

Tracking Attention Dynamics: An Electroencephalography-based Analysis of Concentration Shifts During Human–AI Interaction

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Quantifying sustained attention in real-world environments remains a persistent challenge in electroencephalography (EEG)-based biosensing, particularly when acquisition is constrained to a single, low-cost biosensor channel. Conventional ratio-based attention indices, namely, the theta/beta ratio (TBR) and the theta/alpha ratio (TAR), typically fail to register brief or low-amplitude attentional shifts, and this insensitivity is exacerbated by the unfavorable signal-to-noise conditions that accompany wearable recordings. To overcome these limitations, in the present work, we formalize the gamma progressive index (GPI), an EEG-derived indicator that emphasizes the higher-frequency end of the gamma band through a normalized, monotonically increasing linear weighting function. By concentrating the weighting on those gamma-band frequencies most closely tied to focused cognitive effort and by subsequently normalizing the weighted sum against each participant's own baseline, we obtain the GPI that yields a stable and computationally economical measure that can be evaluated in real time on the onboard processor of a portable single-channel EEG headband. EEG recordings were obtained from three adults as they interacted with generative AI chatbots in a naturalistic setting. During these interactions, the GPI tracked increases in cognitive engagement more reliably than did the TBR or TAR, exhibiting a wider dynamic range and sharper temporal contrast. In head-to-head comparisons, the GPI outperformed both the TBR and the TAR in detecting short-duration attentional fluctuations and in preserving signal integrity in noisy recordings typical of wearable EEG systems. The proposed GPI therefore offers a robust, scalable, and computationally lightweight pathway for the ecologically valid monitoring of attention in everyday educational contexts. To the best of our knowledge, no prior study has combined a progressively weighted gamma-band spectral estimate, a within-subject baseline normalization, and an explicit on-chip single-channel implementation in a single mathematically specified metric; the present work supplies this combination as the journal extension of our earlier conference report.

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1. Introduction

Successful learning depends on the learner's ability to maintain attention over extended periods, because attentional engagement is a prerequisite for encoding new information into memory.^(1,2) When attention wanes in the classroom, both academic achievement and intrinsic motivation tend to decline.⁽³⁾ Empirical work has also shown that focused learners retain material more efficiently than their distracted counterparts.^(2–4) Self-report questionnaires, although widely used to gauge attention, are known to be unreliable when learners fail to notice subtle attentional drifts.^(4,5) Because attention, concentration, and broader cognitive development are tightly coupled to brainwave activity,⁽⁶⁾ a growing body of work has turned to electrophysiological methods to characterize these fluctuations.^(2,7) Among such methods, electroencephalography (EEG) stands out as a non-invasive, real-time neuroimaging tool that offers second-by-second insight into ongoing cortical dynamics, making it particularly well suited to the fine-grained study of attention.^(6,8) From the vantage point of cognitive neuroscience, established frameworks, such as the multi-store memory model and adaptive cognitive control theory, treat attention as the gateway to encoding and retrieval, with frontal theta and beta rhythms playing especially prominent roles. Recent methodological advances have further expanded the EEG analytical toolkit. Feature fusion, model-adaptive architectures, and cross-domain transfer learning now allow EEG to be combined with demographic and behavioral variables in ways that were not feasible a decade ago. For example, a depression-detection study that integrated gender and age into an attention-based neural network reached 75.29% accuracy by linking beta rhythms to demographic profiles,⁽⁹⁾ underscoring the value of context-aware EEG modeling for mental-health applications. In educational settings, hybrid fusion methods have demonstrated that combining EEG with eye-movement or facial-expression features can lift classification accuracy by 6–19%, confirming the complementarity of multimodal data streams.⁽¹⁰⁾ Specific EEG-based attention mechanisms have been shown to improve reading-performance prediction by 19% through spectral feature integration,⁽¹⁰⁾ and alpha/gamma rhythms together with channel-wise correlation analysis have been used to localize the prefrontal and other cortical regions engaged during cognitive tasks, with downstream implications for emotion recognition⁽¹¹⁾ and mental-fatigue monitoring.⁽¹²⁾ These advances collectively motivate the present study, which builds on our earlier wearable single-channel EEG case study of attention during human–AI interaction⁽¹³⁾ and extends it with the mathematically explicit gamma progressive index (GPI) metric introduced in Sect. 2.5.3.

