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EEG Data Quality in Real-World Settings: Examining Neural Correlates of Attention in School-Aged Children

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ABSTRACT— Advances in mobile electroencephalography (EEG) technology have made it possible to examine covert cognitive processes in real-world settings such as student attention in the classroom. Here, we outline research using wired and wireless EEG technology to examine attention in elementary school children across increasingly naturalistic paradigms in schools, ranging from a lab-based paradigm where children met one-on-one with an experimenter in a field laboratory to mobile EEG testing conducted in the same school during semi-naturalistic classroom lessons. Despite an increase of data loss with the classroom-based paradigm, we demonstrate that it is feasible to collect quality data in classroom settings with young children. We also provide a test case for how robust EEG signals, such as alpha oscillations, can be used to identify measurable differences in covert processes like attention in classrooms. We end with pragmatic suggestions for researchers interested in employing naturalistic EEG methods in real-world, multisensory contexts.

Identifying factors that promote attentional engagement in the classroom is of great interest to educators. The high temporal resolution of electroencephalography (EEG) data makes it well suited to track real-time fluctuations in attention, which are not easily observed in or accurately reported on by children. However, questions remain regarding the feasibility of using these methods with young children in real-world settings. To address these challenges, we compare data from two studies that employ stationary (wired) and mobile (wireless) EEG technology to measure covert attentional processes in elementary school children. The goal is to first examine data quality to demonstrate the feasibility of collecting EEG data with increasingly naturalistic paradigms—from individual assessments of lab-based tasks to group activities in classrooms. We then provide an example of the utility of these methods by describing a neural correlate of attention, the alpha-band power, during standardized tasks and classroom-based instructional activities.

In educational neuroscience research, it has been argued that a continuum of research—ranging from studies conducted in tightly controlled labs, semi-naturalistic field settings, to fully naturalistic settings—in combination can provide a foundation of complementary and converging evidence that can ultimately inform educational practice (Janssen et al., 2021; Matusz, Dikker, Huth, & Perrodin, 2019). Recent developments in mobile EEG technology have allowed for the collection of high-quality data in real-world settings, expanding the possibility for researchers to examine neural processes underly learning in the classroom. Yet, research using mobile EEG systems to evaluate emotion, motivation, and attention in educational settings has been conducted mainly with adults (Xu & Zhong, 2018). With young children, these methods have been most frequently applied to the study of clinical populations (e.g., ASD and children with epilepsy) in either laboratories or controlled field studies using lab-based paradigms (Williams et al., 2019; Zheng et al., 2017).

Despite the promise mobile EEG methods offer for examining neuroscientific questions in school settings,

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concerns about the feasibility of using these methods with children—including technical and pragmatic challenges associated with data quality—have not been widely addressed. Mobile EEG studies with children in naturalistic settings often involve less control over environmental stimuli and limitations in isolating specific neurocognitive processes (Janssen et al., 2021). Moreover, EEG recorded from children population is already thought to be susceptible to artifact contamination (Brooker et al., 2019) and limited by short recording duration, concerns that are exacerbated by the amount of movement naturally occurring during real-world interactions. While there are computational methods to remove nonbrain noise and reduce artifacts in EEG data, decisions around preprocessing steps have implications on data quality and retention, which may impact research findings. This further necessitates comparisons of EEG data drawn from different paradigms, to understand the implications of decisions regarding the use of mobile EEG protocols with school-aged populations.

Given data quality concerns, using EEG to examine cognitive processes in the real world requires focusing on robust and stable EEG phenomena. Alpha oscillations (7–12 Hz) recorded over the visual cortex are regarded as one of the most stable EEG oscillatory patterns and have been used to examine attention in children and adults (e.g., Capotosto, Babiloni, Romani, & Corbetta, 2009; Foxe & Snyder, 2011; Lenartowicz et al., 2016). The high signal-to-noise ratio and strong mechanistic bases of alpha signal derived from lab-based studies provide a strong foundation on which to base EEG studies of the same attentional processes in naturalistic settings, including real-world spatial navigation and movement (Ehinger et al., 2014; Liang, Starrett, & Ekstrom, 2018), visual attention during motorcycling (Vaughn et al., 2021), and student engagement during college lessons (Grammer, Xu, & Lenartowicz, 2021).

