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# Educational background's impact on designers' ideation: brain, behavior, and stress

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**Abstract**

Design Neurocognition, a field bridging Design Research and Cognitive Neuroscience, offers new insights into the cognitive processes underlying creative ideation. This study adopts a micro-perspective on design ideation by examining convergent and divergent thinking as its core components. Using 32-channel EEG recordings, it investigates how educational background (Industrial Design Engineering vs. Engineering Design) influences designers'neural activity (alpha, beta, and gamma frequency bands), behavioral responses, and perceived stress during ideation tasks. Data from forty participants reveal a consistent and meaningful interaction between brain activity, behavior, and self-reported stress, highlighting that educational background significantly modulates cognitive and neural patterns during ideation. Importantly, perceived stress shows strong negative correlations with neural power across all frequency bands, suggesting a close alignment between subjective experience and physiological measures. By integrating neural, behavioral, and psychological data, this study advances the understanding of the neurocognitive mechanisms driving design ideation and establishes a methodological foundation for bridging Design and Cognitive Neuroscience. These findings contribute to building a unified evidence base for future human-centred and neuro-informed design research.

## Introduction

In the last two decades, the design research literature has been enriched by contributions that involve biomedical tools to investigate designers' behaviors and reasoning (Lohmeyer and Meboldt, 2016; Borgianni and Maccioni, 2020; Gero and Milovanovic, 2020; Balters et al., 2023).

This pervasive adoption of biomedical equipment has generated a new stream of design research called *design neurocognition* (Gero and Milovanovic, 2020; Balters et al., 2023) or *neurodesign* (Auernhammer and Saggar, 2023), which represents the intersection of cognitive neuroscience (or neurocognition) and design. It implies the use of biomedical devices to track changes in brain activity associated with different cognitive states.

Within this still-evolving field of research, ideation can be viewed as one of the main cognitive processes that bridges cognitive neuroscience and design neurocognition research (Runco, 2018; Lee and Ostwald, 2022), forming a critical interdisciplinary nexus. In cognitive neuroscience, divergent thinking (DT) and convergent thinking (CT) are assumed to represent key aspects of ideation as two contrasting ways of reasoning to solve a problem: DT is likely to lead to original outcomes and CT to conventional outcomes (Guilford, 1968). In design neurocognition, DT and CT are also considered fundamental components of design cognition (Hay et al., 2017), encompassing the generation of multiple ideas and the subsequent refinement and selection of optimal solutions, respectively. Accordingly, DT and CT have been investigated by neuroscientists in creativity research (Jauk et al., 2012; Pidgeon et al., 2016; Benedek, 2018), while design researchers have studied them in design cognition and neurocognition (Cross, 2001; Hay et al., 2017; Cascini et al., 2022; Hu et al., 2022).

However, these two research domains show crucial differences in purposes and methodologies. For instance, neuroscientists usually focus on specific cognitive processes associated with human thinking (e.g., creative thinking; Benedek, 2018), while design researchers focus on broader processes, such as conceptual design, which are usually complex and non-linear, and involve several cognitive activities (Hay et al., 2017). Auernhammer et al. (2021) provide a complete discussion of the research gaps that exist between these two domains, and some initial attempts to merge the two approaches have recently been developed (Jia and Zeng, 2021; Hu et al., 2022; Vieira et al., 2022; Li et al., 2024), though further investigations are still required.

Accordingly, the present work is based on an experimental activity that aims to move a step forward in bridging the gaps between cognitive neuroscience and design, studying designers' activities with a neurocognitive approach. The experiment focuses on design students, adopting the methodological standard from neurocognition. This implies the investigation of specific cognitive processes, such as DT and CT, rather than complex cognitive processes, such as design ideation, where DT and CT are considered crucial. The experiment replicated a revised version of the Alternative Uses Task (AUT, Jauk et al., 2012; Mazza et al., 2023), examining the designers' perspectives. While the AUT is a widely used measure for assessing ideation, it does not fully capture the complexities inherent in design, but it can explore specific fundamental cognitive components of design ideation.

To investigate the complexity of designers' perspectives on ideation tasks, the study involves design students as participants. In these contexts, the educational background represents a relevant variable significantly affecting design reasoning (Todoroff et al., 2021) and neurocognition (Vieira et al., 2022), crucial also in cognitive neuroscience research (e.g., Boller et al., 2017). The educational backgrounds considered are Industrial Design Engineering (IDE) or Engineering Design (ED). IDEs are students with a specific background that integrates industrial design with an engineering approach (i.e., studying arts, design, math, solid mechanics, materials, etc.). At the same time, EDs are students with a heterogeneous background in engineering design (i.e., electronic, industrial, material, and mechanical). Moreover, stress has generally been neglected when exploring differences in educational background, while it represents a crucial variable in design research, strongly affecting designers' activities and outcomes (e.g., Nguyen and Zeng, 2013).

The investigation is performed with a neurocognitive approach by merging a neural perspective, adopting an electroencephalogram (EEG), a behavioral perspective, adopting direct observations, and a closed-form question. The neural activities focus on brain alpha, beta, and gamma waves, while the behavioral analysis refers to participants' performances as a proxy of cognitive load, measuring response time (RT) to generate ideas, the number of words used to vocalize their response, and the perceived stress during the task. Then, these results are cross-investigated.

Accordingly, the present work focuses on the following research questions:

1. Do educational backgrounds (IDE vs ED) influence neural and behavioral measurements during DT and CT?
2. What correlation exists between neural and behavioral measurements in designers during DT and CT?

In summary, this work's contribution lies in exploring the designers' educational background on ideation activities, combined with neurocognitive and behavioral perspectives. Furthermore, the present paper proposes a rigorous and replicable protocol, consistent with the standards requested by the Cognitive Neuroscience domain, thus addressing the need for a standardization of experimental procedures when performing research on design creative ideation (Hay et al., 2020).

The paper is divided into seven sections. Section 'Background and contribution' introduces a literature overview of Design and Cognitive Neuroscience Research. Sections 'Methodology' and 'Data processing' discuss experimental protocols and data used for the analyses. Section 'Results' shows the results derived from the data analysis, and Section 'Discussion' provides and discusses detailed considerations of the findings. Finally, Section 'Conclusion' summarizes the implications of the present study.

## Background and contribution

To elucidate the context of the present work, this section reviews the existing literature, offering a comprehensive overview of key concepts such as creativity, ideation, CT, and DT within the domains of cognitive neuroscience and design. In this overview, educational background and stress emerge as areas requiring a deeper understanding. The concluding subsection outlines the main gaps identified and states the key research questions of this investigation.

### *Psychology and cognitive neuroscience research*

The term "creativity" encompasses heterogeneous definitions and roles, sometimes leading to inconsistent evidence, within different approaches (Benedek et al., 2019). Ideation, a fundamental process facilitating creative thinking, involves cognitive activities such as CT and DT and extends beyond creative processes to encompass analytical problem-solving activities (Runco, 2018).

DT is defined as *the ability to generate various, ideally novel and valuable, solutions to problems lacking a single valid answer* (APA Dictionary of Psychology, 2016). With this definition, DT is integral to understanding creative processes that characterize design. Although not synonymous with creativity, DT is frequently utilized to investigate creative endeavors involving cognitive activities like inhibition of external stimuli, loose semantic associations, and mental imagery (Mazza et al., 2023). Ideation tasks, classified under DT tests, dominate creativity research (Benedek, 2018). While not all creative outcomes are necessarily tied to creative thinking, the importance of DT in creativity is underscored by the extensive research dedicated to it (Runco, 2018).