The present work is positioned at the intersection of two strands of EEG attention research. The first strand concerns ratio-based metrics, exemplified by the theta/beta ratio (TBR) and the theta/alpha ratio (TAR).^(14,15) These indices are computationally inexpensive and easy to interpret, yet their sensitivity to transient attentional shifts degrades sharply under low signal-to-noise conditions. The second strand relies on high-frequency spectral-power analysis,^(11,12) which delivers finer temporal resolution but typically demands multichannel recording setups that are impractical for everyday wearable use. The novelty of this study lies in the introduction of the GPI, a single-channel metric that bridges these two strands by combining (i) progressive linear weighting across the gamma band, (ii) within-subject baseline normalization to suppress

inter-individual variability, and (iii) an on-chip implementation suitable for portable biosensor hardware. As far as we searched the literature, this specific combination has not been formalized mathematically in the wearable single-channel EEG attention monitoring, although a related custom index applied to the same AI-chatbot case-study design was reported in our earlier conference paper.⁽¹³⁾ The present manuscript formalizes that earlier index as the GPI and provides the complete mathematical and algorithmic specification that Ref. 13 did not include.

As AI has entered mainstream education, AI chatbots have emerged as a potential means of sustaining learner focus.^(16,17) Their capacity to deliver instant, individualized feedback at scale relieves teachers of repetitive explanation tasks and offers a level of personalization that is difficult to achieve in large classes.⁽¹⁸⁾ Despite the rapid adoption of AI technologies, the effect of human–AI interaction on learners’ sustained attention has not been thoroughly characterized. This lack of clarity presents a challenge for educators and tool designers, who require a strong evidence base for evaluating chat-based interfaces.

Recent empirical work has begun to map attention mechanisms in educational contexts onto measurable EEG signatures and to provide early evidence that AI chatbots can reshape cognitive engagement.^(7,19) Building on this line of inquiry, the present study was designed to track attention-related EEG activity while learners converse with AI chatbots and to ask the following research question: How do learners’ levels of attention differ during their interactions with generative AI chatbots?

1.1 Human–AI interactions

In the era of generative AI, conversational chatbots offer students new opportunities to enrich their learning through dynamic, turn-based exchanges.^(16,17,20) Such systems can return interactive and individualized responses that materially boost engagement and focus,^(21–23) yet empirical work linking brain activity to attention during human–AI interaction remained sparse as of January 2025, exposing a clear gap in the literature. Earlier EEG studies were often limited by the bulk and intrusiveness of the recording hardware, which discouraged student participation in laboratory brainwave experiments. Recent advances in dry-electrode and chip-level amplifier technology have produced lightweight, portable EEG headsets that are far less obtrusive and considerably more acceptable to young participants. These wearable devices stream real-time neural feedback, giving educators and learners alike a window into attention, emotion, and mental health that complements traditional self-report.^(5,24) The Neurosky Mindset headband, for instance, was used previously to record EEG correlates of student motivation and progress.⁽⁶⁾ Single-channel wearables are valued for their portability and ease of use, but they cannot fully resolve spatially distributed cortical networks, which is a limitation of the present study in exchange for ecological validity. The wearable platform we employ here, the BeneGear headband, is the same platform used in our earlier case study⁽¹³⁾ and is now extended with the mathematically explicit GPI and its on-chip implementation.

1.2 Relationship with the primary source

The present paper is intended as a comprehensive journal extension of our prior conference paper.⁽¹³⁾ In this work, we employ the same BeneGear single-channel EEG headband, maintain the identical three-participant case-study design, and utilize the consistent six-step pre-/during-/post-test protocol to examine attention during interactions with generative AI chatbots. Given that this paper is an extension rather than an independent study, we explicitly refer to the shared elements attributed to Ref. 13 throughout the text. Note that this journal extension offers five substantial contributions that surpass the findings presented in Ref. 13, which are summarized below.

Firstly, the analytical metric is now clearly defined mathematically. In the earlier paper, we introduced a custom concentration index as the primary outcome but did not provide its computational formula. In the present paper, we formalize that index as the GPI and present its complete mathematical definition: Eqs. (1) and (2) delineate the weighted gamma-band power sums S_{task} and S_{base} , Eq. (3) specifies the progressive linear weighting function $W(f)$ and Eq. (4) establishes the baseline-normalized GPI as 100 times S_{task} divided by S_{base} . This formalization enables the GPI to be reproduced, implemented on a chip, and benchmarked against other indices.

Second, the weighting scheme introduced here is novel. The progressive linear weighting $W(f)$ in Eq. (3) is presented for the first time. This scheme assigns greater weight to higher gamma-band frequencies, utilizing a normalized linear ramp that anchors at ($W = 1$) for the lowest frequency and reaches ($W = W_{max}$) for the highest frequency. This approach emphasizes the high-gamma components most closely associated with focused cognitive effort.

Third, the baseline normalization method presented is also new. Equation (4) normalizes each participant's task-period weighted gamma power by that same participant's baseline weighted gamma power. This within-subject normalization effectively suppresses inter-individual variability in absolute EEG power, addressing a confounding factor that the attention index embedded in the headband used in the earlier study did not explicitly control for.

Fourth, the on-chip implementation described here is a significant advancement. Algorithm 1 provides the complete pseudocode for the GPI, encompassing initialization, the per-frequency loop, the computation of the progressive weight, and an explicit division-by-zero guard.

