AI, emotion, and collaboration: A neurocognitive investigation of learning

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Abstract. The growing integration of Generative Artificial Intelligence in education raises questions about its effects on collaborative learning. This study examines how AI support and emotional priming interact during dyadic collaboration, focusing on inter-brain synchronization, perceived learning, product identification, and objective performance. Eighty-eight students were assigned to 44 dyads in a 2×2 factorial design (AI support × emotional priming), completing a collaborative text comprehension task with or without ChatGPT. EEG hyperscanning recorded simultaneous neural activity from both partners throughout the task. No significant effects emerged for inter-brain synchronization. However, a significant AI × Priming interaction was found for perceived learning and product identification: each manipulation alone improved these outcomes, while their combination neutralized them. No effects were observed for team cooperation or objective performance. These findings suggest that AI and emotional priming do not combine additively, with relevant implications for the design of AI-augmented learning environments.

Keywords. AI-supported learning, Generative AI, EEG Hyperscanning, Inter-brain synchronization, cooperative learning, emotional priming, collaborative learning

1. Introduction

The widespread adoption of Generative Artificial Intelligence (GAI) in educational contexts is reshaping collaborative learning. While AI-based tools can enhance engagement, self-regulated learning, and access to feedback [1–3], growing evidence highlights that AI assistance may reduce mental effort and depth of processing, fostering an illusion of learning [4–6], even in team settings. These issues are particularly relevant

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in collaborative learning, where effectiveness depends on social interaction, shared intentionality, and cooperation [7]. Productive collaboration emerges when learners are emotionally and cognitively aligned, supporting explanation, regulation, and knowledge convergence [8]. This process enhances not only perceived learning and satisfaction [9], but also a sense of connection with teammates and psychological identification with the jointly produced work [10], which becomes incorporated into one's sense of self [11].

In parallel, brief social priming tasks can rapidly increase closeness, trust, and cooperation even among strangers, enhancing interpersonal synchrony at both behavioral and neural levels [12,13].

Within Two-Person Neuroscience, cooperation and learning are understood as emerging from inter-brain synchronization between interacting individuals [14]. EEG hyperscanning studies indicate that neural coupling in theta, alpha, and beta bands reflects the alignment of attention and shared representations during cooperative learning [15], and predicts better learning outcomes and social closeness [16].

Building on this literature, the present study investigates whether emotional priming and AI use can support collaborative learning, examining (a) how AI affects cooperation, learning outcomes, and joint task identification, and (b) whether fostering emotional connection enhances neural alignment and learning effectiveness, particularly in AI-mediated collaboration.

2. Methodology

2.1. Design

The study adopted a 2×2 between-subjects factorial design manipulating AI support (AI: present vs. absent) and collaboration priming (Priming: present vs. absent), yielding four conditions: AI × Priming, AI × No Priming, No AI × Priming, and No AI × No Priming.

2.2. Participants

Eighty-eight university students (N=88) were recruited and randomly assigned to 44 dyads. Participants were unacquainted prior to the experiment. Sixty-six participants identified as female (75%). The mean age of the participants was 22.3 years old.

2.3. Procedure

Figure 1 illustrates the experimental protocol and procedure. In priming conditions, dyads completed a brief task adapted from a scrambled sentence paradigm [17], designed to promote a positive emotional framing of collaboration (~ 5 min). All dyads then engaged in a cooperative learning task (~ 20 min), consisting of a text comprehension activity regarding an economic theory, and its application to a case study, followed by two open-ended questions to be answered on a shared computer. Depending on the experimental condition, participants completed the task either with or without AI support; in the AI-assisted condition, dyads were allowed to use ChatGPT to support their responses.

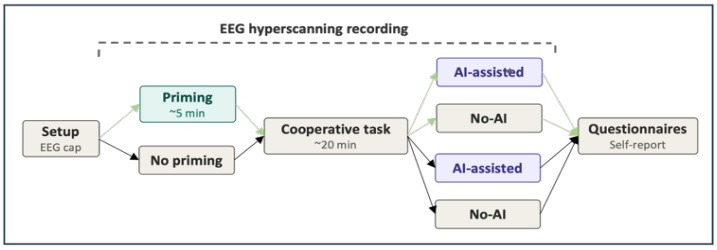


Figure 1. Experimental procedure and protocol

Neural activity from both participants was recorded simultaneously using EEG hyperscanning throughout task execution. Finally, the participants completed a questionnaire for objective and subjective measures. Figure 2 illustrates the experimental set-up. The two participants, each wearing an EEG cap, sat side by side and interacted with one another and with a shared computer to complete the experimental task. At the beginning of the experiment, the shared PC sent a Transistor-Transistor Logic (TTL) pulse, which was distributed to each EEG recording PC by means of an EEG Synchronisation Box [18], to establish a common starting point.