The AUT, one of the most popular DT tasks (Benedek et al., 2019), can explore both CT and DT within its revised protocol (Jauk et al., 2012). Other widely recognized DT tasks are the Torrance Tests of Creative Thinking (TTCT; Torrance, 1968) and the Remote Association Task (RAT; Mednick, 1968).

Exploring ideation through methods like EEG and fMRI has provided valuable insights into understanding the underpinning activations (Benedek et al., 2019). From a neurocognitive standpoint, DT is linked to higher alpha (brain bands are described in Figure 2) event-related synchronization (ERS, i.e., an increase in band power associated with a specific event) than CT (Benedek, 2018). Cortical alpha waves are thought to facilitate neural inhibition, allowing individuals to shift attention from the external world (Klimesch et al., 2007) to their internal world. This phenomenon is crucial in design (Jia and Zeng, 2021). Conversely, the occurrence of alpha event-related desynchronization (ERD, i.e., a decrease in band power associated with a specific event) is typically associated with analytical problem-solving or logical reasoning (Benedek, 2018). Hence, alpha synchronization is thought to prompt DT, while alpha desynchronization might facilitate CT. Recent research suggests that synchronization in high-frequency bands (beta and gamma) might be associated with CT, not with DT (Mazza et al., 2023).

### *Design research*

Design research focuses on the processes and methods involved in designing, the context in which design occurs, and research-based design practices (Blessing and Chakrabarti, 2009). A key area is design cognition, which examines the mental activities of designers (Cross, 2001), particularly during the conceptual design phase (Hay et al., 2017). Traditional protocol-based approaches have left some knowledge gaps in understanding designers' reasoning and minds,

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underscoring the need for complementary neuroimaging methods, such as EEG and fMRI, to reveal the covert neural mechanisms underpinning design thinking (Gero and Milovanovic, 2020).

Much of the work in design neurocognition has focused on conceptual design, with an emphasis on ideation (Borgianni and Maccioni, 2020; Balters et al., 2023). In this context, creativity has been widely explored, representing the main aspect that enables designers to generate novel solutions for complex problems, particularly during conceptual design (Cross, 2001). Within design research, significant attention is given to studying creativity by exploring various cognitive constructs (e.g., convergence and divergence; Cross, 2001), cognitive processes (e.g., memory retrieval, idea association; Hay et al., 2017), and reasoning approaches (e.g., deduction, induction, abduction; Cascini et al., 2022).

In design, ideation is both a creative process and a cognitive activity where designers explore and generate ideas and concepts (Gonçalves and Cash, 2021), resulting in verbal descriptions and sketches as outcomes. During conceptual design activities, where ideation is recognized as a critical activity (Cash and Štorga, 2015), it can also be defined as "microscopic ideation" occurring at a "micro-level" (Lee and Ostwald, 2022).

The ideation processes in design can be divided into two main phases: idea generation and idea evaluation (Gonçalves and Cash, 2021), commonly characterized by divergence (and DT) and convergence (and CT), respectively, as described by the "Double Diamond" model (Cross, 2001). In divergence phases, DT is essential to generate ideas (Lee and Ostwald, 2022), achieve creative outcomes, and expand the design space (Cross, 2001; Shah et al., 2003). In contrast, CT dominates convergent processes, where the design space is contracted by discarding ideas (Cross, 2001). Accordingly, the exploration of fundamental cognitive components of designing (i.e., DT and CT) is becoming increasingly common in design research (Yin et al., 2023; Li et al., 2024).

Studies have explored how neural measurements are affected by different types of design tasks (Liu et al., 2018), the use of structured or unstructured techniques to idea generation (Shealy et al., 2020), the decision-making (Goucher-Lambert, 2017), and the mental processes involved in problem-solving and open design tasks (Vieira et al., 2022). Generally, higher levels of brain activation are linked to more creative results (Soroush and Zeng, 2024). Especially, task-related power in alpha is associated with better design outcomes (Li et al., 2024). Gender differences have also been investigated (e.g., Vieira et al., 2022b), though the results remain inconclusive. Due to the complexity of gender factors, involving several socio-cultural aspects, this variable is outside the scope of the current work. For a comprehensive literature review on the main findings related to design neurocognition, refer to Balters et al. (2023).

In design research, the impact of educational background has been highlighted in various studies. From a practical perspective, IDEs and EDs play distinct roles in product development, and this can affect their cognitive styles (Kozbelt et al., 2010). Accordingly, while IDEs prioritize aesthetics, usability, and user experience, using ideation and market analysis to create appealing designs, EDs focus on functionality and manufacturability, applying technical knowledge to ensure the product works as intended (Wölfel, 2008).

From a design cognition perspective, industrial designers are less prone to design fixation and generate a greater diversity of solutions compared to engineering designers (Agogué et al. 2013). In contrast, engineers tend to focus on predefined goals and optimizing the processes (Todoroff et al., 2021). Cognitively, IDEs exhibit significant differences from EDs (Yilmaz et al., 2013), extended to design team tasks (e.g., Singh et al., 2011).

However, in design neurocognition, studies have shown no significant differences in neural responses to problem-solving and open design tasks between mechanical engineers and industrial designers, while differences have been observed between mechanical engineers and architects (Vieira et al., 2020; Vieira et al., 2022). The impact of educational background on neurocognitive design activities is still in the early stages of investigation, with mixed findings (Nguyen and Mougenot, 2022).

Additionally, brain activation is impacted by cognitive overload, which can easily turn into stress, a crucial variable in design literature. Designers typically work under low-to-medium stress, with occasional spikes of higher stress (Nguyen et al., 2014). Interestingly, the type of design activity does not directly influence individual stress levels (Nguyen and Zeng, 2014). Research suggests that cognitive performance peaks under moderate stress and declines as stress levels increase, indicating that optimal creativity occurs when mental stress is kept at a moderate level (Yang et al., 2023). Recent experiments have examined how stress-reducing environments affect designers' performance and brain activity (e.g., Ignacio and Shealy, 2023).

Stress influences cognitive processes such as memory, learning, and problem-solving (Nguyen and Zeng, 2014). Understanding individual sensitivity to stress and its effects on cognitive performance can help designers manage stress more effectively during design tasks.

### Research gaps and questions

Although each of these findings contributes valuable insights, the research field remains somewhat fragmented, lacking a cohesive direction, particularly from the perspective of designers (Hay et al., 2020). Few studies address the industrial implications of Design Neurocognition (e.g., Jia and Zeng, 2021; Hu et al., 2022b).

As a result of the different perspectives, in this study, ideation is defined as the set of cognitive activities involved in the generation and evaluation of ideas, particularly relevant during conceptual design (Gonçalves and Cash, 2021; Lee and Ostwald, 2022).

While the use of isolated tasks enables controlled analysis of the distinct cognitive demands and neural signatures associated with each mode of thinking (also defined as basic cognitive constructs), this approach inevitably simplifies the inherently fluid, iterative, and integrated nature of real-world design processes. This modifies the cognitive framework of conceptual design presented in Hay et al. (2017), with a new layer of basic cognitive constructs (e.g., CT, DT, etc.), as reported in Figure 1. Notably, basic cognitive constructs are rarely experienced in isolation; instead, they dynamically interact throughout the different design phases, where designers oscillate between generating, evaluating, refining, re-generating ideas, and other cognitive design activities. Accordingly, the basic cognitive constructs are characterized by having a one-to-many relationship with the cognitive design activities, but their relevance is conditioned by the design phase. In particular, as expressed by the Double Diamond model (Cross, 2001), concept generation and concept evaluation are dominated, respectively, by DT and CT. This methodological simplification is therefore not intended to reduce the complexity of design cognition but to provide a focused lens through which to examine its fundamental components and their neural underpinnings, an essential step toward better understanding and modelling the richness of creative design behavior beyond standard tasks such as the AUT.