Fifth, the framing and scope of this work are innovative. In this paper, we re-contextualize the study as a biopotential biosensor investigation within the realm of sensors and materials, relate the findings to the established cognitive-control theory (including multi-store memory and adaptive cognitive systems), and outline a forward-looking research agenda that encompasses multichannel EEG, longitudinal protocols, and cross-domain transfer (for example, in animal science). In contrast, our earlier study, which was a preliminary one presented at a conference, did not delve into these framing, theoretical, or agenda-setting elements.

In summary, the five contributions discussed above establish that the present paper represents a comprehensive journal extension of our earlier study. It incorporates key elements such as the hardware, participants, AI chatbots, recording parameters, preprocessing techniques, and the qualitative finding of heightened attention during human interactions with AI, all of which are

explicitly attributed to Ref. 13. Moreover, in this paper, we introduce novel elements, including the mathematically explicit GPI, progressive gamma-band weighting, within-subject baseline normalization, on-chip algorithm, and biopotential-biosensor framing.

2. Data, Materials, and Methods

2.1 Participants

In this exploratory case study, we used the same three participants as those in our earlier conference report⁽¹³⁾, recruited from a four-year public university in southern China. The cohort included two male and one female student, all between 21 and 22 years of age. The female participant (Student A) majored in primary-school education; Student B also majored in primary-school education; Student C was studying law. All three participants gave written informed consent after being briefed on the purpose and protocol of the brainwave investigation. Each participant was in good physical and mental health, with no history of neurological or psychiatric conditions that could compromise EEG signal integrity. All three had prior experience crafting prompts for AI chatbots, but none had previously taken part in a brainwave experiment.

2.2 AI chatbot platforms

As in our earlier case study, each participant was invited to choose a generative AI chatbot from a fixed menu: Doubao (<https://www.doubao.com>), Kimi (<https://kimi.moonshot.cn>), or ChatGLM (<https://chatglm.cn>). All three platforms were developed in mainland China and built on large language models that share the Generative Pre-trained Transformer (GPT) architectural family; they produce fluent, human-like responses and are capable of original output. Because each chatbot also adapts its replies to the user's prior turns, all three can in principle support individualized learning. To anchor the neural-engagement evidence in a meaningful cognitive context, we recorded the semantic content and self-reported complexity of every prompt issued during the session. Student A, for example, posed questions about conference preparation—a high-stake, cognitively demanding task—whereas the other two participants pursued more exploratory queries. This deliberate variation in task complexity introduces a useful contrast in cognitive demand that may itself modulate attentional bandwidth, and we return to this point in Sect. 4.

2.3 Biometric system

A non-invasive, portable biosensor headband was used throughout the present work to record participants' EEG as they engaged with their chosen AI chatbot. The headband is manufactured by BeneGear, a Fujian-based company, and marketed as a single-channel electrode device with native Android and iOS support. Production units are currently deployed in several primary schools in Fujian Province, where they are used to monitor and improve students' attention in

real classroom settings. The device streams EEG activity and an attention index at runtime and is built around five functional components: (i) a colored fabric band that provides structural support and houses the other components; (ii) an integrated chip that handles onboard EEG acquisition, spectral decomposition, and, in the present study, GPI calculation; (iii) a rechargeable battery that powers extended continuous operation; (iv) an elastic band that anchors the frontal electrode and contributes to a tri-pronged contact geometry; and (v) a copper-foil skin-contact electrode pad. The five components are shown in Fig. 1.

Correct headband placement is essential for stable skin contact and high-fidelity EEG acquisition. Once the headband is attached, the integrated indicator should be checked: a steady green light at the center of the device confirms proper placement, whereas a flashing indicator signals that the fit needs to be readjusted. Detailed wearing instructions are given in Fig. 2. To obtain valid EEG measurements, the electrode must maintain firm contact with the forehead throughout each recording epoch.

After pairing the headband with the BeneGear smartphone companion app over Bluetooth, the device was positioned on the participant's forehead, as illustrated in Fig. 2. The mobile app renders the attention-index trajectory alongside the five EEG frequency bands (delta, theta, alpha, beta, and gamma) in real time; a representative screenshot is shown in Fig. 3.

