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EEG analysis of elementary students during paper-based and tablet-based learning and assessment

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ABSTRACT

This study investigated elementary students' cognitive responses to different learning and assessment media using electroencephalography (EEG). In a repeated-measures EEG experiment, 20 elementary students experienced four conditions combining paper and tablet media. While the learning medium itself showed no significant effect on cognitive states, the assessment phase revealed a clear congruency effect. Specifically, the paper-learning-to-paper-assessment condition produced significantly higher concentration and brain activity compared to the incongruent paper-learning-to-tablet-assessment condition. These findings provide physiological validation for the encoding specificity theory and redirect attention from media comparison to contextual alignment. For classroom practice, this highlights the need to align learning and assessment media to help students maintain focus and perform effectively, particularly in increasingly digital learning environments.

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1. INTRODUCTION

The rapid advancement of digital technology has reshaped educational environments. Traditional paper-based instruction is increasingly shifting toward tablet- and PC-based learning. Digital tools are often praised for improving accessibility and learner engagement [1]–[3]. However, concerns remain regarding diminished attention, shallow processing, and increased cognitive overload [4]–[6]. While digital media can raise extraneous cognitive load through multitasking and complex interfaces, paper-based media provide visual stability and a fixed layout that supports comprehension [7], [8]. As such, the choice of media is not merely a matter of content delivery but a critical factor that shapes learners' cognitive processing strategies.

Despite the expanding use of digital devices in schools, empirical evidence on their cognitive effects remains inconclusive. Much of the existing research has relied on outcome-based indicators such as test performance or self-report questionnaires. These measures are limited in capturing learners' real-time attention, engagement, and cognitive load. This is particularly relevant for today's generation Alpha elementary students, who have grown up immersed in digital technology [9], [10]. Prior research indicates that digital familiarity and competence are positively associated with learning performance [11], [12]. However, whether these factors translate into measurable differences in cognitive responses has not been systematically tested.

Another overlooked factor is media congruency—the alignment between learning and assessment media. Encoding specificity theory suggests that memory retrieval improves when learning and recall occur under matching conditions [13]. This implies that congruency between learning and testing media could strengthen learners' cognitive responses. Yet few studies have examined this phenomenon using physiological measures such as electroencephalography (EEG). This gap remains significant in the literature.

To address these issues, the present study investigates the cognitive responses of elementary school students, measured via EEG within paper-based learning (PL) and tablet-based learning (TL) environments. Furthermore, we explore whether media congruency between the learning and testing phases modulates cognitive engagement. For this purpose, participants were subjected to four conditions: PL followed by paper-based testing (PLPA) or tablet-based testing (PLTA), and TL followed by paper-based testing (TLPA) or tablet-based testing (TLTA). EEG, a non-invasive neuroimaging technique with high temporal resolution, was employed to monitor EEG, with concentration, brain activity, and stress levels serving as validated indicators of cognitive engagement [14]–[16]. A repeated-measures design was employed, allowing for direct within-subject comparisons of media effects as all participants experienced each learning and testing condition. By examining the impact of different media combinations on these EEG indicators, this study exploratively provides evidence-based recommendations for optimizing digital learning environments in elementary schools. Accordingly, this research seeks to answer the following questions:

- RQ1. How do EEG indicators (concentration, brain activity, and stress) differ between PL and TL?
- RQ2. How do EEG indicators (concentration, brain activity, and stress) differ according to the congruency between the learning medium and the testing medium?

2. THEORETICAL BACKGROUND

2.1. Digital vs. PL

Digital devices such as tablets, laptops, and personal computers have increasingly been recognized for their educational potential by improving access to information and offering interactive content that enhances learners' autonomy and engagement [2], [3]. Students who are proficient in using digital tools naturally develop higher levels of digital literacy and often perform better in technology-mediated learning environments [11], [12]. Given this, elementary school students—who have grown up with digital technology since birth—may be particularly well positioned to benefit from digital learning environments.

However, while digital learning environments offer increased flexibility and efficiency, they are also subject to criticism for potentially increasing cognitive load. Cognitive load theory posits that learners have a limited capacity for processing information within their working memory [17]. From this perspective, digital media may impose extraneous cognitive load due to visual and auditory stimuli, multitasking potential, and interface features such as scrolling and screen switching [14], [15], [18]. These distractions can disrupt comprehension of core content and reduce learners' ability to engage in deep processing [16]. This is especially relevant for elementary students, whose self-regulation skills are still developing, making them more vulnerable to externally driven cognitive demands [16], [19].

In contrast, PL is reported to minimize extraneous load by providing visual stability, fixed physical layout, and limited navigation demands, thereby creating an environment more conducive to focused learning [7], [8]. Long texts tend to yield significantly better comprehension outcomes on paper than on digital media, likely due to the absence of scrolling and other distractors [20], [21]. Moreover, the spatial predictability and tactile interactions associated with paper—such as turning pages, underlining, or handwriting—enhance memory through embodied engagement [7], [21]. Sensory experiences like the feel and smell of paper have also been shown to act as contextual cues that support recall [22], [23].

