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Neural signatures of STEM learning and interest in youth

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A R T I C L E I N F O

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A B S T R A C T

Understanding the neural mechanisms underlying interest in Science, Technology, Engineering, and Mathematics (STEM) and learning is crucial for fostering creativity and problem-solving skills, key drivers of technological and educational growth. Traditional methods of assessing STEM interest are often limited by cultural and human biases, highlighting the need for more objective approaches. This study utilizes Electroencephalography (EEG) to identify neural markers linked to STEM interest and course-specific cognitive demands in young learners enrolled in a specialized private STEM program, including courses such as 3D Design, Programming, and Robotics. Specifically, Power Spectral Density (PSD) and Functional Connectivity (FC) were analyzed within theta, alpha, and beta frequency bands, which are associated with performance monitoring, creativity, and executive functioning. The findings reveal a significant negative correlation between STEM interest and brain activity in the frontal (F3, F4) and prefrontal regions (FP1, FP2) in the theta ($r = -0.44$, $p = 0.2732$; $r = -0.77$, $p = 0.0268$; $r = -0.84$, $p = 0.0096$; $r = -0.62$, $p = 0.0990$) and beta bands ($r = 0.43$, $p = 0.2843$; $r = -0.56$, $p = 0.1524$; $r = -0.83$, $p = 0.0110$; $r = -0.75$, $p = 0.0328$), indicating engagement in working memory and executive processing. Additionally, course-specific brain activity patterns reveal that Robotics is characterized by denser long-range FC networks, associated with problem-solving, while 3D Design exhibits more sparse yet efficient networks, indicative of creative ideation. A consistent beta band FC pattern between central and left-frontal areas reflects cognitive synchronicity and lateralization. These findings contribute to understanding the neurocognitive markers involved in STEM interest and learning, offering a framework for assessing and fostering engagement in STEM education through objective, neuroscience-based approaches.

1. Introduction

Advancing Science, Technology, Engineering, and Mathematics (STEM) education is pivotal for nurturing creativity and critical thinking skills, extending beyond mere career preparation to lay the groundwork for innovative problem-solvers (Kier et al., 2013) while also serving as a driving force in fostering a multifaceted approach to learning (Johnson et al., 2021). Despite the widespread use of psychometric instruments to measure STEM interest, several challenges highlight the need for a more comprehensive approach to both inspiring and assessing engagement in these fields, including (1) the lack of real-time insights into learning processes (Mayer, 2016; Cho et al., 2024), (2) an emphasis on learning outcomes rather than the cognitive processes involved (Li, Schoenfeld, et al., 2020), (3) cultural differences that influence response biases (Reynolds et al., 2021), and (4) human bias in self-assessment questionnaires (Mau et al., 2019), including issues related to honesty, introspection, and accuracy (Kunasegaran et al., 2023). Recognizing these challenges, fostering STEM interest from an early age becomes essential not only for addressing the limitations of traditional assessment methods but also for nurturing creative thinking and problem-solving abilities, ultimately preparing children to navigate the complexities of the modern world (van Tuijl & van der Molen, 2015; Wagner et al., 2019).

Current vocational interest measures rely on psychometric tests and personality assessments based on established models and theories (Tyler-Wood et al., 2010). Among these, Holland's vocational model is widely recognized as the foundation for much of the research on vocational interest to date (Mikolajczak et al., 2010), which links

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occupational themes to personality typologies, suggesting that vocational interests are an expression of personality (Holland, 2008). In the last decades, significant advances in quantitative biometrics, particularly Electroencephalography (EEG) (Chi et al., 2005; Johannisson, 2016), have demonstrated its potential to predict personality traits, including those from the 16 Personality Factor theory (Maksimenko et al., 2018) and the Big Five personality traits (Li, Hu, et al., 2020). These findings position EEG as a powerful, quantitative tool for exploring personality traits (Saffiera et al., 2020), offering the potential for its application in the study of vocational interests.

EEG records brain waves from the scalp, standing out for its high temporal resolution and millisecond precision (Lozoya-Santos et al., 2022); hence, being able to identify cognitive states such as mental fatigue (Ramírez-Moreno, Carrillo-Tijerina, et al., 2021) and emotion (Blanco-Ríos et al., 2024) through Event-Related Potentials (ERP) (Pidgeon et al., 2016). Spectral analysis of the EEG signal traces significant similarities to various types of cognition, in which the spectral content is divided into frequency bands: Delta (δ) with deep sleep (1–4 Hz), theta (θ) with interruptions of consciousness (4–8 Hz), alpha (α) with relaxation and general attention (8–13 Hz), beta (β) with active thinking (13–30 Hz), and gamma (γ) with perception and high-order cognition (30–100 Hz) (Kropotov, 2009; Ramírez-Moreno, Díaz-Padilla, et al., 2021). Other authors associate α with consciousness and working memory, and β with motor behavior (Damasio, 2005). Some other authors, such as Klimesch et al. (1994), also divide alpha by lower alpha (7.5–10 Hz) and upper alpha (10–12.5 Hz), in which upper alpha is related to difficulty in semantic processing, and so displays a downward trend with alpha power (Klimesch et al., 1994).

The current study only uses three frequency bands for analysis: θ, α, and β; as θ is related to working memory and performance monitoring (Başar et al., 1999; Cohen, 2017; Klimesch, 1999, 2012; Moretti et al., 2009; Nigbur et al., 2011) and selective attention (Başar-Eroglu et al., 1992; Klimesch et al., 1994); α to creativity (Beaty et al., 2019; Erickson et al., 2018; Fink et al., 2008; Perchtold-Stefan et al., 2023; Stevens & Zabelina, 2019; Volf & Tarasova, 2010), spatial attention (Cohen, 2017; Klimesch et al., 1993) and working memory (Başar, 1999; Başar et al., 1997; Klimesch, 2012); and β to active thinking (Damian-Chavez et al., 2021; Erickson et al., 2018; Klimesch, 2012).

EEG has been a widely used tool in order to comprehend human creativity: Perchtold-Stefan et al. (2023) explored malevolent creativity using a novel psychometric test, which was correlated with strong alpha oscillations on frontal and temporal cortical sites; these sites have also been involved in conventional creative ideation (Beaty et al., 2019). Other studies search for creativity in arts, such as dancers using Alpha/Theta neurofeedback for creativity (Alpha) and stress (Theta) in order to improve their expressive creativity on a classical divergent thinking test (Gruzelier et al., 2014). Studies also analyze creativity in musical improvisation, Adhikari et al. (2016) found reduced alpha power over all electrode clusters and reduced beta power over frontal and parietal clusters, in line with other authors (Stevens & Zabelina, 2019) and focused on frontal and right-hemisphere activity (Rosen et al., 2020); conversely, Sasaki et al. (2019) state increases in theta, alpha, and upper beta at prefrontal and perceptual motor cortical (FP1, FP2, Pz). Creativity and thinking skills seem to have an inverse relationship, as Lopata et al. (2017); Fink et al. (2007) showed higher frontal alpha synchronization during creative ideation of ideas, while intelligence task elicited less alpha synchronization; this goes in line with past studies that showed that alpha power is more significant for an uncommon object than common uses (Stevens & Zabelina, 2020); thus lower alpha power would show more rational thinking than creative thinking.

While EEG stands out for its high temporal resolution, it falls short in spatial resolution for pinpointing particular anatomical structures. In neuroscientific research, an additional quantitative tool frequently employed with an opposite trend is Functional Magnetic Resonance Imaging (fMRI); this method assesses alterations in blood flow to provide complementary insights (Lozoya-Santos et al., 2022). Various studies employ fMRI to identify anatomical brain structures related to cognitive states (Pidgeon et al., 2016), as Klimesch (2012) found cognitive demand at the Inferior Frontal Gyrus (IFG), Temporal Pole (TP), and Frontopolar Cortex (FPC), which are also related to STEM learning process (Delahunty, 2023). In creative thinking, various regions have been identified, such as the Middle Temporal Gyrus (MTG) for identifying usefulness in novel designs, Medial Temporal Lobe (MTL) for new association formation in creativity, and hence novelty and usefulness of creative ideas (Ren et al., 2020); in addition to FPC regions, implicated in the access, selection, retrieval, and integration of concepts not commonly associated (Abraham et al., 2012); and also Medial Premotor Cortex (MPC) and Default Mode Network (DMN) (Bashwiner et al., 2020).

EEG and fMRI both assess activation patterns in specific brain regions. Nevertheless, signal processing algorithms can be employed to analyze the signals and determine the synchronization or desynchronization rate between two designated brain zones; this process helps map a connectivity pattern, forming either a unidirectional or bidirectional graph based on the calculated metric (Sporns, 2010). Functional Connectivity (FC) quantifies the statistical synchrony between two specified anatomical brain regions by analyzing their respective activation patterns; this measurement indicates whether there are influences between the two given brain regions (Cruz-Garza et al., 2020). Many studies use FC to give more elaborated insights regarding control, as it is associated with working memory and creativity (Paz-Baruch & Maor, 2023), developing scientific talent (Zhang et al., 2020), and even in Alzheimer's disease studies (Sankari et al., 2011). Creativity, on the other side, has been related to increased FC in the right hemisphere (Dolan et al., 2018), right sensorimotor (Balters et al., 2023), between premotor and prefrontal areas (Pinho et al., 2014), between Anterior Cingulate Cortex (ACC) and Dorsolateral Prefrontal Cortex (DLPFC) (Liang & Liu, 2018; Yao et al., 2017), and between frontal and temporal lobes (Liu et al., 2017).

Another critical cognitive metric is learning, a fundamental aspect that has been measured using both EEG and fMRI. These techniques aid in the identification of regions associated with learning, enhancing our understanding of brain functioning and providing a quantitative evaluation of performance (Morales-Menendez et al., 2021). Different authors have investigated this cognitive feature using EEG, which reports a decrease in β and γ during their learning process (Gutiérrez & Ramírez-Moreno, 2015), decrease in frontal channels during successful memory encoding in α (Gutierrez et al., 2015), as well as an association between α and β bands at frontal regions and STEM interest (Martínez et al., 2021). EEG has also been used to measure more abstract metrics, negatively associating learning with low attention (Ghali et al., 2019) and passive learning (Qu et al., 2018). fMRI, on the other hand, identified critical areas on top arithmetic performers, such as low activation of left angular gyrus (P5, P3) (Menon et al., 2000) and high activation at parietal and frontal cortices (Grabner et al., 2007). Moreover, a comprehensive fMRI study between novice and experienced engineering students was conducted by Cetron et al. (2019), in which the occipitotemporal cortex was a critical region involved in action representations; furthermore, Cetron et al. (2020) showed that novice engineers had premotor representations (PMC) at frontal and parietal regions, while experienced engineers had primary motor (M1) representations at ventral PFC and parietal regions.

The current study examines PSD and FC to identify neural markers linked to STEM interest and analyze how brain activity patterns vary across disciplines, using a specialized private STEM program to address the country's limited support for STEM education (Rojas & Segura, 2020). Specifically, the research questions of this study are as follows:

(1) How do brain activity patterns differ across STEM disciplines in young learners, and what do these differences reveal about course-specific cognition demands?

(2) What are the distinct neural markers that most strongly correlate with changes in STEM interest, and how do these correlations vary by type of STEM course?

Section 2 describes the participants (Section 2.1), the signal acquisition device used, the experimental design (Section 2.2), the STEM-CIS psychometric test used (Section 2.3), in addition to also describing the EEG signal pre-processing (Section 2.5), signal processing (Section 2.6) to extract PSD (Section 2.6.2) and FC (Section 2.6.1) features, and how the statistical analysis was performed (Section 2.7). Section 3 used the EEG-extracted features to contrast each course's unique brain activation patterns (Section 3.1), examine their correlation with the STEM-CIS psychometric test (Section 3.2), and perform a linear regression analysis with the most correlated features (Section 3.3). The most critical findings are then discussed extensively in Section 4, where Section 4.1 addresses research question (1) and Section 4.2 addresses research question (2).

2. Materials and methods

2.1. Participants

Participants consisted of 13 children (M $=$ 11, F $=$ 2), with ages ranging from 6 to 15 years ($\mu = 11$, $\sigma = 2$). All participants were enrolled in three sequential courses on 3D Design, Programming, and Robotics offered by MachineCare Education (MCE), an extracurricular educational company based in Monterrey, Mexico. Participants and their parents or legal guardians signed an informed assent and consent form, respectively, in accordance with the 1964 Helsinki Declaration. Both children and adults were informed about the study, their rights, risks, and benefits, and remained in close contact with the research team.

For the inclusion criteria, they had to be current students from MCE; in addition, they should have taken a course on all the subjects for at least one period (3 months) before the test. Finally, they would agree to attend face-to-face sessions and have signed the respective assent and consent form for participating. Regarding exclusion criteria, students could not participate if they manifested being under medical treatment or having a psychiatric diagnosis. In addition, they were not considered if they were left-handed, suffered from cardiac illness, or consumed foods or beverages with high sugar levels or caffeine at least 12 h before the study.