The Current Investigation

Here, we present two studies conducted in the same school with 5- to 10-year-olds. The first study collected EEG data while children participated in two lab-based tasks conducted individually with an experimenter in a field laboratory with a wired EEG system, and the second is a semi-naturalistic study with data collected simultaneously from children engaging in classroom activities using a wireless EEG system. We first examine the feasibility and limitations of collecting high-quality EEG data with young students in naturalistic school settings by comparing the quality of data drawn from two paradigms that involve activities children commonly experience at school but vary in the degree of naturalism of the context (e.g., field lab or classroom) in which these activities were conducted. Next, to exemplify how these methods can be used to address educational questions, we explore differences in alpha power, as a measure of student attention, when children engaged in different tasks or classroom activities. We conclude with insights gained from collecting EEG data with young children in schools.

METHODS

Participants

In both studies, kindergarten to 4th-grade students (Field lab: $N = 46$, $M_{\text{age}} = 6.62$ yrs.; classroom: $N = 10$, $M_{\text{age}} = 7.36$ yrs) were recruited from a university-associated, community-based school. Children were identified as 36% white, 20% Latino, 9% Asian, 7% African American, 20% Biracial, and 8% as other, with the majority from families reporting upper-middle-class income. All study procedures were approved by the university and the school-associated institutional review boards.

Procedures

In Study 1, EEG testing took place in a field laboratory set up in a school office, during which children completed tasks individually with a trained researcher. Here, we report EEG data collected during passive video watching of a 4-min clip of an episode of the Magic School Bus (MSB; May & Bastein, 1996). In addition, children completed the Impossibly Perfect Circles task (IPC, Gagne, Van Hulle, Aksan, Essex, & Goldsmith, 2011), in which children were asked to draw a perfect circle (crayon and paper) while receiving feedback. These two tasks were selected because they are standardized measures that also mimic the experiences children might have in everyday lectures or challenging school activities.

EEG recording for Study 2 was conducted during an after-school "neuroscience camp" where children participated in lessons implemented by a teacher on the research team. Two or three students in each session were outfitted with EEG caps and joined a group of students in a classroom to participate in the lesson during which continuous EEG recording was conducted. Although the activities were modeled after children's experience in their regular classroom, all of the content presented, activities conducted, and materials used were designed and implemented with experimental fidelity and control. Instructional activities included a brief mindfulness session, teacher-led instruction (e.g., lecture), and student-led activities (e.g., seated work). Details of methods and procedures for both studies are provided in Supporting information.

Shared EEG Data Reduction and Analysis

When processing data drawn from both studies, we applied two preprocessing pipelines, one being well-established in adult ERP research and the other being less restrictive with parameters commonly applied to developmental EEG data. EEG epochs that contained nonbrain artifacts were deleted during this step, and participants with more than 55% of epochs removed due to artifacts were not included in analyses.

Alpha frequency bands (7–11.5 Hz) were determined based on previous developmental literature and values were calculated using the mean power value for each spectrum range, normalized by the global power (1–50 Hz range) per channel at sites Pz, POz, O1, and O2.

Data Analysis

EEG data quality was first compared using the percentage of nonbrain artifacts identified and the percentage of deleted EEG epochs from each task or activity. The root mean square (RMS) value for each EEG epoch was calculated and averaged as an additional estimate of the noise on EEG for each task or classroom activity (Scanlon, Townsend, Cormier, Kuziek, & Mathewson, 2019). We then explored the internal consistency of alpha power by splitting EEG data into odd and even epochs. Using a multilevel regression approach, we examined data loss, as well as alpha power, between tasks within Study 1 and among different instructional activities within Study 2.[1] *Posthoc* comparisons with Tukey adjustment were performed to examine the effect of each instructional activity on alpha power.

RESULTS

Four children in Study 1 did not complete EEG recording and thus were excluded from analyses. Before preprocessing, one additional child was excluded from each study due to excessive EEG artifact caused by technical failures. In both studies, significantly more epochs were retained with a less restrictive preprocessing pipeline (lab: $\chi^2(1) = 26.56$, $p < .001$; classroom: $\chi^2(1) = 44.00$, $p < .001$); however, no differences were found between the alpha results from two pipelines (lab: $\chi^2(1) = .01$, $p = .92$; classroom: $\chi^2(2) = .49$, $p = .78$). Thus, we only present results using the child pipeline. Additional results regarding power at beta, gamma, and theta band are provided in the Supporting Information.