While the AUT is primarily focused on finding problems for a given solution (bottom-up), design focuses on developing solutions for a problem (top-down). The adoption of AUT cannot represent a complete design activity, but it can be considered representative of a sub-process of design, namely DT. AUT measures DT skills and

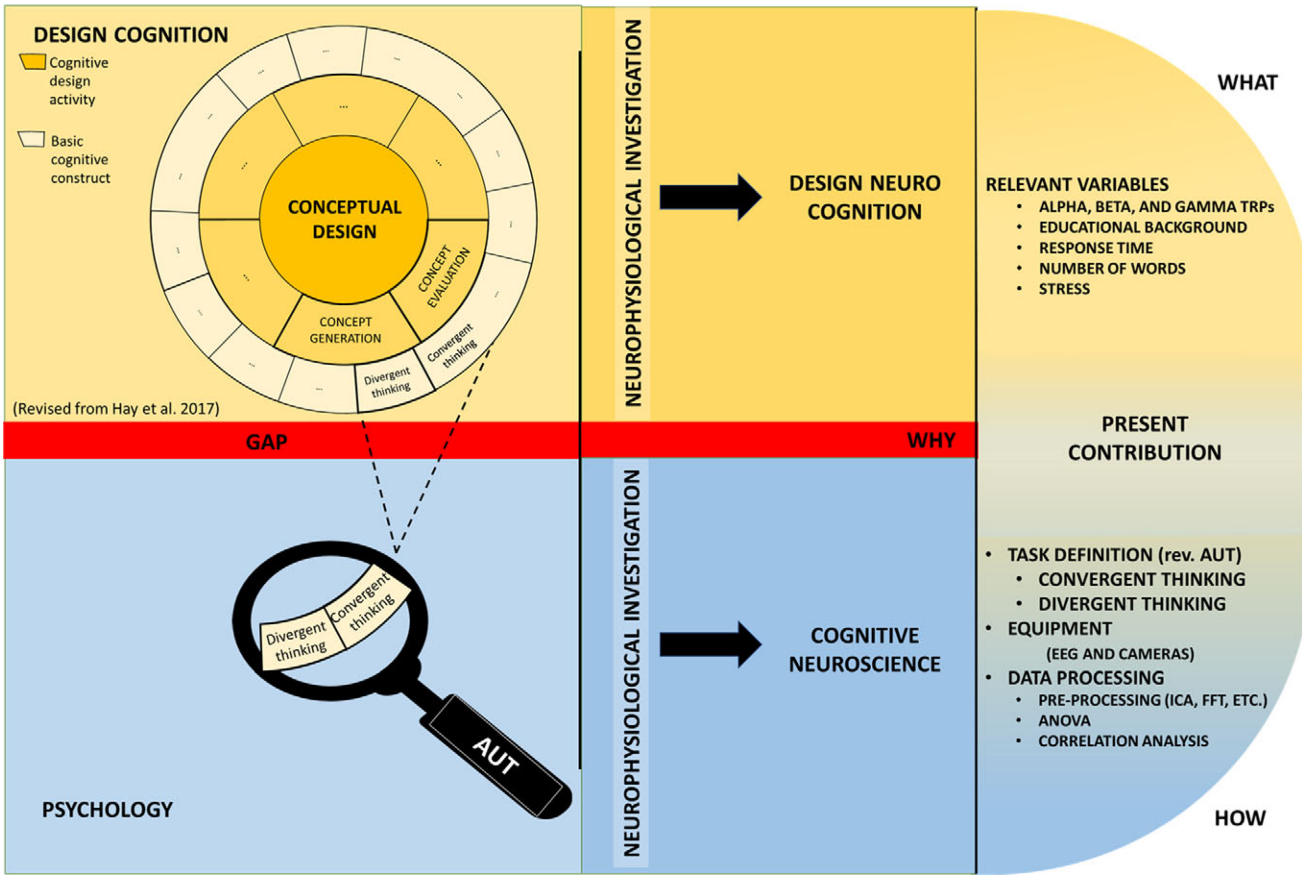


**Figure 1.** Research framework. The conceptual design cognition model is revised from Hay et al. (2017), introducing a new layer of basic cognitive constructs from Psychology literature, such as convergent and divergent thinking.

performances correlated with improving design ideation outcomes (Erwin et al., 2022). Additionally, DT tasks, like AUT, represent design ideation without specific boundaries, as some methods require (e.g., brainstorming or 6-hats), enhancing creative outcomes (König et al., 2023). AUT aligns with specific design challenges, such as defining secondary uses for objects (Liao and MacDonald, 2021) or studying product affordance in usability design (Fiodorova and Shu, 2023).

Accordingly, this study aims to investigate designers' neural and behavioral responses during CT and DT, which are foundational to design ideation, as follows:

(1) neural activity across frequency bands (Benedek et al., 2019; Mazza et al., 2023), which are widely used to infer cognitive engagement and mental processes in ideation (Gero and Milovanovic, 2020)
- alpha: associated with internal attention, creative inhibition,
- beta: linked to object recognition and sustained attention,
- gamma: related to integrative cognitive processing;

(2) behavioral indicators (Nguyen and Zeng, 2014; Dumas et al., 2018; Liu et al., 2018), generally adopted in protocol studies (Cross, 2001):
- RT and the number of words representing proxies of cognitive effort and fluency, and ideational productivity and richness
- perceived stress level, as a subjective mental load.

These neural and behavioral indicators provide complementary insights into ideation: while EEG-derived TRPs offer a physiological trace of cognitive load and attentional states, behavioral responses reflect the observable output and subjective experience of the ideation process. Together, they allow for a multidimensional analysis of how ideation unfolds across individuals with different educational backgrounds and under varying stress conditions.

While Li et al. (2024) investigated neural activities while performing DT and CT as separate activities and in the context of design tasks, the findings are preliminary. Recent literature explores alpha activation in ideation for design students (Ahad et al., 2023) and the neural activity associated with DT and CT in complex design problems (Milovanovic et al., 2021). Designers' specific backgrounds are often neglected, referring to designers as a general term.

Educational backgrounds yield intriguing results in design ideation (Gonçalves and Cash, 2021). While different backgrounds have been shown to significantly impact cognitive activities in other domains (e.g., Parasuraman and Jiang, 2012), the influence of diverse educational backgrounds within the design neurocognition field remains underexplored. Current literature demonstrates limitations in delving into the distinctions between IDE and ED, lacking a comprehensive examination from both neural and behavioral viewpoints. At the same time, the differences between IDE and ED in design cognition refer to broad design activities, while differences in each cognitive activity involved in conceptual design (such as DT and CT) are still not explored. Our study seeks to address this gap by investigating how different types of design education impact neurocognitive processes in ideation tasks.

While previous studies underscore the significance of designers' educational background and stress, these factors have been

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investigated separately. Exploring the literature, stress represents a relevant variable in these tasks, and stress management interventions can enhance both designers' performance and mental health. To the best of our knowledge, how the design educational background interplays with stress remains unexplored in the design neurocognition literature. Understanding the interplay between stress and educational backgrounds might enable the development of more targeted and effective interventions. Moreover, there is a notable methodological gap in the comparison of design ideation, neglecting to integrate both neural and behavioral perspectives. These research gaps motivate the exploration of designers' differences in both neural activation (investigating alpha, beta, and gamma bands) and behavioral responses (RT, number of words, and perceived stress) while performing DT and CT tasks. This study also aims to explore how designers' overall perceived stress relates to their underlying neural activity during ideation tasks, providing insight into how cognitive mindset and subjective experience interplay in design cognition. The research framework of the present contribution is depicted in Figure 1.