In sum, digital and paper-based media differ not only in format but also in the cognitive environments they create, shaping learners' attention, processing, and strategies in distinct ways. For digital-native elementary students, familiarity with digital tools can foster engagement, but limited self-regulation may increase distraction and overload, so media effects must be interpreted in light of developmental stage and technological fluency. This perspective supports the need to examine digital and PL not only through performance outcomes, but also through physiological indicators of cognitive engagement. Such an approach can offer more nuanced insights for designing learner-centered educational environments.

2.2. EEG as a measure of cognitive engagement

EEG has emerged as a widely used tool in educational psychology and learning sciences for the real-time measurement and analysis of learners' cognitive responses during learning processes. EEG allows for non-invasive monitoring of the brain's electrical activity with high temporal resolution (in the millisecond range), making it well suited for tracking dynamic changes in learner engagement. Unlike behavioral or self-report methods, EEG has the unique advantage of capturing unconscious cognitive states and is thus regarded as a suitable instrument for exploring attention and cognitive load on a physiological level [24], [25].

EEG signals are composed of several frequency bands, among which gamma (γ), high beta (Hβ), mid-beta (Mβ), low beta (Lβ), alpha (α), and theta (θ) waves are commonly interpreted as basic indicators of cognitive states. In general, θ waves (4-8 Hz) are associated with drowsiness or memory retrieval, α waves (8-13 Hz) with relaxation and emotional stability, beta waves (13-30 Hz) with focused attention and logical reasoning, and γ waves (above 30 Hz) with high-level information integration and deep concentration. The power distribution across these bands reflects different psychological and cognitive conditions and serves as the foundation for deriving composite EEG metrics [26], [27].

In this study, three composite EEG indices were used to assess learner states: concentration, brain activity, and stress. The concentration index is based on the theta-to-beta power ratio (TBR), which has traditionally been used as a physiological marker of attention [28]. In this study, the TBR was interpreted as an indicator of sustained attention during task performance and labeled as "concentration". This interpretation aligns with prior EEG studies; for example, sustained attention has been defined as concentration, with TBR interpreted as its physiological expression [29]. Thus, TBR reflects both attention and task engagement and is widely adopted as a valid marker of cognitive focus.

Brain activity was measured using SEF90, defined as the spectral edge frequency below which 90% of the EEG signal power is contained. Higher SEF90 values indicate elevated cognitive arousal and task-related mental load [30]. In contrast, the stress index is derived from the power level in the Hβ range (>20 Hz) and reflects performance pressure experienced by the learner [31].

EEG-based learning analytics has already been applied in a variety of educational contexts. For instance, one study experimentally examined how learners' concentration varied when exposed to text, text-with-graphics, and video formats in mobile learning environments using EEG data and found that text-only materials yielded higher concentration than multimedia formats [32]. Another study demonstrated a significant relationship between learners' interest levels and EEG-derived concentration scores [33], [34]. As such, EEG is increasingly used not only to evaluate learning outcomes but also to monitor cognitive processes during learning. It provides valuable insights into engagement, fatigue, and affective states, especially in digital media environments, and thus holds promise for enhancing the quality of educational experiences.

2.3. Encoding specificity and media congruency

The encoding specificity theory posits that the success of memory retrieval largely depends on the similarity between the contextual conditions present during the encoding of information and those present during recall [13]. Learners do not encode information in isolation; rather, they encode it in conjunction with the surrounding physical and psychological context. When similar contextual cues are reactivated at the time of retrieval, recall accuracy and efficiency are significantly enhanced. This theory has been validated across a range of memory studies—including paired-associate recall, environmental context matching, and mood-state congruency—and has recently gained empirical support in educational settings as well [35]–[37].

This theoretical framework offers meaningful insights for educational practice, particularly regarding how context congruency between learning and assessment environments may influence both performance and cognitive responses. More recent extensions of the theory suggest that media themselves may function as contextual cues, implying that when the same medium is used for both learning and assessment, the environmental continuity can act as a powerful retrieval aid [37], [38]. Differences between media—such as interface design, navigational structure, and information presentation—can affect the consistency between learners' encoding strategies and the cognitive strategies required during assessment.

Indeed, several behavioral studies have reported enhanced performance when learning and assessment were conducted using the same medium [37]. However, these studies have largely focused on outcome-based metrics such as test scores, without exploring how learners' real-time cognitive states (e.g., concentration or processing load) may be affected during assessment under varying media conditions. Additionally, the reliance on self-report measures or performance outcomes has limited the ability to obtain objective indicators of cognitive strain or discomfort, particularly among young learners like elementary school students, who may lack the metacognitive capacity for accurate self-assessment.

To address these limitations, this study employs EEG-based physiological indices (concentration, brain activity, stress) to examine how media congruency between learning and assessment influences cognitive responses. This approach aims to empirically investigate how not only the type of media but also the media congruency affects learners' immersion and cognitive resource allocation. The findings are expected to offer a theoretical and practical foundation for incorporating contextual cues into the design of digital learning environments, thereby contributing to more effective and learner-centered instructional practices.

3. METHOD

This study employed a repeated-measures design in which each participant was exposed to all experimental conditions. This within-subject approach enhances the reliability of condition comparisons, especially in studies with a limited sample size. Moreover, it allows for the quantitative analysis of physiological responses obtained via EEG, thus offering methodological rigor in capturing intra-individual variation.

