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Proactive neural preparation across individual handwriting strokes: links to tool properties and cognitive performance

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Abstract

Handwriting is a hierarchical cognitive–motor skill governed by proactive and reactive control. Despite being inherently tool-mediated, it remains unclear how the physical properties of a handwriting tool are integrated into this hierarchy during handwriting and whether such tool-dependent control relates to cognitive performance. By achieving high-precision time synchronization between electroencephalography and tablet-recorded digital pen logs, we examined whether neural activity during handwriting tasks tunes to pen-tip friction on a stroke-by-stroke basis and how this relates to movement efficiency and cognitive performance. Handwriting exhibited theta/alpha inter-trial coherence surrounding pen-down events, whereas line drawing did not; this phase alignment did not differ by pen-tip friction. Pen-tip effects were most evident in the pre–pen-down activity; the medium-friction tip, typically judged to be similar to the participants' usual pen, produced the largest pre–pen-down amplitude. Larger pre–pen-down activity was associated with shorter stroke duration and higher maximum stroke velocity. In addition, larger pre–pen-down and smaller post–pen-down activities in the calculation task were associated with higher accuracy. These results demonstrate stroke-level anticipatory tuning to tool physical properties and indicate that proactive processing links pen-surface mechanics to efficient handwriting and cognitive performance.

Introduction

Handwriting is a highly complex, hierarchical, cognitive-motor activity characterized by control processes ranging from high-level cognitive planning to low-level neuromuscular execution, in which higher-level structures specify stroke sequences that are translated into muscle-specific commands and continuously adjusted via peripheral feedback[1]. Effective handwriting control involves proactive and reactive processes[2,3]. Proactive control involves the anticipation and preparation of movements through the retrieval of internal model[4,5] or motor programs[6–8] that specify abstract writing features, such as stroke sequences and spatiotemporal structure[2,9,10], whereas retroactive control relies on sensory feedback, mainly visual and proprioceptive, to monitor and adjust ongoing movements[11–14].

Crucially, handwriting is inherently tool-mediated, requiring tuning to the implement (e.g., pen, stylus) and surfaces (e.g., paper, tablet) whose physical properties determine the sensory feedback available during writing[15–17]. These properties affect not only feedback-based reactive control but also proactive control with memory-based internal models. This perspective aligns with broader tool-use research, which demonstrates that motor control depends on internal models that incorporate the dynamics of the tool and body[18–20]. Similarly, handwriting engages models that continuously predict the sensory consequences of strokes (forward model) and compute motor commands for execution (inverse model) by adapting to the unique physical characteristics of the tool.

The physical properties of writing tools can significantly alter handwriting dynamics and force production[15–17,21–23]. For instance, the smooth, low-friction surface of a tablet often results in larger, less precise strokes compared to pencil-on-paper because reduced friction dampens proprioceptive feedback and necessitates compensatory motor strategies[23]. These motor adjustments have tangible cognitive and educational implications. A previous study showed that children practicing with plastic-tipped digital pens frequently produced oversized, less-legible letters and subsequently performed worse on reading and writing assessments than did their peers trained with traditional pen-and-paper[24]. Thus, the empirical evidence underscores a critical relationship between the physical characteristics of the tool, handwriting behavior, and broader cognitive outcomes. However, how the physical properties of a tool are integrated into hierarchical control during handwriting and whether such tool-dependent control is related to cognitive performance remain unclear.

To address this gap, we simultaneously recorded electroencephalography (EEG) and pen movement and pressure data with millisecond-precision time locking, while participants performed handwriting tasks (written calculation and copying) using a digital pen with interchangeable tips (low, medium, and high friction) (Fig. 1). Based on the idea that the stroke is the fundamental motor unit of handwriting[25–27], we time-locked EEG and pen measurements to the onset of each stroke (pen-down) and examined the effect of tip friction. The analyses were segmented into pre–pen-down and post-pen-down windows, with post–pen-down window divided into the early and late phases[28]. This segmentation allowed the comparison of proactive, internal-model-based processing (pre) and feedback-dependent reactive/execution control (early/late post) without conflation and enabled assessment within a common temporal frame of links to kinematic and kinetic indices and task performance. This design revealed the temporal profile of proactive and reactive processes in the integrated tool–body–brain system at a stroke-level resolution.

Recent EEG and intracranial recording studies have characterized writing-related brain dynamics with millisecond precision[9,28–34]. A previous study showed theta-band phase alignment surrounding pen-down events[28], indicating that the intrinsic approximately 5 Hz rhythm of handwriting couples with ongoing theta activity[2]. This phase alignment was stronger for the dominant hand. Additionally, the study identified a pen-down–locked "writing event related potential (ERP)" whose amplitude was modulated by handedness after pen-down. These findings establish effector-dependent effects around the contact. However, it remains unclear if extrinsic tool physical properties, such as pen-tip friction, reproduce the modulations in theta-band phase alignment surrounding pen-down events and in the pen-down–locked ERP amplitude that are observed for the effector (handedness). Additionally, it is unclear if these effects emerge as anticipatory activities immediately before pen-down on a stroke-by-stroke basis. Furthermore, the relationship between this tool-dependent neural process and affective states and cognitive performance remains unclear. Because the tactile sensation of a tool can alter motivation or frustration and these affective states consequently modulate motor

execution[35–37], elucidating the respective contributions of tool properties and affective states is essential for interpreting brain–behavior links in handwriting.

In the present study, we filled these gaps in knowledge. Theta/alpha inter-trial coherence (ITC)[38] surrounding pen-down events during handwriting tasks (but not during line drawing) showed no differences in pen-tip friction. Notably, pen-friction effects appeared not only immediately after pen-down but also as differences in pre-pen-down ERP amplitudes. The medium-friction pen tip, which was most often rated as similar to the participants' usual pen, produced the largest pre–pen-down amplitude. Moreover, larger pre–pen-down activity, together with smaller post–pen-down activity, was associated with more efficient movement and higher cognitive performance. Together, these findings demonstrate stroke-level anticipatory tuning to the tool's physical properties during handwriting and provide compelling evidence for proactive motor processing that supports skilled, rapid, and complex handwriting.

Results

Pen tip ranking of subjective similarity to pens used daily and preferences

Before discussing the neural and kinematic/kinetic results, we first assessed how the participants perceived the three pen tips. We analyzed the subjective ratings of perceived similarity to the participants' usual pen and writing comfort for the low-friction (LF), medium-friction (MF), and high-friction (HF) tips (Fig. 1C). A chi-square test on similarity rankings revealed a significant deviation from the expected distribution, $\chi^2(4) = 12.75$, $p = 0.013$.

The standardized residuals indicated that the MF tip was significantly more likely to be rated as the most similar to the participants' usual pen (1st rank, std. resid. = 2.38, $p < 0.05$) and less likely to be rated as the least similar (3rd rank, std. resid. = − 2.17, $p < 0.05$) (Fig. 1C). By contrast, the HF tip was significantly more likely to be rated as the least similar (std. resid. = 3.03, $p < 0.01$), suggesting a perceptual distinction from the familiar writing experiences of the participants. However, a separate chi-square test on preference rankings showed no significant differences across pen types ($\chi^2(4) = 4.88$, $p = 0.300$), indicating that writing comfort preferences were not strongly differentiated by pen type.

Pen-down-locked theta/low-alpha ITC in handwriting

We investigated whether handwriting exhibited low-frequency neural phase alignment across trials. Significant theta- and low-alpha band ITC were consistently observed across both writing tasks (i.e., calculation and copying) at the centro-occipital sites, spanning from before to after the pen-down event (Supplementary Table 1), whereas line drawing showed no reliable ITC (Fig. 2). For both calculation and copying, occipital electrodes showed an earlier onset and a longer duration of significant ITC than did the central electrodes. Within the central region, the ITC at C3 tended to begin slightly earlier than that at C4 in both tasks. The copying task exhibited a broader temporal extent of the ITC than the calculation task at both the central and occipital sites. Critically, a Linear Mixed Model (LMM) showed that in the theta band (4–8 Hz), the degree of phase alignment across trials exhibited no significant main effects of *Pen-tip friction* or *Task* and their interaction at centro-occipital sites (Supplementary Table 2). To control for power confounders, we tested whether the theta-band power in the region of interest (ROI) exceeded zero for each task; no significant power increase was observed at any electrode (Supplementary Table 3). These results indicate a robust pen-down–locked theta band (low-alpha) ITC in handwriting, without detectable modulation by pen type.

