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Taking notes with different writing devices influences learning processes but not performance: an EEG study comparing ink pens, digital pens, and keyboards

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Notetaking with digital devices during asynchronous online learning remains controversial. This study investigated how three writing devices—ink pens, digital pens, and laptops—interact with active (verbatim) vs. constructive (question) notetaking strategies during video lectures. During a within-design laboratory experiment, EEG data was recorded while 33 undergraduate students took notes for learning sessions using different notetaking devices and strategies, followed by immediate post-tests. Time-frequency analysis revealed significant differences in theta, alpha, beta, and gamma band power across devices, and significant interaction effects in beta, gamma, and theta/beta values. Both pen types showed higher alpha, beta, and gamma power and lower theta/beta ratios compared to keyboards, particularly in occipital regions associated with sustained visual attention. However, interaction effects indicate the importance of notetaking strategy, and immediate post-test performance showed no significant differences across conditions. The findings suggest that notetaking media influence learning processes and attention sustainment differently, though immediate performance outcomes remain similar. This has implications for designing asynchronous online learning environments and guiding notetaking practices in those settings.

KEYWORDS
attention, digital pen, EEG, engagement, ink pen, keyboard, notetaking

1 Introduction

Learning asynchronously from pre-recorded videos is a prevalent part of online learning, but this process comes with an array of issues. One of the biggest challenges of online learning is the retention of engagement (Dewan et al., 2019). Taking notes has been suggested as a potential method for heightening cognitive engagement, as notetaking is a complex process that can facilitate active learning (Bui and Myerson, 2014). However, the question of how to take notes effectively presents a more complicated issue. Is it better to take notes by hand–on paper or on a tablet screen–or to type them out on a laptop? Additionally, when using various devices to take notes, is the act of writing down given information verbatim more or less effective than creating one's own questions about the lecture?

Laptops and tablets are increasingly being used to take notes (Aguilar-Roca et al., 2012). However, research remains contentious on whether notetaking with digital devices is effective. Studies of word recognition after using a keyboard or pen to learn new letters in children and adults revealed that writing letters out by hand was more effective than learning letters by pressing a button on the keyboard (Kiefer et al., 2015; Longcamp et al., 2008; Mangen et al., 2015). In research more related to the context of online learning, experiments have been designed to compare longhand (handwriting) notetaking and notetaking with a laptop. Several of these studies have shown that longhand notetaking is more effective, performance-wise, than using a laptop, especially when the notes are reviewed afterwards (Bui et al., 2013; Luo et al., 2018; Mueller and Oppenheimer, 2014). This is particularly true in performance regarding questions of conceptual understanding (Horbury and Edmonds, 2020; Mueller and Oppenheimer, 2014).

Yet other studies directly contest and contradict these results. For example, Fiorella and Mayer (2017) found that those who took notes with a laptop performed better on tests after a period of review, and Morehead et al. (2019) were unable to replicate Mueller and Oppenheimer's findings. Urry et al. (2021) even show results that are the opposite of those found by Mueller and Oppenheimer. Luo et al. (2018) suggest that this lack of consensus could arise because notetaking media affect the types of notetaking strategies used. Laptop users often record notes in a more text-based, verbatim fashion, while those who use longhand tend to use more spatial images or symbols in a generative way in their notes (Fiorella and Mayer, 2017; Luo et al., 2018; Mueller and Oppenheimer, 2014). Artz et al. (2020) likewise point to other possible factors that could influence the effect of digital notetaking on performance, such as individual characteristics. This points to differences in learning processes according to notetaking media.

Digital pens represent yet another conundrum in the issue of notetaking media. They differ from ink pens in terms of tactile feedback, due to the smooth characteristics of a screen compared to paper, which may lead to difficulties in learning (Alamargot and Morin, 2015). On the other hand, learning new letters with a digital pen proved to be more effective in increasing word recognition for adults who were familiar with using tablets (Osugi et al., 2019). Writing with a digital pen also facilitates visuomotor coordination more than typing (Vinci-booher et al., 2016), resulting in higher synchronicity in neural oscillations in the theta band range (Askvik et al., 2020). Digital pens may encourage similar engagement to ink pens, or may differ altogether.

Such conflicting results point to the need for a targeted investigation comparing the learning processes afforded by different notetaking media. Support in the forms of feedback or learning design, as well as how students utilize video functions such as annotations in an online environment influences engagement in online learning (Seo et al., 2021), which means that different forms of engaging with content via notetaking may also play a part in how writing devices impact learning. Chi and Wylie (2014) posit that because verbatim notetaking is an act of selecting which information to retain, it is considered active notetaking; using notetaking to ask questions is a more generative process that integrates the learner's experience with the content, thus making it constructive notetaking. While such generative processing may lead to increased cognitive load, the cognitive load is considered germane and effective for learning (DeLeeuw and Mayer, 2008; Fiorella and Mayer, 2016). Constructive notetaking is considered more effective than active notetaking, resulting in increased memory and better connection of concepts (Bauer and Koedinger, 2007; Ponce et al., 2020). Taken together with results from Luo et al. (2018) that indicate handwriting devices (i.e., ink or digital pens) could be more conducive for spatial and generative notetaking, whereas keyboards could encourage verbatim notes, it appears writing device could be coupled with notetaking strategy during the learning process.

Engagement during notetaking can be reflected in measures of attention from brain waves (Ko et al., 2016); thus, electroencephalography (EEG) data can be utilized to disentangle the effects of notetaking strategies and writing devices. Based on prior research, it can be hypothesized that constructive notetaking will lead to better engagement compared to active notetaking; this can be reflected in theta/beta ratios in brain wave oscillations, as this measure is viewed as a marker for attention (Ko et al., 2016; Zivan et al., 2023). On the other hand, different writing devices may also influence engagement. When different writing devices better afford notetaking, engagement will likely increase, manifesting in heightened levels of attention. If writing devices themselves influence engagement, levels of attention will differ by device regardless of notetaking strategy. Differences in movement when using different writing devices may also influence brain waves, changing oscillations related to motor skills (Alamargot and Morin, 2015; Vinci-booher et al., 2016).

Thus, the present study examines the learning process involved in notetaking during online learning to elucidate the connection between three notetaking media—ink pens, digital pens, and laptops—and constructive or active notetaking activities. To investigate this process, we consider the underlying neural mechanisms of notetaking with various devices. This study uses electroencephalography (EEG) data to both amplify and specify our understanding of learning processes associated with notetaking media. Neural data can point to changes in neural activity such as attention during the learning process (Cohen, 2014) and differences in learning that are not evident in performance (McLaughlin et al., 2004). In particular, neural data can provide insights into changes in attention, a key aspect of cognitive engagement in online learning yet one that is difficult to capture behaviorally (Dewan et al., 2019). By understanding how generative or verbatim notetaking is related to notetaking media, we can use this knowledge to suggest strategies to encourage meaningful learning—learning that uses technology effectively to engage students—in asynchronous online learning.

The research questions for this study are as follows: (1) How do learning processes differ when using different notetaking media? (2) How does learning performance differ according to notetaking media?

2 Materials and methods

2.1 Participants

A total of 36 healthy, Korean-speaking undergraduate students in South Korea were recruited for participation in the study. Of the 36 participants, 3 were excluded due to excessive artifacts (peak-to-peak amplitude >100 μV) in the EEG data. All participants were at least 18 years of age ($M = 22.73$, $SD = 2.41$), and had experienced at least one semester of asynchronous distance learning. Of the 33 participants, 22 were female and 11 were male.