2.2. Signal acquisition

The EEG signals were recorded through LiveAmp 8 (Brain Products GmbH, Gilching, Germany), a mobile scalp EEG that includes eight active gel electrodes arranged according to the international 10–20 system: Two at the prefrontal region (Fp1, Fp2) (Mu et al., 2017), two at the frontal region (F3, F4), two at the central region (C3, C4), one at midline parietal (Pz) and one for electrical reference at midline central (Cz). EEG data was measured in microvolts (μV) at a sampling frequency of 250 Hz. BrainVision Recorder (Brain Products GmbH, Gilching, Germany) was used to monitor electrode impedance levels, with values $<$20 kΩ, indicated by a green electrode color. Gel was gradually applied to each electrode until all electrodes turned green, which showed that the right amount of gel was applied, and thus the recording could start. LabStreamingLayer (LSL) LiveAmp (Brain Products GmbH, Gilching, Germany) was used to transmit EEG scalp data to a custom Python script file based on BrainFlow, which is a modern library with various functions to acquire, parse, and analyze EEG data, as well as other types of data from multiple biosensors such as Electromyography (EMG), Electrocardiography (ECG).

2.3. Experimental protocol

The experimental protocol is described graphically in Fig. 1. Recordings were taken one at a time at the physical MCE center, where each student participated in self-paced, online personalized classes guided by an instructor following a structured curriculum. Students engaged in project-based learning through an interactive platform, actively participating in problem-solving, direct questioning, and hands-on challenges. This resulted in a structured and dynamic learning experience across participants.

Courses consist of three topics: 3D Design, Programming, and Robotics. In each course, students learn according to their level of expertise, hence being challenged through a course that suits their capabilities. Table 1 describes the software employed during each course, the most related Psychology Experiment Building Language (PEBL) based on (Mueller & Piper, 2014), and the cognitive processes involved. Even though all STEM courses require the cognitive process of problem-solving, each distinct course develops distinct types of cognition, such as spatial visualization for 3D Design, strategic thinking for Programming, and executive control for Robotics.

In 3D Design, students learn to understand a three-dimensional plane with their systems of coordinates XYZ, design objects and bodies of revolutions, in addition to extrusions and other deformations, thus developing their spatial vision; in Programming, they learn programming logic through a high-level block-based visual programming language, which requires them to divide and structure a problem on a step-by-step basis, thus improving their planning, order and problem-solving abilities; in Robotics, they learn a real-life application of the knowledge acquired from both 3D Design and Programming courses, as they are faced with problems such as building a LEGO® MINDSTORMS® robot, and further writing a program in order for it to operate autonomously, thus learning abilities such as math, physics, programming, logic, planning, design.

For the EEG recording, a calibration phase was first recorded, which consisted of placing the equipment and asking the student to be in a relaxed state for 1-min Eyes Open (EO) and 1-min Eyes Closed (EC) before each course. Afterward, the student started the course, and the recording continued until he/she finished it. From the collected course data, the first 5 min (min) of each course were removed. The following 15 min were extracted, yielding a signal length of 225,000 samples (250 samples/s $\times$60 seconds/min $\times$15 minutes/course) per channel, covering from $t = 5$ min to $t = 20$ min. This period likely represents students who are warmed up and engaged in the course, reflecting an active learning state (Freeman et al., 2014; Qu et al., 2018). The data was cut this way because the length of the courses varied depending on the student's level of experience: The most experienced students had courses lasting over an hour, while inexperienced students had courses lasting twenty minutes at most. Due to device malfunctioning and students opting out of the study, only data from 8 students was used in the current study, as they had a complete course on each topic and their respective calibration phase.

2.4. Assessment tools

Vocational interest was measured using an electronic, adapted version of the engineering subscale of the STEM-CIS before and after each class. STEM-CIS is a psychometric questionnaire consisting of 11 items measuring interest in STEM subjects (Kier et al., 2014), and it has been to middle school and elementary school children (Babarović, 2021; Grimmon et al., 2020). Two adaptations were made. First, the words “engineering” and “engineer” in each item were substituted for the subfields being studied (e.g., “I can do well in activities that involve engineering” modified as “I can do well in activities that involve 3D Design/Programming/Robotics”). Second, the questionnaire was translated into Spanish, as there was no Spanish version of this instrument published at the time of the experiments. Reliability and validity

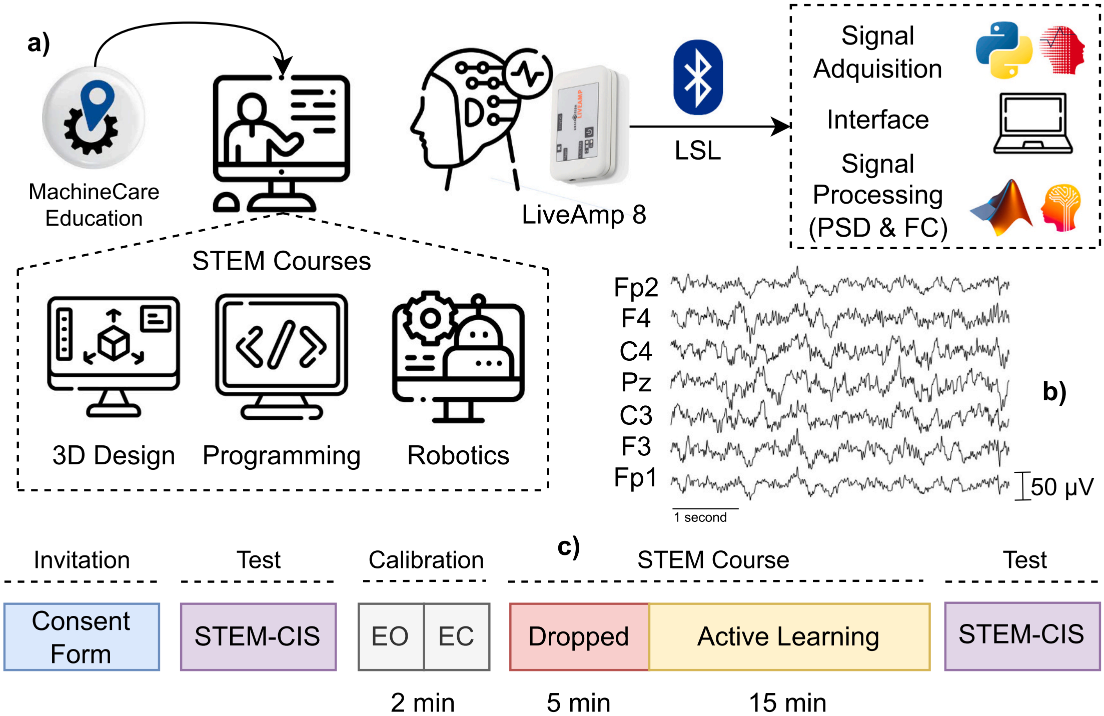

Fig. 1. Graphical representation of the experimental protocol: a) Courses are taken by MCE students online, provided by MachineCare Education in three flavors: 3D Design, Programming, and Robotics; a LiveAmp 8 and LSL Bluetooth protocol were used in order to acquire the EEG data using a laptop as interface, based on a Python script and various Brain Products GmbH, and further processed using both EEGLab from Matlab and Brainflow from Python, b) EEG pre-processed data from the seven channels (Fp1, F3, C3, Pz, C4, F4, Fp2), c) Schematic diagram of the experimental setup for a given recording, starting from invitation and consent form, following an initial STEM-CIS test, EEG calibration phase using Eyes Open and Eyes Closed, the actual course learning in which the first 5 min were dropped in order to acquire only data in which students were actively engaged, and finally a final STEM-CIS test for a given course.

Table 1
Software used in each STEM course, related Psychology Experiment Building Language (PEBL), and the cognitive processes involved at each task, based on (Cho et al., 2024; Mueller & Piper, 2014).

STEM Course	Software Used	Related PEBL Behavioral Test	Cognitive Process
3D Design	• Tinkercad • Makers Empire • UltiMaker Cura	• Manikin Task (Carter & Woldstad, 1985) • Mental Rotation Task (Berteau-Pavy et al., 2011) • Device Mimicry (Mueller, 2010)	• Planning • Spatial visualization • Problem-solving
Programming	• Tynker Pro • MakeCode Arcade • Arduino	• Tower of London (Anderson et al., 2012) • Digit Span (Croschere et al., 2012) • Item/Order Task (Perez et al., 1987)	• Sequential processing • Strategic thinking • Problem-solving
Robotics	• Abilix Krypton • LEGO® Mindstorms • LEGO® Education	• Tower of London (Anderson et al., 2012) • Berg's Wisconsin Card Sorting Test (Berg, 1948) • Connections Test (Salthouse et al., 2000)	• Planning • Executive control • Problem-solving

analyses indicated adequate results except for the last item ("I know someone in my family who is a 3D Designer/Programmer/Robotics professional"), which was excluded from the subsequent evaluation.

The questionnaire consisted of a five-point Likert scale response format, from strongly disagree to strongly agree (0 to 4, where 0 represents strongly disagree and 4 represents strongly agree). Due to students having taken at least one course for at least one period prior to the experiment, they exhibited a high interest in STEM subjects before ($\bar{x}_{Design} = 3.20$, $\bar{x}_{Programming} = 3.06$, $\bar{x}_{Robotics} = 3.15$) and after the course ($\bar{x}_{Design} = 3.13$, $\bar{x}_{Programming} = 3.11$, $\bar{x}_{Robotics} = 3.40$). Because of that, the change in STEM interest is evaluated (ΔI) and further correlated to biometric EEG signals. Therefore, the difference in STEM interest for each participant in each course is then displayed in Table 2; the change in STEM interest is calculated by subtracting the mean STEM interest at their psychometric evaluation after the course, with their respective mean STEM interest before the course.

Through an ANOVA analysis, it was determined that differences in STEM interest were not influenced by age ($F(1,31) = 0$, $p = 0.984$), years of learning at MCE (student experience) ($F(1, 31) = 0$, $p = 0.998$), gender ($F(1, 31) = 0.027$, $p = 0.872$), and level of schooling (e.g., grades 1 to 12) ($F(1, 31) = 0.122$, $p = 0.729$), with the type of course being the only close to being statistically significant ($F(2,31) = 2.216$, $p = 0.125$).

Table 2
Participant's change in STEM interest (ΔI) before and after the course, based on an adapted version of the STEM-CIS psychometric evaluation for the given STEM subfields (3D Design, Programming, Robotics). There is higher total interest in the Robotics course (1.7) when contrasted with 3D Design (−0.5), while Programming is in the middle of interest (0.7), with some students showing high values of both positive and negative interest.

No.	3D Design	Programming	Robotics	$\bar{x}$
01	−0.1	0.1	0.6	0.20
03	−0.6	−0.1	−0.5	−0.40
04	−0.1	0.3	0	0.06
06	−0.1	−0.9	−0.3	−0.43
09	0.6	0.5	0.4	0.50
10	−0.2	−0.1	0.5	0.06
11	0.4	0.6	1.3	0.76
13	−0.4	0.3	−0.3	−0.13
Σ	−0.5	0.7	1.7	0.62

2.5. Signal pre-processing

The EEG signal data pre-processing pipeline consisted of first using the standardized pre-processing (PREP) pipeline (Bigdely-Shamlo et al., 2015) from the EEGLAB package, which detrends using high-pass of 1 Hz, removes line noise by using multiples of 60 Hz, and also provides a robust average reference, which iteratively identifies bad channels on a given frame in order to interpolate them, and thus provide an average reference not affected by artifacts; all channels were used in order to perform this robust referencing. Furthermore, a Finite Impulse Response (FIR) Butterworth 4^{th} order bandpass filter $0.1-50$ Hz was applied; later, data was cleaned using the Artifact Subspace Reconstruction (ASR) algorithm (Mullen et al., 2013) ($\kappa = 20$), which corrected bad periods characterized by short-time high-amplitude artifacts. Additionally, a linear filter FIR transition band (0.25–0.75 Hz) removed channel drift, and finally, via the ICLabel plugin, an Independent Component Analysis (ICA) was performed in order to remove muscle, heart, eye, and noise artifacts (keeping components that were >70 % brain), in the pursuit of isolating only brain signals.

2.6. Signal processing

2.6.1. Functional connectivity

Using EEG coherence, an association pattern between distinct time series can be created (Friston et al., 1993), hence not only measuring the brain activity of a single region but also the connection between two regions. This brain connectivity metric involves transient interactions among various brain regions, including synchronizations and desynchronizations (Alanis-Espinosa & Gutiérrez, 2020).

