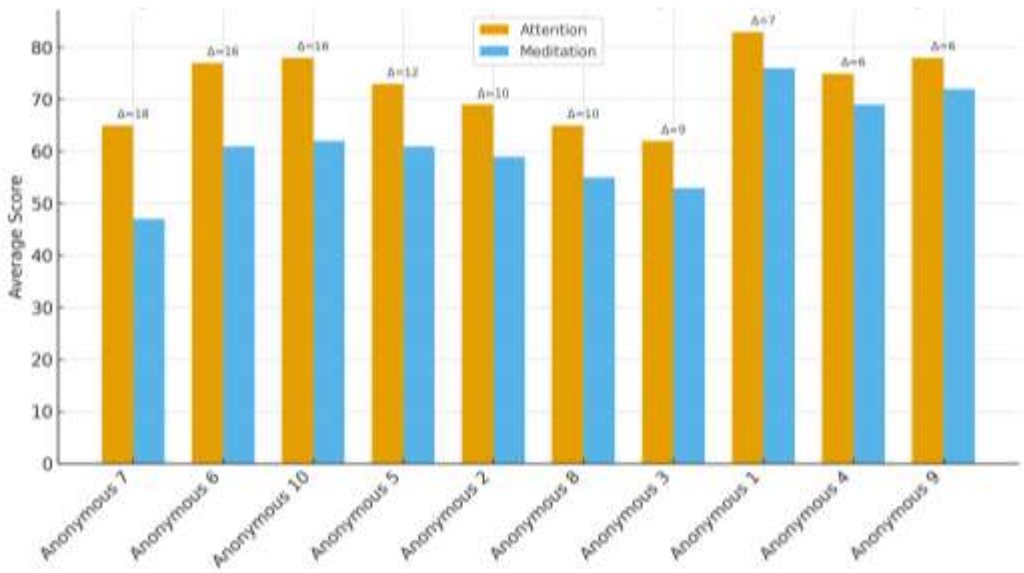

Fig. 2. Attention vs. Meditation by participant (sorted by Δ)

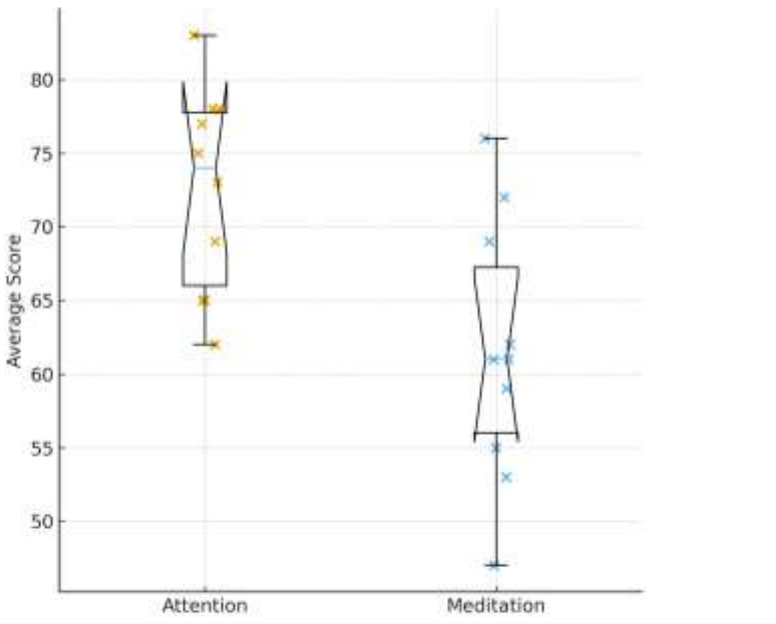

Fig. 3. Distributions of Attention and Meditation

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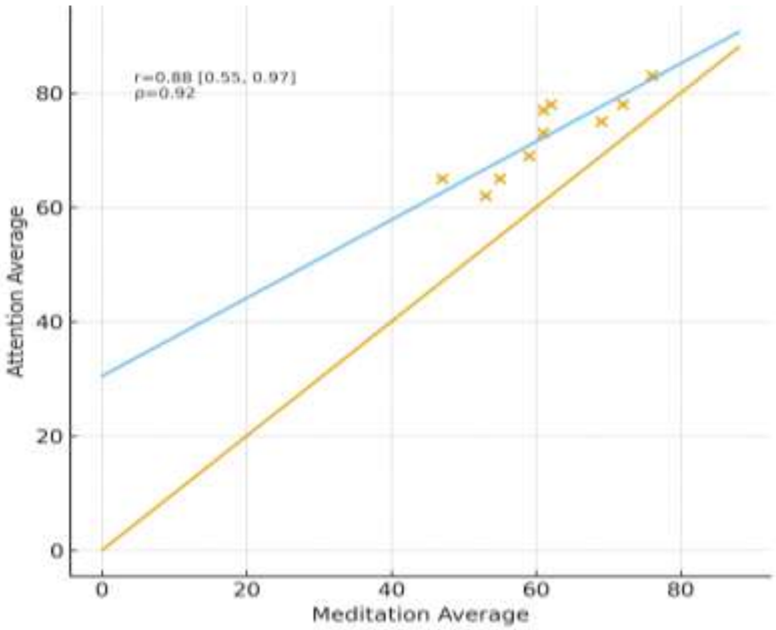