2.2 Experiment procedure and tasks

An EEG-based experiment was conducted to elucidate the relationship between notetaking devices and learning processes (Figure 1). Participants first completed a brief survey to examine their familiarity with each notetaking medium. They then went through three sessions of video lectures while wearing an EEG cap. Each session included one 10-minute video lecture explaining 10 pseudowords and their meanings, resulting in a total of 30 pseudowords learned. A pretest was conducted with a separate set of participants, who listed words they felt were associated with each pseudoword. Explanations for the pseudowords were formulated to exclude the meanings of the words mentioned in the pretest, to control for potential prior associations. The video was composed of voice-overs on PowerPoint slides, with each slide pertaining to one minute of explanation for one pseudoword and its meaning. Topics used in the lecture were ones that are likely unfamiliar to the participants, in order to control for background knowledge.

While watching the lecture, participants took notes with various notetaking materials, in a randomized order to control for content and directional bias. When writing with an ink pen, participants were given 3 blank sheets of paper (A4 size) along with a 3-color ink pen. When writing with a digital pen, they were given a digital tablet on which a blank note was provided via an application. Lastly, typing with a laptop entailed typing notes on a laptop with a blank WordPad displayed on the screen (Figure 2).

During the video lecture, participants were given two different types of directions. One direction induced active notetaking activities, i.e., “please write down important words that you hear from the lecture verbatim”, whereas another encouraged constructive notetaking activities, i.e., “please write down any questions you have about the lecture”. For five slides of each

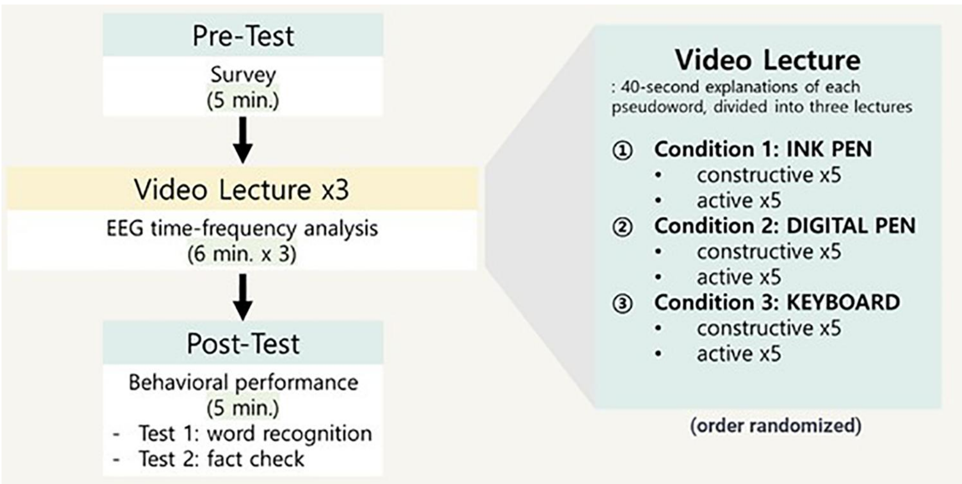

FIGURE 1
Stages of the experiment.

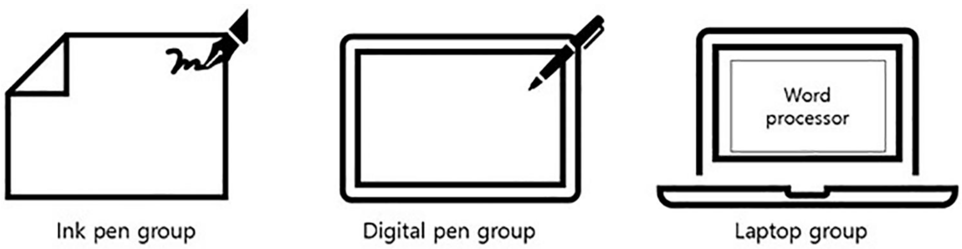

FIGURE 2
Notetaking methods according to group.

lecture, participants followed one direction, and for the other five slides, they took notes according to the other direction. To control for the possibility that the order in which active and constructive prompts are given influence the outcome, the experiment made use of counterbalancing measures.

A post-test was administered immediately after the lecture to assess learning performance. This post-test consisted of word recognition questions (Test 1), and sentence comprehension questions (Test 2). Using the software 'PsychoPy', participants viewed and responded to words or sentences that appeared sequentially on the computer screen in front of them. In Test 1, participants were told to press 'm' when a word they recognized from the lecture appeared on the screen, and 'z' if they did not recognize the word. They were likewise instructed to press 'm' when they saw a factually correct sentence (based on the information given during the lecture), and to press 'z' if that sentence was incorrect in Test 2. The words and sentences were presented in a randomized order. 30 filler words were provided to balance out the number of times participants pressed 'm' and 'z' in Test 1, and 15 of the 30 sentences in Test 2 were made factually incorrect.

2.3 EEG data collection and analysis

EEG is a method of data collection that collects and shows electrical signals from the brain. EEG uses electrodes placed on the scalp to draw and record brain waves, which are representations of the electrophysiological responses the brain has when processing information or engaging in activities. In this study, EEG recordings were obtained with a 32-channel active electrode system (actiCHamp and Brain Vision Recorder, Brain Products, Germany), at a sampling rate of 1,000 Hz. Ag/AgCl electrodes were placed according to the international 10–20 system, and referenced to FCz. All the electrode impedances were kept below 20kOhms using NaCl-based conductive gel and by abrading the skin below the electrodes.

EEG signals were first preprocessed with an IIR filter in BrainVision Analyzer with a bandpass filter of 3–60 Hz and a notch filter at 60 Hz to control for noise from electrical devices. Ocular Correction ICA was conducted with the same software, to filter out saccadic eye movement and blinks. The data was then segmented into trials of 40 s, with a 500 millisecond baseline period before the stimulus used for baseline correction. Manual preprocessing was also utilized; using EEGLAB, electrodes were re-referenced to the average, and additional manual rejection of line noise, muscle components, and components other than brain components was conducted using independent component analysis (ICA).

Time-frequency analysis is the analysis of continuous brain waves by frequency power. With time-frequency analysis, neural oscillations are represented in a graph with the x axis representing time, and the y axis representing frequency (Hz). Thus, this analysis graphs changes in the power (dB) of certain frequencies over time. We performed time-frequency analysis using the FieldTrip toolbox (version 20230328) in MATLAB (Oostenveld et al., 2011). Trials were averaged by each device and condition, so that there were a total of six averaged sets for each participant (ink pen—constructive, ink pen—active, digital pen—constructive, digital pen- active, keyboard—constructive, keyboard—active). These sets were imported into FieldTrip and subjected to baseline correction using the function 'ft_baseline'. Wavelet transformation was then conducted to investigate spectral power changes over time. Morlet wavelets were used with the wavelet parameter set to 5, with 23 logarithmically spaced frequency steps for each time bin of 0.5 s (Cohen, 2014, 2016).