After the signal for each channel was pre-processed, frequency bands were extracted using a 6^{th} order Butterworth band-pass FIR filter on a window size of 6 s (Yuvaraj et al., 2016). As it was previously established in the introduction in Section 1, the only three frequency bands in which we were interested are the following: θ (4–8 Hz), α (8–13 Hz), β (13–30 Hz). Afterward, pairwise combinations were created in order to establish unidirectional FC metrics between a set of channels at a given frequency band; the number of combinations is given by Eq. 1, where n is the number of channels ($n = 7$), and $r = 2$ due to unidirectional combinations without replacement, thus having a total of 21 pairs for each frequency band, which give us a total of 63 FC features.

$$C(n, r) = \frac{n!}{(n-r)!r!} \tag{1}$$

FC was calculated using the coherence metric (Yuvaraj et al., 2016), which was computed as in Eq. 2. Where $C_{S_1S_2}$ is the cross-covariance of S_1 and S_2, $C_{S_1S_1}$ is the auto-covariance of S_1, and $C_{S_2S_2}$ is the auto-covariance of S_2, each covariance is calculated at a specific frequency f; thus, each pair of signals for a given set of channels would have a unique correlation score at frequency band f. The EEG coherence was calculated by applying the aforementioned band-pass FIR filter, then using the *Coherence* function from the Scipy package in Python for a given set of channels at a specific frequency band, further averaging coherence for all the windows.

$$\mathrm{COH}_{S_1S_2}(f) = \frac{|C_{S_1S_2}(f)|^2}{C_{S_1S_1}(f) \cdot C_{S_2S_2}(f)} \tag{2}$$

In order to compare and average across subjects, each COH coefficient was normalized according to their EO's COH (Ramírez-Moreno, Carrillo-Tijerina, et al., 2021); thus, the normalized COH (COH_N) at a given frequency band was calculated using the course COH (COH_C) and the EO COH (COH_{EO}), as in Eq. 3.

$$\mathrm{COH}_N(f) = \frac{\mathrm{COH}_C(f) - \overline{\mathrm{COH}}_{EO}(f)}{\overline{\mathrm{COH}}_{EO}(f)} \tag{3}$$

2.6.2. Power spectral density

Power Spectral Density (PSD) represents the average frequency content of EEG activity based on the Fast Fourier Transform (FFT) algorithm (Forbes et al., 2022). It was computed using *BrainFlow*'s PSD calculation using the Welch method (Zhao & He, 2013) on the pre-processed data at one-second windows with half-a-second overlap, in addition to a Blackman-Harris window function. PSD was then divided into power for each frequency band defined in Section 2.6.1, referred to as Band Power (BP). BP for each frequency band was normalized similarly to in COH; therefore, the normalized BP for each course at a specific frequency band is calculated as in Eq. 4.

$$\mathrm{BP}_N(f) = \frac{\mathrm{BP}_C(f) - \overline{\mathrm{BP}}_{EO}(f)}{\overline{\mathrm{BP}}_{EO}(f)} \tag{4}$$

2.7. Statistical analysis

Statistical analysis was done using R. One-tailed paired t-tests were performed between calibration EO and course C pre-processed signals, as well as between courses' comparisons using their normalized values; this was done for both FC and PSD with the given set of channels or channel pairs depending on the modality. A one-tailed t-test tests the null hypothesis for one tail of the distribution, either the lower or upper tail, in order to compare whether a sample is smaller or larger than the other. Since the tested samples (EO and C) are related, a paired t-test have to be used (Ahrens et al., 2014). In addition, due to the use of pre-processed data instead of the normalized data, a Shapiro-Wilk test for normality was also performed on both EO and C signals. The reported p-values were adjusted with the Bonferroni correction, which controls the increase in Type I errors when conducting multiple comparisons (Boslaugh, 2012).

Given the small sample size, statistical significance was achieved by considering the p-value and the effect size given by Cohen's d. This is a standardized effect size for measuring the difference between two group means (Hsieh et al., 2022; Lakens, 2013); the effect size could be small ($d = 0.2$), medium ($d = 0.5$), or large ($d = 0.8$) (Cohen, 1988). It was calculated based on Eq. 5, where $\overline{x_C}$ and $\overline{x_{EO}}$ represent the average value for course and eyes open data, respectively, while s_C and s_{EO} represent their standard deviation.

$$d = \frac{\overline{x_C} - \overline{x_{EO}}}{\sqrt{\frac{s_C^2 + s_{EO}^2}{2}}} \tag{5}$$

A sensitivity analysis was performed in order to calculate the required effect size d to achieve a power of 80 % ($1 - \beta = 0.80$) (Ahrens et al., 2014), where β is the probability of committing a Type II error (Boslaugh, 2012). Given the desired power, the sample size per group ($n = 8$) and a significance level or probability of committing a Type I error ($\alpha = 0.05$), G*Power (3.1.9.7) (Faul et al., 2007) estimated an effect size of 0.98 ($|d| = 0.98$); thus, each paired t-test comparison must have $p < 0.05$ and $|d| > 0.98$ in order to be considered significant.

In addition, Pearson's correlation coefficient (r) was also used to quantify the linear relationship between PSD and FC measurements with the change in STEM interest score (Candela-Leal et al., 2022). The metric's domain is ($-1 \geq r \geq 1$), in which a high correlation value (-1 or 1) would indicate that two series of data are linearly correlated; for instance, whether the correlation is positive or negative would indicate a positive or negative correlation, respectively. The metric is calculated as in Eq. 6, in which x represents a series of data (source features such as PSD or FC) and y is another series of data (target feature such as ΔI).

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}} \tag{6}$$

3. Results

3.1. PSD and FC analysis across STEM courses

Based on the normalized BP, the topoplots in Fig. 2 were created, which represent the respective BP value across subjects allocated within their XY position at the head, this taking into account standard names of the electrodes and their respective position in θ and ϕ coordinates, according to biosemi montage using *MNE* library from Python (Gramfort, 2013). Activation color bars were created for each frequency band in order to assess the course's differences and hence characterize them according to each band.

According to each course's topoplots, distinct patterns emerge: 3D Design activated brain patterns in the right hemisphere in both the central and frontal areas (F4, C4), while both Programming and Robotics activated left-hemisphere areas (C3). According to the θ frequency band, 3D Design got higher activation patterns in the frontal, central, and temporal areas, with the highest being in the frontal right hemisphere (F4), while both Programming and Robotics exhibit lower activation patterns in the same area (C4, F4). In the α frequency band, 3D Design also has the highest brain activation patterns in the fronto-central right area (C4, F4), while Programming does not show a clear activation pattern, and Robotics exhibits high activation in the right hemisphere's central area (C4). Lastly, in the β frequency band, the highest activation patterns are displayed by both Robotics and Programming in the left hemisphere's central area (C3), along with a slightly higher activation in the right hemisphere's frontal area (F4), which is also presented by 3D Design; in addition, Programming has the highest negative BP activation patterns in the temporo-central region, following 3D Design and lastly Robotics. Programming had the most negative BP values in the prefrontal region of every frequency band, following Robotics and the last 3D Design.

Table 3 shows the statistically significant ($p < 0.05$) measurements for each course compared to the calibration EO phase; every measurement has a large effect size ($|d| > 0.98$). Focusing on the first BP modality, both Programming and Robotics exhibit significant decreases in the prefrontal activity (Fp1, Fp2) in the β band when taking the course compared to the EO phase (F $= -3.53$, $p = 0.0335$, d $= -1.33$; F $= -2.76$, $p = 0.0988$, d $= -1.07$).

On the other hand, based on the normalized coherence COH_N values, Fig. 3 was created, in which strong positive coherence is represented with blue, weak positive coherence with light blue, weak negative coherence with light red, and strong negative coherence with red. The color bar indicates these values, showing that FC connections had to be at least weak in order to be drawn.

Based on the FC patterns in the θ band, 3D Design has this unique frontal-clustered type of network in which both inter-hemispheric and intra-hemispheric connections between central and prefrontal channels take place, which is slightly different from the Robotics network, in which central-prefrontal connections only take place intra-hemispherically; while the strongest connections are between frontal regions and central regions. In contrast, Programming has the sparsest network with a more central-clustered type, although overall, the connections between F3-F4 are found in all courses. Moreover, in the α band, the prefrontal region has the highest degree in 3D Design, as FP1 is strongly connected to C3, C4, and Pz, while FP2 is connected to F3 and Pz; this is shared to some extent in the Robotics course while adding some new connections from Programming as C3-F4, while Programming has a unique, strong connection between the central channels C3-C4. Lastly, in the β band, Robotics have the densest network, in addition to having stronger positive links during the course than when compared to the EO phase; however, overall, in the β band, the three STEM courses exhibit overlapping network structures, including connections from central and frontal electrodes to prefrontal electrodes, predominantly involving the connections between C3-FP1 and F3-FP2, which might represent a consistent flow of information between sensorimotor and executive control; in addition to F3 having the highest degree, hence working as a hub for connections between FP2, C3, Pz and C4.

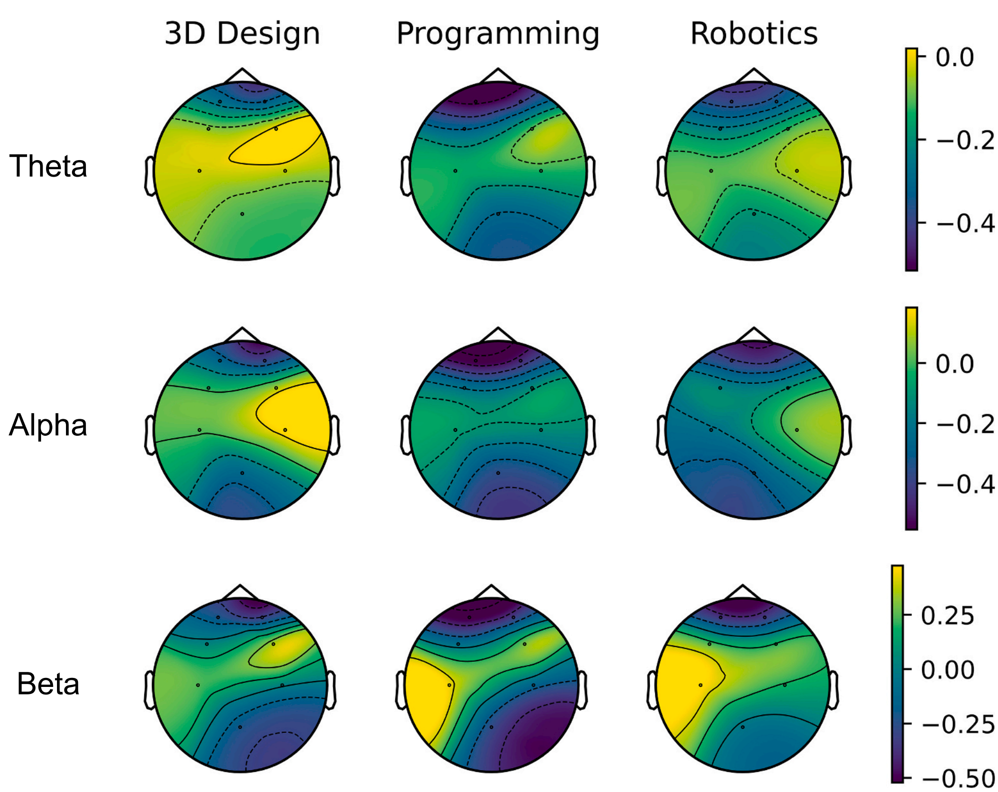

Fig. 2. Normalized band power BP_N for each frequency band of interest (θ, α, β) at each course. Positive values indicate that the BP during the course phase had higher values than during the calibration phase, while negative values would indicate that they were lower compared to the calibration phase.

Table 3
One-sided paired t-test. Statistically significant ($p < 0.05$) pair of electrodes for each course according to EO ($n = 8$).

Modality	Course	Frequency band	Channel / Channel Pair	F	p	d	$p_{S,L}$	$p_{S,EO}$
Power	Programming	β	Fp1	−3.53	0.0335	−1.33	0.2769	0.5005
	Robotics	β	Fp1	−2.76	0.0988	−1.07	0.4649	0.6282
Coherence	3D Design	θ	C4-Fp2	−4.24	0.0401	−0.71	0.3032	0.1684

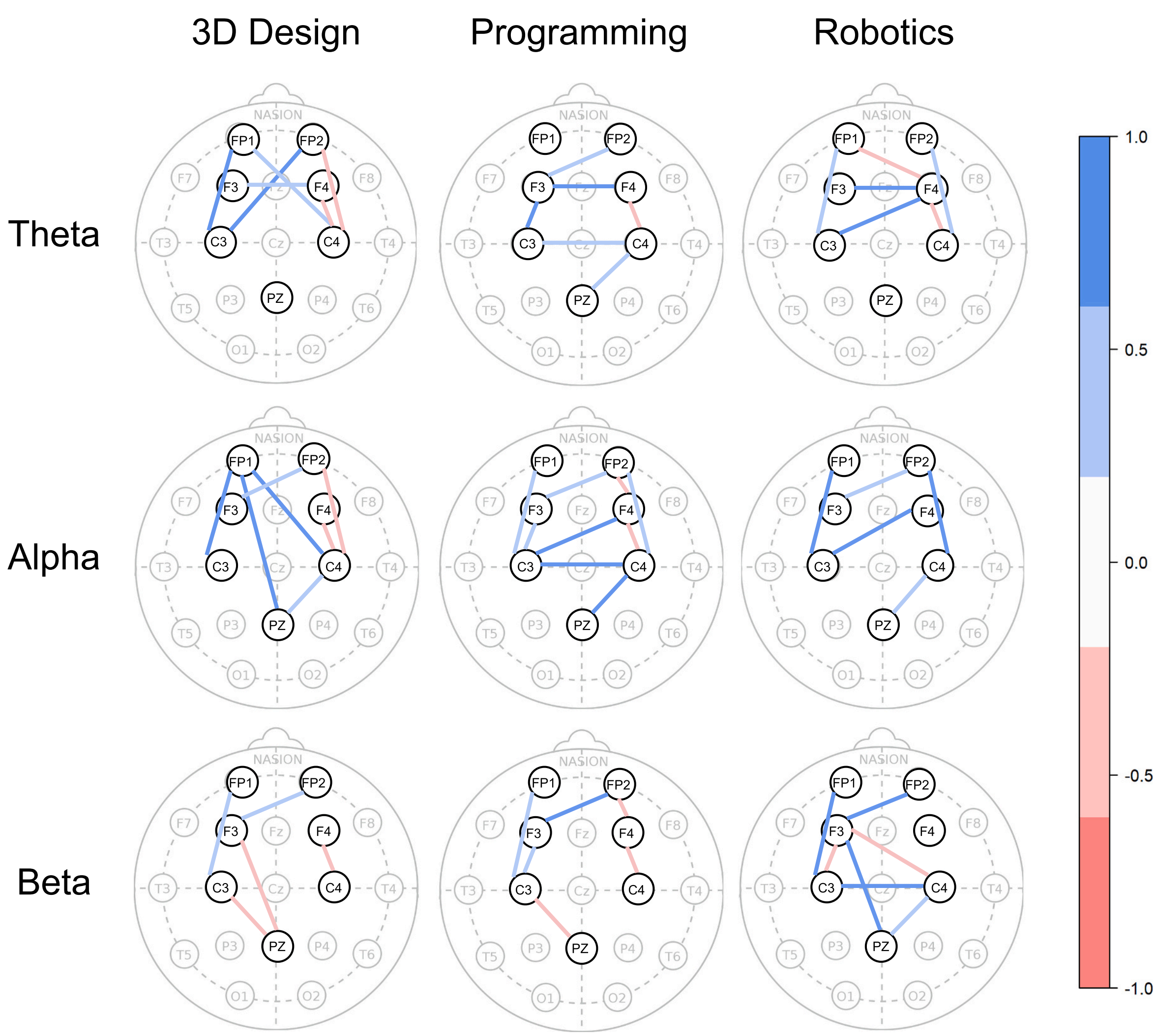

Fig. 3. Functional Connectivity patterns from normalized coherence COH_N at a given frequency band for each course averaged across subjects. The color bar on the right shows the mapping for each strong/weak coherence with a positive/negative value; shallow coherence values were not even included due to their low impact on the FC pattern.