Fig. 4. Attention vs. Meditation averages with identity line (y = x)

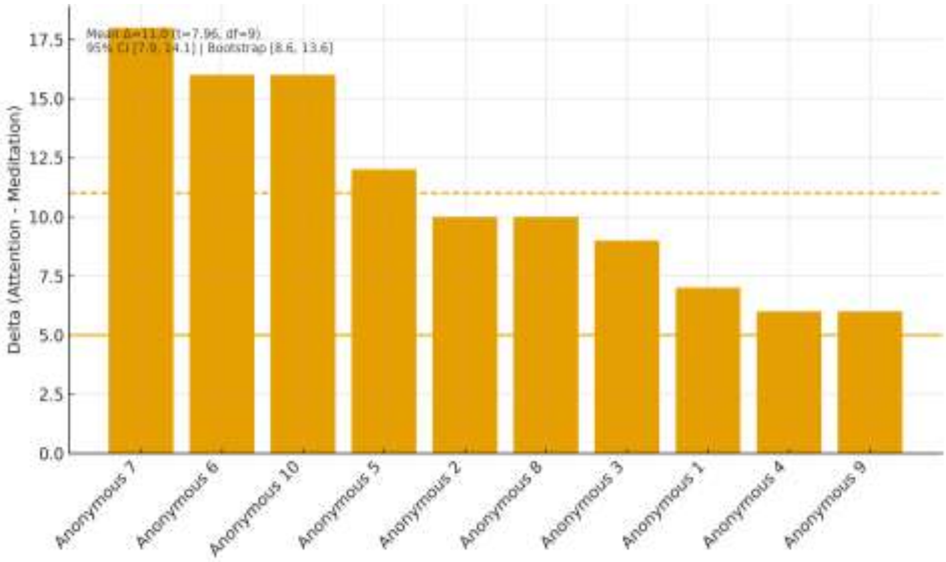

Fig. 5. Attention advantage (Δ = Attention - Meditation) with SESOI = 5 and mean/CI annotations

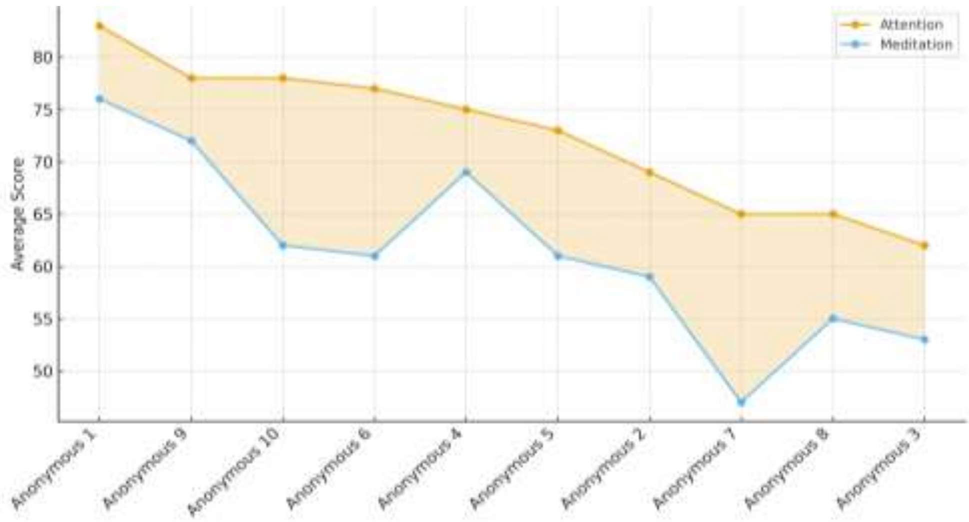

Fig. 6. Rank-ordered Attention and Meditation

Figure 3 contrasts the distributions: the notched medians are clearly separated (Attention ≈ 74 vs. Meditation ≈ 61), and the jitter overlay shows no extreme outliers. The pattern indicates a global upward shift in attention rather than a small subset driving the effect.