In the current study, the focus was mainly on exploring what frequencies may relate to the connections between learning processes and writing devices. However, special attention was given to beta waves (waves with a frequency of 12–30 Hz). Beta waves are related to waking states and attention, and decreases in beta wave power in temporal and occipital areas of the cortex are known to relate to decreases in energy and sustained attention (Ko et al., 2017). In particular, theta/beta ratio is often used as a measure for sustained attention (Zivan et al., 2023). If the theta/beta ratio is higher, attention levels are considered lower. In addition to beta and theta/beta power, changes in theta (4–7 Hz), alpha (8–12 Hz) and gamma (30–60 Hz) frequency power were also taken into account, as these frequencies are likewise associated with changes in attention.

2.4 Statistical analysis

For pre-experiment survey results, descriptive statistics were calculated for each item with a focus on patterns of familiarity. Average familiarity for each notetaking device, as well as the number of participants who ranked each device differently, were reported.

Statistical analysis for EEG time-frequency analysis was conducted by averaging oscillation power for each device and condition by participant, then conducting repeated-measures ANOVA with the ez, afex, and emmeans packages in R. The ANOVA model included the within-subjects factors tool type (ink pen, digital pen, keyboard) and condition (constructive, active) and used participants as a random factor. Separate analyses were conducted for the different electrodes (Fp2, F7, F3, Fz, F4, FC5, FC1, FC6, C3, Cz, C4, CP5, CP1, CP2, CP6, P7, P3, Pz, P4, P8, T7, T8, O1, Oz, O2). Models were applied for each band power (alpha, beta, theta, gamma) as well as for the theta/beta power ratio. To control for multiple comparisons across 25 electrodes, False Discovery Rate (FDR) correction was applied to the p-values from the ANOVA tests.

Electrodes showing significant effects after FDR correction were subjected to *post-hoc* pairwise comparisons of all tool*condition combinations using estimated marginal means with Bonferroni adjustment. Additionally, to explore changes in beta oscillations more specifically, difference waves were calculated by subtracting active from constructive oscillations, then these difference waves were subjected to wavelet transform. These results were then compared by writing device with the 'depsamplesFunivariate' function with the 'analytic' method in FieldTrip. The p values from these results were used to mask visualized data for beta waves at the occipital electrodes, as the occipital area is known to be related to changes in sustained visual attention.

We additionally examined whether participants' self-reported familiarity with each writing tool warranted inclusion as

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covariates across all EEG frequency bands. The three familiarity scores showed low intercorrelations across all participants (ink pen–digital pen: $r = -.07$; ink pen–keyboard: $r = -.34$; digital pen–keyboard: $r = -.14$), indicating no multicollinearity concern. Because familiarity was a participant-level variable, these correlations were identical across frequency bands. For each band, a pooled screening analysis using linear mixed models [power~familiarity + (1|participant) + (1|electrode)] tested whether each familiarity score predicted EEG power across electrodes. None of the covariates reached significance in any band (all $p \geq .142$). Within-tool confound checks — tests of whether each familiarity score predicted power specifically within its matched tool condition — similarly yielded no significant results in any band (all $p \geq .233$), with the exception of digital pen familiarity in the gamma band, which approached but did not reach significance in both the pooled ($\beta = -4.68$, $t = -1.84$, $p = .075$) and within-tool checks ($\beta = -5.03$, $t = -1.82$, $p = .079$).

To further verify that covariate inclusion did not meaningfully alter the pattern of results, we compared linear mixed model ANOVAs [LMM-ANOVA: power~tool × condition + (1|participant)] against LMM ANCOVAs [power~ink pen familiarity + digital pen familiarity + keyboard familiarity + tool × condition + (1|participant)] for each electrode and frequency band, with familiarity scores entered as standardized continuous predictors. No electrodes changed significance status between the two models for any effect or frequency band, confirming that the observed EEG effects are not attributable to pre-existing differences in tool familiarity. Although LMM-ANOVAs and the repeated-measures ANOVAs depicted previously yielded consistent results for main effects, because repeated-measures ANOVA was a more sensitive model for the within-subjects design of this study and for detecting interaction effects, the results from repeated-measures ANOVA were reported as the primary analysis in our findings.

Post-tests results were likewise analyzed in R using repeated-measures ANOVA to compare between different tool*condition combinations. The two different tests were separately analyzed. Covariates for familiarity were likewise added to control for device familiarity, but adding covariates did not change the statistical significance of the results.

3 Results

3.1 Survey results

The pre-experiment survey asked participants to rate how familiar they were with each notetaking device on a scale of 1–5, with 5 representing 'highly familiar'. On average, more participants rated their familiarity with the keyboard ($M = 3.58$, $SD = 1.28$) higher than that of the ink pen ($M = 2.94$, $SD = 1.27$). Many students also rated their familiarity with the digital pen highly ($M = 3.42$, $SD = 1.54$), with many students rating their familiarity at 4 or 5 points (Figure 3).

Participants were also asked to rank the three devices according to familiarity. Most participants who responded they felt most familiar with a digital pen ($n = 12$) preferred the ink pen slightly more than the keyboard ($n = 9$). Over half of the students who were most familiar with an ink pen ($n = 7$) chose a keyboard as their second preference ($n = 4$). Students who felt most comfortable with a keyboard ($n = 14$) were slightly more likely to be familiar with digital pens ($n = 8$).

3.2 EEG time-frequency results

EEG time-frequency analysis was conducted to examine differences in learning processes when using various notetaking media. Repeated-measures ANOVA analyses for each electrode, within each band power, revealed differences between the pens and keyboards conditions. For the theta band, differences spanned across multiple areas of the brain, with all areas (electrodes C3, C4, CP1, CP2, CP5, F7, FC1, FC5, FC6, Fp2, P3, P4, P7, P8, Pz, O1, O2, Oz, T7, T8) exhibiting higher relative power for keyboards compared to both ink and digital pens (Table 1). No interaction effects were observed.

For the alpha band, significant differences between writing devices were observed at electrodes C4, F4, O2, and Oz, with relative power consistently higher for digital pens, then ink pens, with keyboards showing the lowest power (Table 1). For electrodes C3 and F3, the ANOVA revealed significant differences between active and constructive conditions, with

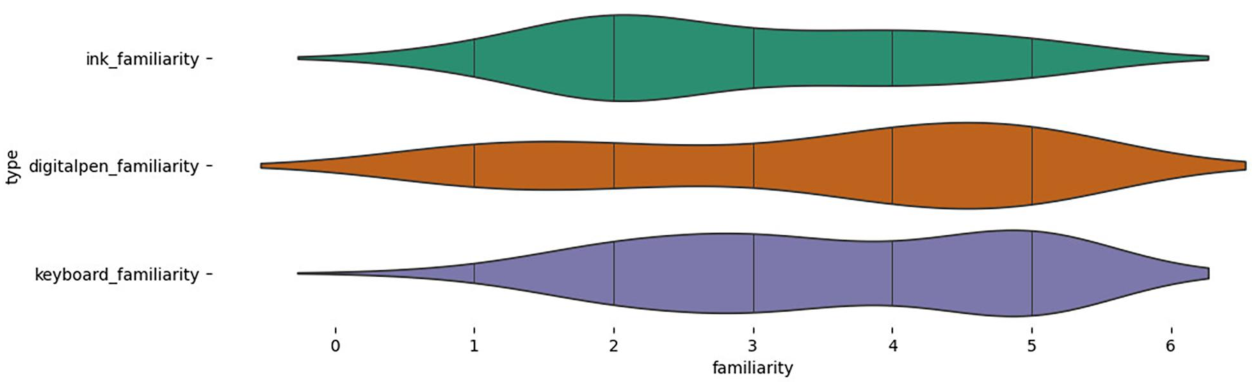

FIGURE 3
Familiarity of devices. Familiarity for each device was indicated on a scale of 1 (unfamiliar) to 5 (highly familiar). Results were plotted in a violin plot using the Seaborn library in Python.