Effects of task and pen on pen-down–locked EEG amplitude

Given that pen-down induces phase alignment (ITC) that does not differ by pen, we investigated whether the response amplitude (ERP), rather than phase locking, was modulated by pen type. The grand-averaged ERPs time-locked to pen-down (stroke onset) exhibited a triphasic morphology across tasks and pen tips, with a pre–pen-down positive peak (approximately 40 ms), an early negative peak (approximately 50 ms), and a later positive peak (approximately 130 ms) (Fig. 3A). LMM for single-trial EEG amplitudes revealed significant main effects of *Pen-tip friction* in the pre–pen-down (-70 to -10 ms) at the left central site (C3: $F(2, 106343) = 9.34$, $p = 0.002$) and early post–pen-down (20–80 ms) windows at the left central (C3: $F(2, 106195) = 8.76$, $p = 0.004$) and occipital sites (O1: $F(2, 106408) = 8.33$, $p = 0.006$), with no significant *Task* × *Pen-tip friction* interaction (Table 1). In the pre–pen-down window, the MF tip—most frequently rated as similar to usual pen of the participants—elicited the largest positivity, exceeding both LF ($p = 0.028$) and HF tips ($p = 5.09 \times 10^{-5}$) (Fig. 3B, Supplementary Table 4). In the early post–pen-down window, the HF tip, least similar to the usual pen, evoked greater negativity than did the LF (C3: $p = 0.002$; O1: $p = 0.004$) and MF tips (C3: $p = 3.25 \times 10^{-4}$; O1: $p = 4.09 \times 10^{-4}$). Meanwhile, no significant *Pen-tip friction* effect emerged in the late window (100–160 ms; Table 1), indicating that the effect of pen-tip friction on the pen-down–locked ERP is temporally confined to a brief interval immediately surrounding the pen-down, emerging in the pre- and early post–pen-down windows but not in the late window (> 100 ms).

Table 1
Task and pen-tip friction effects on writing ERPs estimated using a linear mixed-effect model

Ch	Fixed effect	Pre-pen-down				Early post–pen-down				Late post–pen-down			
		F	df	Corrected p		F	df	Corrected p		F	df	Corrected p	
C3	Task	0.68	1, 103070	1.000		28.51	1, 99580	2.80×10^{-6}	***	23.15	1, 103584	4.20×10^{-5}	***
	Pen-tip friction	9.34	2, 106343	0.002	**	8.76	2, 106195	0.004	**	2.14	2, 106363	1.000	
	Task × Pen-tip friction	1.51	2, 106402	1.000		1.76	2, 106332	1.000		2.65	2, 106411	1.000	
C4	Task	0.01	1, 86325	1.000		16.81	1, 93550	0.001	**	36.02	1, 102804	6.28×10^{-8}	***
	Pen-tip friction	5.36	2, 105495	0.099		0.57	2, 105901	1.000		1.03	2, 106332	1.000	
	Task × Pen-tip friction	0.09	2, 105971	1.000		2.99	2, 106183	0.857		1.91	2, 106397	1.000	
O1	Task	32.22	1, 105853	4.28×10^{-7}	***	68.75	1, 104852	$< 7.99\times10^{-15}$	***	73.29	1, 105092	$< 7.99\times10^{-15}$	***
	Pen-tip friction	3.20	2, 106437	0.737		8.33	2, 106408	0.006	**	5.65	2, 106416	0.078	
	Task × Pen-tip friction	2.55	2, 106442	1.000		4.81	2, 106431	0.163		5.98	2, 106434	0.058	
O2	Task	25.58	1, 105838	1.23×10^{-5}	***	48.07	1, 103545	1.41×10^{-10}	***	39.82	1, 103933	9.22×10^{-9}	***
	Pen-tip friction	1.29	2, 106437	1.000		0.25	2, 106361	1.000		0.02	2, 106376	1.000	
	Task × Pen-tip friction	1.939	2, 106441	1.000		2.73	2, 106411	1.000		3.31	2, 106418	0.695	

Note. Ch: EEG electrodes. F and df: *F* values and degrees of freedom from Type III *F*-tests using the Kenward–Roger method. Corrected p: Holm-adjusted *p*-values for multiple comparisons. Statistical significance levels: *$p < 0.05$, **$p < 0.01$, and ***$p < 0.001$.

In addition, the main effect of *Task* was observed in all three time windows (Table 1). Relative to copying, calculation showed larger pre–pen-down positivity at occipital sites, larger early post–pen-down negativity, and larger late positivity at the central and occipital sites (Fig. 3B).

Stroke-level associations between EEG amplitude and handwriting kinematics and kinetics

Table 2 presents the descriptive statistics (means and standard deviations [SDs]) for the number of trials and four kinematic and kinetic features (stroke length, stroke duration, maximum stroke velocity, and maximum pen pressure) for each task and pen-tip friction condition. All kinematic and kinetic features showed the significant effects of *Task* and *Pen-tip friction* (Supplementary Tables 5–7; Supplementary Fig. 1).

Table 2
Writing characteristics for each task and pen tip

Writing characteristics	Calculation			Copying		
	LF	MF	HF	LF	MF	HF
Number of trials	897.56	854.81	848.69	1480.50	1431.56	1482.50
SD	331.70	280.07	363.19	386.82	459.20	511.07
Stroke length (mm)	10.35	10.08	10.08	4.14	4.08	4.12
SD	1.26	1.11	0.92	0.60	0.63	0.62
Stroke duration (ms)	260.69	269.09	261.94	247.47	273.48	236.39
SD	49.87	58.00	38.88	103.62	137.16	84.79
Maximum velocity (mm/ms)	0.30	0.29	0.29	0.21	0.18	0.21
SD	0.03	0.03	0.03	0.08	0.09	0.08
Maximum pressure	0.67	0.61	0.62	0.64	0.59	0.60
SD	0.09	0.11	0.09	0.08	0.11	0.08

Note. Means and standard deviations (SDs) were calculated by computing the average of each measure for each participant across trials and then these participant-wise means within each task-by-friction condition. The reported standard deviation reflects the inter-subject variability within each condition. LF, MF, and HF denote low, middle, and high friction, respectively.

To investigate whether pre–pen-down activity, which showed the strongest pen-tip effect, was related to the kinematics and kinetics of the subsequent stroke, we fitted an LMM to the single-trial data. The results showed that pre–pen-down activity significantly affected stroke duration, maximum velocity, and maximum pressure (Supplementary Table 8). Regarding stroke duration, a greater pre–pen-down EEG amplitude was significantly associated with decreased stroke duration ($F(1, 106427) = 7.39$, $p = 0.007$) (Fig. 4A). This relationship was consistent across task types, as there was no significant interaction between pre–pen-down EEG amplitude and task type ($p = 0.571$). Regarding maximum velocity, a greater pre–pen-down EEG amplitude was significantly associated with increased velocity ($F(1, 106427) = 8.21$, $p = 0.004$) (Fig. 4B. Similarly, this positive relationship remained consistent across task types, with no significant interaction between pre–pen-down EEG amplitude and task type ($p = 0.083$). Regarding maximum pressure, pre–pen-down EEG amplitude significantly affected the pressure in the interaction with task type ($F(1, 106427) = 9.32$, $p = 0.002$). Post-hoc analysis revealed that the positive association between pre–pen-down EEG amplitude and maximum pressure was statistically significant and stronger in the calculation task (Estimate = 0.0016, $t(106427) = 4.18$, $p = 2.91 \times 10^{-5}$) than in the copying task, where this association was not statistically significant (estimate = 0.0001, $t(106427) = 0.44$, $p = 0.659$) (Fig. 4C). By contrast, stroke length was not significantly affected by pre–pen-down EEG amplitude ($F(1, 106429) = 0.87$, $p = 0.351$). No significant interaction between pre–pen-down EEG amplitude and task type was observed for stroke length ($p = 0.565$).

Beyond the specific effects involving the pre–pen-down EEG amplitude, a significant main effect of task type was consistently observed across all four kinematic/kinetic variables. Specifically, the calculation task yielded higher values than the copying task for all measures (all p-values $< 2.22 \times 10^{-16}$).

Effect of mood states on pre–pen-down activity

Pen-tip friction significantly affected neural activity during handwriting. To examine whether the significant effects of the pen tip on handwriting-related neural activity, mainly observed pre–pen-down at C3, are directly attributable to pen properties or occur via a potential pathway involving participants' mood states, we extended the LMM for single-trial EEG amplitudes, allowing the inclusion of mood scores (*Frustration* and *Motivation*) and their interactions as fixed effects.