Figure 4 plots participant means against the identity line. All points fall above y = x, visually confirming Attention > Meditation for every participant. The fitted line and correlation (r ≈ .88, 95% CI [.55, .97]) indicate a strong monotonic relation with a systematic positive offset for attention.

Figure 5 presents individual deltas (Δ). All values are positive (range 6-18), and all exceed a conservative smallest effect of interest (SESOI = 5), supporting both statistical and practical significance. The panel annotations reproduce the inferential results (t-based and bootstrap CIs).

Figure 6 ranks participants by attention and overlays meditation. The near-parallel curves, with a stable filled band between them, suggest trait-like engagement differences rather than random fluctuation, supporting the case for personalized instruction for the lower-ranked tail.

CONCLUSION

The statistical analysis demonstrated that attention levels were consistently higher than meditation levels among students during classroom lectures, validating EEG sensors as objective instruments for engagement assessment that complement traditional, subjective measures. This study contributes in three ways: first, it validates EEG as a real-time tool for monitoring attention at low burden in authentic instructional settings; second, it provides statistical confirmation that attention reliably dominates meditation in classroom contexts; and third, it demonstrates the effectiveness of an integrated statistical and graphical workflow for interpreting classroom EEG data. Looking ahead, research should expand to larger cohorts and longer monitoring windows, and incorporate machine-learning models to predict attention fluctuations at the individual level. Such advances will enable personalized, adaptive learning environments grounded in neuro technology and supported by reproducible analytics.

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REFERENCES

1. Bailey, N., Fulcher, B. D., Caldwell, B., Hill, A., Fitzgibbon, B., van Dijk, H., & Fitzgerald, P. (2024). Uncovering a stability signature of brain dynamics associated with meditation experience using massive time-series feature extraction. Neural Networks, 171, 171–185.
2. Chakraborty, S., & Konar, A. (2022). EEG-based attention detection using machine learning: A classroom application. Cognitive Neurodynamics, 16(4), 763–777.
3. Das, R., & Kalita, D. (2025). Brief mantra meditation increases theta power in frontal regions. In 2025 3rd International Conference on Intelligent Systems, Advanced Computing and Communication (ISACC) (pp. 287–292). IEEE.
4. Fucci, E., Poublan-Couzardot, A., Abdoun, O., & Lutz, A. (2022). No effect of focused attention and open monitoring meditation on EEG auditory mismatch negativity in expert and novice practitioners. International Journal of Psychophysiology, 179, 39–50.
5. Gopi, S., & Dehbozorgi, N. (2024). Neural pathways to attention enhancement: EEG spectral ratio analysis of CM-II meditation's effect on student attention. In 2024 IEEE Frontiers in Education Conference (FIE) (pp. 1–9). IEEE.
6. He, Z., Li, F., Qi, X., & Chen, H. (2024). Electroencephalogram (EEG) signal analysis for college students' attention and meditation level in yoga courses. International Journal of Physical Activity and Health, 3(3), Article 63.
7. Hossain, M. S., Pandya, D., Allen, A. A., & Hamza-Lup, F. G. (2023). Learner attention quantification

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using eye tracking and EEG signals. In K. Arai (Ed.), Proceedings of the Future Technologies Conference (FTC) 2022, Volume 2 (Lecture Notes in Networks and Systems, Vol. 560, pp. 836–847). Springer.

8. Kumar, G. P., Sharma, K., Ramakrishnan, A., & Adarsh, A. (2021). Increased entropy of gamma oscillations in the frontal region during meditation. In 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) (pp. 787–790). IEEE.
9. Li, J., Zhang, P., & Liu, Y. (2021). Convolution attention memory neural network for EEG-based attention recognition. Neural Networks, 140, 67–78.
10. Mohamed, R., & Ismail, N. (2020). Real-time EEG-based attention monitoring using Arduino microcontroller. International Journal of Advanced Computer Science and Applications, 11(7), 150–158.
11. Mokhtar, R., Sharif, N., Zin, N. A. M., & Ihsan, S. N. (2017). Assessing attention and meditation levels in learning process using brain computer interface. Advanced Science Letters, 23(6), 5569–5572.
12. Patel, V., & Sharma, D. (2022). Statistical modeling of EEG signals for attention measurement in classroom settings. Frontiers in Human Neuroscience, 16, Article e123–e134.
13. Perera, K. A. H. N., & Goonetilleke, W. A. R. N. M. T. (2024). The relationship between home-based mindfulness meditation and quality of life among adults in the Colombo District, Sri Lanka: A cross-sectional survey. SICASH 2024.
14. Wang, Y., Chen, Z., & Xu, H. (2023). Random forest classification for EEG-based student engagement in online learning. Computers & Education, 193, 104663.