TABLE 1 Significant band power differences between writing device.

Frequency	Electrode	*F*	ges*	*p*-FDR	Mean power		
					Ink pen	Digital pen	Keyboard
Theta	C3	11.664	0.006	<0.001	90.98	93.81	105.31
	C4	5.896	0.007	0.010	99.19	96.78	110.25
	CP1	9.996	0.007	<0.001	93.77	96.27	108.64
	CP2	13.345	0.011	<0.001	96.36	98.73	114.37
	CP5	13.741	0.007	<0.001	187.57	191.77	217.95
	F7	7.324	0.003	0.003	252.15	270.96	288.60
	FC1	7.849	0.003	0.002	30.15	31.61	33.40
	FC5	7.321	0.004	0.003	145.12	152.54	166.32
	FC6	5.728	0.005	0.011	153.17	151.14	169.11
	Fp2	7.912	0.002	0.002	281.50	294.40	316.58
	O1	12.485	0.009	<0.001	345.74	359.95	404.06
	O2	10.438	0.009	<0.001	349.92	365.48	406.57
	Oz	12.242	0.011	<0.001	341.41	353.24	397.54
	P3	13.868	0.010	<0.001	195.73	205.26	235.66
	P4	20.33	0.016	<0.001	205.76	214.19	250.26
	P7	9.264	0.007	<0.001	305.29	311.43	355.56
	P8	12.769	0.009	<0.001	317.13	324.42	368.63
	Pz	13.335	0.010	<0.001	167.62	171.20	196.96
	T7	10.661	0.005	<0.001	236.49	238.53	269.67
	T8	6.657	0.005	0.005	273.50	264.47	299.84
Alpha	F4	5.213	0.005	0.014	55.59	58.37	52.05
	C4	5.397	0.012	0.024	74.52	80.19	63.24
	Oz	4.501	0.018	0.015	258.92	275.66	226.13
	O2	6.195	0.024	0.004	278.90	298.08	236.39
Beta	Oz	7.366	0.048	0.005	135.73	154.54	103.55
	O2	12.429	0.060	<0.001	154.52	168.88	107.80
Gamma	Fp2	6.417	0.024	0.010	57.91	66.40	45.98
	Fz	7.540	0.024	0.005	5.30	5.83	4.41
	P4	6.029	0.022	0.014	19.41	20.53	16.11
	O1	5.996	0.040	0.014	65.63	81.40	45.69
	O2	14.055	0.090	<0.001	85.21	99.78	46.07
	Oz	10.806	0.073	<0.001	72.04	87.38	43.10

*ges, generalized eta squared.

higher alpha band power for the constructive conditions (C3 constructive M = 61.00, active M = 53.53, F = 9.68, ges = 0.008, $p = 0.014$; F3 constructive M = 58.60, active M = 54.59, F = 6.96, ges = 0.002, $p = 0.042$). However, *post-hoc* analysis only showed significant differences for the O2 and Oz electrodes, between both active and constructive conditions for digital pens and the active condition for keyboards.

Significant beta band differences were only observed for the electrodes O2 and Oz. Both showed similar patterns to the alpha band power differences, with power for digital pens being highest, band power while taking notes with an ink pen coming next, and power while typing notes with a keyboard appearing significantly lower (Table 1). Interestingly, a significant interaction effect between writing devices and active/constructive conditions was also observed at the O2 electrode (ink pen constructive M = 143.49, ink pen active M = 165.54, digital pen constructive = 155.23, digital pen active = 182.53, keyboard constructive = 109.75, keyboard active = 105.85, F = 6.595, ges = 0.004, $p = 0.009$) (Table 2). *post-hoc* pairwise comparison also showed that differences between digital pens and keyboards were significant across active and constructive conditions, while ink pen active and constructive conditions were only significantly higher in beta band power compared to the keyboard active condition (Figure 4).

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TABLE 2 Significant interaction effects between writing device and notetaking strategy.

Frequency	Electrode	*F*	ges	*p*-FDR	Mean power					
					Ink pen		Digital pen		Keyboard	
					Constructive	Active	Constructive	Active	Constructive	Active
Beta	O2	6.595	0.004	0.009	143.49	165.54	155.23	182.53	109.75	105.85
Gamma	O2	7.457	0.006	0.005	73.59	96.82	90.78	108.77	47.39	44.76
Theta/beta	CP5	5.170	0.007	0.016	3.59	3.96	3.77	3.64	4.26	4.93
	CP6	4.228	0.008	0.030	3.77	3.77	4.21	3.75	4.45	5.03
	F3	4.67	0.005	0.022	3.04	3.23	2.99	3.05	3.26	4.00
	F7	4.61	0.005	0.023	3.75	3.73	3.96	3.76	4.08	4.66
	FC5	4.559	0.007	0.024	3.54	3.90	3.66	3.64	3.82	4.67
	FC6	4.37	0.006	0.027	3.38	3.75	3.46	3.53	3.63	4.44
	O1	7.547	0.008	0.003	3.18	2.85	3.22	2.80	4.29	4.61
	O2	5.421	0.006	0.013	3.00	2.74	2.86	2.51	4.16	4.47
	Oz	6.127	0.007	0.008	3.16	2.90	3.06	2.67	4.32	4.69
	P3	5.064	0.006	0.017	3.63	3.86	3.94	3.78	4.38	5.01
	P8	6.409	0.006	0.006	3.45	3.26	3.54	3.31	4.34	4.77
	T7	5.762	0.007	0.010	3.53	3.71	3.51	3.38	3.92	4.64
	T8	5.519	0.006	0.013	3.43	3.49	3.20	3.03	3.97	4.57