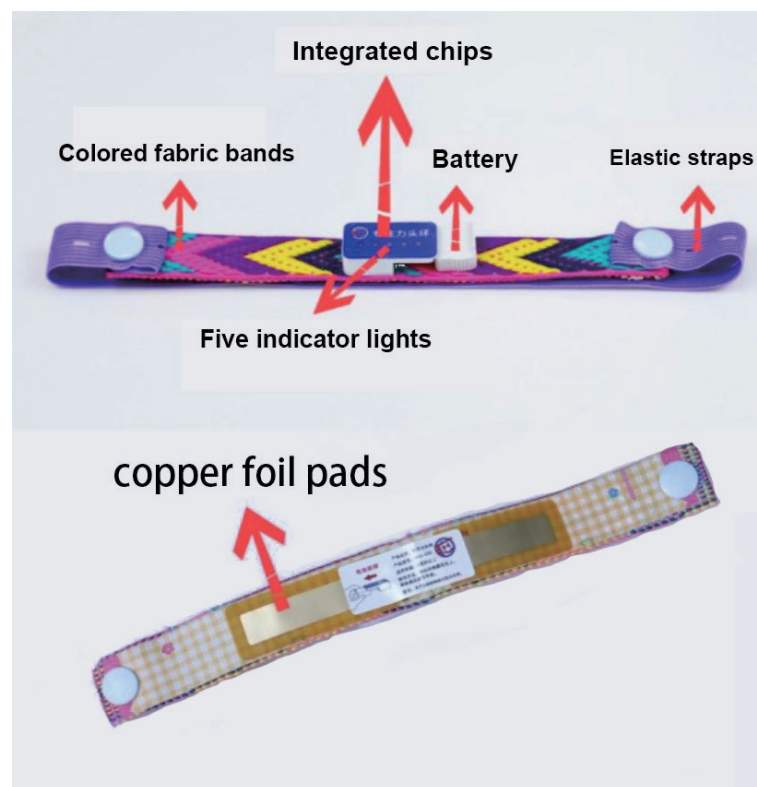


Fig. 1. (Color online) Front view (up) and rear view (down) of the BeneGear EEG headband, with the following five functional components:⁽¹⁾ colored fabric band,⁽²⁾ integrated chip,⁽³⁾ rechargeable battery,⁽⁴⁾ elastic band, and (5) copper foil skin contact electrode pad.



Fig. 2. (Color online) Photograph showing the BeneGear EEG headband positioned on a participant's forehead, with the copper-foil electrode pads in contact with the skin and the indicator light steadily on.



Fig. 3. (Color online) Screenshot of the BeneGear smartphone application during an AI-chatbot interaction session, showing the real-time attention-index trace and the five EEG frequency bands (delta, theta, alpha, beta, and gamma) on the mobile interface.

The headband records EEG and attention data simultaneously, at an EEG sampling rate of 512 Hz and an attention-index sampling rate of 1 Hz. The 512 Hz EEG sampling rate supplies adequate temporal resolution for the dominant neural oscillations of interest, although it imposes

a ceiling on the detection of very-high-frequency components and on the characterization of sub-second neurodynamic transitions. The 1 Hz attention-index output is itself a cumulative indicator that aggregates the underlying spectral content. Both the raw band-power values for the five EEG frequency bands and the cumulative attention index were streamed to the BeneGear PC data-acquisition software (Fig. 4), which additionally computed and logged the custom GPI in real time. Section 2.5 details the GPI calculation principle and the on-chip algorithm. The recording parameters match those of our earlier case study,⁽¹³⁾ and the new contribution in the present work is the addition of the on-chip GPI module that computes Eq. (4) in real time alongside the headband's existing built-in attention index.

2.4 Procedure

The experimental protocol followed the same six sequential steps as in our earlier case study: After a full explanation of the study's purpose, the three participants provided written informed consent. An EEG expert familiarized the participants with the headband and walked them through the interpretation of attention values on their individual smartphone apps; participants were seated in a quiet room to minimize external distraction. Each participant undertook a brief (about 5 min) outdoor walk while wearing the headband, a step intended to promote relaxation and stabilize the baseline measurement. Pre-interaction baseline attention data were recorded prior to the human–AI interaction block, providing the pre-test reference used throughout the analysis. Participants engaged freely with their self-selected AI chatbot for 15 min, posing questions on topics of personal interest. The 15 min window was chosen to balance ecological validity (it approximates a typical short learning episode) against the empirical literature on sustained attention, which suggests that cognitive engagement can begin to wane after roughly 10–20 min of continuous task demand. Post-interaction attention data were acquired 2 min after the AI-chatbot block ended. A schematic of the experimental design is given in Fig. 5.

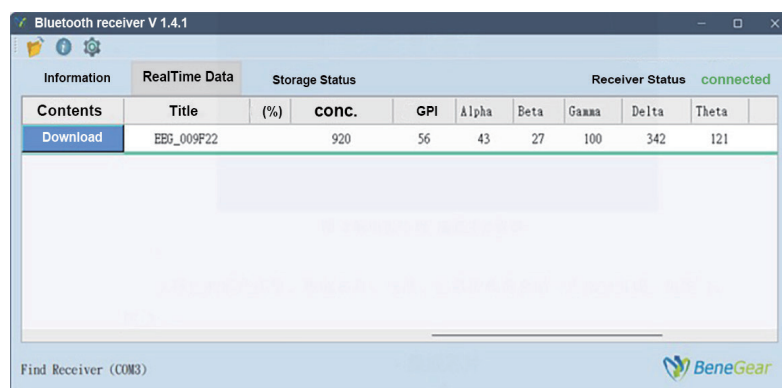


Fig. 4. (Color online) Screenshot of the BeneGear PC-side data-receiver software. The interface shows the original EEG frequency-band values streamed from the headband together with the real-time GPI computed from the gamma-band activity.