According to the literature presented, to address RQ1 and RQ2, we formulate the following hypotheses:

**H1.1:** *Educational background influences neural measurements during DT and CT.*

**H1.2:** *Educational background influences behavioral measurements during DT and CT.*

**H2:** *Neural and behavioral measurements of designers' interplay during DT and CT.*

These hypotheses were tested using the procedures detailed in Section 'Statistics'.

## Methodology

The methodology employed in this study integrates established practices from the existing literature to address the outlined research questions. First, the measurements adopted are detailed. Then, the task (AUT) and the equipment (EEG) are presented. Finally, participants with the previous elements generate the experimental setting.

### *Measurements for neural activity and behavioral response*

The methodologies and equipment adopted depend on the research aims in the domains of design (Blessing and Chakrabarti, 2009) and design neurocognition (Gero and Milovanovic, 2020). For this reason, the measurements for neural activity and the behavioral response are detailed in this section.

#### Neural activity measurements

In this study, we employed electroencephalography (EEG) to examine brain waves, allowing the measurement of the brain's electrical activity by detecting spontaneous or evoked changes in electrical brain potentials (APA Dictionary of Psychology, 2016). The EEG device consists of a cap, a variable number of electrodes strategically placed on the scalp, an amplifier, and a recorder.

EEG waves are characterized by five key features: frequency, topography, amplitude, phase, and latency (APA Dictionary of Psychology, 2016). In Cognitive Neuroscience, frequency and topography are crucial features for investigating cognition. The frequency is associated with five clusters of brain waves: gamma, beta, alpha, theta, and delta, each playing distinct roles, as reported in Figure 2. Topography examines different regions of the brain, typically linked to specific functions. This study focuses on the Frontal, Central, Parietal, Temporal, and Occipital cortex areas,

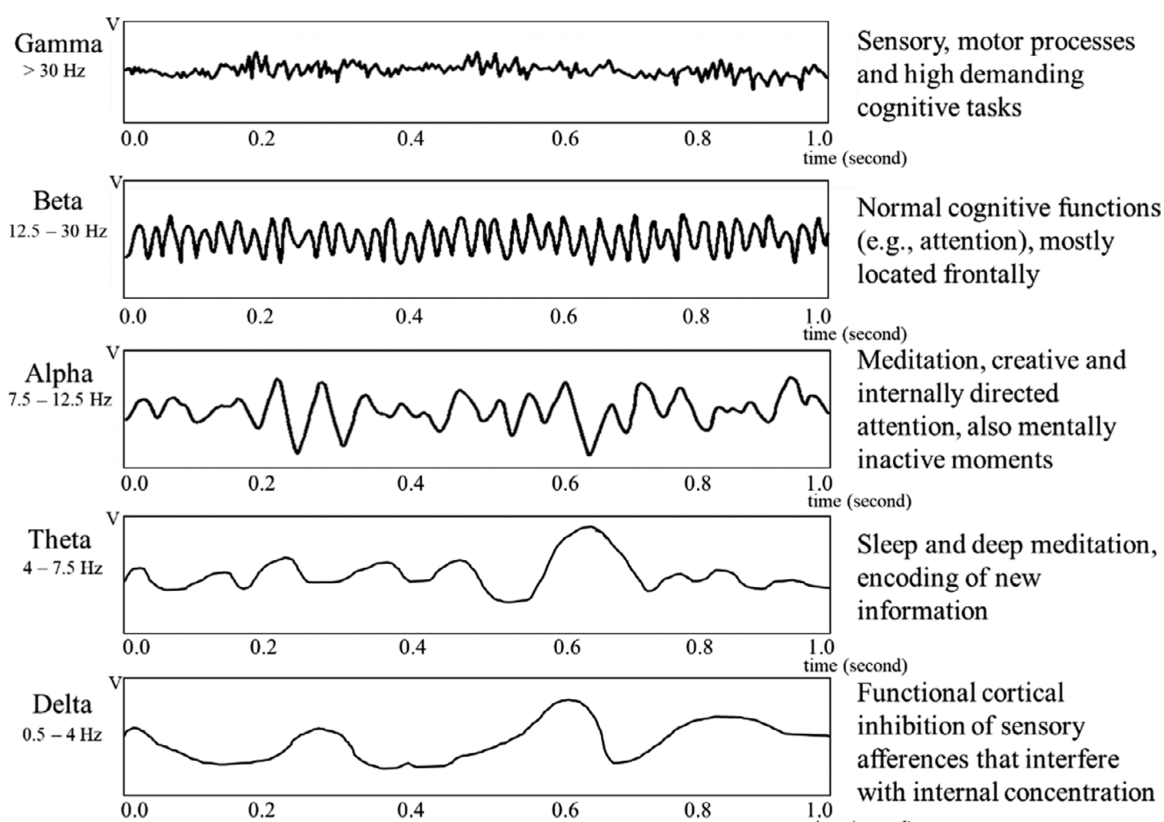


**Figure 2.** Brain waves and their roles.

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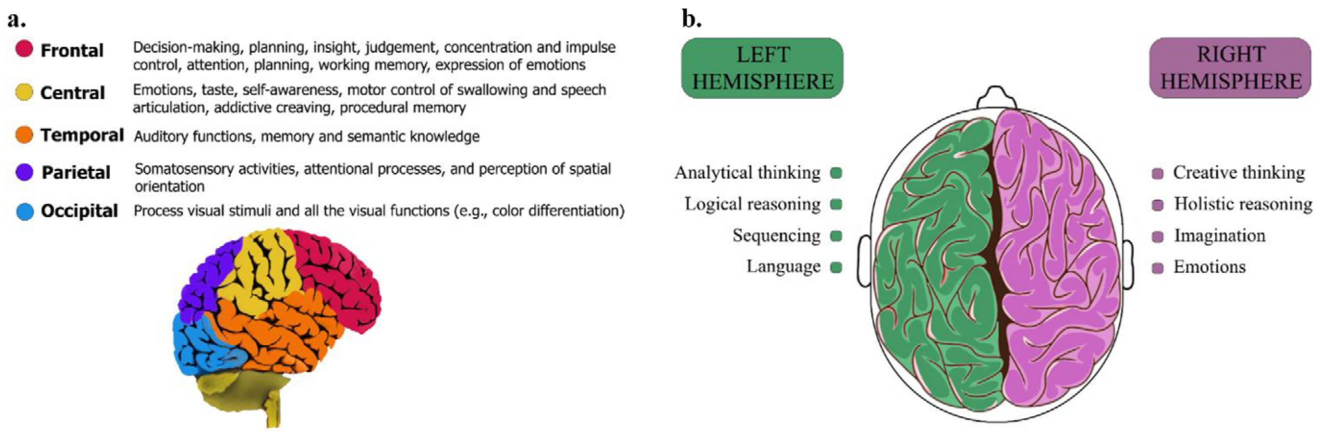


**Figure 3.** (a) Brain areas and their main functions (b) Brain hemispheres and their main functions.

described in Figure 3a. Moreover, topographic analysis is also linked to the left and right hemispheres, characterized by different roles in cognitive activities, as shown in Figure 3b. The direct link between a specific brain region or hemisphere with specific functions is an approach that tends to generalize some results. These links show several conflicts in the literature, and their meaning is still under debate (e.g., Dietrich and Kanso, 2010; Corballis, 2014). Only a few functions have been recognized with specific regions (e.g., language; Corballis, 2014). However, some studies have shown potential lateralization of creative thinking (e.g., Jauk et al., 2012; Aberg et al., 2017), making these explorations relevant for the present work.