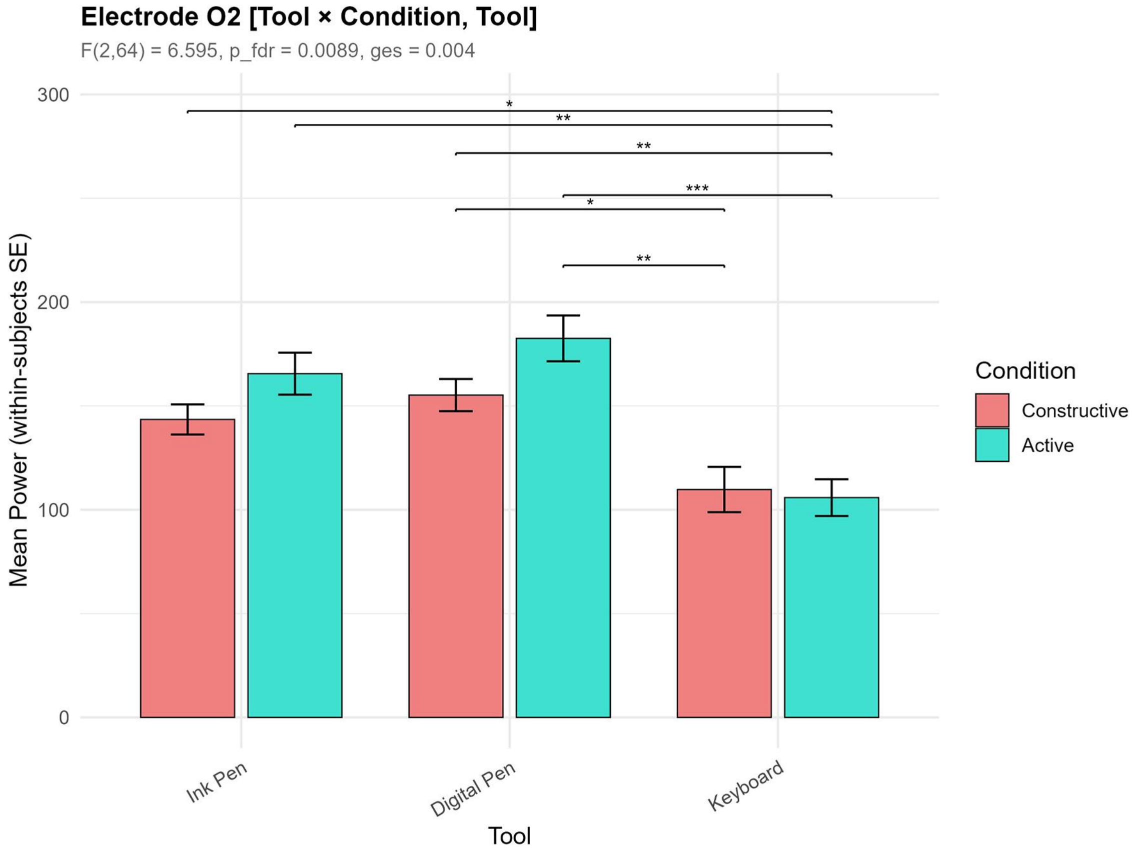

FIGURE 4
Beta power by writing device and condition at electrode O2. Relative mean beta power for each condition are represented in the bar graph above, with error bars indicating the standard error. Asterisks are used to denote significant differences for pairwise comparison between conditions (*: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$).

Theta/beta differences were, like theta differences, spread across cortical areas; however, more electrodes in the frontal region (F3, F4) also yielded significant differences. After FDR correction for multiple comparisons across electrodes, significant main effects of writing devices were observed at 26 electrodes spanning frontal, central, parietal, and occipital regions (all p_FDR <.05). At these electrodes, keyboard use was consistently associated with higher theta/beta ratios (keyboard M = 3.44–4.73 across electrodes, ink pen M = 2.76–3.98, digital pen M = 2.65–4.00), indicating relatively greater theta power or reduced beta power compared to handwriting conditions. Significant effects for differences by notetaking device were also evident at electrodes C3 (constructive M = 3.42, active M = 3.94, F = 5.513, ges = 0.016, $p = 0.039$), FC1 (constructive M = 3.31, active M = 3.68, F = 6.738, ges = 0.013, $p = 0.024$), and FC2 (constructive M = 3.49, active M = 3.90, F = 7.102, ges = 0.010, $p = 0.021$), with active conditions showing higher theta/beta power. Significant writing device × condition interactions were observed at 13 electrodes (CP5, CP6, F3, F7, FC5, FC6, O1, O2, Oz, P3, P8, T7, T8; all $p < .05$) (Table 2). *post-hoc* pairwise comparisons (Bonferroni-corrected) revealed that keyboard use during active conditions produced the highest theta/beta ratios across these electrodes (all comparisons vs. keyboard active: $p < .05$). An example showcasing the trends of theta/beta power at the electrode O2 is represented in Figure 5.

Gamma band differences were observed in the electrodes Fp2, Fz, O1, O2, Oz, and P4. Similarly to the alpha and beta band power trends, gamma band power for digital pens was higher than ink pens, with both handwriting tools having higher gamma band power relative to keyboards. No differences were observed for active and constructive conditions, but at the O2 electrode there was an interaction effect between writing device and condition (ink pen constructive M = 73.59, ink pen active M = 96.82, digital pen constructive M = 90.78, digital pen active M = 108.77, keyboard constructive M = 47.39, keyboard active M = 44.76, F = 7.457, ges = 0.006, $p = 0.005$) (Table 2). *post-hoc* pairwise comparisons indicated that differences between digital pens and keyboards was particularly salient, though the ink pen active condition had significantly higher gamma power than both keyboard conditions, whereas the ink pen constructive condition was only significantly higher than the keyboard active condition.

Additional difference wave analysis also showed significant differences between the conditions. Figure 6 shows an example at the O2 electrode of difference wave heatmaps for each condition, with time and frequency bins with statistically non-significant differences across conditions masked. In the ink pen and digital pen conditions, beta wave synchrony differences seem prevalent compared to the keyboard condition, especially for lower beta frequencies. The ink pen condition and digital pen condition look relatively similar, although for some time segments the digital pen condition shows stronger differences in beta wave synchrony in higher beta frequencies. Put together with the repeated-measure ANOVA tests, these results indicate

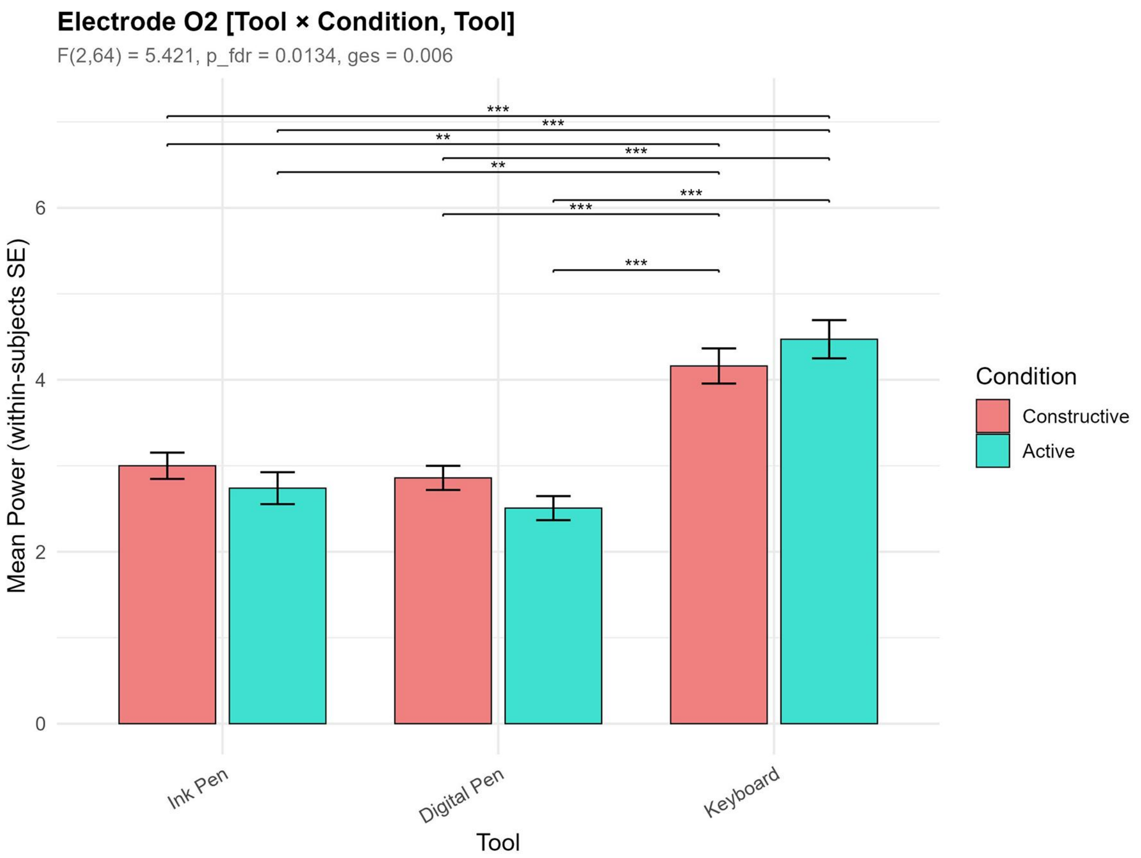

FIGURE 5
Theta/beta power by writing device and condition at electrode O2. Relative mean beta power was divided from relative mean theta power for each participant to obtain each theta/beta value.

significantly higher beta power for the active conditions when using ink or digital pens, compared to constructive notetaking—while in the keyboard condition, similar beta power is observed for both active and constructive conditions. Overall, larger differences were especially observable for lower to mid-beta frequencies.