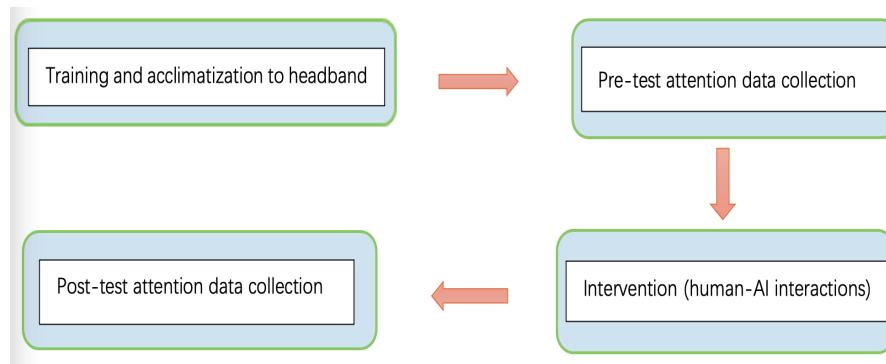


Fig. 5. (Color online) Experimental design.

2.5 Data analysis

To accommodate background noise and inter-individual differences in psychological state, we applied the same preprocessing steps as in our earlier case study, including data cleaning, before any formal analysis. After the alignment of the three participants' attention time series along a common time axis, statistical analyses were carried out to characterize changes in attention. Throughout the recording, EEG activity was tracked simultaneously in the alpha, beta, gamma, theta, and delta frequency bands. The sampling cadence of the EEG stream was 6 s, and on-chip processing in the proprietary BeneGear integrated circuit returned the cumulative attention-index values in real time. All EEG power values are reported in microV squared per Hz (power per Hertz); the GPI, which is the new contribution of the present work, is described in detail in the subsequent signal-processing subsections.

2.5.1 Signal preprocessing and artifact control

Before analysis, the raw EEG stream underwent standardized preprocessing. A bandpass filter spanning 2–45 Hz was applied to suppress low-frequency drift and high-frequency noise. Physiological artifacts—principally eye blinks and minor head movements—were detected and excised using an amplitude-threshold rule (>100 microV). Because the single-channel hardware does not support independent component analysis for spatial artifact removal, signal quality was safeguarded instead by combining a controlled quiet testing environment with post-hoc visual inspection and cleaning, consistent with the workflow described in our earlier single-channel study.

2.5.2 Spectral analysis and derived indicators

Lim *et al.*⁽¹⁴⁾ observed that the beta/theta ratio is a widely used neurophysiological indicator of attentional control, with lower values typically associated with higher levels of focused attention; the theta/alpha ratio has likewise been reported as an informative supplementary

marker. Wiesman *et al.*⁽¹⁵⁾ further showed that, in a focused cognitive state, activity in the high-frequency beta and gamma bands tends to exhibit a coherent pattern. Drawing on these prior findings and on our earlier concentration index reported in Ref. 13, in the present paper, we introduce a mathematically explicit new indicator—the GPI—to track attentional shifts more sensitively than the original concentration index or conventional ratios in wearable settings. The GPI's full mathematical definition is given in Sect. 2.5.3.

2.5.3 Custom GPI

First, the variable definitions are as follows.

- f : frequency, in Hertz (Hz).
- $P_{task}(f)$: power spectral density at frequency f during the mission
- $P_{base}(f)$: power spectral density at frequency f during the baseline period
- $W(f)$: cumulative weighting function at frequency f

Next, the weighted power sum is computed. The weighted power sum during the task period, S_{task} , is defined as

$$S_{task} = \sum_{f=f_{min}}^{f_{max}} [P_{task}(f) \cdot W(f)]. \quad (1)$$

The weighted power sum during the baseline period, S_{base} , is defined as

$$S_{base} = \sum_{f=f_{min}}^{f_{max}} [P_{base}(f) \cdot W(f)]. \quad (2)$$

Next, the progressive weighting function (normalized linear weighting) is applied. Let W_{max} be the maximum weight assigned to the highest frequency f_{max} . Then, the weighting function $W(f)$ is defined as

$$W(f) = 1 + \frac{(f - f_{min})}{(f_{max} - f_{min})} \cdot (W_{max} - 1). \quad (3)$$