For the scope of the present paper, results are focused only on the alpha, beta, and gamma bands because of their relevance in creative thinking and DT (Benedek, 2018; Hu et al., 2022a; Vieira et al., 2022; Ahad et al., 2023). Although theta and delta frequency bands have been associated with stress and cognitive load in previous research, we chose to exclude these bands from our analysis to focus on the other bands that have been closely linked to design ideation and attentional processes (Mazza et al., 2023).

## Behavioral response measurements

Behavioral assessments play a pivotal role in protocol analysis studies, where designers' actions during a task are systematically observed to evaluate their quality and gain insights into designers' cognition (Litster and Hurst, 2020). Among the several behavioral variables, RT assumes critical importance in both Design and Cognitive Neuroscience research. RT serves as an indicator for cognitive processes and individuals' behavioral response patterns. Widely adopted to measure mental ability in cognitive tests, as well as levels of knowledge, experience, and emotions (Sideridis and Alahmadi, 2022), the time taken to complete a task often correlates with concurrent cognitive actions prevalent in design contexts (Kavakli and Gero, 2002). Due to its high positive correlation with cognitive overload, RT frequently serves as a proxy for the latter (Nguyen et al., 2018).

A prevalent protocol in Design Research is the think-aloud method, which requires designers to articulate their thoughts while executing a specific task (Shealy et al., 2023). Verbalization serves as an expression of the designers' reasoning (Hay et al., 2017). The number of words measures individuals' response length. This can serve as a behavioral indicator of cognitive effort, as the more extensive verbal output may reflect increased mental processing and response elaboration (Corps and Pickering, 2024). Furthermore, their educational aspirations impact individuals' response length (Denscombe, 2008). This might potentially be influenced by individuals' educational backgrounds. Understanding this measure might be relevant for design research, particularly in areas such as semantic analysis (Sarkar et al., 2010) and prompt generation for AI support tools (Ye et al., 2024), where the quantity and quality of verbal input can significantly influence outcomes.

Finally, surveys are other methods adopted in protocol analysis to explore human behavior, largely adopted in Design Cognition, where they often represent the only source of information for introspective and retrospective data (Xue and Desmet, 2019). Then, the perceived stress was measured with a closed question at the end of the entire experiment, prompting participants to quantify their "stress" on a 1-to-5 Likert scale. EEG data are analyzed at a high temporal resolution on a trial-by-trial basis, and, on the other hand, perceived stress is measured once post-task to capture the cumulative subjective state. While the mismatch of these measurements introduces a limitation of this study, the comparison of them offers a broader perspective on how sustained cognitive and emotional experiences align with neural patterns.

### *Equipment*

*iMotions 7.2* was utilized to record, combine, and synchronize neural and behavioral data.

The EEG utilized was a *BrainVision ActiCHamp*, developed by *BrainProducts GmbH* (Figure 4a). The sampling rate was *500 Hz*, and no online filters were applied. For the location of electrodes on the scalp, the international *system 10–20* was used (Figure 4b). Thirty-three electrodes were positioned: thirty-one on the scalp, one on the nose tip as a reference, and one ground electrode in the Fpz position. The three midline electrodes (Fz, Pz, Oz) were excluded from the analyses to account for potential hemispheric lateralization. The electrodes' impedance was kept below *5 kOhm.*

With the protocol analysis approach, two cameras directly observed and recorded the designers.

### *Task*

The experimental protocol employed is a refined version of the AUT introduced by Jauk et al. (2012). Participants engaged in two conditions, where they were asked to identify (i) the most common use (representing CT) and (ii) the most uncommon use (representing DT) for everyday objects. While the AUT provides valuable insights into creative thinking and ideation processes, it may not entirely reflect the

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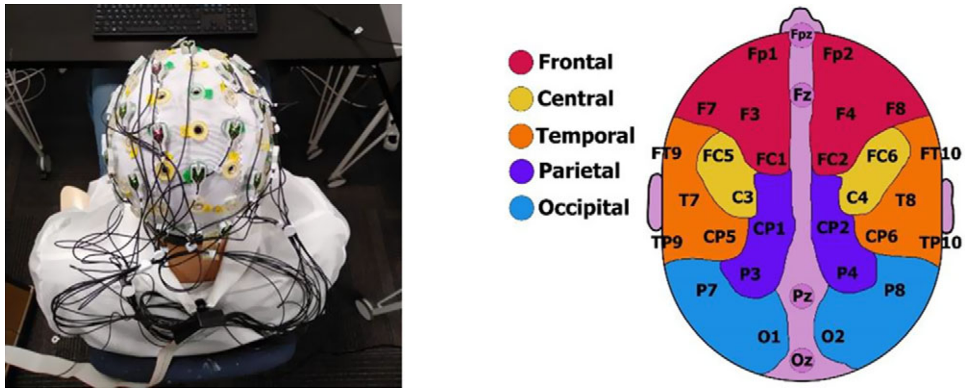


**Figure 4. (a)** EEG cap montage on a participant; **(b)** Electrodes topography adopted for EEG analyses (Mazza et al., 2023).

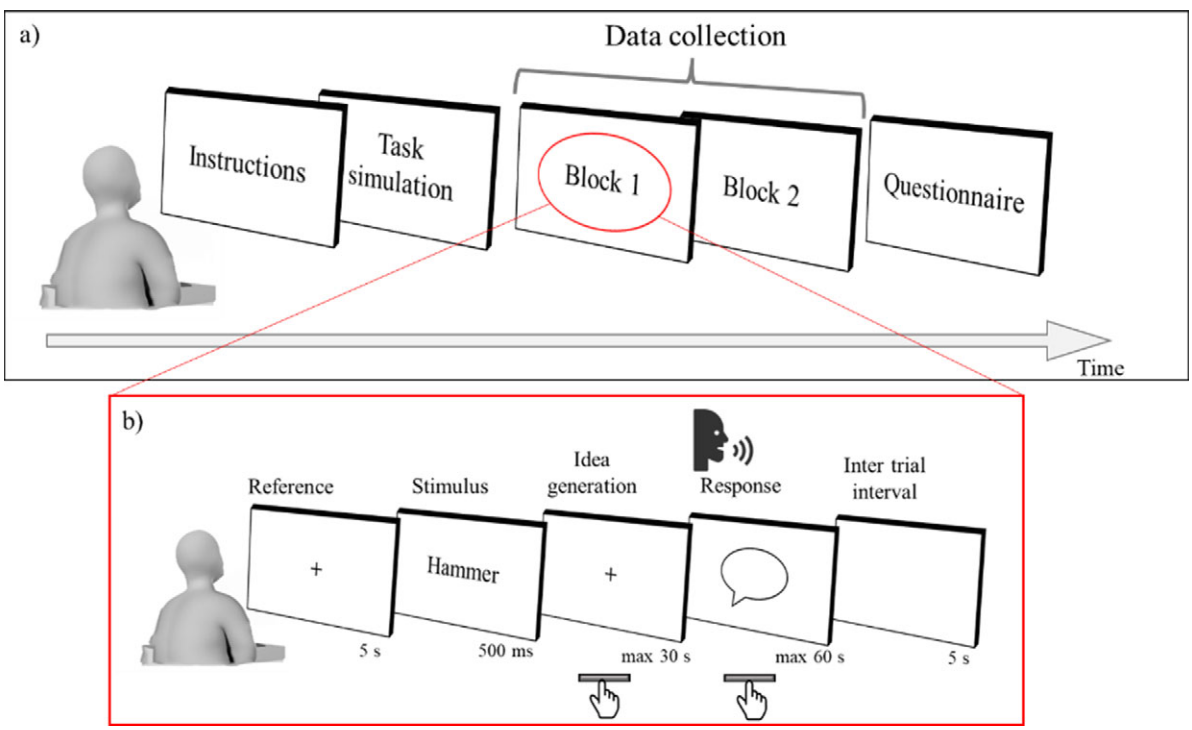


**Figure 5. (a)** The task procedure; **(b)** The trial sequence.

multifaceted nature of design ideation. Our choice of the AUT was guided by its ability to elicit measurable neurocognitive and behavioral responses that are relevant to some aspects of design cognition and ideation in general. This allows us to extend the comparison of findings with literature from different domains, such as creativity.