3.3 Posttest results

Posttest results were not statistically significant, regardless of condition. During Test 1, which measured word recognition, participants appeared to score marginally better for words learned with active notetaking, using an ink (active: M = 3.34, SD = 1.26; constructive: M = 3.16, SD = 1.19) or digital pen (active: M = 3.59, SD = 1.13; constructive: M = 3.31, SD = 1.15). On the other hand, the scores for words learned through constructive notetaking in the keyboard condition (M = 3.66, SD = 0.90) were slightly higher than for words learned with active notetaking (M = 3.27, SD = 1.26) (Figure 7).

In Test 2, which measured comprehension of definitions of the words, differences were again statistically insignificant across devices and strategies, but scores were slightly higher for words learned with constructive notetaking for the ink pen (active: M = 3.09, SD = 1.18; constructive: M = 3.39, SD = 0.95) and the keyboard (active: M = 2.76, SD = 1.23; constructive: M = 3.16, SD = 1.27). For the digital pen, however, words learned with active notetaking resulted in slightly higher mean scores (active: M = 3.06, SD = 1.14; constructive: M = 2.88, SD = 1.05) (Figure 8).

4 Discussion

Our results suggest that different notetaking media support different learning processes, though those processes may be equally effective in terms of recognition and comprehension performance. Three aspects of our results are highlighted in this section. First, different devices led to different patterns in EEG band power. Significant differences in theta, alpha, beta, and gamma, and theta/beta power were found across devices. Total power calculations for each condition showed differing trends for digital and ink pens compared to keyboards. Digital pens consistently showed the highest relative power for alpha, beta, and gamma bands, with ink pens showing similarly high relative power and significantly differing from keyboards. Theta band power also differed significantly amongst writing devices with consistently higher theta band power for keyboards. Theta/beta ratios also showed that keyboards had the highest values compared to the other devices.

Taken together, band power differences for writing devices seem to suggest better engagement with pens compared to keyboards. The higher alpha power values for digital pens and

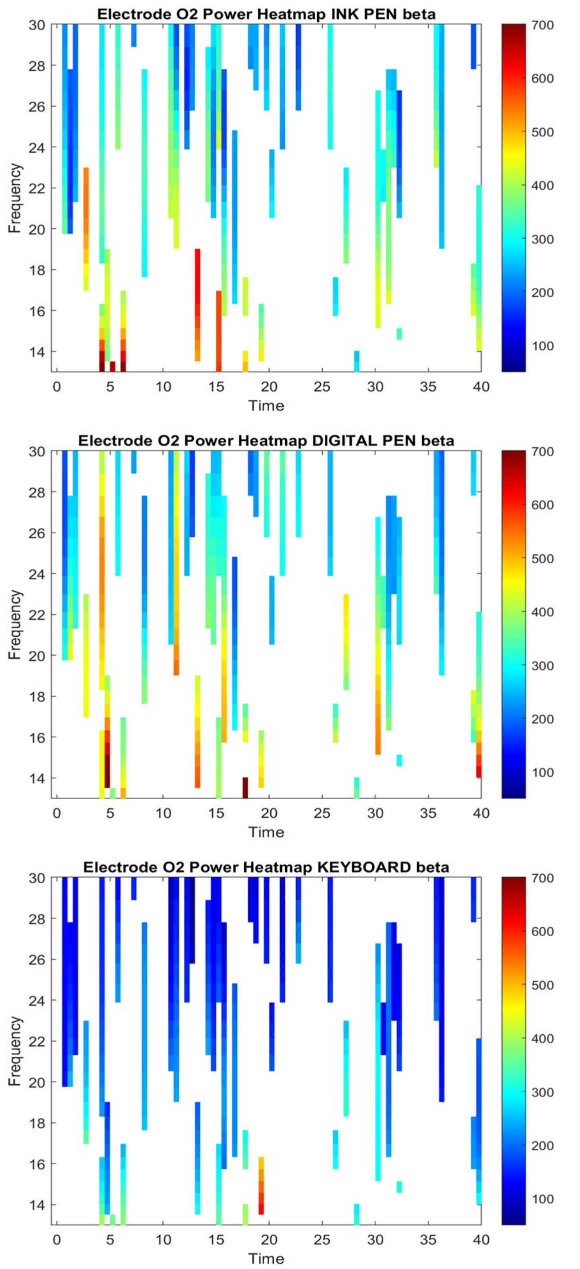

FIGURE 6
Difference waves over time at electrode O2, masked by ANOVA significance. Relative beta power was significantly higher for ink pens and digital pens compared to keyboards across the 40 s video.

ink pens appear to indicate better focused attention and inhibitory control (Bonnefond and Jensen, 2013; Jokisch and Jensen, 2007), whereas similarly higher beta and theta/beta values (especially in the occipital area electrodes) index increased visual sustained attention (Ko et al., 2017; Zivan et al., 2023) and less mind-wandering (van Son et al., 2019) while notetaking with ink or digital pens. Higher gamma power values, especially in the occipital area, could represent heightened declarative memory encoding processes (Osipova et al., 2006) for the pens compared to keyboards. This appears to support findings from previous literature that emphasizes handwriting over typing (Bui et al., 2013; Luo et al., 2018; Mueller and Oppenheimer, 2014).

However, some results also complicated the claim that pens were more conducive to learning processes than keyboards. Higher theta power during keyboard notetaking could indicate higher focus, memory processing, and consolidation (Marano et al., 2025; Osipova et al., 2006; Tan et al., 2024; van der Weel and van der Meer, 2024). These results seem to differ from Askik et al. (2020) and van der Weel and van der Meer (2024), in which theta synchrony was found to be higher for handwriting compared to typing and was attributed to the relative need for fine motor coordination in handwriting. This may have been due to the complexity of the task in this study, with typing occurring using both hands and rapid movements (Pinet and Longcamp, 2025). Thus, keyboard notetaking could also engage motor processes in the brain and connect to memory processing in tasks that involve prolonged and complex typing in conjunction with information processing of the lecture. Moreover, digital pens showed higher relative power for alpha, beta, and gamma bands, perhaps indicating that writing with a digital pen is not the middle ground between writing with an ink pen and typing with a keyboard; instead, it has closer characteristics to handwriting and may even induce different neural processes. This could perhaps be linked to the different tactile and visuomotor processes associated with digital pen writing (Alamargot and Morin, 2015; Askvik et al., 2020; Vinci-booher et al., 2016). Together, these results point to the potential role of embodied cognition in shaping engagement during notetaking, which has been much discussed in the literature (Korte and Körkkö, 2024; Marano et al., 2025).