Regarding frustration, significant main effects were found for *Pen-tip friction* ($F(2, 80.1) = 5.63$, $p = 0.005$) and *Frustration* ($F(1, 89.3) = 4.35$, p = 0.040), as well as a strong interaction between *Task* × *Frustration* ($F(1, 83.4) = 15.26$, $p = 1.90 \times 10^{-4}$) (Supplementary Table 9). Post-hoc tests on this interaction showed that greater frustration was significantly associated with a decrease in pre–pen-down activity in the calculation task (Estimate = -0.21, $t(86.8) = -3.72$, $p = 0.0003$), whereas this association was not significant in the copying task (Estimate = 0.05, $t(86.9) = 1.20$, $p = 0.232$) (Fig. 5A; Supplementary Table 9).

Regarding motivation, significant effects were observed for *Pen-tip friction* ($F(2, 81.4) = 6.86$, $p = 0.002$) and *Task* × *Motivation* interaction ($F(1, 81.5) = 7.21$, $p = 0.009$), whereas the main effect of *Motivation* was marginal ($F(1, 95.3) = 3.84$, $p = 0.053$) (Supplementary Table 10). Post-hoc tests revealed that *Motivation* was associated with a positive correlation in pre–pen-down activity in the calculation task (Estimate = 0.17, $t(94.4) = 3.20$,

$p = 0.002$), whereas no significant trend was observed in the copying task (Estimate = 0.002, $t(95.8) = 0.04$, $p = 0.970$) (Fig. 5B; Supplementary Table 10).

These findings indicate that the pen-tip effects on pre–pen-down activity persist even after accounting for mood states, suggesting a direct effect of pen properties. Additionally, the findings revealed that mood states affected pre–pen-down activity in a task-dependent manner.

Neural and kinematic/kinetic correlates of calculation performance

Finally, we investigated whether pre– and post–pen-down neural activities and kinematic/kinetic variables predicted response accuracy in the calculation task. The LMMs included ERP amplitudes at C3 and O1 across three time windows (pre–, early post–, and late post–pen-down) and four kinematic/kinetic measures (stroke length, duration, maximum pressure, and maximum velocity). Model selection based on the Akaike Information Criterion with correction (AICc)[39] identified five key predictors, showing a variable importance of 1.0: pre–pen-down and late post–pen-down and at C3, stroke length, maximum velocity, and stroke duration (Supplementary Table 11). The optimized model ($R^2c = 0.55$; Fig. 6A) indicated that higher accuracy was associated with greater pre–pen-down positivity (Estimate = 5.43, $t(42) = 4.39$, $p = 7.48 \times 10^{-5}$; Fig. 6B), smaller late post–pen-down positivity (Estimate = − 4.55, $t(42) = -3.53$, $p = 0.001$; Fig. 6C), faster maximum stroke velocity (Estimate = 5.75, $t(42) = 3.01$, $p = 0.004$; Fig. 6D), and longer stroke length (Estimate = 2.61, $t(42) = 2.16$, $p = 0.037$; Fig. 6E). Stroke duration was not a significant factor ($p = 0.377$).

Discussion

The present study characterized the neural dynamics of tuning to the physical properties of a writing tool during handwriting, using simultaneous time-locked EEG and kinematic/kinetic recordings. Pen-tip friction exhibited significant effects before and after pen-down. Pre–pen-down activity was the largest for the medium-friction tip, which most participants judged to be similar to their usual pen, and larger pre–pen-down activity predicted shorter stroke duration and higher peak velocity. In the written calculation task, accuracy (the proportion of correctly answered problems among those solved by the participant) was higher when pre–pen-down activity was larger and post–pen-down activity smaller. Together, these findings demonstrate stroke-level anticipatory neural tuning to tool properties in handwriting and provide strong evidence for proactive motor processing that links pen–surface mechanics to cognitive performance.

Handwriting exhibited significant theta- and low-alpha-band ITC surrounding pen-down events, whereas line drawings showed no comparable phase alignment. These findings support the idea that handwriting rhythmicity (approximately 5 Hz)[2] is synchronized with ongoing theta oscillation in the brain[28,29], and it is further supported by evidence showing that handwriting more strongly engages widespread theta/alpha-band connectivity than does typing[32]. Our findings suggest that the brain synchronizes ongoing oscillations with the temporal cadence of a stroke when a motor plan is already established, such as when writing familiar characters, regardless of the involvement of higher linguistic processing. Our findings are consistent with and extend those of previous study showing that theta-band oscillations phase lock to the onset of intended actions and rhythmically modulate perceptual sensitivity[40]. In our study, theta phase alignment around stroke onset (pen-down) similarly reflected preparatory synchronization in a rhythmic motor task (handwriting), suggesting that phase locking facilitates the timely execution of predictive motor commands in well-practiced sequential behaviors.

In contrast, the theta-band phase alignment for pen-down events showed no significant effect of pen-tip friction, although the time–frequency pattern of ITC varied across electrodes and tasks. Within the limits of our design and statistical power, this suggests that phase alignment does not vary strongly with tip friction. Pei et al. (2021)[28] reported that bias of the theta phase distribution, an index of phase synchrony, was stronger for the dominant hand than for the non-dominant hand, indicating that alignment can be enhanced by skill and habitual use. Taken together, these findings suggest that subtle tool manipulations such as changes in pen friction may not disrupt theta-phase synchrony during handwriting to the extent observed for stable effector-related factors such as handedness. Thus, the coupling between memory-guided motor rhythms and neural oscillations during handwriting appears to be robust against fine-grained variations in tool properties.

Furthermore, Pei et al. (2012)[28] showed that the effector-related effects of handedness emerge after pen-down. In contrast, in our data, tool effects appeared mainly before pen-down. Pen-tip friction effects were evident in the amplitude of the pre–pen-down ERP (-70 to -10 ms), most prominently at left central sites. The medium-friction tip, which most participants judged to be similar to their habitual writing instrument, elicited the greatest pre–pen-down activity. Because this tip was perceived as closely resembling the habitual tool, the motor system could reuse long-term sensorimotor memories related to pen–surface dynamics, enabling faster retrieval and parameterization of the appropriate motor program. This reuse reflects the automation of handwriting, where well-learned internal models support efficient, low-variability stroke production with minimal cognitive load[2,3]. Reusing a well-learned internal model reduces the state-estimation uncertainty at stroke onset and permits a higher preparatory output gain, which is expressed as a larger pre–pen-down ERP. Stroke is considered the basic motor unit of handwriting[25–27]. Each stroke specifies its direction, amplitude, and duration, and these parameters must be set prior to contact. Therefore, pen-tip friction acts at the stroke level by shaping this parameterization, which is reflected in stroke-locked preparatory activity. The larger pre–pen-down ERP for the medium-friction tip indicates a more efficient stroke-by-stroke tuning when the tool properties match long-term experience. This pattern demonstrates that the motor system proactively adjusts the output gain to match the expected frictional resistance.

The functional relevance of this anticipatory (proactive) activity was evident in stroke-level motor outcomes. Greater pre–pen-down activities at C3 predicted a shorter stroke duration and higher maximum velocity across tasks, reflecting more efficient execution. In line with a proactive tuning account[5], this pattern suggests that before contact, the system proactively leverages a well-learned internal model of pen–surface dynamics to prepare for a forthcoming stroke, specifying its direction, amplitude, and duration in advance[18]. When tip friction aligns with long-term experience, the state estimation is more precise and preparatory recruitment is stronger, which yields faster strokes with higher peak velocities. This reuse of internal models may reflect cerebellar mechanisms for the predictive control of tool dynamics[18], as well as sensorimotor representations in which the tool becomes integrated into the body schema[19,20]. Notably, in the high-load calculation task, stronger preparatory activity correlated with increased pen pressure, which is consistent with a proactive stabilization strategy to maintain contact and precision under cognitive demand.

Pen-tip friction continued to exert a significant influence on pre–pen-down proactive activity even after accounting for mood ratings (frustration and motivation), indicating a direct effect of tool properties on neural preparation for writing strokes. Mood states contributed to the pre–pen-down activity; however, their impact was modest and task-dependent. In the calculation task, frustration showed a negative association with pre–pen-down amplitude, whereas motivation showed a positive association. These neural patterns may reflect a mechanism underlying the behavioral phenomenon whereby mood can alter handwriting performance, as previously reported[36,37,41]. Our results suggest that emotions can modulate motor planning without overriding the primary effect of pen-tip friction.