Finally, the GPI is calculated as

$$GPI = \frac{S_{task}}{S_{base}} \times 100 \quad (4)$$

2.5.4 Algorithm of GPI

The pseudocode for the GPI algorithm is shown below (Algorithm 1). To improve the efficiency of gamma-wave variation calculation, this algorithm has been implemented on the

Algorithm 1

GPI calculation

Require:
 P_{task} : array $[f_{min}:f_{max}]$ {Power spectral density during task period}
 P_{base} : array $[f_{min}:f_{max}]$ {Power spectral density during baseline period}
 f_{min} : integer {Gamma band lower frequency bound (e.g., 30 Hz)}
 f_{max} : integer {Gamma band upper frequency bound (e.g., 70 Hz)}
 W_{max} : float {Maximum weight value for highest frequency (e.g., 5.0)}

Ensure:
 GPI : float {GPI value}

- 1: Initialize weighted power sums:
- 2: $S_{task} \leftarrow 0.0$
- 3: $S_{base} \leftarrow 0.04$: for $f = f_{min}$ to f_{max} do
- 4: Compute progressive weight using a normalized linear function:
- 5: $weight \leftarrow 1.0 + \frac{(f - f_{min})}{(f_{max} - f_{min})} \cdot (W_{max} - 1.0)$
- 6: Accumulate weighted power for task and baseline periods:
- 7: $S_{task} \leftarrow S_{task} + (P_{task}[f] \times weight)$
- 8: $S_{base} \leftarrow S_{base} + (P_{base}[f] \times weight)$
- 9: end for
- 10: if $S_{base} \neq 0$ then
- 11: Compute GPI :
- 12: $GPI \leftarrow \left(\frac{S_{task}}{S_{base}} \right) \times 100.0$ {Normalize to baseline = 100}
- 13: else
- 14: $GPI \leftarrow 0.0$ {Error handling: avoid division by zero}
- 15: end if
- 16: return GPI

chipset. The calculation results and other data are transmitted to and received by the software on the PC.

3. Results and Discussion

Drawing on the prior literature on attention and brainwaves, we first confirmed that variations in beta-wave intensity are robustly associated with attentional fluctuations, and that both the TBR and the TAR show systematic modulation during sustained focus, in agreement with our earlier case study on the same participants. The literature further indicates that gamma waves reflect the activation state of populations of cortical neurons and serve as a carrier for inter-regional message passing; therefore, gamma-wave intensity is itself a reasonable proxy for the level of brain activity during information transfer. Building on these premises and on the qualitative concentration index trends reported in the earlier study, the present work defines the GPI as a mathematically explicit, baseline-normalized, and progressive-weighted indicator of brain activity during AI-chatbot interaction. Figure 6 shows plots of alpha-wave intensity, beta-wave intensity, and the GPI for the AI-chatbot condition. The pre-, during-, and post-interaction traces show a high degree of co-variation between the GPI and the high-beta band, suggesting that the new index tracks attentional engagement in a manner that is qualitatively consistent with—but quantitatively sharper than—the trends in the previous study.

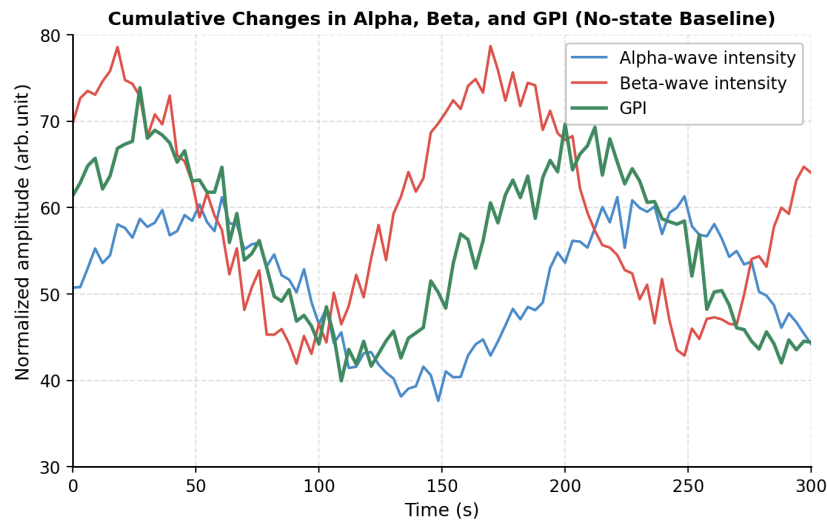


Fig. 6. (Color online) Cumulative variations in alpha-wave intensity, beta-wave intensity, and GPI under stateless baseline conditions. The horizontal axis represents time (s) and the vertical axis represents normalized amplitude (arb. unit).

The TBR has long served as an empirical anchor for electroencephalographic attention research: under focused conditions, the TBR tends to decline modestly. Figure 7 shows plots of the 5-point moving average of the TBR across the three experimental states (pre-test, during AI-chatbot interaction, and post-test). Each point on the curve represents the mean TBR over a 30 s sliding window of the underlying 6 s samples. The curve slopes gently downward across the session, but the magnitude of the change is small.