Study 1: Lab-Based Paradigms with a Wired EEG System

EEG Quality and Data Loss

Forty-one children in Study 1 are included in the data analysis, all having retained over 54% of epochs in EEG data. The average number of deleted electrodes was 0.84 (SD = 1.20, range 0–4). About 0.009% (SD = .020%) of continuous EEG data was marked as containing nonbrain artifacts by automated algorithms in Brain Vision Analyzer (BVA; Brain Product, Germany). An average of 3.50% (SD = 6.25%, range 0%–27.54%) of epochs was excluded from alpha power analysis across MSB and IPC (see Table 1). The percentage of deleted epochs did not differ significantly between tasks, $t(72) = .90$, $p = .37$, $r = .11$. Single-trial RMS in EEG data for the MBS task ($M_{RMS\text{-}MBS} = 10.65$, $SD_{RMS\text{-}MBS} = 2.10$) did not differ significantly from RMS for the IPC task ($M_{RMS\text{-}IPC} = 10.77$, $SD_{RMS\text{-}IPC} = 2.18$; Wilcoxon signed rank test: $z = 0.64$, $p = .52$).

Alpha × Tasks Results

Alpha power measures showed excellent split-half reliability in both MSB and IPC tasks, $r > .99$, $p < .001$. Alpha power was slightly higher while children watched the MSB video ($M_{Bus} = 1.884$) than during the IPC ($M_{IPC} = 1.711$; see Figure 1b). However, this difference was not statistically significant, $\chi^2(1) = 1.34$, $p = .25$, indicating that attentional engagement was comparable during both lab tasks.

Study 2: Classroom-Based Paradigm with a Wireless EEG System

EEG Quality and Data Loss

After preprocessing, 55% of EEG epochs were retained for all but one child, who was not included in subsequent analyses. The average number of deleted electrodes was 1.33 (SD = 1.41, range 0–4). About 0.22% (SD = 0.39%) of continuous EEG data was marked as containing nonbrain artifacts and was deleted from the power spectra analysis. On average, 18.21% (SD = 18.78, range 3.98%–51.00%) of epochs were excluded (see Table 1). The percentage of removed epochs did not differ across instructional activities, $\chi^2(2) = 0.71$, $p = .70$, indicating that the degree of data loss was comparable across conditions in the classroom-based investigation. Similarly, no significant differences were across the single trial RMS calculated from the mindfulness

Table 1
Percentage of Epochs Removed as a Function of Tasks or Instructional Activities with Standard Deviations

Study 1: Lab	Bus	Circle		Overall
% of Epochs removed	2.79 (7.98)	4.67 (7.88)		3.5 (6.25)
Study 2: Classroom	Mindfulness	Teacher-led	Student-led	Overall
% of Epochs removed	14.93 (16.87)	17.82 (14.54)	16.59 (20.78)	18.21 (18.78)