In addition, the early post–pen-down window (20–80 ms) showed a pen-tip friction effect, with a larger negativity under high friction. This pattern is consistent with the interpretation that under higher friction, the initial response to contact is enhanced; greater resistive load and lateral shear at the pen tip–surface interface amplify tactile and proprioceptive afference and increase the salience of contact onset[15]. This, in turn, recruits additional sensorimotor integration immediately after pen-down. Our results indicate that pre–pen-down proactive activity sets the initial condition of a stroke, whereas early reactive processing accommodates the physical consequences of contact under higher resistance Notably, this pen-dependent reactive processing was not detected in the late post–pen-down window (100–160 ms). Given that the mean stroke duration was 230–270 ms, this window remained within the ongoing stroke in most cases. These observations suggest that reactive adjustments to pen friction operate primarily within the first 100 ms after contact, with minimal additional pen-dependent processing thereafter. These results are consistent with those of previous kinematic studies showing that reduced surface friction impairs stroke fluency and increases movement variability[15–17].

Our results indicate that stroke-level EEG and kinematics can predict cognitive performance. Higher pre–pen-down positivity predicted greater calculation accuracy, whereas late post–pen-down positivity showed an inverse relationship, implying that successful performance relies on strong proactive preparation, followed by more efficient and less resource-intensive reactive processing[2]. Notably, the early post–pen-down window did not emerge as a predictor of accuracy. This dissociation is informative: early post-activity appears to reflect immediate contact evaluation that is amplified under high friction, whereas late post-activity indices sustain reactive updating that, when can draw resources away from task goals when over-recruited. Together with the kinematic pattern—shorter stroke duration and higher peak velocity accompanying larger pre–pen-down activity—these findings suggest that accuracy is supported when proactive recruitment is strong and late reactive demand remains low.

Kinematic signatures mirrored this neural efficiency: accuracy was higher when the maximum stroke velocity was greater and the stroke length was longer. In a written calculation task prioritizing solving quickly rather than maximizing handwriting legibility, we interpreted this pattern as evidence that well-prepared smooth strokes are less affected by frictional resistance and free cognitive resources for the calculation. A higher peak velocity is consistent with strong proactive preparation, whereas longer strokes indicate that the movement amplitude was not overly constrained, reducing brief hesitations and small corrective moves.

Our findings extend the findings of prior studies linking handwriting quality to performance in related cognitive domains[42–48] and align with accounts of automation in handwriting[3,49]. Pre–pen-down proactive activity sets the initial conditions of a stroke and predicts kinematic fluency (shorter duration and higher peak velocity), which supports higher accuracy in speeded written calculations. Practiced strokes operate in a largely automated mode with minimal attentional involvement, allowing the allocation of cognitive resources to the computation itself[44,49]. By contrast, a larger late post–pen-down activity is negatively related to accuracy, indicating that sustained reactive updating can draw resources away from task goals when over-recruited. Thus, pen-tip friction indirectly affects cognitive performance by shifting the balance toward proactive preparation and away from late reactive corrections.

This study had several limitations. Our EEG analysis focused on central and occipital sites, limiting the coverage of broader brain networks. In addition, mood ratings were collected per task and friction condition rather than per stroke, which prevented the characterization of rapid affective fluctuations and their coupling with neural and kinematic/kinetic responses. Finally, our cognitive outcomes were restricted to a speeded written calculation task. Therefore, generalization to other domains and legibility-focused contexts remains undetermined. Nevertheless, the present findings show that proactive activity links the properties of the writing tool (pen-tip friction) with kinematic efficiency and cognitive performance. Our results clarify how proactive and reactive processes jointly shape skilled sequential handwriting using a tool. These insights lay the groundwork for developing human-friendly writing tools that support learning, rehabilitation, and creativity.

Methods

Participants

Nineteen adult participants were recruited based on the following inclusion criteria: native Japanese speakers, right-handed, normal or corrected-to-normal vision, and no history of psychiatric or neurological diseases. In addition, the participants did not regularly use digital pens for notetaking, memos, or drawing for more than a few days, as heavy users of digital pens may be sensitive to differences between their daily use devices and the devices used in the experiments, which could affect brain activity.

Data from three participants were omitted from further analysis: one participant did not follow the study instructions, and two participants did not properly record their pen logs. Thus, we analyzed the data of 16 participants (seven women, 21–47 years old). Ethics Committee for Human Research of National Institute of Information and Communications Technology approved the study protocol. All the participants provided written informed consent before participating in the study.

Writing materials and tasks

Two writing activities were conducted during the experimental task (Fig. 1A). The first task was a written calculation. Each sheet for this task contained 12 written multiplications with two-digit numbers, which differed among the sheets. The participants were instructed to solve problems as quickly and accurately as possible. The second task was a Kanji copying task that involved hand-copying a document written in Kanji characters, with careful attention paid to each character and stroke. Each script comprised two pages, and each sheet consisted of nine lines of vertical writing (4–18 Kanji characters per line). The participants were instructed to carefully and accurately write the characters on a blank line next to the models. Additionally, a line-drawing task was performed to compare the two writing tasks. For each problem, there were nine dots on the left side, with some connected by lines, and nine dots on the right side. The participants were instructed to draw the same figure on the right as the sample on the left by connecting the dots. The order in which the lines were drawn and the number of strokes were to be determined by the participants. Each sheet comprised four different problems, and each set consisted of five sheets.

Writing tools

During each task, the participants viewed a PDF version of the task sheet on a pen display (Wacom MobileStudio Pro 16, DTH-W1621; Wacom Co., Ltd.) and wrote or drew using a digital pen (Wacom Pro Pen 2, KP504E; Wacom Co., Ltd.). To investigate the effects of writing tool properties on brain activity, we used three types of interchangeable pen tips with varying friction coefficients (Fig. 1C). The LF tip was made of polyoxymethylene (POM), a durable engineering plastic with self-lubricating properties (coefficient of friction = 0.13). The MF tip was composed of compressed felt fibers embedded in plastic (coefficient: 0.16), resembling the texture of a marker pen. The HF tip was made of an elastomer, a soft rubber-like material with the highest friction (coefficient: 0.18), thus mimicking the resistance associated with writing with a rubber tip.

To examine whether the distribution of the perceived similarity and writing preference rankings differed across pen types, we conducted separate chi-square goodness-of-fit tests. Participants ranked the three pen-tip types on two dimensions: (1) perceived similarity to their usual writing instrument and (2) subjective writing preference, using ordinal ranks from 1 (most similar or most preferred) to 3 (least similar or least preferred).

For each evaluation type, contingency tables were constructed with pen-tip type as the row variable and rank as the column variable. Pearson's chi-square test was used to assess the independence between the pen-tip type and rank. When a significant chi-square result was observed, standardized residuals were computed to identify the pen-tip rank combination that contributed the most to the overall association. Residuals with an absolute value > 2 were interpreted as indicating statistically meaningful deviations from the expected frequency under the null hypothesis of independence. This analysis was conducted in R[50] using the dplyr[51] and DescTools[52] packages for data manipulation and non-parametric correlation analysis (Kendall's tau-A).

Experimental procedure

Participants completed the experiment over three separate sessions, each spaced at least 1 week apart. During EEG recordings, a PDF version of the task sheet was displayed on a tablet device. The participants performed each task using a digital pen, and they were instructed to tap a designated square in the upper-right corner of the sheet to mark the beginning and end of each task (Fig. 1B). After completing one sheet, they proceeded to the next sheet and continued the sequence until the 15-min time limit was reached.

The order of the friction conditions across the three sessions and that of the tasks within each session were randomized for each participant. After each task, participants rated their mood using two items—"I feel frustrated" (Frustration) and "I'm full of motivation" (Motivation)—on a 5-point Likert scale (0 = "not at all" to 4 = "extremely").

EEG acquisition

We conducted EEG measurements synchronized with pen logs using the system depicted as the following procedure. The tablet CPU time was recorded in a log file. Simultaneously, the CPU time was sent from a time-delivery dongle (DN-5477, TAMURA CORPORATION, Tokyo, Japan) attached to the tablet to the two measurement devices via Bluetooth, achieving microsecond-level precision. A microphone (MMA6482-KIT, Marutsuelec Co., Ltd., Tokyo, Japan) was placed near the tablet and the tap sound was captured at the beginning and end of each task (Fig. 1B). This tap sound was measured using an external signal measurement device (TIME SYNC.EXT.UNIT; Miyuki Giken Co., Ltd., Tokyo, Japan).