During instructions, participants were instructed to generate practical and effective solutions for daily problems. Each participant is assigned 40 everyday objects, randomly allocated to either the "common" or "uncommon" condition using a block design (20 + 20). This approach balances sufficient data sampling, as suggested by Jauk et al. (2012), and participant fatigue, a crucial consideration in maintaining data quality (Nguyen et al., 2019). Additionally, object names, as stimuli, were translated into participants' native languages to eliminate potential cognitive interference due to translation (Rojo López, 2015).

The task procedure is detailed in Figure 5a, while the trial sequence is illustrated in Figure 5b. Measures are linked to the "reference" (serving as a baseline) and "idea generation" (as the activation related to the task). The "response" was excluded due to potential artifacts associated with vocalization.

## Participants

A total of 40 healthy volunteers were recruited as participants, comprising students from Luleå University of Technology. The gender distribution included 11 females and 29 males (M = 23.67, SD = 2.55, range = 19–29 years). To ensure a baseline level of understanding, a standard zero-level training was provided during the task instructions for all participants to balance any potential previous experience. While age-related declines in DT are generally associated with individuals over the age of 40 (Palmiero, 2015), our sample consisted of much younger participants, with a maximum age of 29. Therefore, we assumed that age-related differences would not significantly impact the results since the scope of the work was

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to explore different educational backgrounds. The participants were recruited with different educational backgrounds: 17 IDEs, with a specific background in Industrial Design Engineering, and 23 EDs, with a background in engineering design (i.e., electronic, industrial, material, and mechanical). None of the participants reported any neurological disorder. Handedness was determined using the Edinburgh Handedness Inventory.

Participants in this study spoke eight different native languages, with a balanced distribution across the educational background groups. None of the participants were native English speakers. Before the experiment, each participant was given the choice to complete the task either in English or their native language. To accommodate their preferences and minimize potential cognitive interference due to translation (Rojo López, 2015), all object names used as stimuli were translated into the selected languages by participants. This approach ensured that linguistic variations did not introduce confounding effects, providing consistency in the cognitive processing of stimuli across different language backgrounds.

### *Ethical clearance*

Prior to data collection, the experimental design underwent a thorough review and received approval from the Institutional Review Board (IRB) at the University of Turin. In alignment with ethical research practices, all participants were provided with detailed information about the study's purpose, procedures, potential risks, and benefits. Written informed consent was obtained from each participant before commencing the experimental sessions, ensuring their voluntary participation and understanding of the study. This protocol was implemented to uphold the highest ethical standards in research involving human subjects.

### *Experimental setting*

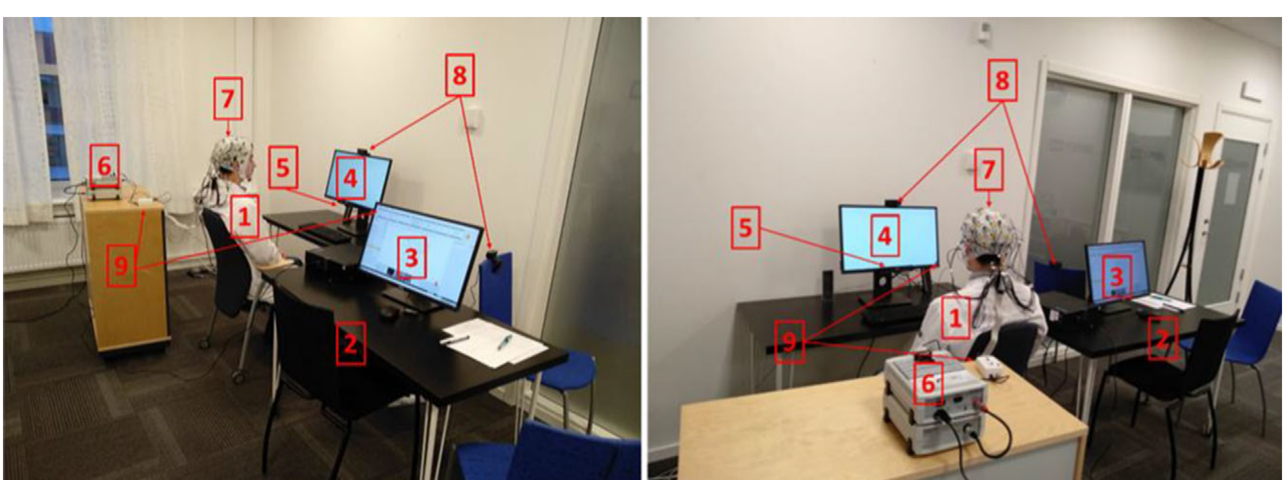
The experimental setting enforced a static posture, with participants situated *60 cm* away from the screen, positioned on a table, as reported in Figure 6. Before each experiment, participants received instructions to minimize movements and activities unrelated to the assigned task.

## Data processing

The processing and analysis of EEG neural data were conducted using *Matlab* (version *R2020a, The Mathworks Inc.*) with the *EEGLAB (v2019)* toolbox.

Analyzed windows corresponded to the entire idea generation phase in each trial. The first 500 ms from each window were excluded to eliminate evoked activity, retaining only induced activity. Raw data underwent filtering with a 0.5 Hz high-pass FIR filter and a 50 Hz notch filter. Portions of data affected by significant artefacts were removed through visual inspection. Subsequently, channels capturing highly noisy signals were interpolated using spherical spline interpolation. An independent component analysis (ICA) and visual inspection were also applied to eliminate other noise related to other physiological (e.g., ocular and muscular) and non-physiological artifacts. Accordingly, the main criteria for visual inspections were related to topography and power spectrum. About topography, components with activities mainly centered in one or a few electrodes were suspected as muscular activities, with particular attention to the frontal electrodes (the most affected by ocular activities. On the other hand, components widespread or dipolar were linked to brain activity. For the power spectrum, components with flat or particularly high frequencies, with strong power, were considered muscular activities, especially if they presented high kurtosis. Only trials with at least one component linked to brain activity were considered valid.

While previous research provides no evidence about the role of handedness, left-handed participants and those encountering recording issues were excluded (7 of 40) to control for potential hemisphere dominance effects. These participants were excluded because less than 50% of the recorded trials were considered valid to ensure data reliability and interpretability. This threshold aligns with standard EEG preprocessing guidelines, which aim to balance the benefits of including additional participants, increasing the within-group variability linked to individual differences, against the inclusion of new participants, which contributes meaningful contributions to the overall dataset. A total of $N = 33$ subjects were considered for analyses, with 866 valid trials included. The power in each frequency band was extracted using Welch's method (Welch,



1. Participant's workstation 2. Researchers' workstation 3. Control Monitor 4. Task presenting Monitor 5. Eye-tracker
6. Signal amplifier 7. EEG cap and Electrodes 8. Cameras 9. Photodyode (sensor and recorder)

**Figure 6.** Instrumental setting.

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1967), with a 1 s window length and a step of 500 ms. The division of the signals into bands follows the ranges presented in Figure 1.