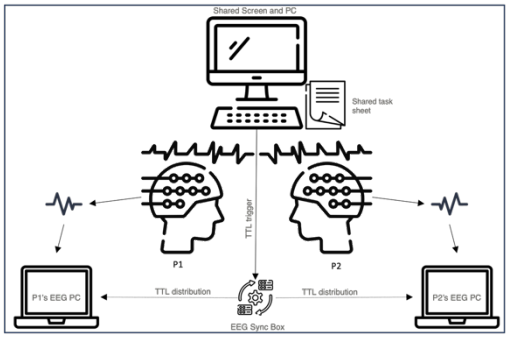


Figure 2. Hyperscanning and experimental set-up.

Icons credits: Freepik (EEG, shared computer, sync, paper sheet), The Icon Tree (waves), Good Ware (laptop) on Flaticon.com.

2.4. Measures

Inter-brain synchronization was assessed via EEG hyperscanning across delta, theta, alpha, and beta frequency bands using Phase Lag Index (PLI) measures [19]. Graph-theoretical indices were derived for each inter-brain network: Clustering Coefficient (CC), reflecting local network organization; Characteristic Path Length (CPL), capturing average node-to-node distance; Global Efficiency (GE) and Local Efficiency (LE), indexing communication efficiency at global and local levels respectively; Modularity (M), quantifying network subdivision into distinct clusters; and Strength (S), representing the sum of connection weights per node [20].

Perceived learning was measured using an adapted version of the Feeling of Learning (FOL) scale (4 items, 5-point Likert) [21], with two additional items assessing task comprehension. Team cooperation (TC) was measured with a 4-item scale adapted from [22] on a 7-point Likert scale. Product identification was assessed using a modified Inclusion of Other in the Self scale (IOS) [11], in which the 'other' was replaced with the

team's final product (7-point pictorial scale). Objective learning outcomes were assessed through a 10-item multiple-choice quiz based on the experimental task content.

2.5. Statistical analysis

To assess the effects of AI use and emotional priming on neural coupling, repeated-measures ANOVAs were conducted for each PLI-derived network metric (CC, CPL, GE, LE, M, S), with AI and Priming as between-subjects factors and Frequency Band as a within-subject factor. Greenhouse–Geisser corrections were applied where sphericity was violated.

For subjective measures (FOL, IOS, TC), the dyad was used as the unit of analysis rather than the individual, given the non-independent nature of data collected from partners who shared the same experimental interaction. A difference score (Δ) was therefore computed for each variable by subtracting one partner's score from the other's within each dyad (Partner A - Partner B), yielding a single value per pair that captured within-dyad discrepancy. Following Kenny, Kashy, and Cook [23], Δ should be interpreted as an index of within-dyad discrepancy, and not a directional measure: its magnitude reflects how much the two partners' scores diverged, while its sign merely reflects the arbitrary order of subtraction and carries no substantive meaning. A $|\Delta|$ of 2, for example, reflects the same discrepancy whether Partner A scored 2 points above or below Partner B. Accordingly, the sign of Δ should not be interpreted directionally when the group mean is described. Additionally, IoS and FoL were measured on different scales (IOS: 1–7; FOL: 1–5); while difference scores within each measure are internally consistent, their magnitudes should not be compared across the two scales. A series of 2×2 factorial ANOVAs (AI×Priming) was then conducted on these difference scores. Greenhouse–Geisser corrections were applied where sphericity was violated.

Objective learning performance was analyzed at the individual level using a non-parametric Kruskal-Wallis test, given a significant violation of normality.

3. Results

Regarding the effects of AI × Priming × Frequency Band on any of the PLI-derived network metrics, no significant effects emerged. Specifically, the interaction was not significant for CC, ($F(2.09, 77.15)=0.67$, $p=.52$, $\eta p^2=.018$), for CPL ($F(2.57, 95.08)=.76$, $p=.50$, $\eta p^2=.02$), for GE ($F(2.17, 80.24)=0.17$, $p=.86$, $\eta p^2=.005$), for LE ($F(2.58, 95.36)=.77$, $p=.50$, $\eta p^2=.02$), for M ($F(3.32, 122.92)=1.43$, $p=.24$, $\eta p^2=.037$), and for S ($F(2.62, 96.90)=.40$, $p=.72$, $\eta p^2=.011$).

Table 1. Results of repeated-measures ANOVA for the AI × Priming × Frequency Band interaction across PLI-derived network metrics (CC, CPL, GE, LE, M, S). Following sphericity violations, Greenhouse–Geisser correction was applied to the p-values of CC, CPL, GE, LE, and S.

Metric	Effect	F	p	ηp^2
CC	AI x Priming x Band	0.670	0.521	0.018
CPL	AI x Priming x Band	0.763	0.450	0.020
GE	AI x Priming x Band	0.173	0.858	0.005

LE	AI x Priming x Band	0.768	0.500	0.020
M	AI x Priming x Band	1.426	0.240	0.037
S	AI x Priming x Band	0.403	0.724	0.011

No significant main effects emerged for either AI use or emotional priming across all subjective variables. However, a consistent and significant AI×Priming interaction was found for two subjective outcomes.