According to Table 3, which shows statistically significant changes in coherence between the course and EO, only the 3D Design course exhibited a statistically significant difference, which was a decrease in the right intra-hemispheric connection between the central and pre-frontal region (C4-Fp2) in the θ band ($F = -4.24$, $p = 0.0401$, $d = -0.71$).

3.2. PSD and FC correlates of STEM interest

Change in STEM interest (ΔI) for each course in Table 2 was used as a target feature, in which the normalized BP and FC were used as source features to find EEG-related features to cognitive-related variables. In order to determine which features were related the most, Pearson's correlation coefficient (r) was used as in Eq. 6, in which x is a biometric source feature from either BP or FC while y is the change in STEM interest.

A barplot of Pearson correlation coefficients applied to averaged BP_N and ΔI is shown in Fig. 4. A unique r is obtained for each frequency band combination (θ, α, β) with the STEM course (3D Design, Programming, Robotics). Overall, each course has its unique pattern of correlations, disregarding the frequency band; in this sense, each course will be analyzed individually for each frequency band and then further contrasted with each other course.

Focusing on the 3D Design course, it has the highest negative correlation in the prefrontal region (Fp1, Fp2), as both in α ($r = -0.77$, $p = 0.0251$; $r = -0.71$, $p = 0.0502$) and β ($r = -0.83$, $p = 0.0109$; $r = -0.75$, $p = 0.0327$), the correlation on these two channels was the highest, with the exception of the θ band, in which the right frontal channel (F4) had a higher negative correlation ($r = -0.76$, $p = 0.0268$) than the right prefrontal channel (Fp2) ($r = -0.62$, $p = 0.0990$). Both the θ and β

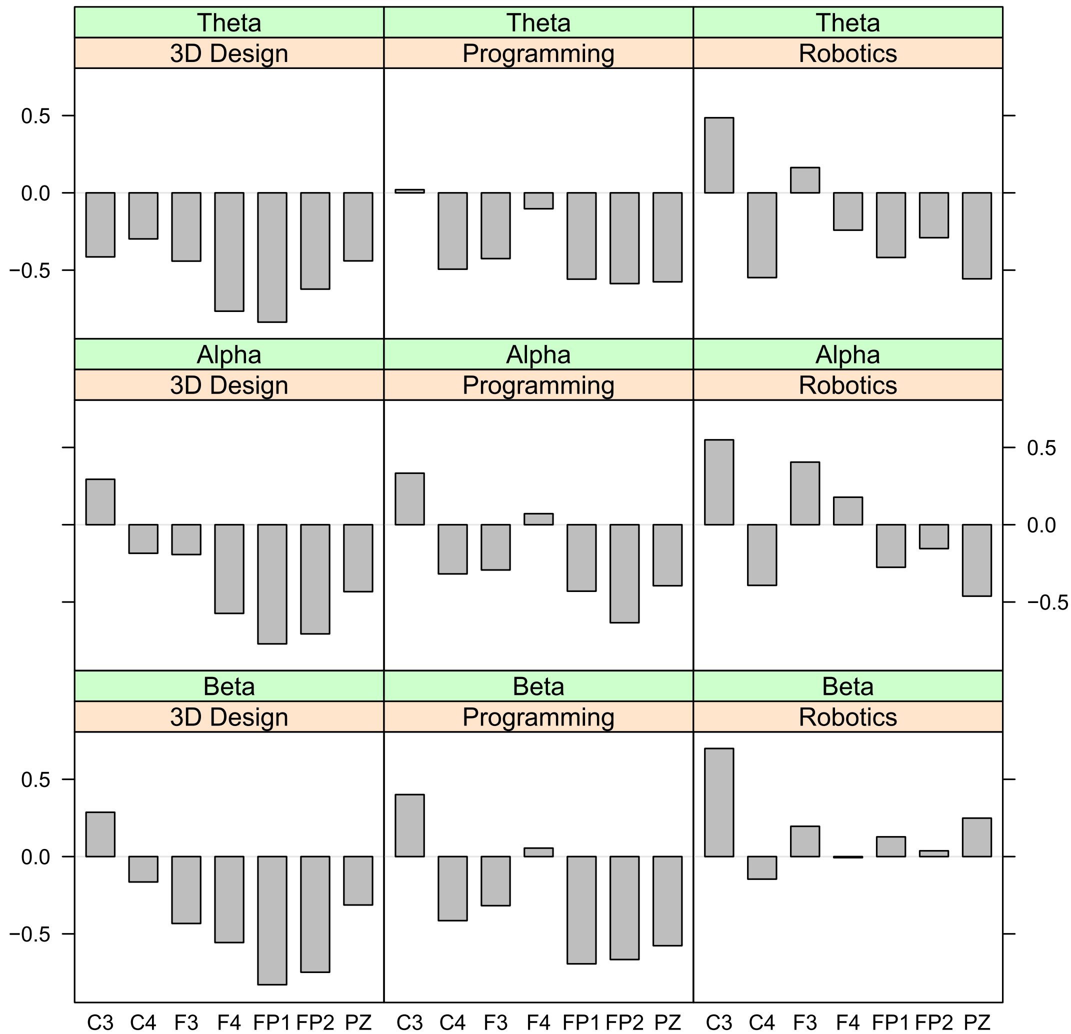

Fig. 4. Barplots of Pearson correlation coefficient on averaged BP_N and ΔI, for each frequency band and course.

barplots have a similar pattern, exhibiting an overall negative correlation in the prefrontal region (Fp1, Fp2) ($r = -0.84$, $p = 0.0096$; r = −0.83, $p = 0.0110$) (r = −0.62, p = 0.0990; r = −0.75, $p = 0.0328$), frontal lobe (F3, F4) ($r = -0.44$, $p = 0.2732$; $r = 0.43$, $p = 0.2843$) (r = −0.77, p = 0.0268; $r = -0.56$, $p = 0.1524$), parietal lobe (Pz) (r = −0.44, $p = 0.2750$; $r = -0.31$, $p = 0.4501$), and central region (C4) ($r = -0.30$, $p = 0.4735$; $r = -0.16$, $p = 0.6975$), with the exception of the brain activity in the left central channel (C3), exhibiting a negative correlation in the θ band ($r = -0.41$, $p = 0.3074$), and a positive correlation in the β band ($r = 0.29$, $p = 0.4912$). An interesting difference between the α and β band is that the correlation between the left frontal channel (F3) is less in the α band ($r = -0.19$, $p = 0.6472$; $r = -0.43$, p = 0.2843), nearly similar to the unrelated central channels (C3, C4) (r = 0.29, $p = 0.4797$; $r = -0.18$, $p = 0.6616$).

On the other hand, the Programming course also has a well-defined pattern among the frequency bands (θ, α, β), in which the prefrontal region also has the highest negative correlations (Fp1, Fp2) (r = −0.56, $p = 0.1504$; r = −0.43, $p = 0.2876$; $r = -0.69$, $p = -0.0563$) ($r = -0.59$, $p = 0.1261$; $r = -0.63$, $p = 0.0914$; $r = -0.67$, $p = 0.0714$), following the parietal lobe (Pz) ($r = -0.58$, $p = 0.1352$; $r = -0.39$, $p = 0.3331$; r = −0.58, $p = 0.1346$). However, different from the 3D Design course, the right frontal channel (F4) ($r = -0.10$, $p = 0.8084$; $r = 0.08$, 0.8666; $r = 0.05$, $p = 0.8972$) is not as nearly as relevant as the left frontal channel (F3) (r = −0.43, $p = 0.2933$; $r = -0.29$, $p = 0.4817$; $r = -0.32$, $p = 0.4434$), further following the central channels, in which the left central channel (C3) ($r = 0.02$, $p = 0.9615$; $r = 0.33$, $p = 0.4194$; $r = 0.40$, $p = 0.3248$) has a positive correlation and the right central channel a negative correlation (C4) ($r = -0.49$, $p = 0.2136$; r = −0.32, $p = 0.4425$; r = −0.41, $p = 0.3073$), except for the θ band in which the left central channel has a weak correlation (r = 0.02, p = 0.9615).

Finally, the Robotics course has a unique pattern of correlations, which is quite different from the previous two courses: There is a clear, strong positive correlation in the left central channel (C3) ($r = 0.49$, $p = 0.2223$; $r = 0.55$, $p = 0.1587$; $r = 0.70$, $p = 0.0536$) and a strong negative correlation in the right central channel (C4) ($r = -0.55$, $p = 0.1594$; r = −0.39, $p = 0.3365$; $r = -0.15$, $p = 0.7305$), with the left central channel increasing its correlation as the frequency increases. In contrast, the right central channel has the inverse trend, which means that the difference in absolute correlations increases as the frequency increases, thus having the most negligible differences in the θ band ($|r| = 0.49$, p = 0.2223; $|r| = 0.55$, p = 0.1594) and the highest differences in the β band ($|r| = 0.70$, p = 0.0536; $|r| = 0.15$, p = 0.7305). Moreover, the prefrontal region is less important than in the other STEM courses, despite exhibiting a negative correlation trend. The parietal lobe (Pz) is more relevant, exhibiting a strong negative correlation in the θ and α band (r = −0.56, $p = 0.1521$; $r = -0.46$, $p = 0.2492$), a slight negative correlation in the left prefrontal region (Fp1) ($r = -0.42$, $p = 0.3027$; $r = -0.28$, $p = 0.5093$), and a high positive correlation in the left-hemisphere frontal channel (F3) in the α band ($r = 0.41$, $p = 0.3194$).

A similar approach to obtaining the Pearson correlation coefficient on a normalized band power for each channel was used to assess the importance of each coherence measurement. This involved using the previously shown FC patterns in Fig. 3, and correlating them with the change in STEM interest ΔI via the Pearson correlation coefficient. Due to having a pair of channels instead of a single channel, a heatmap was used in order to display the correlation values in Fig. 5. The color bar is similar to the one used for the FC patterns, in which strong positive correlation values are represented with blue, weak positive with light blue, weak negative with light red, and strong negative with red. Finally, low correlation values, as well as those corresponding to the same channel, are displayed with white color.

Regarding the first course, 3D Design, in the θ band, it has a strong negative correlation at intra-hemispheric connections between central and frontal regions (C3-Fp1, C3-F3, and C4-F4, C4-Fp2) ($r = -0.66$, $p = 0.0725$; $r = -0.87$, $p = 0.0050$) (r $= -0.49$, $p = 0.2170$; $r = -0.45$, $p = 0.2658$), in addition to inter-hemispheric connections to the central region (C3-C4) (r $= -0.67$, $p = 0.0694$) and the parietal lobe (C3-Pz, C4-Pz) ($r = -0.90$, $p = 0.0025$; $r = -0.70$, $p = 0.0537$). In the α band, the same strong negative trend on intra-hemispheric connections is also displayed, although central and parietal regions are not as relevant. Additionally, a new trend emerges with strong positive inter-hemispheric connections between the central and frontal areas (C3-F4, C3-Fp2, and C4-F3, C4-Fp1) ($r = 0.61$, $p = 0.1068$; $r = 0.63$, $p = 0.0937$) ($r = 0.72$, $p = 0.0457$; $r = 0.66$, p $= 0.0725$). Finally, in the β band, there is a strong positive correlation in short inter-hemispheric connections between central and frontal regions (C3-F4, C4-F3) ($r = 0.68$, $p = 0.0630$; r $= 0.68$, $p = 0.0634$), which is observed across all frequency bands, except for the negative correlation between the left-hemisphere central region and the parietal lobe (C3-Pz) ($r = -0.73$, $p = 0.0379$).

On the other hand, in the second course on Programming, there are few differences between frequency bands (θ, α, β) when considering strong positive/negative correlations. However, a clear trend is shown disregarding the frequency band, as a strong positive correlation is present between the prefrontal channels (Fp1-Fp2) ($r = 0.65$, $p = 0.0782$; $r = 0.77$, $p = 0.0254$; $r = 0.69$, $p = 0.0567$), while strong negative correlations are found at intra-hemispheric connections between the central region and the frontal region (C3-Fp1, C4-F4) ($r = -0.91$, $p = 0.0018$; $r = -0.81$, $p = 0.0137$; $r = -0.74$, $p = 0.0358$) (r $= -0.62$, $p = 0.1038$; r $= -0.67$, $p = 0.0705$; r $= -0.76$, $p = 0.0297$).