Throughout each task, EEG and electrooculography (EOG) signals were continuously recorded using a custom eight-channel wearable EEG device[53] based on PolymateMini AP108 (Miyuki Giken Co. Ltd., Tokyo, Japan); this supported CPU time synchronization. The EEG signals and pen-log data were synchronized by aligning the start time of the pen's contact with the screen with the onset of the initial tap sound.

Regarding EEG measurements, we used dry electrodes (Unique Medical Co. Ltd., Tokyo, Japan) positioned at F7, F8, C3, C4, O1, and O2 according to the International 10–20 system. Additionally, an electrode was placed above the left eye to capture vertical EOG components. This helped remove noise from blinking and eye movements in the EEG signals. All signals were sampled at 500 Hz, using the left mastoid as the ground and the right mastoid as the reference.

Pen-down–locked EEG

The EEG data were preprocessed using MATLAB (MathWorks, Inc.) and the EEGLAB toolbox[54]. An FIR bandpass filter of 1–45 Hz (5,000th order) was applied to the continuous EEG and EOG signals. Artifacts primarily from eye movements and blinking were excluded from the EEG signals using noise reduction processing with independent component analysis. All recorded signals were re-referenced offline to the average of all EEG channels. For each channel, the signals from 500 ms before to 1000 ms after the onset of pen-down were extracted for every pen tip and task. Moreover, we excluded the following specific trials from further analysis: those exceeding ± 60 μV in either EEG or EOG channel, those that had a pen-down action occurring 70 ms prior to the pen-down on set, and those containing missing values.

To compute the pen-down–locked ERPs, trials were averaged for each participant, electrode, task, and pen tip. Baseline correction was applied using an interval of 500–200 ms before the onset of pen-down. Afterward, grand-averaged ERPs were obtained from all the participants to characterize the overall waveform morphology and determine the time windows for subsequent analyses. Based on this morphology showing a triphasic positive–negative–positive pattern, three time windows were defined: pre–pen-down (− 70 to − 10 ms), early post–pen-down (20–80 ms), and late post–pen-down (100–160 ms). The mean amplitudes within each window were calculated for each participant, pen tip, task, and electrode using trial-level data. Subsequently, we computed the mean amplitude within each time window for each participant, pen tip, task, and electrode.

Based on a previous study[28], we applied an LMM to single-trial EEG amplitudes within these defined time windows across the two writing tasks, three pen tips, and all participants. The model included the task, pen tip, and their interaction as fixed effects and the participant as a random effect. We considered that the effect of the stroke length was part of the overall effect of the pen tip. The model was established as follows:

EEG amplitude ~ Task * Pen-tip friction + (1|Participant)

Type III *F*-tests were conducted using the Satterthwaite approximation for the degrees of freedom. Because multiple LMMs were conducted across different time windows and electrodes, Holm correction was applied to all resulting *p*-values to control for family-wise error rate across the entire set of statistical tests. When the main effect of the pen-tip friction was statistically significant, we performed pairwise comparisons across pen tips using Holm-adjusted *p*-values. All statistical tests were two-tailed, and the significance threshold was set at 0.05. LMM analyses were conducted in R[50] using the *lmerTest*[55], *lme4*[56] and *emmeans*[57] packages, and model predictions was performed using the *ggeffects* package[58] and plotted using *the ggplot2* [59]and *ggsci*[60] packages.

ITC around pen-down

Time–frequency analysis was conducted using MATLAB (MathWorks, Inc.) in combination with the FieldTrip toolbox[61]. EEG preprocessing followed the same procedure as the ERP analysis, except that the epoch length was extended to -1000 to 1500 ms relative to the pen-down event. Wavelet transformation was applied to the preprocessed EEG signals using a three-cycle complex Morlet wavelet, with frequencies of 3.2–45.2 Hz, in 0.8 Hz increments and time steps of 10 ms.

To assess whether phase alignment shows the pre– to post–pen-down interval in handwriting tasks, we computed the ITC for each electrode, task, and friction condition across the above frequency range, with an a priori focus on the theta/low-alpha band. The Rayleigh test was applied to each time–frequency point of the ITC and averaged across pen tips and participants for each task and electrode. As no significant ITC ($p > 0.05$) was observed in the line-drawing task, subsequent analyses focused exclusively on the two handwriting tasks (calculation and copying). Based on the Rayleigh test results, time–frequency windows of interest were defined for each task, common across pen tips and restricted to the theta band (4–8 Hz). Furthermore, LMMs were constructed and analyzed using the same R packages and procedures described above (see *Pen-down–locked EEG*) to examine how the theta-band ITC was modulated by task and pen tip. The dependent variable was the mean ITC value within a predefined time–frequency window.

Kinematic and kinetic features and their neural correlates

Regarding kinematic/kinetic analysis, the time of interest was set to -500 to 1000 ms relative to the onset of a pen-down event for each stroke, similar to the EEG analysis. As in the EEG analysis described below, trials that included a pen-down event occurring 70 ms before pen-down onset were excluded. For each stroke, the following four kinematic and kinetic features were computed for each task and friction condition per participant: stroke length, stroke duration (time in contact with the tablet), maximum stroke velocity, and maximum pen pressure. Pen pressure during each stroke was normalized across all strokes between zero (no touch) and one (full touch). Based on the distribution of the stroke duration,

trials with durations exceeding 1500 ms were excluded. Similarly, based on the distribution of stroke lengths, trials with stroke lengths > 20 mm for the two writing tasks (i.e., calculation and copying tasks) were removed from the analysis. The analysis was conducted using MATLAB (MathWorks, Inc.).

LMMs were constructed to examine the relationship between pre–pen-down neural activity and the kinematics/kinetics of the corresponding stroke. These models included pre–pen-down EEG amplitude (pre-EEG), task type, and their interaction as fixed effects and participant as a random effect. For each kinematic/kinetic variable (e.g., maximum pressure), a separate LMM was specified as follows:

Kinematic/kinetic measure ~ Pre-EEG * Task + (1 | Participant)

When significant fixed effects or interactions were identified, post hoc analyses were conducted to estimate the marginal means and perform pairwise comparisons. Degrees of freedom were estimated using the Satterthwaite approximation, and *p*-values were adjusted using the Holm method to control for multiple comparisons. For significant interactions, simple slope analyses were performed to assess the statistical significance of the continuous predictor's slope within each level of the categorical variable and to compare slopes across levels. All LMMs and their visualizations were constructed and analyzed using the R packages and procedures described above (see *Pen-down–locked EEG*).

Mood effect on pre-pen-down activity

Given the significant effects of friction conditions on pre–pen-down neural activity, we further investigated whether these neural responses were directly affected by pen-tip properties or indirectly mediated by mood states induced during the handwriting task. We used trial-averaged EEG amplitudes at specific electrodes and time windows, which showed a significant pen-tip effect in the LMM for single-trial EEG (see *Pen-down–locked EEG*). This averaging was performed because mood scores were collected only once for each condition (per task and pen tip). Fixed effects included task type, pen-tip type, z-scored frustration or motivation scores, and their interactions; participant was modeled as a random intercept. The model formula is as follows:

ERP amplitude ~ Task * Pen-tip friction + Mood score + Task:Mood score + (1 | Participant)

LMMs and their visualizations were constructed and analyzed using the R packages and procedures described above (see *Pen-down–locked EEG*).

Neural and kinematic/kinetic predictors of calculation performance

To examine whether pre– and post–pen-down neural activity and kinematic/kinetic variables predicted cognitive performance, we fitted an LMM for calculation accuracy, which was defined as the proportion of correctly answered questions for each participant. The analysis was performed in two steps. First, a global model was specified with fixed effects, including trial-averaged EEG amplitudes in three time windows (pre-, early post-, and late post–pen-down) at electrodes C3 and O1, where pen-tip effects were observed. Additional fixed effects included kinematic and kinetic measures, with participation as a random effect. All predictors were z-scored prior to the estimation. The formular for the global model is as follows:

Accuracy ~ Pre-ERP_{C3} + Early-post-ERP_{C3} + Late-post-ERP_{C3} + Pre-ERP_{O1} + Early-post-ERP_{O1} + Late-post-ERP_{O1} + Length + Duration + Velocity + Pressure + (1 |Participant)

Second, we generated all the subset models from the global model and ranked them using the second-order AICc[39], which adjusts for small sample sizes. Models within $\Delta AICc \leq 2.0$ of the best model were retained. Variable importance scores (the sum of the weights across the models) were computed for each predictor. The variable importance scores were computed as the sum of the weights across all the models containing the variable. Predictors with importance > 0.3 were included in the final model. This analysis was conducted using the same R packages and procedures described above (see *Pen-down–locked EEG*), along with *MuMIn*[62] packages.