The derived variable is the Task-Related Power (TRP) calculated for the analyzed bands, measured in $\mu V^2$. TRPs were calculated per electrode, trial, and subject as the difference between the mean log-transformed band-power of the idea generation period and the corresponding reference period, defined by the equation (Jauk et al., 2012):

$$TRP = log(PowerActivation) - log(PowerBaseline) \quad (1)$$

Positive values of TRPs indicate synchronization (ERS), while negative values indicate desynchronization (ERD).

Participants' behavioral responses were recorded in terms of time and wording, measuring RT and the number of words in each ideation phase. Through a visual inspection of video-recorded data, participants' activities were segmented into baseline (while a pre-trial reference cross was presented on the screen as an inter-trial pause), elaboration of stimuli (stimulus), ideation (post-stimulus reference cross), and vocalization (speech balloon). This was also crucial for validating the correspondence of the trial sequence, shown in Figure 4. a, into different cognitive states and for removing muscular artefacts and other sources of noise for the neural measures. Two aspects were measured: response time (RT), corresponding to the duration of the ideation phase, and the number of words, corresponding to the number of words used by participants to describe their ideas. The researchers directly monitored the participants' behavioral data, which was subsequently validated using recorded data.

Finally, the generated ideas were transcribed for evaluation to assess participants' engagement with the different task conditions based on their originality. Four external raters, unaware of the task conditions, rated the originality of the ideas using a Likert scale ranging from 1 to 4.

### Statistics

All the factors are listed in Table 1 for the statistical data analyses, detailing their levels and summarizing their descriptions.

Due to the multitude of factors considered, Supplementary Appendix A.1 provides a summary of the statistical analyses that were conducted. For the neural activities, three 4-way ANOVAs explore the activations over the scalp, considering different brain regions (with Area_F) in the two hemispheres (Hemisphere_F) and how they interplay with different educational backgrounds (Background_F) during different types of thinking (Condition_F). These ANOVAs consider, respectively, alpha, beta, and gamma TRPs as dependent variables.

Post-hoc analyses were conducted using Tukey's Honest Significant Difference (HSD) test via the pairwise_tukey() function in Pingouin (Jupyter Notebook), which adjusts p-values for multiple comparisons and controls the family-wise error rate across all pairwise contrasts. The results are fully reported in Supplementary Appendix B.

For the behavioral response, two 2-way ANOVAs explore the effects of educational background on the number of words and RT in the two types of thinking, respectively. On the other hand, the perceived stress is compared among the two educational backgrounds through a t-test to verify if designers with different educational backgrounds perceive stress differently in ideation tasks.

Finally, correlation analyses are conducted to evaluate the relationship between neural activity and behavioral response.

## Results

This section describes the results of the statistical analyses. The factors related to the conditions are examined in conjunction with

**Table 1.** Factors for statistical analysis

| Variables | Levels | Description |
|---|---|---|
| **Area (Area_F)** *independent variable within-subjects* | Frontal vs Central vs Temporal vs Parietal vs Occipital | To understand to what extent lobes are involved than others and if other factors could be involved (e.g., language, motor; etc.) |
| **Condition (Condition_F)** *independent variable within-subjects* | Convergent vs Divergent | To identify the cognitive paths in the task and to confirm previous results (Benedek, 2018), common uses are linked to the Convergent (thinking) condition, while uncommon uses are linked to the Divergent (thinking) condition. |
| **Educational background (Background_F)** *independent variable between-subjects* | ED vs IDE | As an explorative analysis, to understand if the cerebral activities could be related to the educational background, representing a new exploration in the field, and for which evidence is still missing (Vieira et al., 2022) |
| **Hemisphere (Hemisphere_F)** *independent variable within-subjects* | Right vs Left | To investigate if the cognitive activities are higher/lower in the right vs left hemisphere, as established in the previous literature (Corballis, 2014) |
| **Response time** *dependent variable* | Continuous | The time used by the participant before being ready to vocalize the solutions/ideas generated |
| **Number of Words** *dependent variable* | Continuous | The number of words used by the participant to vocalize the idea/solution |
| **Perceived stress** *dependent variable* | 1–5 (Likert scale) | The level of perceived stress by participants during the entire task |
| **Originality** *within-subjects* | 1–4 (Likert scale) | The degree to which the idea is not only novel but is also ingenious, imaginative, or surprising |

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the educational background to assess their influence and interaction concerning neural activity, behavioral response, and perceived stress.

Only outcomes with p-values < .05 are deemed significant, while p-values <0.1 are considered weakly significant; however, they may indicate potential trends or associations that merit further exploration. On the other hand, p-values < .001 are defined as strongly significant. To have a clearer understanding of these findings, all the statistical results, including effect size, are reported in Supplementary Appendix B.

### *Educational background in convergent and divergent thinking*

To validate participants' engagement with the different task conditions, a t-test was conducted to compare the originality of ideas generated in the two conditions. The results show a strongly significant difference in originality between the conditions ($T = 29.51$, $p < .001$). As expected, ideas generated in the Divergent condition (Mean = 2.86, SD = 0.72) were rated as more original than those generated in the Convergent condition (Mean = 1.11, SD = 0.40). Therefore, the factor condition can be considered a reliable proxy for distinguishing between CT and DT.

### Neural activity

To investigate the neural activations under different task conditions and the impact of educational background, three 4-way ANOVAs (area×background×condition×hemisphere; 5×2×2×2) are conducted, each focusing on alpha, beta, and gamma TRPs as dependent variables. The non-significance of statistical tests on