At last, regarding the third course on Robotics, in the θ band, a strong positive correlation is found between the right central region and the prefrontal region (C4-Fp1, C4-Fp2) ($r = 0.62$, $p = 0.1041$; r $= 0.62$, $p = 0.1017$), in addition to the long-range connection between the right prefrontal channel and the parietal lobe (Fp2-Pz) ($r = 0.74$, $p = 0.0370$). In the α band, a clear pattern of strong positive correlation is shown at inter and intra-hemispheric connections between the right central region to the frontal areas (C4-F3, C4-F4, C4-Fp1, C4-Fp2) ($r = 0.71$, $p = 0.0478$; $r = 0.75$, $p = 0.0336$; r $= 0.68$, $p = 0.0644$; r $= 0.75$, $p = 0.0331$), in addition to the long-range aforementioned connection (Fp2-Pz) ($r = 0.73$, $p = 0.0388$). In contrast, the left central region has a strong negative correlation with some frontal regions (C3-F4, C3-Fp1) (r $= -0.67$, $p = 0.0699$; $r = -0.60$, $p = 0.1140$). Finally, in the β band, a clear cluster of strong positive correlations is displayed between the prefrontal region, the frontal region, and the parietal lobe (Fp2-F3, Fp2-

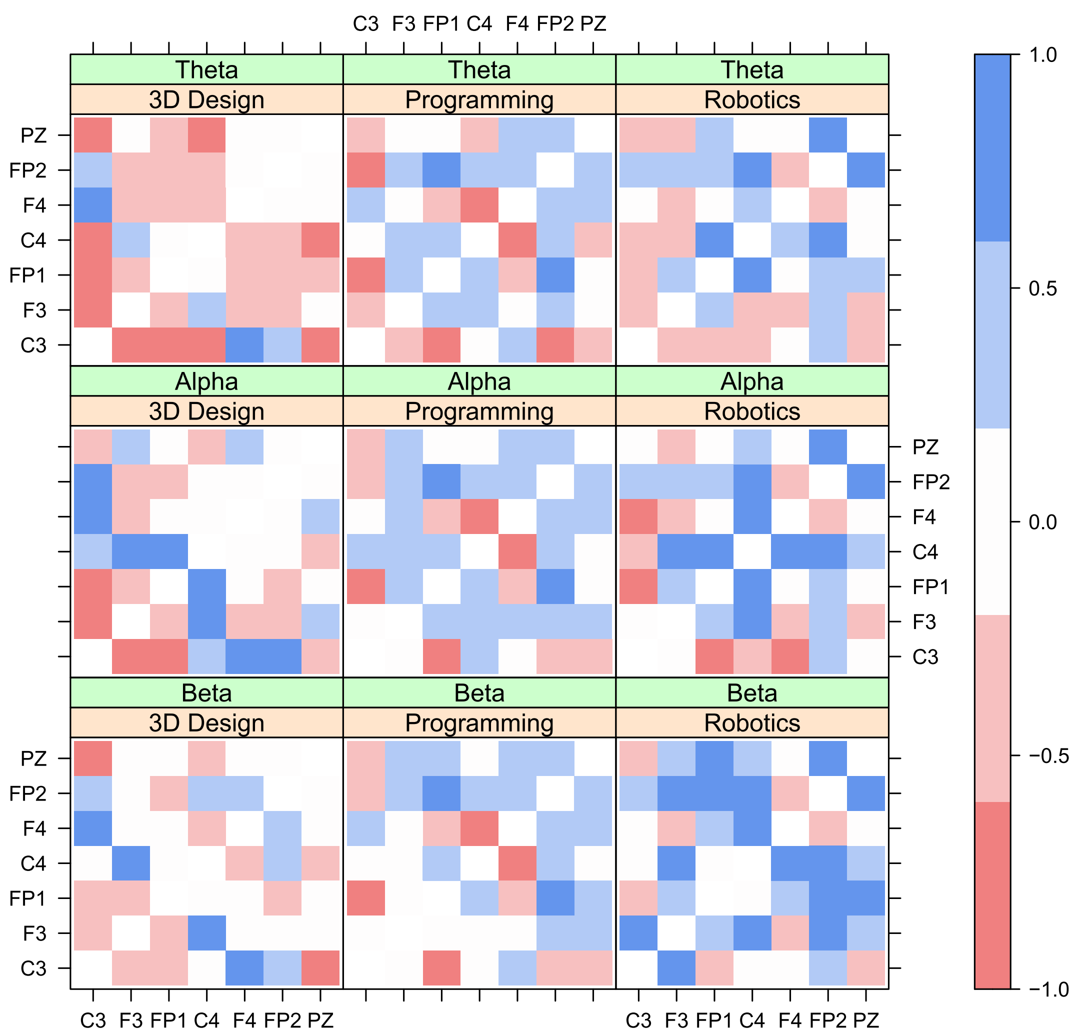

Fig. 5. Heatmaps of Pearson correlation coefficient on averaged COH_N and ΔI for each frequency band and course.

Fp1, Fp2-Pz, Fp1-Pz) (r = 0.72, p = 0.0437; r = 0.73, p = 0.0387; r = 0.81, p = 0.0155; r = 0.68, p = 0.0657), in addition to intra and inter-hemispheric connections between the central regions and the frontal areas (C3-F3, and C4-F4, C4-Fp2, C4-F3) (r = 0.72, p = 0.0436) (r = 0.79, p = 0.0187; r = 0.74, p = 0.0356; r = 0.65, pp. = 0.0826).

3.3. Regression analysis

Based on the insights gathered in the previous Section 3.2, multiple one-variable linear regression models were fitted using the normalized source features BP_N and COH_N, and the target feature ΔI. Instead of using the source features as the independent variable at the X-axis, which is how results are shown conventionally, it will be presented at the dependent Y-axis as in (Adhikari et al., 2016), to learn how having a positive or negative interest in STEM after given course would increase or decrease the normalized power/coherence. Fig. 6 shows the most relevant linear regression plots, which not only are related to the enthralling insights regarding BP/FC previously described in Section 3.2 but also have a statistically significant linear regression fit ($p < 0.05$); the fitted model is shown with a red line, and a different point figure is used for each STEM course.

Regarding the band power analysis on the top, only the 3D Design course had statistically significant fits; the left prefrontal channel was discussed as the most related feature ΔI when using Pearson's correlation coefficient, disregarding the frequency band. The θ_{FP1} and β_{FP1} plots had the best fit, with nearly a 1-to-1 negative relationship between normalized power and ΔI; α_{FP1} also had a statistically significant, although lower fit ($r = -0.833$, $p = 0.0252$). On the other hand, θ_{F4} and β_{FP2}, which were the second highest correlated features, also exhibit a strong negative fit, along with the highest trend on Programming β_{FP1} ($r = -0.445$, $p = 0.0563$).

On the other hand, regarding the coherence analysis at the bottom, there were other courses aside from 3D Design that had statistically significant fits. However, the plot with the best fit was θ_{F3-C3}, with a nearly 1-to-1 negative relationship starting from 0.5 COH_N and going down to -1, spanning the entire ΔI; in addition, θ_{Pz-C3} also exhibited a strong fit ($r = -0.9686$, p = 0.0025). One of the most prevalent trends in Programming, disregarding the frequency band (C4-F4), also shows a strong fit β_{C4-F4}, although there is limited information when $\Delta I < 0$, as the majority of students had a positive interest after taking the programming course; in addition, other previously mentioned trends, such as β_{FP1-C3} ($r = -1.7362$, p = 0.0358), were observed. Moving on to the third plot, a significant negative trend is observed between the left central region and\ the parietal region β_{C3-Pz} in 3D Design is significant. Finally, a positive trend in the intra-hemispheric connection between the left central region and the frontal region in Robotics β_{F3-C3}.

4. Discussion

The current study presents a multifaceted analysis of EEG brain-

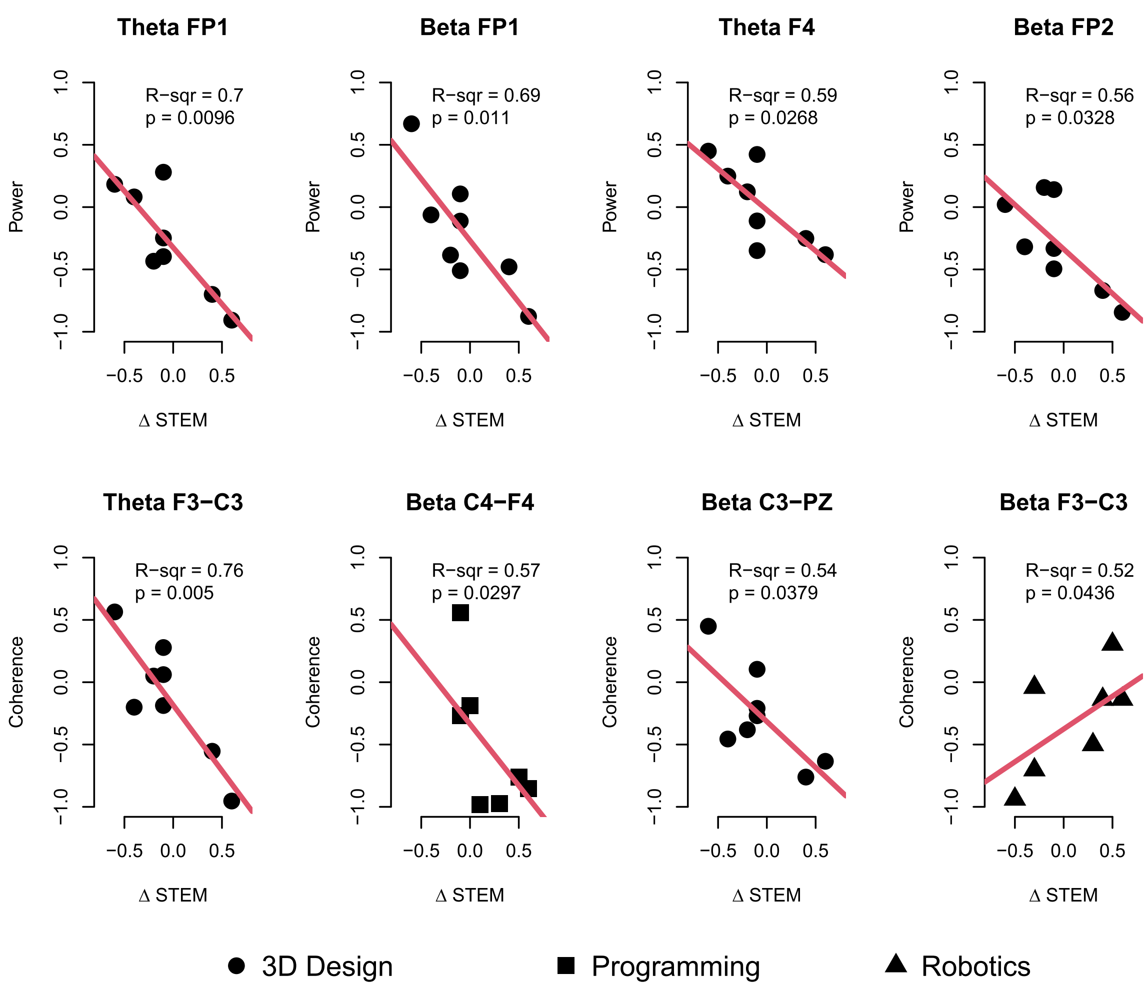

Fig. 6. Most relevant, statistically significant ($p < 0.05$) linear regression plots of normalized band power BP_N (top) and normalized coherence COH_N (bottom) for each STEM course (3D Design: Dot, Programming: Square, Robotics: Triangle). Each black point figure represents a single student, and the red line is the fitted, one-variable, linear regression model. Only the 3D Design course had statistically significant PSD features, thus only plots from this course are shown. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

waves of 13 young STEM learners while taking a STEM course (3D Design, Programming, Robotics). The analysis includes both band power analysis across three different frequency bands (θ, α, β) via PSD calculation using the Welch method, and brain network FC analysis based on the previously mentioned frequency bands through coherence calculation. In addition to using the aforementioned calculations as source features to assess course-related differences, a linear regression analysis was performed between the EEG features and change in STEM interest, a cognitive measure obtained by applying the STEM-CIS psychometric test to students before and after each course.

4.1. Course-specific PSD and FC insights

Regarding theta (θ), a prevalent inter-hemispheric connection (F3-F4) and strong frontal lobe activation were observed across STEM courses. This indicates full prefrontal region engagement in planning and coordinating movements (Başar-Eroglu et al., 1992), increased cognitive control demands (Cohen, 2017; Klimesch et al., 1994; Nigbur et al., 2011), as well as enhanced error awareness with subsequent post-error cognitive control (Zheng & Wynn, 2022). Beta (β) exhibited consistent patterns among the three STEM courses; robust FC was established between the central and frontal left hemisphere areas with the prefrontal region (C3-Fp1, F3-Fp2) (Zhang et al., 2020), indicating information flow and synchronicity (Sejnowski & Paulsen, 2006), with Programming and Robotics even showing a significantly higher F3-Fp2 connection when compared to the calibration phase. These two areas were also the most activated based on BP analysis, in which 3D Design had the most activation in the right hemisphere while both Programming and Robotics in the left hemisphere, suggesting brain Functional Cerebral Asymmetry (FCA) depending on the task (Chen et al., 2018).