Declarations

Funding declaration

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Data availability

The data that support the findings of this study are available from the corresponding

author upon reasonable request.

Code availability

All data analysis codes will be made available by the corresponding author on request.

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Author contributions

A.S.I. conceived the study. Y. N., A. S. I., K. N. and A. K. designed the experiments. A. K. and T. K. provided the writing device technology. K.N. prepared all experimental setups. A.M. collected data. K.N. and Y.H. performed the data preprocessing. A.S.I. designed the analysis plan and conducted the statistical analyses. Y.N. and H.W. provided critical feedback on data analysis. A.S.I. drafted the manuscript.

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Figures

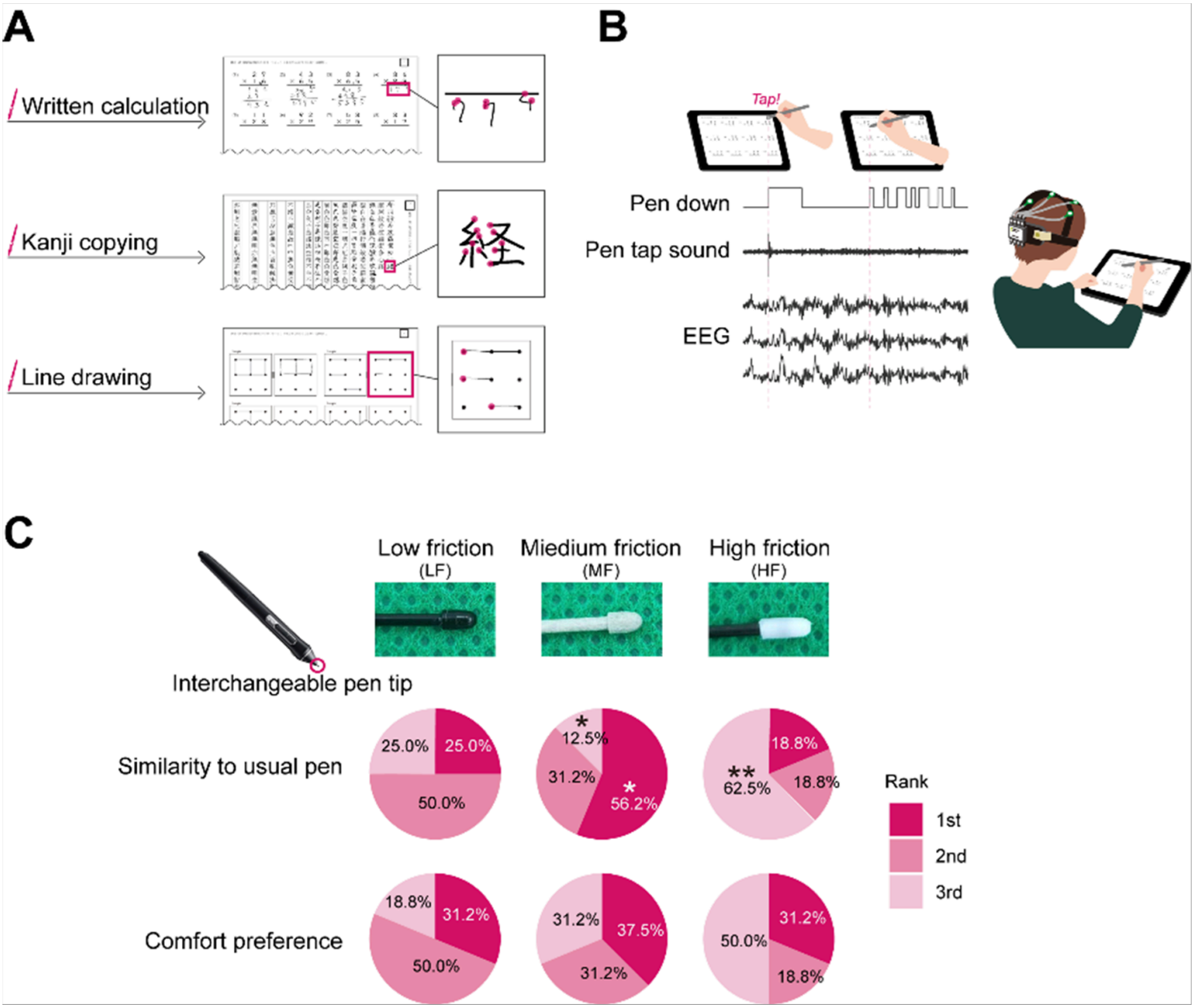


Figure 1

Experimental tasks, setup, and writing tools. A. Participants performed two handwriting tasks (written calculation and Kanji copying) and a non-linguistic line drawing task. Calculation involved solving two-digit multiplications as quickly and accurately as possible, whereas copying required accurate reproduction of characters. The line drawing task required replicating dot-connected figures, serving as a visuomotor control. **B.** EEG was recorded while participants wrote and drew on a tablet with a digital pen. Task onset and offset were marked by tapping a designated square on the screen, and tap sounds were captured by a microphone for precise time alignment. Tablet-recorded pen data and EEG signals were time-synchronized with high temporal precision. **C.** Three interchangeable pen tips with distinct friction coefficients were used: low friction (LF, polyoxymethylene), medium friction (MF, felt fiber), and high friction (HF, elastomer). Pie charts show the distribution of participants' ordinal rankings for each pen type in terms of perceived similarity to their usual writing instrument (upper) and writing comfort preference (lower). Asterisks (*) indicate statistically significant deviations from expected frequencies based on Pearson's chi-square test and standardized residuals. The MF tip was significantly more likely to be rated as most similar to participants' usual pen (1st rank, std. resid. = 2.38, $p < 0.05$) and less likely to be rated as least similar (3rd rank, std. resid. = −2.17, $p < 0.05$). The HF tip was significantly more likely to be rated as least similar (3rd rank, std. resid. = 3.03, $p < 0.01$), suggesting a perceptual distinction from participants' familiar writing experience. No significant differences were observed in writing comfort preference rankings across pen types.

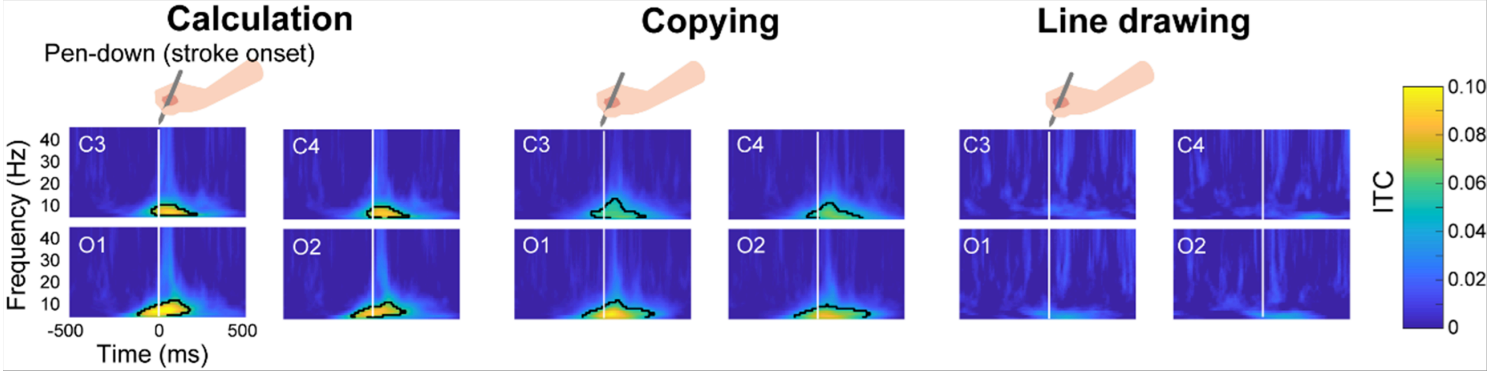


Figure 2

Inter-trial coherence for handwriting strokes. Inter-trial coherence (ITC) in the theta/low-alpha band (3.2–12 Hz) was observed during handwriting tasks (calculation and copying), spanning the pre– to post–pen-down interval at both central and occipital sites, whereas no significant ITC was detected for the line drawing task. Significant time–frequency windows for each task and electrode are provided in Supplementary Table 1. Occipital electrodes showed an earlier onset and longer duration of significant ITC than did central electrodes (e.g., calculation: C3, 4–8 Hz, −30 to 220 ms; O1, 3.2–10 Hz, −110 to 180 ms; copying: C3, 3.2–12 Hz, −60 to 240 ms; O1, 3.2–11.2 Hz, −110 to 290 ms). Within the central region, ITC at C3 tended to begin slightly earlier than that at C4 in both tasks. The copying task exhibited a broader temporal extent of ITC than the calculation task at both central and occipital sites.