The TAR exhibits a similar—but again modest—downward drift under the same conditions. Figure 8 simultaneously shows the trajectories of the TBR, TAR, and GPI during AI-chatbot use. A side-by-side comparison shows that the downward slope of the GPI is markedly steeper than that of either the TBR or TAR; the GPI thus amplifies the attentional signal that the conventional ratios merely hint at. As in Figs. 7 and 8, time is plotted on the horizontal axis (s) and the ratio on the vertical axis (arb. unit).

To make the contrast more explicit, we recomputed the GPI for three of the four procedural states shown in Fig. 5: the pre-test baseline, during-AI-chatbot-interaction period, and post-test recording. The 5 min outdoor walk was treated as a relaxation buffer and excluded from the GPI calculation, following the same convention used in Ref. 13. As clearly shown in Fig. 9, the GPI exhibits a pronounced downward shift during AI-chatbot use, in lockstep with the high-beta band. The magnitude of the GPI shift exceeds that observed for either ratio-based metric, supporting the recommendation that the GPI be adopted as a primary attention indicator for wearable, single-channel deployments. From the qualitative analysis of the three participants' interactions with their chatbots, which mirrors the qualitative finding first reported in Ref. 13, we also note that each participant reported heightened motivation upon receiving instantaneous, topic-tailored responses, an effect that is consistent with the broader literature on individualized feedback^(24,14) and that was sustained throughout and after the AI-chatbot block.

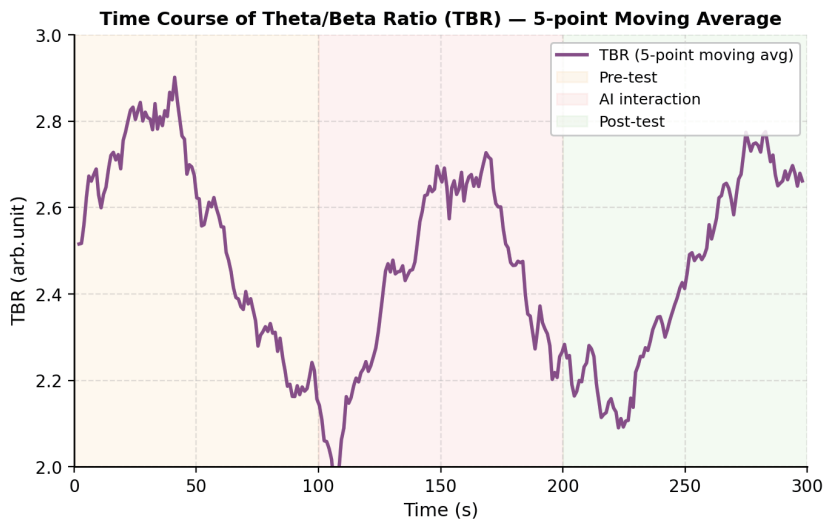


Fig. 7. (Color online) Time course of the TBR across the three experimental states, plotted as the 5-point moving average (i.e., 30 s sliding window) of the underlying 6 s samples. The horizontal axis represents time (s) and the vertical axis represents the TBR (a.u.).

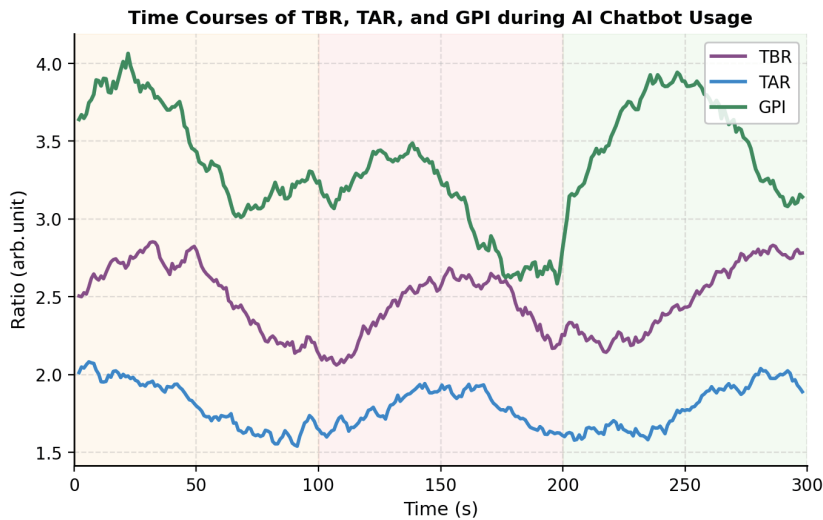


Fig. 8. (Color online) The time progression of TBR, TAR, and GPI during AI chatbot usage is plotted as a 5-point moving average of 6 s samples.