Alpha (α), predominantly in the right hemisphere, 3D Design exhibited the highest activation, followed by Robotics, while Programming showed no activation. This suggests that visual stimuli may trigger (α) activation in the right hemisphere, which is associated with creativity (Rosen et al., 2020), in addition to supporting that lower α is linked to more rational than creative thinking (Stevens & Zabelina, 2020). Creativity also showcased intra-hemispheric synchronization in brain functioning between the sensorimotor area and the prefrontal region (C3-Fp1, C4-Fp2), suggesting that creativity thrives when synchronization between sensory perceived and actions (Cruz-Garza et al., 2020; Ramírez-Moreno et al., 2023). Additionally, some course-related differences are likewise discernible, as both Programming and Robotics exhibited short-range connections. In contrast, 3D Design exhibited more long-range connections, thus indicating that 3D Design had more adaptive mechanisms (Caeyenberghs et al., 2015), as well as more stable (Arvin et al., 2022) and efficient (Ouyang et al., 2017) creative networks.

Another notable finding was the functional brain network differences underlying each task. Although the same cognitive coefficient was evaluated (ΔI) and the various STEM courses belong to the same domain, the brain dynamics of the young students had to adapt depending on the course in order to increase their interest in it. The findings were primarily found in working memory (θ) and executive control (β), supporting neuroplasticity theory, which suggests that the nervous system is able to reorganize its structure, functions, or connections given an intrinsic or extrinsic stimuli (Mateos-Aparicio & Rodríguez-Moreno, 2019). This is further supported by activity-dependent mechanisms, often referred to as synaptic plasticity (Berlucchi & Buchtel, 2008; Markram, 2011).

A finding of this kind was regarding the difference in range and lateralization of FC patterns: While the Programming course exhibited negatively correlated intra-hemispheric and long-range connections, the 3D Design course not only exhibited an opposite correlation trend but also had inter-hemispheric and short-range connections. This suggests that while Programming requires flexible adaptation and independent thinking patterns regarding planning and executive control (Shulman et al., 1997), 3D Design requires intertwined, deep, connected short-range agreements between brain hemispheres (Latora & Marchiori, 2003). Similar findings on the use of Programming to engage cognitive skills have been observed not only in children but also in older adults with Mild Cognitive Impairment (MCI) (Demetriadis et al., 2015), suggesting potential applications across the lifespan. Another important finding was regarding the difference in brain region synchronization: While the Robotics course exhibited positively correlated connections between the prefrontal region, sensorimotor region, and parietal lobe, 3D Design had negatively correlated connections in the same regions. This suggests that while Robotics require denser, sharper, long-range networks that produce network-wide synchronization (Dosenbach et al., 2010) when doing particular technical tasks, 3D Design requires sparser networks that are more efficient (Latora & Marchiori, 2001); thus, brain regions that operate independently are most effective in creative tasks.

4.2. Neural markers of STEM interest

The frontal and prefrontal regions exhibited critical insights on beta (β) in Programming and Robotics, regions reported to be correlated to the STEM learning process (Delahunty, 2023) and deemed essential in access and integration of concepts not commonly associated (Abraham et al., 2012). Even though PSD was negatively correlated with ΔI in 3D Design and Programming, an opposite trend was found for FC in Programming and Robotics; this suggests crucial function integration in the prefrontal region for effective task execution (Klimesch, 2012) while allowing students to learn course content (Muldner & Burleson, 2015). Moreover, the negative relationship between the prefrontal region and frontal lobe activation in the θ and β bands in 3D Design implies a trade-off: Less academic burden correlates with increased STEM interest (Ghali et al., 2019; Olivas et al., 2021). Interestingly, no correlation was found in the right frontal region (F4) for Programming compared to 3D Design, suggesting different cognitive demands between the two courses, likely in visuospatial processing (Balters et al., 2023; Pidgeon et al., 2016).

In both PSD and FC analyses, when correlating source features with ΔI, a consistent pattern of positive and negative correlations emerged, disregarding the frequency band. Notably, the prefrontal region showed this pattern in both 3D Design and Programming at PSD analysis, as well as in Programming at FC analysis. These recurring patterns highlight the brain's fractal organization, reflecting structural connectivity behavior (Bassett et al., 2006), as some of the brain's FC patterns can be explained by the structural connections linking regions of the cerebral cortex (Honey et al., 2009). This temporal correlation among distributed neural signals plays a crucial role in encoding objects, figure-ground segregation, and perceptual grouping (Sporns et al., 1989, 1991), which is indicative of strong FC patterns in children, potentially reflecting early-stage network organization and contributing to their structural connectivity development (Geng et al., 2016; Supekar et al., 2010).

4.3. Limitations

This preliminary study involved a small, convenience sample of 13 participants recruited from MCE, an extracurricular STEM education company. Although the brain imaging data supported our hypotheses, a larger sample size is needed to improve the generalization power of the findings to the broader young student population. It is worth noting that other studies in this field have reported differences in STEM learning, mathematical thinking, and creative thinking using data from a similar sample size: 12 (Delahunty et al., 2020; Dikker et al., 2017; Qu et al., 2018), 13 (Aziz-Zadeh et al., 2012), 14 (Wang et al., 2023), and 15 (Ellamil et al., 2012; Yin et al., 2024).

Moreover, given the underrepresentation of women in engineering and computer science fields (Goy et al., 2017; Sassler et al., 2017), the sampling method reflected this gender disparity, resulting in a predominantly male sample; hence, this study was unable to capture brain activity differences related to gender. A further study should not only increase the sample size but also account for gender and cultural factors, with the objective of exploring the extent to which gender (Giannouli, 2023; Gonzalez et al., 2019; Vieira et al., 2021; Vieira et al., 2022) and different cultural contexts (Giannouli, 2018) in design cognition and creativity influence brain activity patterns during STEM learning. Finally, a future direction would explore how psychological gender-derived differences in math anxiety and STEM-related attitudes (Megreya et al., 2025), observed even in children (Xie et al., 2024), are reflected in brain activity patterns during learning.

5. Conclusion

In conclusion, this paper highlights the importance of fostering interest in children, especially considering their developing brain networks. The comprehensive quantitative analysis of cognitive and neurological brain dynamics, employing FC and PSD measurements, offered valuable insights into the neural mechanisms underlying STEM interest.

The strengths of this study lie in its naturalistic environment, capturing spontaneous brain activity during regular classroom sessions using Mobile Brain-body Imaging (MoBI) technology (Cruz-Garza et al., 2020; Sujatha Ravindran et al., 2019). Despite its strengths, the study has notable limitations, including a small sample size of 8 participants and limited coverage of brain regions. Future research could address these limitations by incorporating ERP analysis and expanding the channel coverage for a more comprehensive understanding of brain dynamics.

The findings highlight significant insights, supporting theories that academic burden can impact STEM interest and emphasizing the importance of cognitive load control in fostering engagement (Vogel & Schwabe, 2016), in addition to various relationships between brain activity and STEM interest. Notably, the identification of 3D Design course as the most creativity-demanding, likely reinforced by visuospatial stimuli, emphasizes the importance of considering the nature of tasks in engaging students. Additionally, the high correlation between the prefrontal region and frontal lobe with STEM interest underscores the critical role of these brain regions in fostering learning. Moreover, executive task lateralization across STEM courses, with technical subjects showing left hemisphere activation and artistic subjects showing right hemisphere activation, underscores the diverse cognitive demands inherent in different disciplines. Furthermore, the observed course-related differences in brain synchronicity, evident as segregation and convergence in interconnections between lobes and cognitive areas, suggest that sensorimotor and executive control functions may operate independently or collaboratively, revealing the complex cognitive dynamics across diverse educational arenas.

Overall, this paper contributes significantly to our understanding of the intricate neural mechanisms underlying STEM interest and emphasizes the importance of targeted interventions to foster engagement and learning in children. Further studies with larger sample sizes can provide a deeper understanding of these dynamics and inform the development of interventions aimed at enhancing STEM interest and learning outcomes.

CRediT authorship contribution statement

Milton O. Candela-Leal: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Myriam Alanis-Espinosa:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Data curation, Conceptualization. **Jorge Murrieta-González:** Validation, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Jorge de-J. Lozoya-Santos:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Mauricio A. Ramírez-Moreno:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Data curation, Conceptualization.

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Declaration of competing interest

The authors declare no conflict of interest.

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Data availability

Data will be made available on request.

References

Abraham, A., Pieritz, K., Thybusch, K., Rutter, B., Kröger, S., Schweckendiek, J., Stark, R., Windmann, S., & Hermann, C. (2012). Creativity and the brain: Uncovering the neural signature of conceptual expansion. *Neuropsychologia, 50*(8), 1906–1917.

Adhikari, B. M., Norgaard, M., Quinn, K. M., Ampudia, J., Squirek, J., & Dhamala, M. (2016). The brain network underpinning novel melody creation. *Brain Connectivity, 6*(10), 772–785.

Ahrens, W., Pigeot, I., & (Eds.).. (2014). *Handbook of epidemiology*. New York, NY: Springer New York.

Alanis-Espinosa, M., & Gutiérrez, D. (2020). On the assessment of functional connectivity in an immersive brain-computer interface during motor imagery. *Frontiers in Psychology, 11*.

Anderson, K., Deane, K., Lindley, D., Loucks, B. & Veach, E. (2012). The effects of time of day and practice on cognitive abilities: The pebl tower of London, trail-making, and switcher tasks. *Pebl tech rep* (pp. 1–5).

Arvin, S., Glud, A. N., & Yonehara, K. (2022). Short- and long-range connections differentially modulate the dynamics and state of small-world networks. *Frontiers in Computational Neuroscience, 15*.

Aziz-Zadeh, L., Liew, S.-L., & Dandekar, F. (2012). Exploring the neural correlates of visual creativity. *Social Cognitive and Affective Neuroscience, 8*(4), 475–480.

Babarović, T. (2021). Development of STEM vocational interests during elementary and middle school: A cohort-sequential longitudinal study. *Journal of Career Development, 49*(6), 1230–1250.

Balters, S., Weinstein, T., Mayseless, N., Auernhammer, J., Hawthorne, G., Steinert, M., … Reiss, A. L. (2023). Design science and neuroscience: A systematic review of the emergent field of design neurocognition. *Design Studies, 84*, Article 101148.

Başar, E. (1999). *Brain function and oscillations*. Berlin Heidelberg: Springer.

Başar, E., Başar-Eroğlu, C., Karakaş, S., & Schürmann, M. (1999). Are cognitive processes manifested in event-related gamma, alpha, theta and delta oscillations in the EEG? *Neuroscience Letters, 259*(3), 165–168.

Başar, E., Schürmann, M., Başar-Eroglu, C., & Karakaş, S. (1997). Alpha oscillations in brain functioning: An integrative theory. *International Journal of Psychophysiology, 26*(1–3), 5–29.

Başar-Eroglu, C., Başar, E., Demiralp, T., & Schürmann, M. (1992). P300-response: Possible psychophysiological correlates in delta and theta frequency channels. A review. *International Journal of Psychophysiology, 13*(2), 161–179.

Bashwiner, D. M., Bacon, D. K., Wertz, C. J., Flores, R. A., Chohan, M. O., & Jung, R. E. (2020). Resting state functional connectivity underlying musical creativity. *NeuroImage, 218*, Article 116940.

Bassett, D. S., Meyer-Lindenberg, A., Achard, S., Duke, T., & Bullmore, E. (2006). Adaptive reconfiguration of fractal small-world human brain functional networks. *Proceedings of the National Academy of Sciences, 103*(51), 19518–19523.

Beaty, R. E., Seli, P. & Schacter, D. L. (2019). Network neuroscience of creative cognition: Mapping cognitive mechanisms and individual differences in the creative brain. *Current opinion in behavioral sciences*, *27*, 22–30. Creativity.

Berg, E. A. (1948). A simple objective technique for measuring flexibility in thinking. *The Journal of General Psychology, 39*(1), 15–22.

Berlucchi, G., & Buchtel, H. A. (2008). Neuronal plasticity: Historical roots and evolution of meaning. *Experimental Brain Research, 192*(3), 307–319.

Berteau-Pavy, D., Raber, J., & Piper, B. (2011). *Contributions of age, but not sex, to mental rotation performance in a community sample* (PEBL Technical Report Series).