3.1. Participants

The participants were 20 sixth-grade students (10 boys, 10 girls) from an elementary school in urban South Korea. To ensure stable EEG measurement and consistent task understanding, students with exceptionally high or low academic performance were excluded, targeting those with average abilities and basic digital familiarity. Suitability was confirmed through teacher interviews, brief student interviews, and an orientation session. Written informed consent was obtained from all students and their guardians after a full explanation of the study.

The sample size of 20 participants was determined considering the study's repeated-measures design, which enhances statistical power by reducing inter-subject variability. To assess the adequacy of this sample size, a sensitivity power analysis was conducted using G*Power. The analysis specified a paired-samples t-test with a significance level of $\alpha=0.05$ (two-tailed) and 80% power ($1-\beta$). The results indicated that the study was sufficiently powered to detect a medium-to-large effect size ($dz \geq 0.65$). This suggests that the experimental design was enough to identify practically meaningful differences if they existed.

3.2. Materials

EEG data were collected using the OmniFit Mindcare portable device, a certified medical-grade system with a two-channel dry electrode setup. This device records EEG signals and also measures photoplethysmography (PPG) signals from peripheral blood vessels. Data were transmitted in real time to a dedicated software via Bluetooth.

The device captures raw EEG signals from γ, Hβ, Mβ, Lβ, α, and θ frequency bands. Based on these, it automatically calculates composite EEG indices: concentration, brain activity, and stress. The device can operate in both eyes-open and eyes-closed conditions, with measurement durations of 1 or 5 minutes. Its reliability and effectiveness in EEG studies have been validated in prior research [39]–[42], making it a suitable tool for tracking meaningful neural responses.

For this experiment, we developed two types of learning materials for PL and TL, and corresponding assessment materials for four distinct conditions by combining the learning and testing media: paper-learning/paper-assessment (PLPA), paper-learning/tablet-assessment (PLTA), tablet-learning/paper-assessment (TLPA), and tablet-learning/tablet-assessment (TLTA). To ensure content equivalency, a panel of experts, consisting of two elementary school teachers and one Ph.D. in Education, independently evaluated each item based on its information load, required cognitive processing, and working memory demands. Discrepancies in their ratings were resolved through discussion, and the items were revised accordingly. This triangulation method secured the internal validity of the experimental stimuli and minimized potential bias in the EEG comparisons.

The learning tasks consisted of three types of stimuli: i) two lines of original song lyrics; ii) nine randomly ordered four-digit numbers, and iii) eight AI-generated characters with assigned names. The corresponding assessments required: i) filling in two missing words from one line of the lyrics; ii) recalling three complete three-digit numbers excluding the first digit from the given sequences; and iii) remembering the names of three characters. The total possible score was 16.

These task types were deliberately chosen to engage different cognitive processes while maintaining comparable levels of difficulty. Memorizing short lines of lyrics required rote verbal recall, engaging the phonological loop of working memory. Recalling digit sequences tapped into sequential working memory and attentional control, as numbers are a standard measure of memory span. Remembering character–name pairs elicited visuospatial encoding and associative memory by requiring participants to bind visual features with verbal labels. Together, these tasks broadly activated verbal, numerical, and visuospatial domains of cognition without overloading any single area, thereby providing a robust basis for eliciting and comparing EEG responses across learning conditions.

Tablet-based tasks were performed on a 10.1-inch touchscreen tablet using a digital pen. Participants used a basic note-taking app to annotate PDF files and complete their tasks. Paper-based tasks were printed on single-sided A4 sheets. All materials were standardized to one page per task or assessment.

3.3. Procedures

Experiments were conducted individually in quiet, distraction-free classrooms after school hours. Each session consisted of a learning phase followed by an assessment phase, with EEG signals recorded continuously throughout. Before starting the experiment, participants underwent a one-minute pre-test to confirm stable EEG signal acquisition. The experimental protocol began only when the participant indicated readiness and EEG signal quality was verified.

To control for order effects, participants were randomly assigned into two groups (10 students per group, balanced by gender). One group first completed the PL task for 5 minutes, followed by 1-minute paper-based and tablet-based assessments, respectively. After a short 3-minute break, the same procedure was repeated using TL materials. The second group followed the reverse order—beginning with TL and alternating the order of assessments. Including preparation and rest, each session lasted approximately 50 to 60 minutes.

3.4. Analysis

EEG data were processed and analyzed using the internal algorithms of the OmniFit Mindcare system. The system's automated pipeline began by pre-processing the raw signal, which was sampled at 250 Hz. The signal was passed through a series of infinite impulse response (IIR) Butterworth filters, including an 8th-order low-pass filter (fc=43 Hz), a 1st-order high-pass filter (fc=2.6 Hz), and a 2nd-order notch filter (band-stop: 55-65 Hz). This procedure was designed to remove high-frequency noise, slow baseline drifts, and power-line artifacts. Following this pre-processing, the system automatically computed composite indicators such as concentration, brain activity, and stress. The three EEG indices used in this study are defined as:

- Concentration: calculated via the TBR, this index reflects attention and immersion during task performance.
- Brain activity: the spectral edge frequency where 90% of the EEG power is concentrated (SEF90), serving as an indicator of cognitive arousal, task load, and information processing speed.
- Stress: derived from the relative power in the Hβ band, indicating performance pressure.