Second, interaction effects in the data showed that notetaking strategy also influences the learning processes during notetaking. Significant differences between strategies but not device for the C3 and F3 electrodes were observed. This could indicate focused attention in suppressing distractors when taking constructive notes, compared to active notetaking (Bonnefond and Jensen, 2013; Jokisch and Jensen, 2007). Interaction effects were also revealed for O2 in beta, O2 in gamma, and across 13 electrodes in theta/beta. Interestingly, constructive notetaking while typing on a keyboard appears to mitigate some differences between handwriting and keyboard notetaking in terms of beta band power. Constructive keyboard notetaking was shown to be not significantly different from the ink pen conditions for beta band power, unlike active keyboard notetaking. Similarly, though no significant interaction effect was observed, differences were only visible for active keyboard and constructive and active digital pen conditions in alpha power. These results may be due to generative processing for constructive notetaking causing additional germane cognitive load (DeLeeuw and Mayer, 2008; Fiorella and Mayer, 2016), leading to similar processing to writing with a pen. This is in line with findings that show that generative, integrative learning processes occur when typing questions about a text (Ponce et al., 2020).

Looking more closely at active and constructive differences within each device shows that beta and gamma power values are higher for the active condition in the ink and digital pen conditions, whereas similar smaller values are observable in the keyboard condition. For theta/beta values, the constructive condition is slightly higher than the active condition when writing with pens, whereas the active condition values are higher for writing with keyboards. The beta and theta/beta

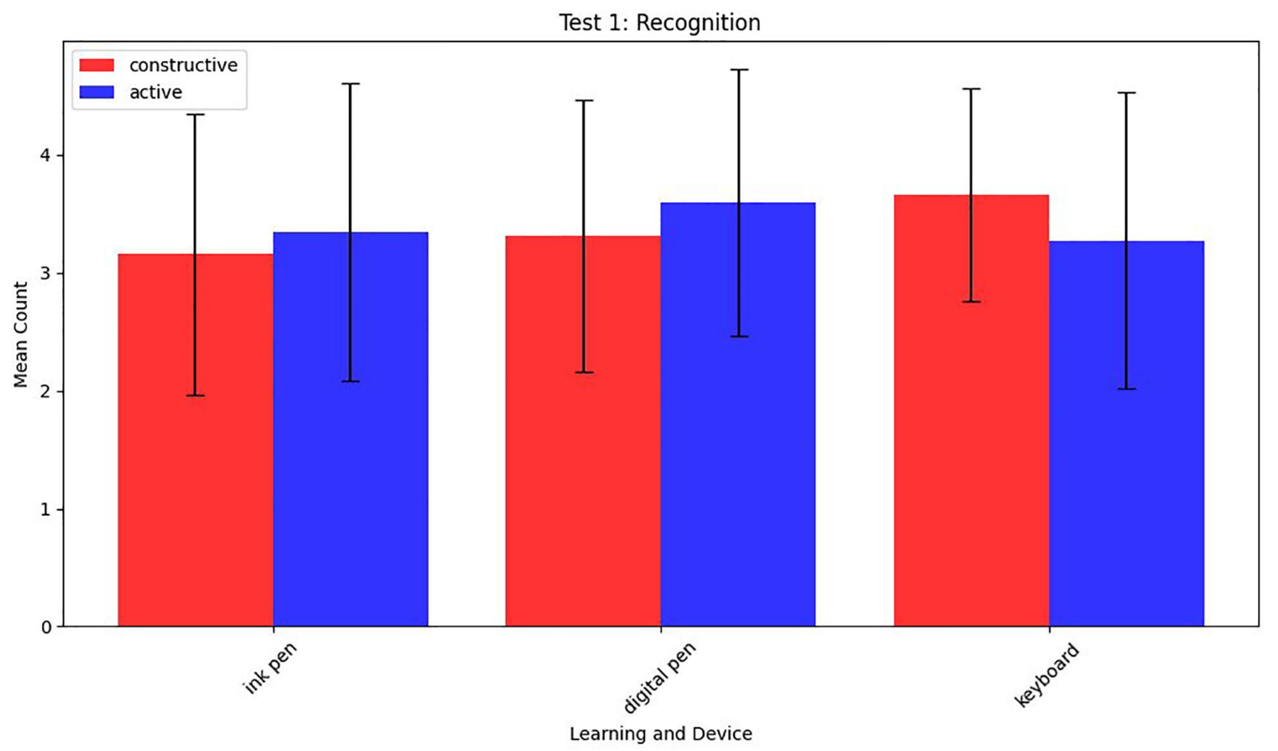

FIGURE 7
Post-experiment test 1 results. No significant differences were observed for device or notetaking strategy in the first posttest, which tested participants' recognition of the learned pseudowords.

values could imply that relatively less cognitive load or effort is required for the processing of constructive relative to active notetaking for pens, although load is still high compared to keyboard notetaking; conversely, less cognitive load is perhaps required for the active condition in keyboard notetaking (Zivan et al., 2023). This implies the differing patterns of processing facilitated by each device, in relation to notetaking strategy. On the other hand, the higher theta/beta and lower beta values for the keyboard condition could also index less attention or even mind-wandering (van Son et al., 2019), suggesting the importance of germane cognitive load or effortful learning in line with generative learning theory (DeLeeuw and Mayer, 2008; Fiorella and Mayer, 2016). The higher gamma power for pens, especially during the active condition, could indicate higher integration of proprioceptive feedback (Ulloa, 2022). Based on the findings of Luo et al. (2018), the active condition could have led to more verbatim notes, leading to more movement in writing, especially when writing with pens.

Third, differences between digital devices did not lead to disparities in learning performance. In the word recognition test (Test 1), the ink pen and digital pen seemed to show slightly better performance for the active condition, whereas the comprehension test (fact check, Test 2) showed that for the ink pen and the keyboard the constructive condition led to marginally better scores. These results were not statistically significant, however, which is in line with the results of Morehead et al. (2019) and Urry et al. (2021). It appears that immediate learning performance does not differ according to writing device, for both active and constructive notetaking activities. In other words, all writing devices and strategies were equally effective in terms of performance, suggesting the different learning processes were effective in their own ways. This could indicate that keyboard notetaking, rather than causing less engagement, provides more efficient processing. Differences between active and constructive scores in general, however, were also found to be insignificant in this study. This differs from the literature on the ICAP framework, which clearly shows better performance for constructive learning compared to active learning (Chi and Wylie, 2014; Bauer and Koedinger, 2007). Our results may deviate from the literature due to immediate rather than delayed testing, and testing of simple memory rather than complex comprehension. Further studies are necessary to better delineate the relationship between active, constructive learning and notetaking devices. For instance, ERP studies could elucidate neural differences in performance in addition to behavioral discrepancies.