Bigdely-Shamlo, N., Mullen, T., Kothe, C., Su, K.-M., & Robbins, K. A. (2015). The PREP pipeline: Standardized preprocessing for large-scale EEG analysis. *Frontiers in Neuroinformatics, 9*, 16.
Blanco-Ríos, M. A., Candela-Leal, M. O., Orozco-Romo, C., Remis-Serna, P., Vélez-Saboyá, C. S., Lozoya-Santos, J.d. J., … Ramírez-Moreno, M. A. (2024). Real-time eeg-based emotion recognition for neurohumanities: Perspectives from principal component analysis and tree-based algorithms. *Frontiers in Human Neuroscience, 18*.
Boslaugh, S. (2012). *Statistics in a nutshell* (2 ed.). Sebastopol, CA: O'Reilly Media.
Caeyenberghs, K., Siugzdaite, R., Drijkoningen, D., Marinazzo, D., & Swinnen, S. P. (2015). Functional connectivity density and balance in young patients with traumatic axonal injury. *Brain Connectivity, 5*(7), 423–432.
Candela-Leal, M. O., Gutiérrez-Flores, E. A., Presbítero-Espinosa, G., Sujatha-Ravindran, A., Ramírez-Mendoza, R. A., de Jesús Lozoya-Santos, J., & Ramírez-Moreno, M. A. (2022). Multi-output sequential deep learning model for athlete force prediction on a treadmill using 3d markers. *Applied Sciences, 12*(11), 5424.
Carter, R., & Woldstad, J. (1985). Repeated measurements of spatial ability with the manikin test. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 27*(2), 209–219.
Cetron, J. S., Connolly, A. C., Diamond, S. G., May, V. V., Haxby, J. V., & Kraemer, D. J. M. (2019). Decoding individual differences in STEM learning from functional MRI data. *Nature Communications, 10*(1).
Cetron, J. S., Connolly, A. C., Diamond, S. G., May, V. V., Haxby, J. V., & Kraemer, D. J. M. (2020). Using the force: STEM knowledge and experience construct shared neural representations of engineering concepts. *Npj science of. Learning, 5*(1).
Chen, Z., Zhao, X., Fan, J., & Chen, A. (2018). Functional cerebral asymmetry analyses reveal how the control system implements its flexibility. *Human Brain Mapping, 39*(12), 4678–4688.
Chi, S. E., Park, C. B., Lim, S. L., Park, E. H., Lee, Y. H., Lee, K. H., … Kim, H. T. (2005). Eeg and personality dimensions: A consideration based on the brain oscillatory systems. *Personality and Individual Differences, 39*(3), 669–681.
Cho, R., Zaman, M., Cho, K. T., & Hwang, J. (2024). Investigating brain activity patterns during learning tasks through eeg and machine learning analysis. *International Journal of Information Technology, 16*(5), 2737–2744.
Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2 ed.). New York, NY: Routledge Member of the Taylor and Francis Group.
Cohen, M. X. (2017). Where does EEG come from and what does it mean? *Trends in Neurosciences, 40*(4), 208–218.
Croschere, J., Dupey, L., Hilliard, M., Koehn, H., & Mayra, K. (2012). *The effects of time of day and practice on cognitive abilities: Forward and backward corsi block test and digit span* (PEBL Technical Report Series).
Cruz-Garza, J. G., Sujatha Ravindran, A., Kopteva, A. E., Rivera Garza, C., & Contreras-Vidal, J. L. (2020). Characterization of the stages of creative writing with mobile eeg using generalized partial directed coherence. *Frontiers in Human Neuroscience, 14*.
Damasio, H. (2005). *Human brain anatomy in computerized images* (2 ed.). New York, NY: Oxford University Press.
Damian-Chavez, M. M., Ledesma-Coronado, P. E., Drexel-Romo, M., Ibarra-Zarate, D. I., & Alonso-Valerdi, L. M. (2021). How does environmental noise impact collaborative activities at the main library of tecnologico de Monterrey?. In *In 2021 43rd annual international conference of the IEEE engineering in Medicine & Biology Society (EMBC)* (pp. 7–10). IEEE.
Delahunty, T. (2023). Neurocognitive and physiological measurment of STEM learning processes. In *International encyclopedia of education(fourth edition)* (pp. 458–471). Elsevier.
Delahunty, T., Seery, N., & Lynch, R. (2020). Exploring problem conceptualization and performance in stem problem solving contexts. *Instructional Science, 48*(4), 395–425.
Demetriadis, S., Giannouli, V., & Sapounidis, T. (2015). *Robot programming and tangible interfaces for cognitive training* (pp. 196–223). IGI Global.
Dikker, S., Wan, L., Davidesco, I., Kaggen, L., Oostrik, M., McClintock, J., … Poeppel, D. (2017). Brain-to-brain synchrony tracks real-world dynamic group interactions in the classroom. *Current Biology, 27*(9), 1375–1380.
Dolan, D., Jensen, H. J., Mediano, P. A. M., Molina-Solana, M., Rajpal, H., Rosas, F., & Sloboda, J. A. (2018). The improvisational state of mind: A multidisciplinary study of an improvisatory approach to classical music repertoire performance. *Frontiers in Psychology, 9*.
Dosenbach, N. U. F., Nardos, B., Cohen, A. L., Fair, D. A., Power, J. D., Church, J. A., … Schlaggar, B. L. (2010). Prediction of individual brain maturity using fmri. *Science, 329*(5997), 1358–1361.
Ellamil, M., Dobson, C., Beeman, M., & Christoff, K. (2012). Evaluative and generative modes of thought during the creative process. *NeuroImage, 59*(2), 1783–1794.
Erickson, B., Truelove-Hill, M., Oh, Y., Anderson, J., Zhang, F. Z., & Kounios, J. (2018). Resting-state brain oscillations predict trait-like cognitive styles. *Neuropsychologia, 120*, 1–8.
Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods, 39*(2), 175–191.
Fink, A., Benedek, M., Grabner, R., Staudt, B., & Neubauer, A. (2007). Creativity meets neuroscience: Experimental tasks for the neuroscientific study of creative thinking. *Methods, 42*(1), 68–76.
Fink, A., Grabner, R. H., Benedek, M., Reishofer, G., Hauswirth, V., Fally, M., … Neubauer, A. C. (2008). The creative brain: Investigation of brain activity during creative problem solving by means of eeg and fmri. *Human Brain Mapping, 30*(3), 734–748.
Forbes, O., Schwenn, P. E., Wu, P. P.-Y., Santos-Fernandez, E., Xie, H.-B., Lagopoulos, J., … Hermens, D. F. (2022). EEG-based clusters differentiate psychological distress, sleep quality and cognitive function in adolescents. *Biological Psychology, 173*, Article 108403.
Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., & Wenderoth, M. P. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences, 111*(23), 8410–8415.
Friston, K. J., Frith, C. D., Liddle, P. F., & Frackowiak, R. S. J. (1993). Functional connectivity: The principal-component analysis of large (pet) data sets. *Journal of Cerebral Blood Flow & Metabolism, 13*(1), 5–14.
Geng, X., Li, G., Lu, Z., Gao, W., Wang, L., Shen, D., Zhu, H. & Gilmore, J. H. (2016). Structural and maturational covariance in early childhood brain development. *Cerebral cortex* (p. bhw022).
Ghali, R., Tato, A. A. N., & Nkambou, R. (2019). Using eeg features and machine learning to predict gifted children. In *The Florida AI research society* (pp. 120–123). AAAI Press.
Giannouli, V. (2018). *Creative thinking and reflective teaching in prospective teachers* (pp. 115–132). IGI Global.
Giannouli, V. (2023). Are sex differences in self-estimated intelligence an elusive phenomenon? Exploring the role of working memory, creativity, and other psychological correlates in young and older adults. *Brain and Behavior: A Cognitive Neuroscience Perspective, 13*(2).
Gonzalez, A. A., Bottenhorn, K. L., Bartley, J. E., Hayes, T., Riedel, M. C., Salo, T., … Laird, A. R. (2019). Sex differences in brain correlates of stem anxiety. *Npj science of. Learning, 4*(1).
Goy, S. C., Wong, Y. L., Low, W. Y., Noor, S. N. M., Fazli-Khalaf, Z., Onyeneho, N., … GinikaUzoigwe, A. (2017). Swimming against the tide in stem education and gender equality: A problem of recruitment or retention in Malaysia. *Studies in Higher Education, 43*(11), 1793–1809.
Grabner, R. H., Ansari, D., Reishofer, G., Stern, E., Ebner, F., & Neuper, C. (2007). Individual differences in mathematical competence predict parietal brain activation during mental calculation. *NeuroImage, 38*(2), 346–356.
Gramfort, A. (2013). Meg and eeg data analysis with mne-python. *Frontiers in Neuroscience, 7*.
Grimmon, A. S., Cramer, J., Yazilitas, D., Smeets, I., & De Bruyckere, P. (2020). Interest in STEM among children with a low socio-economic status: Further support for the STEM-CIS-instrument through the adapted dutch STEM-LIT measuring instrument. *Cogent Educ., 7*(1), 1745541.
Gruzelier, J., Thompson, T., Redding, E., Brandt, R., & Steffert, T. (2014). Application of alpha/theta neurofeedback and heart rate variability training to young contemporary dancers: State anxiety and creativity. *International Journal of Psychophysiology, 93*(1), 105–111.
Gutiérrez, D., & Ramírez-Moreno, M. A. (2015). Assessing a learning process with functional ANOVA estimators of EEG power spectral densities. *Cognitive Neurodynamics, 10*(2), 175–183.
Gutierrez, D., Ramirez-Moreno, M. A., & Lazcano-Herrera, A. G. (2015). Assessing the acquisition of a new skill with electroencephalography. In *In 2015 7th international IEEE/EMBS conference on neural engineering (NER)* (pp. 727–730). IEEE.
Holland, J. L. (2008). *Making vocational choices* (3 ed.). Psychological Assessment Research.
Honey, C. J., Sporns, O., Cammoun, L., Gigandet, X., Thiran, J. P., Meuli, R., & Hagmann, P. (2009). Predicting human resting-state functional connectivity from structural connectivity. *Proceedings of the National Academy of Sciences, 106*(6), 2035–2040.
Hsieh, M.-C., Zhang, Y.-Q., Dong, R., Lee, Y.-C., & yu Ni, C.. (2022). Use of EEG signals, cortisol secretion, and task performance to evaluate the effects of different lighting environments on concentration level in a sustained attention task. *International Journal of Industrial Ergonomics, 92*, Article 103371.
Johannisson, T. (2016). Correlations between personality traits and specific groups of alpha waves in the human eeg. *PeerJ, 4*, Article e2245.
Johnson, C. C., Peters-Burton, E. E., & Moore, T. J. (2021). *STEM road map 2.0: A framework for integrated STEM education in the innovation age*. Routledge.
Kier, M. W., Blanchard, M. R., Osborne, J. W., & Albert, J. L. (2013). The development of the stem career interest survey (stem-cis). *Research in Science Education, 44*(3), 461–481.
Kier, M. W., Blanchard, M. R., Osborne, J. W., & Albert, J. L. (2014). The development of the STEM career interest survey (STEM-CIS). *Research in Science Education, 44*(3), 461–481.
Klimesch, W. (1999). Eeg alpha and theta oscillations reflect cognitive and memory performance: A review and analysis. *Brain Research Reviews, 29*(2–3), 169–195.
Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in Cognitive Sciences, 16*(12), 606–617.
Klimesch, W., Schimke, H., & Pfurtscheller, G. (1993). Alpha frequency, cognitive load and memory performance. *Brain Topography, 5*(3), 241–251.
Klimesch, W., Schimke, H., & Schwaiger, J. (1994). Episodic and semantic memory: An analysis in the EEG theta and alpha band. *Electroencephalography and Clinical Neurophysiology, 91*(6), 428–441.
Kropotov, J. D. (2009). *Quantitative EEG*. Event-Related Potentials and Neurotherapy: Elsevier.
Kunasegaran, K., Ismail, A. M. H., Ramasamy, S., Gnanou, J. V., Caszo, B. A., & Chen, P. L. (2023). Understanding mental fatigue and its detection: A comparative analysis of assessments and tools. *PeerJ, 11*, Article e15744.
Lakens, D. (2013). Calculating and reporting effect sizes to facilitate cumulative science: A practical primer for t-tests and ANOVAs. *Frontiers in Psychology, 4*, 863.
Latora, V., & Marchiori, M. (2001). Efficient behavior of small-world networks. *Physical Review Letters, 87*, Article 198701.

Latora, V., & Marchiori, M. (2003). Economic small-world behavior in weighted networks. *The European Physical Journal B - Condensed Matter and Complex Systems, 32*(2), 249–263.

Li, W., Hu, X., Long, X., Tang, L., Chen, J., Wang, F., & Zhang, D. (2020). Eeg responses to emotional videos can quantitatively predict big-five personality traits. *Neurocomputing, 415*, 368–381.

Li, Y., Schoenfeld, A. H., diSessa, A. A., Graesser, A. C., Benson, L. C., English, L. D., & Duschl, R. A. (2020). On computational thinking and stem education. *Journal for STEM Education Research, 3*(2), 147–166.

Liang, C., & Liu, Y. C. (2018). Effect of adequate non-verbal mnemonic conflict management: Comparing brain activity during idea incubation between different creativity levels. *Clinical Research in Neurology, 1*(2), 1–10.

Liu, Y.-C., Chang, C.-C., Yang, Y.-H. S., & Liang, C. (2017). Spontaneous analogising caused by text stimuli in design thinking: Differences between higher- and lower-creativity groups. *Cognitive Neurodynamics, 12*(1), 55–71.

Lopata, J. A., Nowicki, E. A., & Joanisse, M. F. (2017). Creativity as a distinct trainable mental state: An EEG study of musical improvisation. *Neuropsychologia, 99*, 246–258.

Lozoya-Santos, J.d. J., Ramírez-Moreno, M. A., Diaz-Armas, G. G., Acosta-Soto, L. F., Leal, M. O. C., Abrego-Ramos, R. & Ramirez-Mendoza, R. A. (2022). Current and future biometrics: Technology and applications, chapter 1, (pp. 1–30). CRC Press.

Maksimenko, V. A., Runnova, A. E., Zhuravlev, M. O., Protasov, P., Kulanin, R., Khramova, M. V., … Hramov, A. E. (2018). Human personality reflects spatio-temporal and time-frequency eeg structure. *PLoS One, 13*(9), Article e0197642.

Markram, H. (2011). A history of spike-timing-dependent plasticity. *Frontiers in synaptic. Neuroscience, 3*.

Martínez, G. O., Leal, M. O. C., Alvarado, J. C. O., Soto, L. F. A., Diego Mauricio Botín Sanabria, G. G. D. A., Aimé Judith Aguilar Herrera, E. A. D. J., Espinosa, M. A., Moreno, M. A. R., Menéndez, R. M., Ramírez, R. A. & de Jesús Lozoya Santos Mendoza, J. (2021). Detection of engineering interest in children through an intelligent system using biometric signals. In 2021 international conference on industrial engineering and operations management (IEOM) (pp. 2946–2936). Monterrey, Mexico: IEOM.