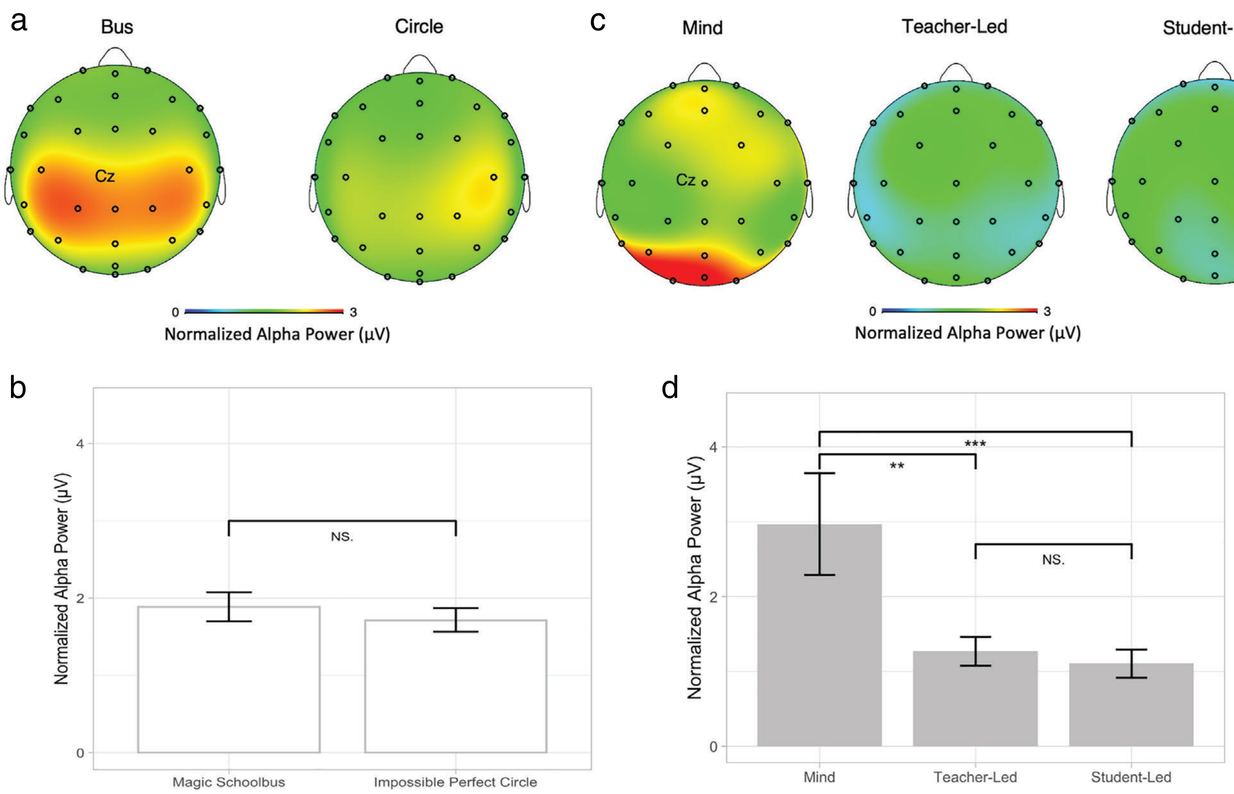

Fig. 1. Effects of Tasks (Study 1) or Instructional Activities (Study 2) on Attention as Indexed by Normalized Alpha Power. (a) Topographic maps for alpha power in study 1 revealed that alpha power was higher when children watched the MSB video and had a posterior scalp distribution. (b) Student attention was measured as mean normalized alpha power for each lab-based task, with error bars representing 95% confidence interval (calculated by bootstrapping). (c) Topographic maps for alpha power in study 2 revealed that alpha power was higher during the mindfulness session and had a posterior scalp distribution. (d) Student attention was measured as mean normalized alpha power for each class activity, with error bars representing 95% confidence interval (calculated by bootstrapping). $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

($M_{RMS\text{-}Mind}$ = 14.51, $SD_{RMS\text{-}Mind}$ = 3.53), teacher-led ($M_{RMS\text{-}Teacher}$ = 14.86, $SD_{RMS\text{-}Teacher}$ = 4.46), and student-led sessions ($M_{RMS\text{-}Student}$ = 13.32, $SD_{RMS\text{-}Student}$ = 1.70; Kruskal-Wallis rank sum test: $\chi^2(2) = 0.56$, $p = .76$).

Alpha × Instructional Activities Results

The internal consistency of alpha power was high in all three activities, rs > .99, ps < .001. Results showed that normalized alpha power varied significantly across different instructional activities, $\chi^2(2)$ = 11.94, p = .003. Alpha power was highest, indicating that children were least attentive to external inputs, during the mindfulness session ($M_{Mindfulness}$ = 2.97) as compared to teacher-led ($M_{Teacher\text{-}led}$ = 1.27, z = 3.50, p = .001) and student-led ($M_{Student\text{-}led}$ = 1.10, z = 3.76, $p < .001$) activities (See Figure 1d). Although mean alpha power in teacher-led instruction was slightly higher than in student-led activities, the difference was not statistically significant, z = .39, p = .92.

DISCUSSION

Understanding the dynamic nature of children's attention in classrooms has important implications for children's learning and academic achievement. Overall, our findings suggest that it is feasible to collect EEG data with young children in increasingly naturalistic settings using lab- and classroom-based paradigms. Furthermore, examination of classroom data revealed preliminary descriptive differences in an EEG index of attention—alpha power—as a function of instructional activities that students engage in. These results demonstrate the potential of using EEG methods to examine attention in real-world settings.

There are many challenges associated with conducting naturalistic EEG studies, including those related to data quality and data loss. Although tasks in Study 1 were modeled on naturalistic activities, data loss was relatively low with the lab-based paradigm. However, it was necessary to remove over twice as much data in the classroom-based paradigm in Study 2, in large part due to movement. As expected, we also found more noise in the EEG data from the classroom-based paradigm than from the lab-based paradigm as indicated by higher RMS values. While working with a researcher in Study 1, children were encouraged to sit at a table as still as possible. In contrast, the classroom-based study was an active space where children sat on a rug during instructions, interacted with teachers and peers, and worked on activities at group tables, as they would in class. In this context, it was challenging to limit participant movement directly without interfering with activities. To counteract these issues, many developmental studies have applied looser preprocessing parameters than those conducted with adults. Here, we applied both adult and child preprocessing pipelines and found that while more epochs were removed in the adult pipeline, no differences in alpha power across experimental conditions were observed between the less and more restrictive parameters.