To precisely compare intra-individual physiological changes, all EEG indices were standardized as z-scores for each participant. Statistical analysis was conducted in two stages, aligned with the learning and assessment phases. In the learning phase, paired-samples t-tests examined EEG differences by learning medium (PL vs. TL). In the assessment phase, a 2 (learning medium)×2 (assessment medium) repeated-measures ANOVA tested main and interaction effects, followed by paired t-tests for specific contrasts (PLPA vs. PLTA; TLPA vs. TLTA). To evaluate the magnitude of the observed differences, Cohen's d was calculated, with thresholds of 0.2 (small), 0.5 (medium), and 0.8 (large) as suggested in prior work [43]. All analyses were performed using IBM SPSS statistics 22.0.

4. RESULTS

Before analyzing EEG differences by learning conditions, this chapter reports descriptive statistics for the composite indices—concentration, brain activity, and stress. The raw EEG bands (γ, Hβ, Mβ, Lβ, α, and θ) are presented in Table 1, as the main analyses focus on the composite measures that better capture learners' cognitive states.

4.1. Descriptive statistics

The descriptive statistics for the learning types and assessment types are summarized in Table 2. Regarding the three composite EEG indices—concentration, brain activity, and stress—concentration was higher in the PL condition (M=0.405, SD=0.439) than in the TL condition (M=0.151, SD=0.565). However, brain activity was slightly lower in the PL condition (M=-0.243, SD=1.233) compared to the TL condition (M=-0.184, SD=0.728). Stress levels were somewhat higher in PL (M=-0.235, SD=1.009) than in TL (M=-0.422, SD=0.552).

When considering both learning and assessment types, concentration was higher in the PLPA condition (M=0.454, SD=0.529) than in PLTA (M=0.169, SD=0.427), whereas the TLPA condition (M=0.278, SD=0.435) showed lower concentration than TLTA (M=0.492, SD=0.532). Brain activity was higher in PLPA (M=0.369, SD=0.795) than in PLTA (M=-0.310, SD=0.726), while TLPA (M=-0.192, SD=0.896) showed lower brain activity than TLTA (M=0.009, SD=0.805). As for stress, PLPA (M=-0.048, SD=0.647) was slightly higher than PLTA (M=-0.211, SD=0.645), whereas TLPA (M=-0.251, SD=0.756) was lower than TLTA (M=-0.175, SD=0.773).

A dataset can be considered normally distributed when skewness values are less than 3 and kurtosis values are less than 8, as suggested in previous literature [44]. In this study, the TL condition in the concentration index showed the highest values (skewness=-2.006, kurtosis=6.735), but both remained within the acceptable thresholds. Thus, the dataset was considered to satisfy the assumption of normality.

Table 1. Descriptive statistics of raw EEG bands

Division		N	M	SD	Min	Max	Skew	Kurt
γ	PL	20	-0.241	0.905	-1.697	1.447	0.511	-0.348
	TL	20	-0.331	0.690	-1.336	1.245	0.747	-0.116
	PLPA	20	-0.003	0.769	-1.215	1.808	0.735	0.110
	PLTA	20	-0.166	0.769	-1.125	1.436	0.854	-0.373
	TLPA	20	-0.291	0.710	-1.314	1.467	0.900	0.386
	TLTA	20	-0.099	0.845	-1.607	1.339	-0.087	-1.044
Hβ	PL	20	-0.235	1.009	-1.771	1.497	0.357	-0.646
	TL	20	-0.422	0.552	-1.223	0.822	0.851	0.073
	PLPA	20	-0.048	0.647	-1.071	1.854	1.325	2.847
	PLTA	20	-0.211	0.645	-0.969	1.285	0.951	0.400
	TLPA	20	-0.251	0.756	-1.271	1.441	1.011	0.241
	TLTA	20	-0.175	0.773	-1.239	1.431	0.537	-0.153
Mβ	PL	20	-0.055	1.086	-1.827	1.720	0.145	-1.019
	TL	20	-0.244	0.664	-1.489	1.117	0.310	0.017
	PLPA	20	0.116	0.826	-1.000	2.038	0.633	-0.082
	PLTA	20	0.078	0.680	-0.818	1.645	0.706	-0.281
	TLPA	20	-0.101	0.991	-1.827	1.787	0.313	-0.575
	TLTA	20	-0.046	0.970	-1.862	1.274	-0.454	-0.871
Lβ	PL	20	-0.305	1.030	-1.868	1.980	0.301	0.017
	TL	20	-0.165	0.701	-1.394	1.133	-0.140	-0.557
	PLPA	20	-0.003	0.884	-1.536	1.846	0.230	-0.637
	PLTA	20	0.280	0.697	-0.992	1.744	0.062	-0.451
	TLPA	20	-0.052	0.944	-1.586	1.949	0.818	0.072
	TLTA	20	-0.077	0.662	-1.963	0.811	-1.307	2.378
α	PL	20	-0.057	1.044	-1.686	2.075	0.275	-0.846
	TL	20	0.059	0.791	-1.359	1.452	-0.160	-0.475
	PLPA	20	-0.010	0.845	-1.404	1.125	-0.146	-1.325
	PLTA	20	0.236	0.854	-1.386	1.436	-0.203	-1.041
	TLPA	20	0.074	0.772	-1.022	1.754	0.343	-0.400
	TLTA	20	0.116	0.842	-1.642	1.235	-0.710	-0.201
θ	PL	20	-0.423	0.629	-1.888	0.924	0.076	1.023
	TL	20	-0.224	0.549	-0.975	1.405	1.278	2.984
	PLPA	20	-0.401	0.466	-1.119	0.485	0.352	-0.949
	PLTA	20	-0.140	0.531	-0.749	1.115	0.919	0.393
	TLPA	20	-0.301	0.573	-1.706	0.633	-0.557	0.691
	TLTA	20	-0.363	0.588	-1.191	1.277	1.180	1.973