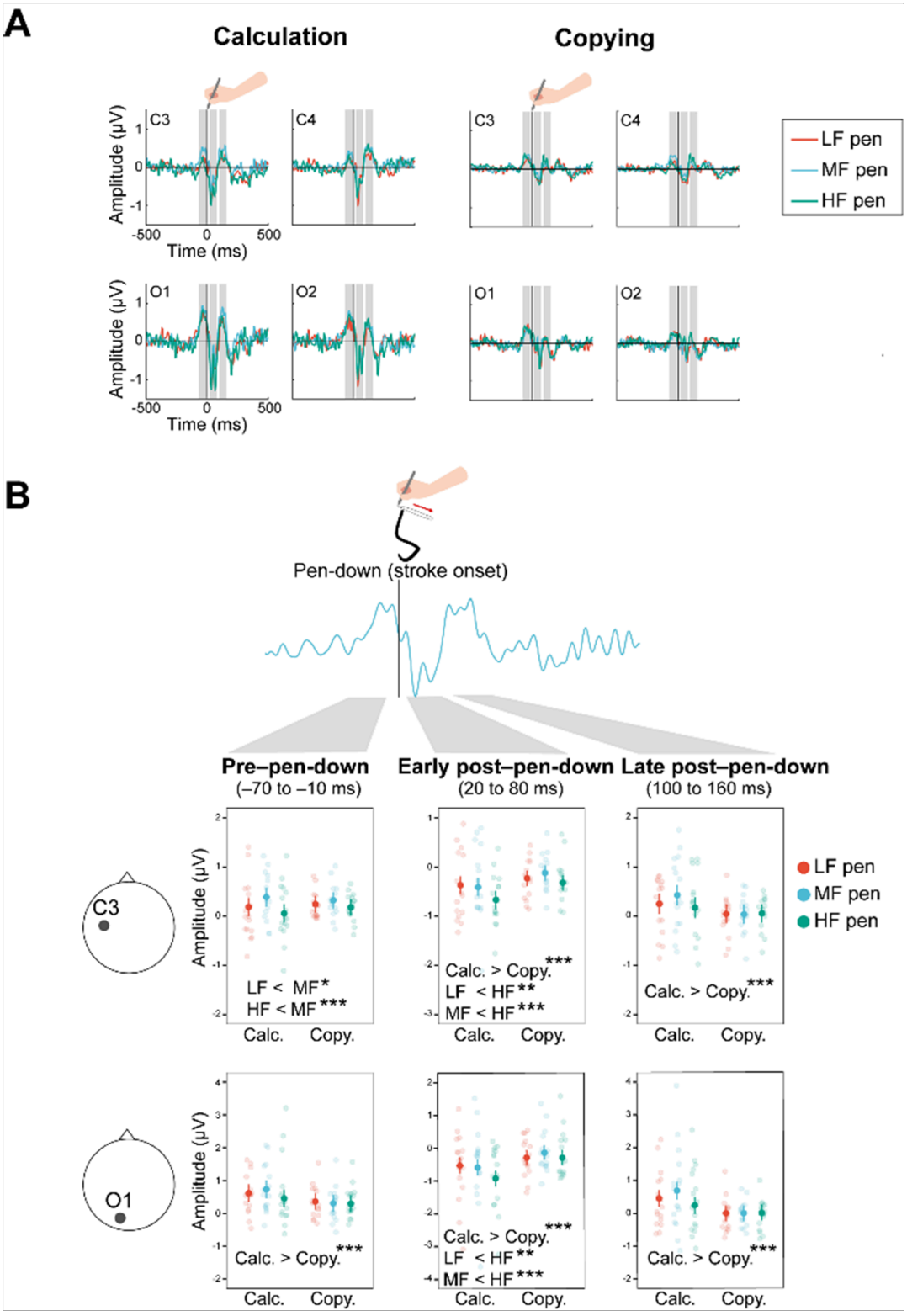


Figure 3

Pairwise differences among pen-tip friction conditions in stroke-locked EEG. A. Grand-averaged ERPs aligned to pen-down events exhibited a triphasic morphology at central and occipital sites across all pen-tip friction conditions and writing tasks: a pre–pen-down positivity (approximately -40 ms), early negativity (approximately 50 ms), and late positivity (approximately 130 ms). **B.** Significant pen-tip friction effects were observed at C3 during the pre–pen-down window (-70 to -10 ms; see Table 1), where the medium-friction tip elicited the largest positivity compared to low and high friction (LF < MF, $p = 0.028$; HF < MF, $p = 5.09 \times 10^{-5}$). During the early post–pen-down window (20–80 ms), high-friction tips produced greater negativity than low and medium friction at both C3 (LF < HF, $p = 0.002$; MF < HF, $p = 3.25 \times 10^{-4}$) and O1 (LF < HF, $p = 0.004$; MF < HF, $p = 4.09 \times 10^{-4}$). Note that "<" indicates smaller amplitude values on the plotted axis, which correspond to less positive or less negative depending on polarity of components. No significant pen-tip friction effect was found in the late post–pen-down window (100–160 ms). All significant task effects revealed

larger amplitudes for the calculation task than for the copying task. Transparent jittered points represent participant-level means. Solid points with error bars denote population-level model-predicted means and their 95% confidence intervals estimated from the linear mixed-effects model. Asterisks denote significant pairwise differences (*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; Holm-adjusted). Full statistics are provided in Supplementary Table 4. LF: low friction, MF: medium friction, and HF: high friction.

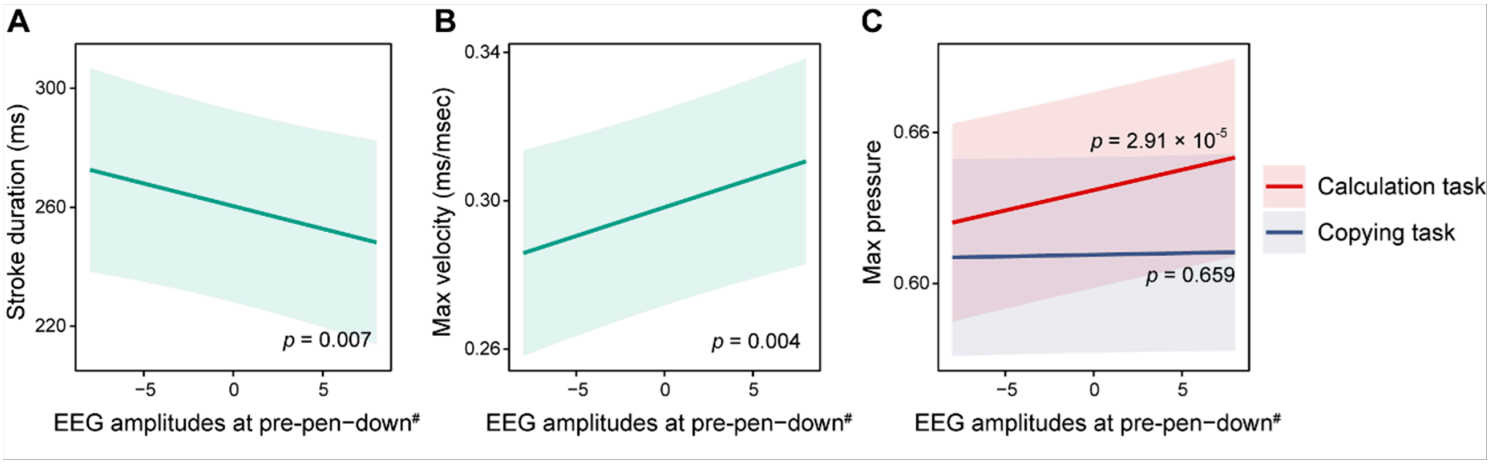


Figure 4

Stroke-level associations between pre–pen-down EEG activity and handwriting kinematics/kinetics. Each panel shows the relationship between pre–pen-down EEG amplitude at C3 (# denotes z-scored values) and a kinematic/kinetic feature of the subsequent stroke, based on linear mixed-effects models. **A.** Greater pre–pen-down positivity was significantly associated with shorter stroke duration across both handwriting tasks (p = 0.007). **B.** Greater pre–pen-down positivity was associated with greater maximum stroke velocity (p = 0.004). **C.** A significant interaction between EEG amplitude and task type was observed for maximum pen pressure (p = 0.002). The positive association between EEG amplitude and pressure was significant in the calculation task ($p = 2.91 \times 10^{-5}$) but not in the copying task (p = 0.659). Solid lines represent model-predicted values and shaded areas indicate 95% confidence intervals.