In the development of both investigations, it was necessary to make trade-offs between naturalistic paradigms and data quality to balance scientific and pragmatic considerations. In Study 1, we implemented protocols to minimize movement artifacts during tasks offering children breaks as needed. Similarly, activities in Study 2 were carefully selected to minimize movement within the classroom. Moreover, we used scripted lessons and structured activities in Study 2 to ensure a clear link between classroom activities and neural data. It is possible that these types of decisions unintentionally altered the nature of student behaviors. With wired EEG equipment, children are directly connected to the EEG amplifier. Even small movement from children could cause the bundle of connecting wires to move, introducing artifacts into the EEG data. Wireless devices are more resistant to this type of noise; however, the risk of data loss due to large movement artifacts appeared to be higher using wireless equipment, at least in more real-world environments. These differences highlight the importance of designing studies with these trade-offs in mind—for example, if wireless technology makes more sense for the investigation, compensating by lengthening recording time to account for data loss would be wise.

Regardless of the increased noise level, we were able to find activity-related differences in alpha power in Study 2, such that alpha power was the highest, and attention the lowest, during the mindfulness activity than in teacher or student-led activities. However, no observable differences were found between the two tasks in Study 1 or between teacher and student-led activities in Study 2. This is inconsistent with similar work with college students, indicating that attention was greater when students engaged in work that they directed than in teacher-led lectures or video-watching (Grammer et al., 2021). A few studies have examined classroom engagement with older students and also identified differences across instructional activities (Bevilacqua et al., 2018; Dikker et al., 2017). This discrepancy could reflect developmental differences or could be attributable to differences in children's experience in the classroom, as both teacher-led and student-led activities are more interactive in elementary school versus high school and college classrooms. Additionally, supplementary analyses revealed that teacher-led activities increased theta-band (4–6.5hz) power and decreased gamma-band (30–50hz) power, indicating transitions to lower wakefulness (Ko, Komarov, Hairston, Jung, & Lin, 2017). Similar trends were presented during the MSB in comparison to the IPC task. While preliminary, our findings highlight the ways in which these methods can be used to detect state differences in children in educational neuroscience investigations.

As educational investigations increasingly employ real-world EEG paradigms with young children, we hope findings from this study could provide concrete information related to feasibility and data quality for researchers designing real-world studies. One limitation of the current comparison is the differences in EEG equipment, participants' mobility levels, and sample sizes between the two studies. Although the comparison we describe here reflects the contrast many researchers will face when choosing between laboratory-based and mobile EEG studies, investigations performed with the same tasks and EEG technology in different naturalistic settings will be valuable to provide direct comparisons of EEG data across contexts. In addition, we recommend future studies include a report of data quality and data loss to allow a more collective understanding and cross-evaluation of investigations in naturalistic settings. Although our interpretation of attention in classrooms is constrained by the small sample size in Study 2, this work serves as a foundation for studies designed to examine the association between teacher instruction and student attention in the classroom. We also recognize the need for convergent measures of attention—both in terms of EEG and event-related potentials, as well as through behavioral observation. Given mixed evidence for convergence between EEG and observational measures of attention, our future work hopes to examine how EEG data can be used to refine and further validate existing behavioral makers of these processes and broaden our understanding of individual differences in children's attention.

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Conflict of Interest

The authors declare that there are no competing interests.

Ethical Statements

Both studies were approved by the Intuitional Review Board of University of California, Los Angeles (IRB#16-001707 and IRB#19-000139). Prior to participating in the study, written informed consent from parents or legal guardians of participating children and oral assent from the children were obtained.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.
Table S1. Summary of Study 1 electroencephalogram (EEG) data in analysis from two processing pipelines, with standard deviations.
Table S2. Summary of Study 2 electroencephalogram (EEG) data in analysis from two processing pipelines, with standard deviations.
Figure S1. Topographic maps for alpha power in study 1 preprocessed with a strict pipeline.
Figure S2. Topographic maps for alpha power in study 2 preprocessed with a strict pipeline.
Figure S5. Topographic maps for theta power (4–6.5 Hz), beta power (12–30 Hz), and gamma power (30.5–50 Hz) in study 1, normalized by global power (1–50 Hz).
Figure S6. Topographic maps for effects of class activities on theta power (4–6.5 Hz), normalized by global power (1–50hz).
Figure S7. Topographic maps for effects of class activities on beta power (13–30 Hz), normalized by global power (1–50hz).
Figure S8. Topographic maps for effects of class activities on gamma power (30.5–50hz), normalized by global power (1–50hz).

NOTE

1 Multilevel linear models have the advantage of handling the problem of residual dependency in repeat-measured data, as in both of our studies presented here. When compared to the conventional repeated-measures ANOVA approach, the multilevel approach also releases the assumption of sphericity in the data and no more corrections (e.g., Greenhouse–Geisser) for *p*-value are required when sphericity is violated.

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