Table 2. Descriptive statistics

Division		N	M	SD	Min	Max	Skew	Kurt
Concentration	PL	20	0.405	0.439	-0.511	1.143	-0.068	-0.451
	TL	20	0.151	0.565	-1.774	0.920	-2.006	6.735
	PLPA	20	0.454	0.529	-0.521	1.229	-0.261	-1.068
	PLTA	20	0.169	0.427	-0.899	0.786	-0.759	0.678
	TLPA	20	0.278	0.435	-0.610	1.125	-0.037	-0.280
	TLTA	20	0.492	0.532	-0.712	1.429	-0.292	0.009
Brain activity	PL	20	-0.243	1.233	-2.231	2.020	0.173	-0.733
	TL	20	-0.184	0.728	-1.571	1.145	-0.199	-0.258
	PLPA	20	0.369	0.795	-0.771	1.745	0.053	-1.356
	PLTA	20	-0.310	0.726	-1.346	0.875	0.380	-1.469
	TLPA	20	-0.192	0.896	-1.451	1.536	0.330	-0.796
	TLTA	20	0.009	0.805	-1.650	1.484	-0.311	-0.482
Stress	PL	20	-0.235	1.009	-1.771	1.497	0.357	-0.646
	TL	20	-0.422	0.552	-1.223	0.822	0.851	0.073
	PLPA	20	-0.048	0.647	-1.071	1.854	1.325	2.847
	PLTA	20	-0.211	0.645	-0.969	1.285	0.951	0.400
	TLPA	20	-0.251	0.756	-1.271	1.441	1.011	0.241
	TLTA	20	-0.175	0.773	-1.239	1.431	0.537	-0.153

4.2. EEG differences by learning type

Paired-samples t-tests and effect size analyses were conducted to compare EEG responses between the paper-based and TL conditions. No statistically significant differences were found between PL and TL in any of the three EEG indices, as in Table 3 and Figure 1. However, the effect size for concentration between PL and TL was moderate (Cohen's d=0.504), suggesting a possible trend favoring PL in terms of concentration, though not reaching statistical significance. In contrast, effect sizes for stress (d=0.230) and brain activity (d=0.059) were relatively low, indicating minimal differences between learning media for these measures, as in Figure 2. Overall, these results suggest that the type of learning media did not have a significant influence on learners' cognitive responses, though a partial effect was observed in the domain of concentration.

Table 3. EEG differences by learning type

Division		N	M	SD	Paired difference M	Paired difference SD	Paired difference SE	t	Cohen's d
Concentration	PL	20	0.406	0.439	0.254	0.775	0.173	1.467	0.504
	TL	20	0.151	0.565					
Brain activity	PL	20	-0.244	1.233	-0.059	1.696	0.379	-0.156	0.059
	TL	20	-0.184	0.728					
Stress	PL	20	-0.235	1.009	0.187	1.165	0.261	0.718	0.230
	TL	20	-0.422	0.552					

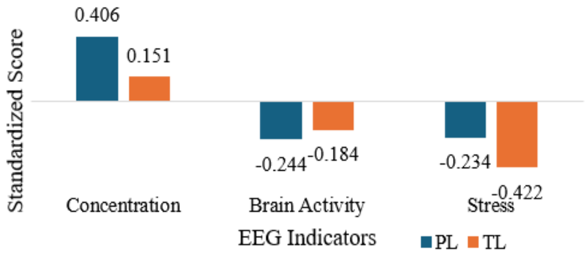

Figure 1. Compare EEG differences between learning types

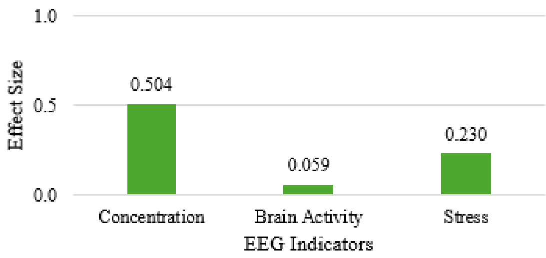

Figure 2. Effect size for EEG differences between learning types

4.3. EEG differences by assessment type according to learning type

To examine the differences in EEG signals by assessment type according to learning type, a 2×2 repeated measures two-way ANOVA was conducted, as in Table 4. First, for concentration, the main effect of learning medium (LM) ($F(1, 19)=0.209$, $p=0.653$, $\eta p^2=0.011$) and the main effect of assessment medium (AM) ($F(1, 19)=0.123$, $p=0.729$, $\eta p^2=0.006$) were not statistically significant. However, the interaction effect between learning medium and assessment medium (LM*AM) was statistically significant ($F(1, 19)=9.300$, $p=0.007$, $\eta p^2=0.329$).