Mateos-Aparicio, P., & Rodríguez-Moreno, A. (2019). The impact of studying brain plasticity. *Frontiers in Cellular Neuroscience, 13*.

Mau, W.-C., Chen, S.-J., & Lin, C.-C. (2019). Assessing high school student's stem career interests using a social cognitive framework. *Education in Science, 9*(2), 151.

Mayer, R. E. (2016). How can brain research inform academic learning and instruction? *Educational Psychology Review, 29*(4), 835–846.

Megreya, A. M., Hassanein, E. E., Al-Emadi, A. A., & Szűcs, D. (2025). Math anxiety mediates the association between gender and stem-related attitudes: Evidence from a large-scale study. *Acta Psychologica, 253*, Article 104689.

Menon, V., Rivera, S., White, C., Eliez, S., Glover, G., & Reiss, A. (2000). Functional optimization of arithmetic processing in perfect performers. *Cognitive Brain Research, 9*(3), 343–345.

Mikolajczak, M., Bodarwé, K., Laloyaux, O., Hansenne, M., & Nelis, D. (2010). Association between frontal eeg asymmetries and emotional intelligence among adults. *Personality and Individual Differences, 48*(2), 177–181.

Morales-Menendez, R. A., Ramírez-Moreno, M. A., & de J Lozoya-Santos, J.. (2021). Real-time biofeedback system for interactive learning using wearables and iot. In *2021 international conference on industrial engineering and operations management (IEOM)* (pp. 2959–2970). IEOM: Monterrey, Mexico.

Moretti, D., Fracassi, C., Pievani, M., Geroldi, C., Binetti, G., Zanetti, O., Sosta, K., Rossini, P., & Frisoni, G. (2009). Increase of theta/gamma ratio is associated with memory impairment. *Clinical Neurophysiology, 120*(2), 295–303.

Mu, Z., Hu, J., & Yin, J. (2017). Driving fatigue detecting based on eeg signals of forehead area. *International Journal of Pattern Recognition and Artificial Intelligence, 31* (05), 1750011.

Mueller, S. T. (2010). A partial implementation of the bica cognitive decathlon using the psychology experiment building language (pebl). *International Journal of Machine Consciousness, 02*(02), 273–288.

Mueller, S. T., & Piper, B. J. (2014). The psychology experiment building language (pebl) and pebl test battery. *Journal of Neuroscience Methods, 222*, 250–259.

Muldner, K., & Burleson, W. (2015). Utilizing sensor data to model students' creativity in a digital environment. *Computers in Human Behavior, 42*, 127–137.

Mullen, T., Kothe, C., Chi, Y. M., Ojeda, A., Kerth, T., Makeig, S., … Jung, T.-P. (2013). Real-time modeling and 3d visualization of source dynamics and connectivity using wearable EEG. In *In 2013 35th annual international conference of the IEEE engineering in medicine and biology society (EMBC)* (pp. 2184–2187). IEEE.

Nigbur, R., Ivanova, G., & Stürmer, B. (2011). Theta power as a marker for cognitive interference. *Clinical Neurophysiology, 122*(11), 2185–2194.

Olivas, G., Candela, M., Ocampo, J., Acosta, L., Aguilar, A., Delgado, E., … Ramírez, R. (2021). Detecting change in engineering interest in children through machine learning using biometric signals. In *2021 machine learning-driven digital Technologies for Educational Innovation Workshop* (pp. 33–40). IEEE: Monterrey, Mexico.

Ouyang, M., Kang, H., Detre, J. A., Roberts, T. P., & Huang, H. (2017). Short-range connections in the developmental connectome during typical and atypical brain maturation. *Neuroscience & Biobehavioral Reviews, 83*, 109–122.

Paz-Baruch, N., & Maor, R. (2023). Cognitive abilities and creativity: The role of working memory and visual processing. *Thinking Skills and Creativity, 48*, Article 101294.

Perchtold-Stefan, C. M., Rominger, C., Papousek, I., & Fink, A. (2023). Functional EEG alpha activation patterns during malevolent creativity. *Neuroscience, 522*, 98–108.

Perez, W. A., Masline, P. J., Ramsey, E. G. & Urban, K. E. (1987). The unified tri-services cognitive performance assessment battery (utc-pab). Technical report, systems research labs., Inc., Dayton, OH and Harry G. Armstrong aerospace medical research lab., Wright-Patterson AFB. Technical rept. Apr 84–Feb 87.

Pidgeon, L. M., Grealy, M., Duffy, A. H. B., Hay, L., McTeague, C., Vuletic, T., … Gilbert, S. J. (2016). Functional neuroimaging of visual creativity: A systematic review and meta-analysis. *Brain and Behavior: A Cognitive Neuroscience Perspective, 6* (10).

Pinho, A. L., de Manzano, Ö., Fransson, P., Eriksson, H., & Ullén, F. (2014). Connecting to create: Expertise in musical improvisation is associated with increased functional connectivity between premotor and prefrontal areas. *The Journal of Neuroscience, 34* (18), 6156–6163.

Qu, X., Sun, Y., Sekuler, R., & Hickey, T. (2018). EEG markers of STEM learning. In *In 2018 IEEE Frontiers in education conference (FIE)* (pp. 1–9). IEEE.

Ramírez-Moreno, M. A., Carrillo-Tijerina, P., Candela-Leal, M. O., Alanis-Espinosa, M., Tudón-Martínez, J. C., Roman-Flores, A., … de J. Lozoya-Santos, J.. (2021). Evaluation of a fast test based on biometric signals to assess mental fatigue at the workplace—A pilot study. *International Journal of Environmental Research and Public Health, 18*(22), 11891.

Ramírez-Moreno, M. A., Cruz-Garza, J. G., Acharya, A., Chatufale, G., Witt, W., Gelok, D., … Contreras-Vidal, J. L. (2023). Brain-to-brain communication during musical improvisation: A performance case study. *F1000Research, 11*, 989.

Ramírez-Moreno, M. A., Díaz-Padilla, M., Valenzuela-Gómez, K. D., Vargas-Martínez, A., Tudón-Martínez, J. C., Morales-Menendez, R., … de J. Lozoya-Santos, J.. (2021). EEG-based tool for prediction of university students' cognitive performance in the classroom. *Brain Sciences, 11*(6), 698.

Ren, J., Huang, F., Zhou, Y., Zhuang, L., Xu, J., Gao, C., Qin, S., & Luo, J. (2020). The function of the hippocampus and middle temporal gyrus in forming new associations and concepts during the processing of novelty and usefulness features in creative designs. *NeuroImage, 214*, Article 116751.

Reynolds, C. R., Altmann, R. A. & Allen, D. N. (2021). *The problem of Bias in psychological assessment*, chapter 1, (pp. 573—-613). Springer International Publishing.

Rojas, G., & Segura, L. (2020). *Mexico's Movimiento STEM and related developments in the state of Querétaro* (pp. 203–224). Springer International Publishing.

Rosen, D. S., Oh, Y., Erickson, B., Zhang, F. Z., Kim, Y. E., & Kounios, J. (2020). Dual-process contributions to creativity in jazz improvisations: An SPM-EEG study. *NeuroImage, 213*, Article 116632.

Saffiera, C. A., Hassan, R., & Ismail, A. R. (2020). Preventive and curative personality profiling based on eeg, erp, and big five personality traits: A literature review. *Journal of Computational and Theoretical Nanoscience, 17*(2), 531–545.

Salthouse, T. A., Toth, J., Daniels, K., Parks, C., Pak, R., Wolbrette, M., & Hocking, K. J. (2000). Effects of aging on efficiency of task switching in a variant of the trail making test. *Neuropsychology, 14*(1), 102–111.

Sankari, Z., Adeli, H., & Adeli, A. (2011). Intrahemispheric, interhemispheric, and distal EEG coherence in alzheimer's disease. *Clinical Neurophysiology, 122*(5), 897–906.

Sasaki, M., Iversen, J., & Callan, D. E. (2019). Music improvisation is characterized by increase EEG spectral power in prefrontal and perceptual motor cortical sources and can be reliably classified from non-improvisatory performance. *Frontiers in Human Neuroscience, 13*.

Sassler, S., Glass, J., Levitte, Y., & Michelmore, K. M. (2017). The missing women in stem? Assessing gender differentials in the factors associated with transition to first jobs. *Social Science Research, 63*, 192–208.

Sejnowski, T. J., & Paulsen, O. (2006). Network oscillations: Emerging computational principles. *The Journal of Neuroscience, 26*(6), 1673–1676.

Shulman, G. L., Fiez, J. A., Corbetta, M., Buckner, R. L., Miezin, F. M., Raichle, M. E., & Petersen, S. E. (1997). Common blood flow changes across visual tasks: Ii. Decreases in cerebral cortex. *Journal of Cognitive Neuroscience, 9*(5), 648–663.

Sporns, O. (2010). *Networks of the brain. The MIT press*. London, England: MIT Press.

Sporns, O., Gally, J. A., Reeke, G. N., & Edelman, G. M. (1989). Reentrant signaling among simulated neuronal groups leads to coherency in their oscillatory activity. *Proceedings of the National Academy of Sciences, 86*(18), 7265–7269.

Sporns, O., Tononi, G., & Edelman, G. M. (1991). Modeling perceptual grouping and figure-ground segregation by means of active reentrant connections. *Proceedings of the National Academy of Sciences, 88*(1), 129–133.

Stevens, C. E., & Zabelina, D. L. (2019). Creativity comes in waves: An EEG-focused exploration of the creative brain. *Current Opinion in Behavioral Sciences, 27*, 154–162.

Stevens, C. E., & Zabelina, D. L. (2020). Classifying creativity: Applying machine learning techniques to divergent thinking EEG data. *NeuroImage, 219*, Article 116990.

Sujatha Ravindran, A., Mobiny, A., Cruz-Garza, J. G., Paek, A., Kopteva, A., & Contreras Vidal, J. L. (2019). Assaying neural activity of children during video game play in public spaces: A deep learning approach. *Journal of Neural Engineering, 16*(3), Article 036028.

Supekar, K., Uddin, L. Q., Prater, K., Amin, H., Greicius, M. D., & Menon, V. (2010). Development of functional and structural connectivity within the default mode network in young children. *NeuroImage, 52*(1), 290–301.

Tyler-Wood, T. L., Knezek, G. A., & Christensen, R. (2010). Instruments for assessing interest in stem content and careers. *The Journal of Technology and Teacher Education, 18*, 345–368.

van Tuijl, C., & van der Molen, J. H. W. (2015). Study choice and career development in stem fields: An overview and integration of the research. *International Journal of Technology and Design Education, 26*(2), 159–183.

Vieira, S., Benedek, M., Gero, J., Li, S., & Cascini, G. (2022). *Brain activity in constrained and open design: The effect of gender on frequency bands* (p. 36). Analysis and Manufacturing: Artificial Intelligence for Engineering Design.

Vieira, S. L.d. S., Benedek, M., Gero, J. S., Cascini, G., & Li, S. (2021). Brain activity of industrial designers in constrained and open design: The effect of gender on frequency bands. *Proceedings of the Design Society, 1*, 571–580.

Vogel, S., & Schwabe, L. (2016). Learning and memory under stress: Implications for the classroom. *Npj science of. Learning, 1*(1).

Volf, N. V., & Tarasova, I. V. (2010). The relationships between eeg θ and β oscillations and the level of creativity. *Human Physiology, 36*(2), 132–138.
Wagner, J., Lüdtke, O., & Robitzsch, A. (2019). Does personality become more stable with age? Disentangling state and trait effects for the big five across the life span using local structural equation modeling. *Journal of Personality and Social Psychology, 116*(4), 666–680.
Wang, L., Yang, J., Sun, B., Wang, D., Liu, R., He, J., & Xia, M. (2023). Influence of high-level mathematical thinking on l2 phonological processing of chinese efl learners: Evidence from an fnirs study. *Thinking Skills and Creativity, 47*, Article 101242.
Xie, Y., Lan, X., & Tang, L. (2024). Gender differences in mathematics anxiety: A meta-analysis of chinese children. *Acta Psychologica, 248*, Article 104373.
Yao, S.-N., Lin, C.-T., King, J.-T., Liu, Y.-C., & Liang, C. (2017). Learning in the visual association of novice and expert designers. *Cognitive Systems Research, 43*, 76–88.
Yin, Y., Han, J., & Childs, P. R. N. (2024). An eeg study on artistic and engineering mindsets in students in creative processes. *Scientific Reports, 14*(1).
Yuvaraj, R., Murugappan, M., Acharya, U. R., Adeli, H., Ibrahim, N. M., & Mesquita, E. (2016). Brain functional connectivity patterns for emotional state classification in parkinson's disease patients without dementia. *Behavioural Brain Research, 298*, 248–260.
Zhang, X., Cheng, L., Dai, D. Y., Tong, W., & Hu, W. (2020). Adolescents with different profiles of scientific versus artistic creativity: Similarity and difference in cognitive control. *Thinking Skills and Creativity, 37*, Article 100688.
Zhao, L., & He, Y. (2013). Power spectrum estimation of the welch method based on imagery EEG. *Applied Mechanics and Materials, 278-280*, 1260–1264.
Zheng, X. Y., & Wynn, S. C. (2022). Midfrontal theta is associated with errors, but no evidence for a link with error-related memory. *Neuroimage: Reports, 2*(4), Article 100129.