The implications of these results span various levels of education. On the individual level, using different devices for different learning processes may be helpful for sustaining attention–in particular, digital pens seem to function more or less similarly to ink pens, perhaps even strengthening the characteristics of ink pens, as can be seen through the stronger alpha, beta, and gamma power results. Keyboards, however, may have different affordances, which can work to facilitate more efficient processing for verbatim notetaking but potentially limited generative processing. These affordances of notetaking media can act as both opportunities and constraints (Hammond, 2010). Understanding such affordances could lead to the

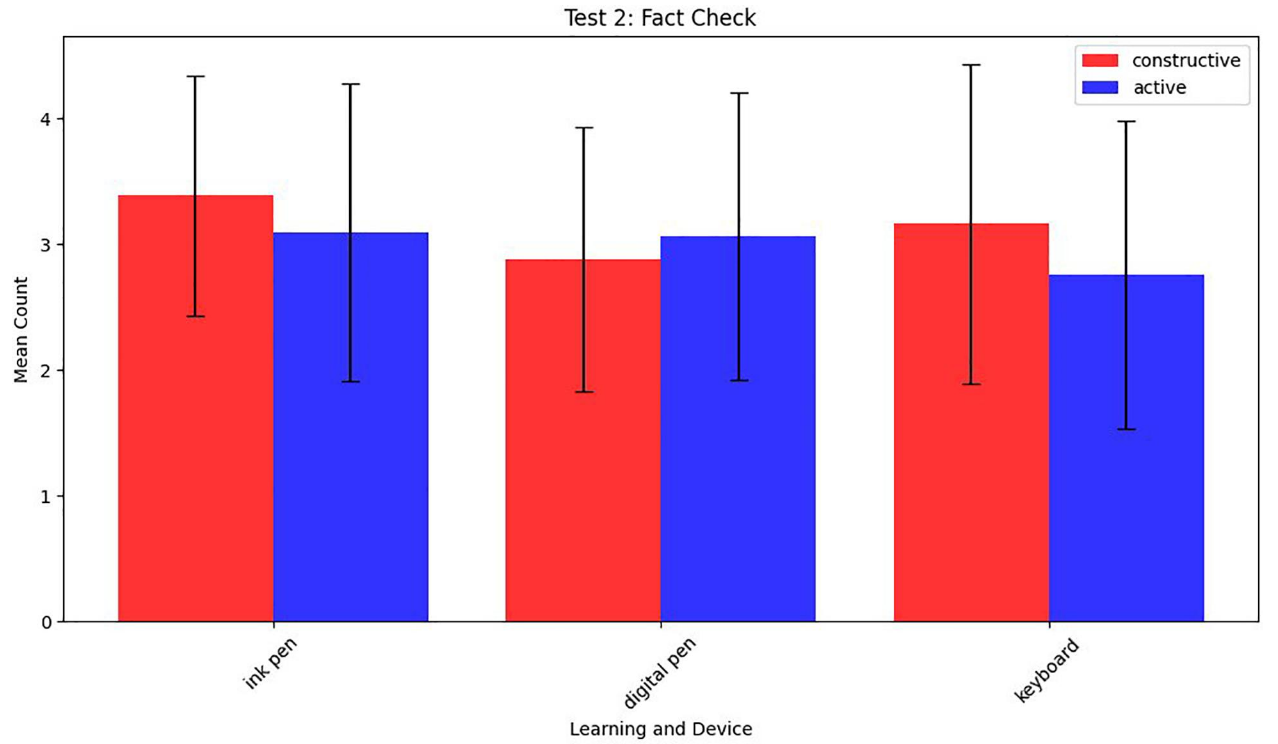

FIGURE 8
Post-experiment test 2 results. No significant differences were observed for device or notetaking strategy in the second posttest, in which participants were asked to check if sentences using the pseudowords were correct or incorrect.

development of better notetaking strategies or activities that in turn enhance meaningful learning (Howland et al., 2015). Sustaining attention in online education settings is often a major issue (Brammer and Punyanunt-Carter, 2022), and our results can suggest incorporating activities that utilize spatial or verbatim notetaking with different writing devices in the design of online learning environments for better engagement.

Limitations of this study included limited exploration into the embodied aspects of notetaking, along with limitations for ecological validity. As we primarily investigated the cognitive engagement elements of notetaking, further experimentation is necessary to probe how notetaking is a process of embodied cognition (Korte and Körkkö, 2024). This calls for design that expands on our design to track generative, spatial and verbal notes, potentially with the use of sensors that can sense the types and moments of notetaking. These designs could also incorporate a procedure that differentiates between muscle artifacts and the motor elements of notetaking. While we rejected muscle artifacts manually during the preprocessing stage, a better, automated preprocessing pipeline could enhance precision as well. In such experiments, analysis based on cluster-based permutation testing could provide better insights into neurophysiological differences across brain areas.

Furthermore, because this study was based on a laboratory experiment, its ecological validity is limited. Online learning is rife with distractions and multitasking (Liu and Gu, 2020), which can influence interaction with notetaking materials as well as engagement. Moreover, various tools are used within asynchronous online learning environments—including but not limited to video playback functions (pause, replay, 2× speed), annotation tools, and graphic organizers (Ponce et al., 2020). Learners' interactions with these tools, as well as their preferences and proficiencies with writing devices or notetaking strategies, could further complicate the notetaking process, making it crucial for further experimentation to engage with more authentic learning contexts. To heighten authenticity, device use preference and proficiency should also be considered and their influence explored in the process of notetaking, building on the results of Artz et al. (2020).

Additionally, while engaging with embodied cognition and designing for more authentic interactions, future studies should take into account physical and mental fatigue over a longer period of time as learners engage with complex, layered learning content. Time constraints within the experiment may have led to less engagement with deep generative thinking during the constructive condition, due to lack of time to interact with the content and lack of depth of the content itself. With longer experiments that ask learners to engage with in-depth content, fatigue may become an important confounding factor for notetaking. Also, with in-depth content, additional measures of post-task performance should assess more dimensions of learning, for example inference and creativity, to go beyond measures of simplistic recognition and comprehension and more deeply investigate authentic embodied cognitive processes in notetaking (Alonso, 2015; Korte and Körkkö, 2024).

Notetaking remains a key activity for elaboration, knowledge construction, and engagement in education (Chi and Boucher, 2023). Investigating what activities are best supported by different writing devices, particularly those based on digital technology, can provide implications for device use within and outside of asynchronous online learning environments. Building upon the current study, future studies are needed to examine different forms of notetaking and learning processes using different devices within the complex environment of digital or face-to-face classrooms. Different notetaking devices and activities may lead to different embodied, distributed systems of learning (Pea, 1993); further investigation is needed to probe these interactions. Exploring these aspects can provide suggestions for practice within and beyond the context of asynchronous online learning.

Data availability statement

The datasets presented in this article are not readily available because EEG data, especially in raw form, may be considered sensitive data. Anonymized data from this experiment are available on request from the first or corresponding author. Due to ethical restrictions, the data are not made publicly available. Requests to access the datasets should be directed to bookyungshin2030@u.northwestern.edu.

Ethics statement

All data in this study was collected in accordance with the principles outlined in the Declaration of Helsinki. Institutional Review Board approval from Seoul National University was acquired before conducting the experiment (No. 2211_003-011). All participants provided written informed consent before participating in the experiment.

Author contributions

BS: Investigation, Visualization, Writing – review & editing, Data curation, Formal analysis, Conceptualization, Methodology, Writing – original draft. MS: Resources, Validation, Writing – review & editing. JK: Writing – review & editing. YC: Writing – review & editing. SL: Funding acquisition, Resources, Writing – review & editing, Supervision.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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