Similarly, for brain activity, the main effect of LM ($F(1, 19)=0.236$, $p=0.632$, $\eta p^2=0.012$) and the main effect of AM ($F(1, 19)=2.293$, $p=0.146$, $\eta p^2=0.108$) were not statistically significant. However, the interaction effect was found to be statistically significant ($F(1, 19)=9.593$, $p=0.006$, $\eta p^2=0.336$). For stress, the main effect of LM ($F(1, 19)=0.240$, $p=0.630$, $\eta p^2=0.012$) and the main effect of AM ($F(1, 19)=0.071$, $p=0.792$, $\eta p^2=0.004$) were not statistically significant. The interaction effect was also not statistically significant ($F(1, 19)=0.995$, $p=0.331$, $\eta p^2=0.05$).

Table 4. Results of repeated measures ANOVA for EEG indices

Division	Source	SS	df	MS	F	ηp²
Concentration	LM	0.109	1	0.109	0.209	0.011
	Error	9.889	19	0.520		
	AM	0.025	1	0.025	0.123	0.006
	Error	3.782	19	0.199		
	LM*AM	1.248	1	1.248	9.300*	0.329
	Error	2.550	19	0.134		
Brain activity	LM	0.293	1	0.293	0.236	0.012
	Error	23.535	19	1.239		
	AM	1.143	1	1.143	2.293	0.108
	Error	9.471	19	0.498		
	LM*AM	3.865	1	3.865	9.593**	0.336
	Error	7.654	19	0.403		
Stress	LM	0.141	1	0.141	0.240	0.012
	Error	11.161	19	0.587		
	AM	0.037	1	0.037	0.071	0.004
	Error	9.886	19	0.520		
	LM*AM	0.286	1	0.286	0.995	0.050
	Error	5.454	19	0.287		

Note: *p<0.05 and **p<0.01

To examine the specific pattern of the interaction, paired-samples t-tests were performed, as in Table 5 and Figure 3. Results showed statistically significant differences in concentration and brain activity only within the PL conditions. Specifically, concentration was significantly higher in the PLPA condition compared to PLTA (M=0.285, t=2.495, p=0.022), and brain activity was significantly greater in PLPA (M=0.679, t=3.504, p=0.002), as in Table 5 and Figure 3.

Table 5. EEG differences by assessment type according to learning type

Division		M	SD	Paired Difference M	Paired Difference SD	Paired Difference SE	t	Cohen's d
Concentration	PLPA	0.454	0.529	0.285	0.511	0.114	*2.495	0.593
	PLTA	0.169	0.427					
	TLPA	0.278	0.435	-0.215	0.637	0.142	-1.508	0.440
	TLTA	0.492	0.532					
Brain activity	PLPA	0.369	0.795	0.679	0.866	0.194	**3.504	0.892
	PLTA	-0.310	0.726					
	TLPA	-0.192	0.896	-0.201	1.026	0.229	-0.874	0.236
	TLTA	0.009	0.805					
Stress	PLPA	-0.048	0.647	0.163	0.911	0.204	0.799	0.252
	PLTA	-0.211	0.645					
	TLPA	-0.251	0.756	-0.076	0.886	0.198	-0.386	0.099
	TLTA	-0.175	0.773					

Note: *p<0.05 and **p<0.01

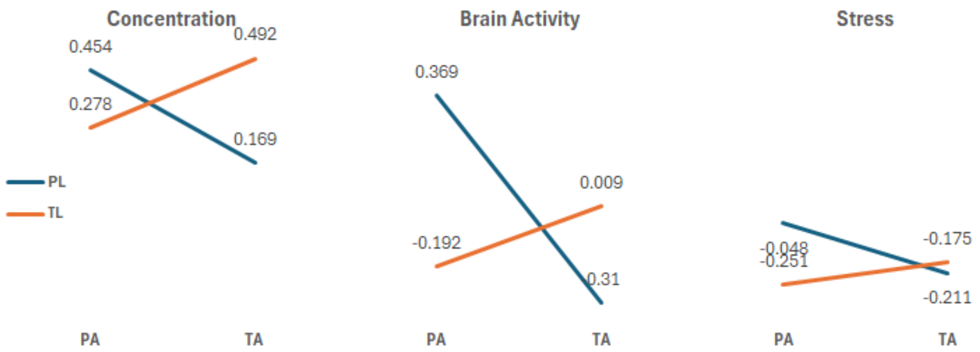

Figure 3. Compare EEG differences by assessment type according to learning type

Effect size calculations revealed a moderate effect for concentration (Cohen's d=0.593) and a large effect for brain activity (d=0.892) in the PLPA vs. PLTA comparison. In contrast, the effect size for stress between TLPA and TLTA was negligible (d=0.099), indicating minimal impact of assessment media in the TL condition, as in Figure 4. These findings suggest that the media used for assessment significantly impacted cognitive responses when learning occurred with paper-based materials, whereas media congruency had a much smaller effect following TL. In other words, evaluation format following PL appears to influence students' cognitive states more substantially, highlighting the importance of media congruency in instructional design—particularly when traditional print-based learning is involved.