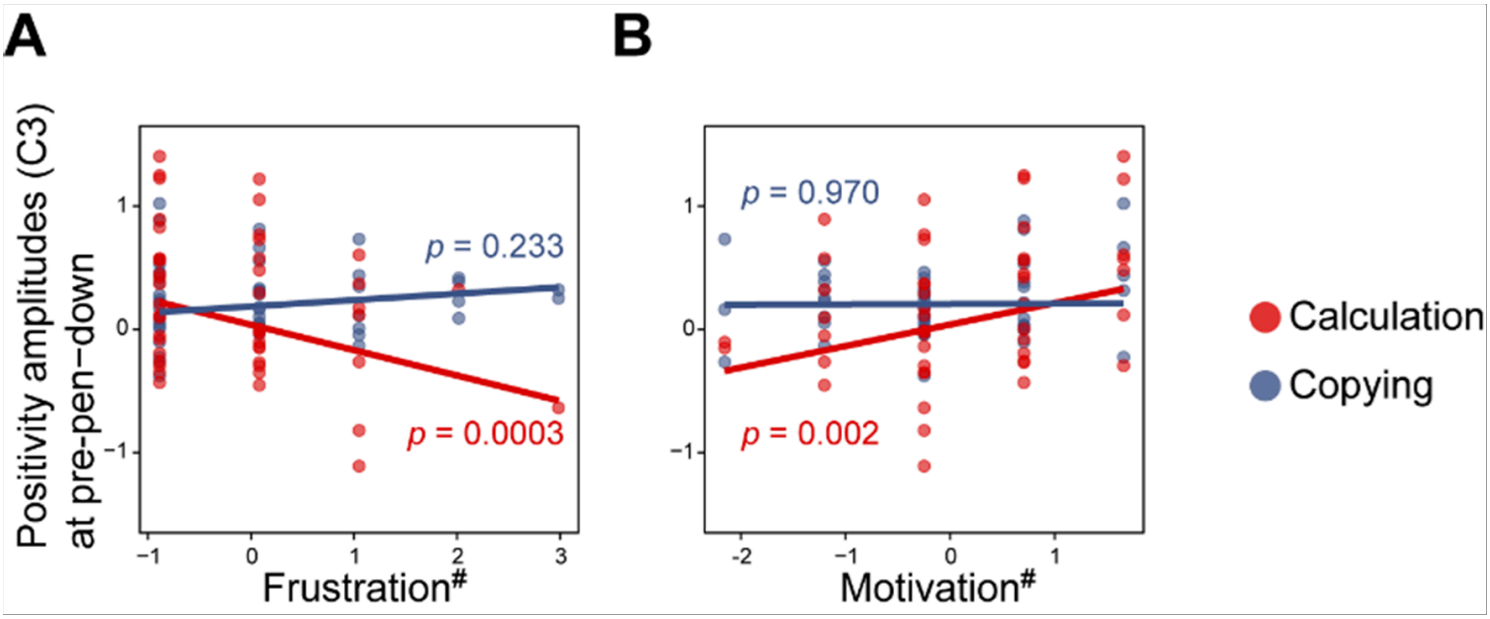


Figure 5

Task-dependent associations between mood states and pre–pen-down ERP amplitude (C3). Frustration showed a significant negative correlation in the calculation task (**A**, Estimate = −0.21, p = 0.0003), whereas motivation exhibited a positive correlation (**B**, Estimate = 0.17, p = 0.002). Neither frustration nor motivation showed significant effects in the copying task. Pen-tip effects on pre–pen-down EEG activity persisted even after accounting for mood states (p< 0.01; Supplementary Tables 9 and 10).

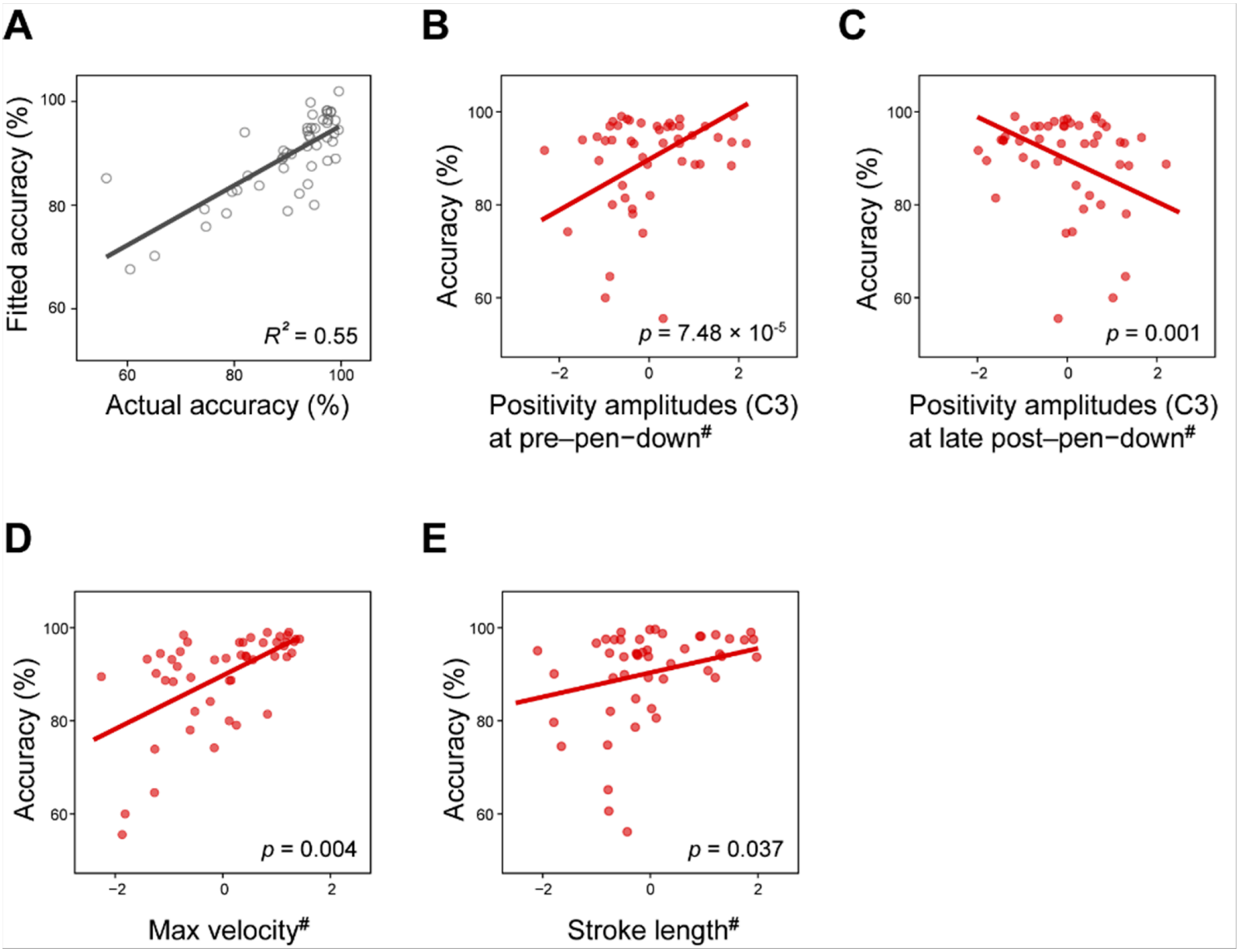


Figure 6

Predictors of calculation accuracy. A. Shows the relationship between actual and model-predicted accuracy; the solid line indicates the linear fit of the optimized model (R^2 = 0.55). The optimized model included pre–pen-down and late post–pen-down ERP amplitudes at C3 and three kinematic features. Higher accuracy was strongly associated with greater pre–pen-down positivity (**B**, $p = 7.48 \times 10^{-5}$) and smaller late post–pen-down positivity (**C**, p= 0.001). Among kinematic predictors, longer stroke length (**D**, p= 0.037) and higher maximum velocity (**F**, p = 0.004) were significant. Dots represent participant-level data for each friction condition (three per participant). For Panels **A**, the solid line indicates the linear fit of the optimized model; for other panels, solid lines represent model-predicted values. # denotes z-scored values.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementalData.docx