Table 2. Results of factorial ANOVAs (AI × Priming interaction) across subjective dependent variables.

Variable	Effect	F	p	ηp^2
ΔIoS	AI × Priming	6.75	.013	.126
ΔFOL	AI × Priming	11.86	.001	.223
ΔTC	AI × Priming	1.05	.311	.025

For ΔIoS (inclusion of the product in the self, product identification), neither AI use ($F(1,40)=3.34$, $p=.075$, $\eta^2=.063$) nor priming ($F(1,40)=3.29$, $p=.077$, $\eta^2=.063$) reached significance as main effects, yet their interaction was significant ($F(1,40)=6.75$, $p=.013$, $\eta^2=.126$). Descriptively, the AI×Priming group had a small difference in scores between participants in IoS ($M=-0.69$, $SD=2.32$), while the AI × No Priming group had a larger distance within the dyads ($M=2.00$, $SD=2.63$). In the no-AI conditions, the pattern reversed: the No AI×Priming group showed a small scoring difference within the dyads ($M=-0.22$, $SD=1.09$), whereas the No AI×No Priming group showed a larger delta ($M=-0.70$, $SD=1.06$). Post-hoc comparisons confirmed that AI use yielded higher ΔIoS delta scores specifically in the absence of priming (AI No Priming vs. No AI No Priming: mean difference = 2.70, $p=.016$), while the AI×Priming condition had significantly lower delta scores than the AI× No Priming condition (mean difference$=-2.69$, $p=.009$).

A significant AI×Priming interaction emerged for ΔFoL (Feeling of Learning) ($F(1,40) = 11.86$, $p = .001$, $\eta^2 =.223$), again with non-significant main effects of AI ($F(1,40)= 0.10$, $p=.754$, $\eta^2=.002$) and priming ($F(1,40)=1.17$, $p=.285$, $\eta^2=.022$). The AI × Priming group showed a mean difference within dyads of ($M=-0.35$, $SD=0.82$), while the AI × No Priming group showed the lowest ΔFoL ($M=0.17$, $SD=0.69$). In the No AI condition, the presence of priming showed a mean difference within dyads of ($M=0.33$, $SD=0.53$), the No AI × No Priming condition showed the largest ΔFoL ($M=-0.65$, $SD=0.74$). Post-hoc comparison indicates that in the No AI Condition, priming significantly reduced ΔFoL when compared to the no priming condition (mean difference = 0.98, $p=.023$). However, in the AI condition, a non-significant difference was found between the AI × Priming and the AI × No Priming conditions.

No significant effects were found for team cooperation (all $Fs < 1.59$, all $ps > .216$). Objective learning performance was uniformly high across all four conditions (overall $M=8.52$, $SD=1.36$), with scores clustering near the ceiling of the scale. No significant effect emerged for AI use ($H(1)=3.01$, $p=.083$, $\eta^2=.023$) nor for emotional priming ($H(1)=.016$, $p=.900$, $\eta^2=.000$).

4. Discussion

The absence of significant effects on inter-brain synchronization may reflect insufficient statistical power, given the limited sample size (~10 dyads per cell), as well as heterogeneous use of ChatGPT across dyads in the AI condition, which may have introduced unsystematic variability. These results nonetheless suggest that AI support does not necessarily impair neural coupling during collaboration, offering a more cautious interpretation of its effects than recent literature implies [5].

At the subjective level, the significant AI×Priming interactions for ΔIoS and ΔFOL reveal that priming boosted the convergence of product identification and perceived learning scores only when AI was absent, and AI increased within-dyad discrepancy in product identification only without priming. The priming condition alone was able, therefore, to make the dyad converge on similar subjective experiences of perceived learning and product identification. This pattern suggests that emotional priming may help reduce relational and cognitive uncertainty within the dyad [8,12].

The absence of effects on team cooperation and objective learning performance, the latter likely attenuated by a ceiling effect, is consistent with the illusion of learning literature: AI assistance may sustain surface-level performance without affecting deeper collaborative processing [4].

5. Conclusion

This study provides preliminary evidence that the interplay between AI use and emotional priming in collaborative learning is more complex than a simple additive model would predict. Rather than reinforcing each other, the two manipulations appear to operate on overlapping mechanisms, with implications for the design of AI-augmented learning environments: attending to the relational and emotional context is paramount as it has strong effects on learners' subjective experience. Several limitations should be acknowledged. The small sample size constrains the generalizability of findings and likely reduced statistical power for neural analyses. A ceiling effect on objective learning performance further limits the sensitivity of the measures. Future research should replicate these findings with larger samples and more demanding tasks, systematically monitor AI usage behavior within dyads, and include delayed retention measures to assess whether the observed subjective effects translate into durable learning differences. Extending this paradigm to naturalistic educational settings and exploring individual moderators (e.g. prior attitudes toward AI, emotional regulation, …) would further clarify the boundary conditions under which AI support enhances or disrupts collaborative learning.

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