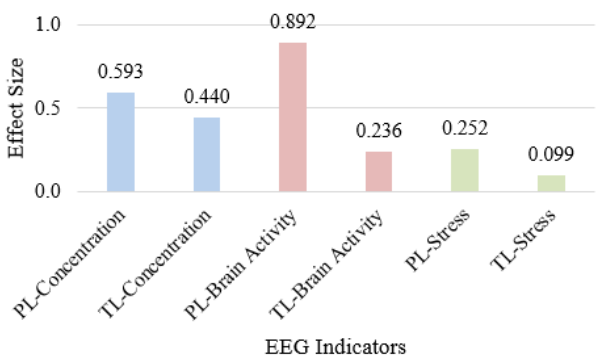

Figure 4. Effect size for EEG differences by assessment type according to learning type

5. DISCUSSION

This study investigated the EEG-based cognitive responses of elementary students in paper- and TL environments. It also further examined the effects of media congruency between learning and assessment contexts. Overall, no statistically significant differences emerged between paper- and TL conditions. However, clear congruency effects were observed in the assessment phase, exclusively under the PL conditions, as in Figure 5.

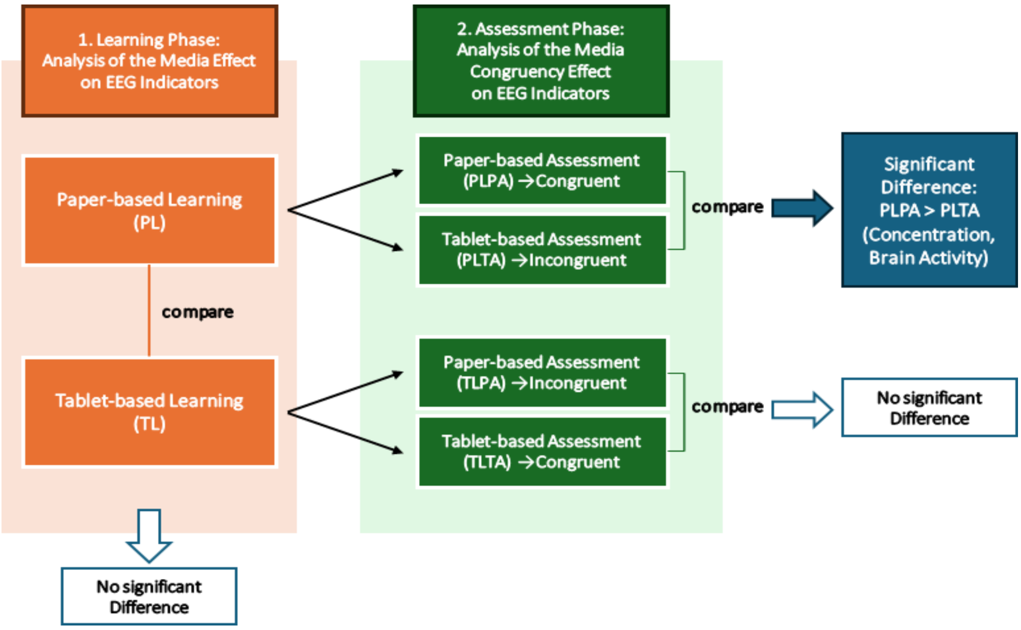

Figure 5. Visual summary of main findings

5.1. Cognitive EEG responses in paper vs. tablet learning conditions

During the learning phase, concentration, brain activity, and stress indicators did not differ significantly between paper and tablet conditions. The effect sizes were consistently small. This suggests that the medium itself had a negligible influence on students' immediate cognitive states.

This finding diverges from earlier studies reporting that digital media hinder sustained attention [14], [15], [18]. The discrepancy may be explained by the controlled design of this study. Both paper and tablet conditions used static, single-page PDFs without scrolling, hyperlinks, or multimedia, which eliminated common sources of extraneous load. The results therefore indicate that cognitive burden is not inherently tied to digital media but depends on how information is structured within the medium.

Another factor is participants' generational background. Unlike earlier studies involving adults or students less familiar with digital devices [14], [45]–[49], the Alpha generation learners in this study are accustomed to digital environments [9]–[12]. Their digital fluency likely reduced cognitive friction when interacting with tablets. In addition, the task was a short memorization exercise with limited reading demands. This minimized potential eye fatigue, a factor known to affect concentration in screen-based reading tasks [46], [50]–[53]. Taken together, the comparable EEG responses across media suggest that learners' developmental stage, task type, and digital familiarity may moderate media effects. This cautions against generalized claims of digital disadvantage.