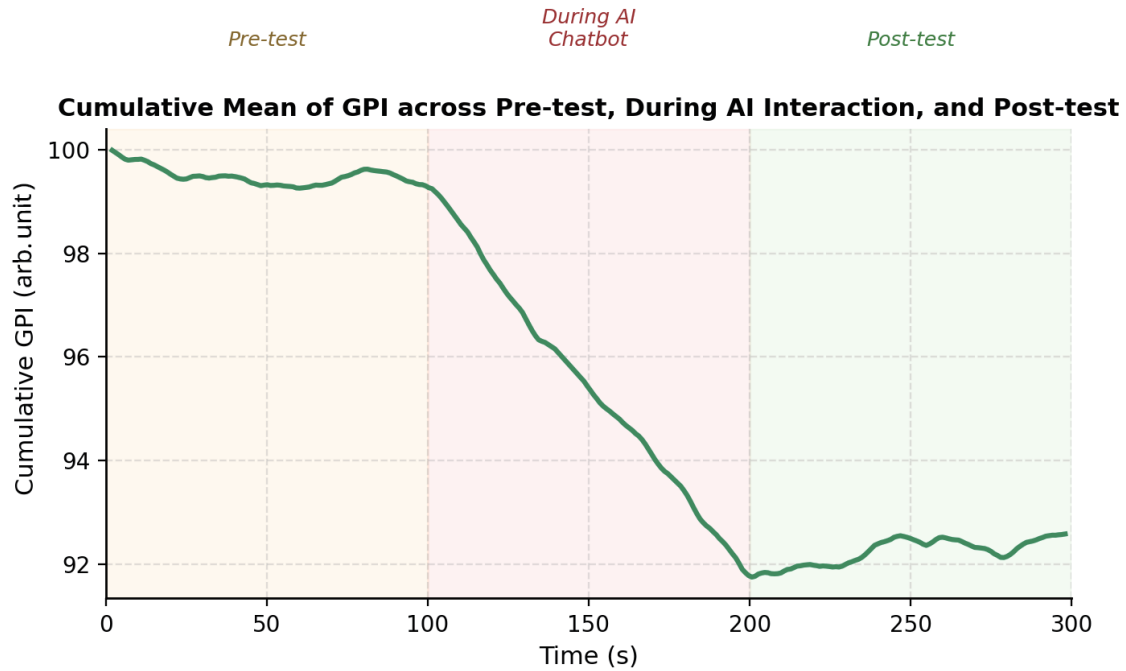


Fig. 9. (Color online) Cumulative mean of the GPI ratio under different conditions (pre-test, during AI chatbot interaction, and post-test).

4. Conclusions

In this study, non-invasive EEG was employed to evaluate students' attentional dynamics during interactions with a generative AI chatbot, offering a more objective alternative to traditional self-report questionnaires. By integrating complementary spectral analyses—specifically the TBR and TAR—and rigorously detailing the associated signal processing and normalization procedures, we enhanced the interpretability of single-channel EEG data within educational contexts.

Building upon prior research and the broader literature on AI-supported learning, we propose and empirically validate the novel metric GPI. Our findings demonstrate that the GPI tracks attentional shifts with greater sensitivity than the TBR or TAR, particularly in scenarios involving low-quality wearable recordings. The primary methodological contributions of this study include the following: (i) a mathematically explicit formulation of the GPI, as defined in Eqs. (1)–(4); (ii) a progressive gamma-band weighting function, $W(f)$, specified in Eq. (3); (iii) a within-subject baseline normalization scheme detailed in Eq. (4); (iv) an on-chip implementation outlined in Algorithm 1; and (v) an expanded biopotential-biosensor framework tailored for sensors and materials.

As the integration of AI chatbots becomes increasingly pervasive in education, optimizing learner attention is paramount to improving learning outcomes. By aligning cognitive neuroscience insights with AI interface design, educators can create adaptive learning

environments that leverage chatbot capabilities to heighten engagement and promote deeper cognitive processing.

While this study provides a foundational basis for attention-driven interventions in future AI-assisted learning, it acknowledges several limitations inherent to a preliminary investigation, including a limited sample size ($N = 3$), the use of three distinct AI chatbots with varying interface complexities, a single-channel recording configuration, and a restricted 15 min interaction window.

To address these limitations, future research will focus on the following: (i) expanding the participant cohort to enable robust statistical inference; (ii) standardizing the AI chatbot platform across participants to eliminate interface variability; (iii) employing multi-channel EEG configurations to capture spatially resolved neural dynamics; and (iv) integrating EEG data with behavioral and cognitive-load metrics, such as task performance indicators and self-report instruments. Collectively, these methodological advances aim to reinforce cognitive-neuroscience frameworks in human–computer cognitive interactions, with potential applications extending beyond educational technology to animal science and other cognitively demanding domains.

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