5.2. Cognitive effects of learning-assessment media congruency

Unlike the learning phase, congruency effects were evident during the assessment phase. Concentration and brain activity were significantly higher when both learning and assessment were conducted on paper (PLPA) compared to the incongruent condition (PLTA). The effect sizes were in the medium-to-large range. This indicates that the observed differences were not only statistically significant but also practically meaningful.

These results align with encoding specificity theory, which posits that memory retrieval improves when learning and recall contexts are consistent [37], [38]. Paper media afford stable information structures and embodied interactions such as page-turning and handwriting [20], [21]. These sensory and behavioral cues appear to function as powerful retrieval aids when the same medium is used for both learning and assessment. In contrast, assessments conducted on tablets may lack these embodied cues, weakening recall despite identical content. Prior research also indicates that handwriting on paper provides richer tactile and kinesthetic feedback compared to stylus-based digital writing [23], [30], [54]. Such embodied experiences may enhance memory encoding. This offers a plausible explanation for the stronger congruency effect in the paper-based condition.

5.3. Implications and academic contributions

The findings of this study offer both practical and academic implications. From a practical perspective, the results emphasize the importance of aligning instructional and assessment media in school contexts. When learning and testing are conducted on the same medium, students exhibit higher levels of concentration and brain activity, suggesting that contextual continuity enhances cognitive engagement. For schools transitioning toward digital platforms, this implies that learning activities and evaluation formats should be carefully coordinated to reduce unnecessary cognitive friction and ensure fairness in assessment. Moreover, the findings highlight that neither paper nor digital media is inherently superior; rather, what matters is minimizing extraneous cognitive load within each medium. Well-designed digital materials, free from distracting features such as scrolling or excessive multimedia, can support learning as effectively as paper-based resources.

At the academic level, this study contributes to the literature by moving beyond test performance or self-report data and providing physiological validation of media effects through EEG. It extends existing research on media congruency by showing that congruency influences not only learning outcomes but also neurocognitive responses, offering deeper insight into the mechanisms of contextual alignment. Furthermore, the study demonstrates the methodological feasibility of conducting EEG experiments with elementary school students, a group seldom examined in neurocognitive research. In doing so, it provides foundational evidence for developing learner-responsive instructional designs and diagnostic tools tailored to children. By bridging educational psychology, instructional technology, and neuroscience, the study underscores the value of interdisciplinary approaches in understanding and optimizing learning in increasingly digital environments.

5.4. Limitations

This study is significant as a pioneering work that explores the cognitive responses of elementary students to different combinations of learning and assessment media. However, as an exploratory study in a novel area, its findings should be interpreted in light of several limitations, which also serve as avenues for future research. First, limitations exist regarding the sample and generalizability. The study involved 20 sixth-grade students; a size intentionally chosen for an exploratory focus on cognitive patterns rather than broad generalization. To enhance statistical power, a repeated-measures design allowed each participant to serve as their own control. Still, the small and homogenous sample limits generalizability, as cognitive characteristics and digital familiarity vary across developmental stages. Future research should therefore employ large-scale, stratified sampling across grade levels to establish stronger external validity.

Second, the study's ecological validity is limited by its experimental design. To isolate immediate cognitive effects of media combinations, tasks were brief (five minutes) memorization activities in a highly controlled lab setting. While necessary for causal exploration, this design does not capture authentic classroom learning, which entails sustained engagement with complex processes like reasoning and collaboration. It also required excluding background variables such as prior digital literacy, motivation, or novelty effects, which were not measured. Future studies should include these as covariates and adopt longitudinal classroom-based designs to assess the long-term, contextually embedded impact of media combinations. Despite these limitations, the significance of this study lies in its pioneering experimental analysis of how learning and assessment media combinations affect students' real-time physiological responses. It provides a foundational step for more sophisticated and expansive research on the effective design of digital learning environments.

6. CONCLUSION

This study proposes a new paradigm in which the discourse on educational technology must move beyond the simple 'paper versus digital' dichotomy and advance toward the core principle of contextual continuity. Particularly for today's digital native learners, it has been demonstrated that the consistency of the learning and assessment environment is a more critical driver of their cognitive engagement than the inherent properties of the medium itself. These findings offer significant implications for future digital education policy and instructional design.

Policymakers must recognize that technology investment should extend beyond the mere distribution of hardware to the construction of an integrated ecosystem where learning and assessment platforms are seamlessly aligned. Furthermore, instructional designers and educators should adopt a workflow-first approach, shifting from the fragmented perspective of considering temporary tool usage to prioritizing how to ensure the consistency and cognitive coherence of tools throughout the entire learning and assessment process. Ultimately, for technology to fully contribute to learning instead of hindering it by creating contextual friction, this principle of media continuity must be established as a cornerstone of modern educational design. In conclusion, by providing neurophysiological evidence for the validity of these design principles, this study holds its significance in laying a crucial theoretical and empirical foundation for creating more effective, equitable, and cognitively optimized digital learning environments for the next generation of learners.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
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CONFLICT OF INTEREST STATEMENT

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

ETHICAL APPROVAL

This study was approved by the Institutional Review Board (IRB No. KNUE-202502-SB-0708-01) of Korea National University of Education.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [HL], upon reasonable request.

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