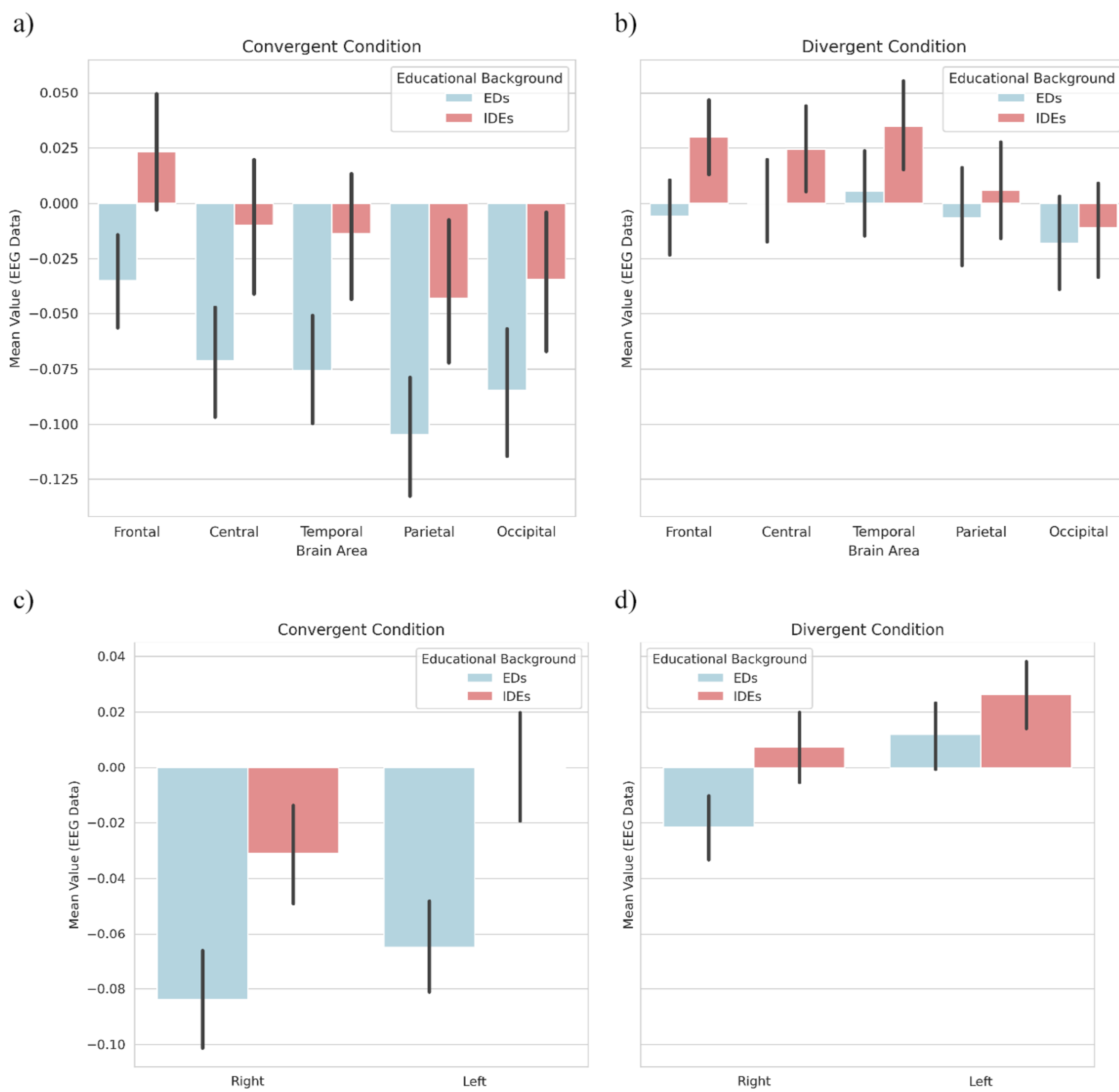


**Figure 7.** **(a)** Alpha TRPs per brain region, grouped by educational background during CT; **(b)** Alpha TRPs per brain region, grouped by educational background during DT; **(c)** Alpha TRPs per hemisphere, grouped by educational background during CT; **(d)** Alpha TRPs per hemisphere, grouped by educational background during DT.

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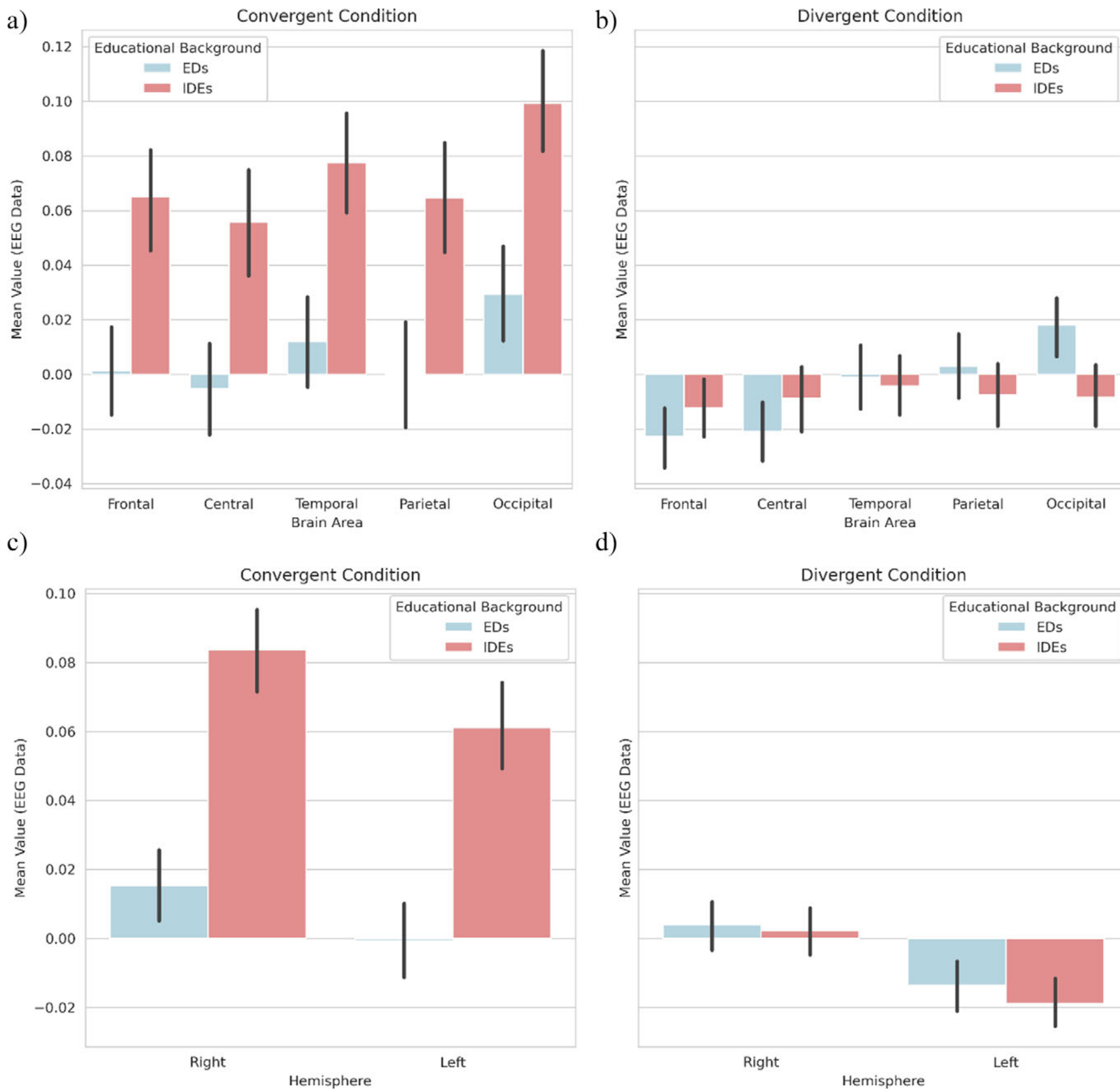


**Figure 8.** **(a)** Beta TRPs per brain region, grouped by educational background during CT; **(b)** Beta TRPs per brain region, grouped by educational background during DT; **(c)** Beta TRPs per hemisphere, grouped by educational background during CT; **(d)** Beta TRPs per hemisphere, grouped by educational background during DT.

the theta band led the authors to the exclusion of this frequency band from this study. Before proceeding with the statistical analysis, the normal distribution of values was successfully tested.

***Alpha TRP.*** All the analyzed factors show highly significant main effects for condition ($F(1, 864) = 100.836$, $p < .001$), background ($F(1, 864) = 51.33$, $p < .001$), area ($F(4, 861) = 7.415$; $p < .001$), hemisphere ($F(1, 864) = 23.666$; $p < .001$). These results are shown in Figure 7.

The educational background and different types of thinking, as the main factors of the study, are deemed relevant in the conducted measurements, with significant interaction ($F(1, 864) = 11.761$; $p < .001$). In general, alpha TRPs show higher values in DT compared to CT, and greater alpha TRPs are linked to IDEs than EDs.

The alpha TRPs show a quite linear decrease over areas, from frontal to occipital regions, more evident in the CT condition, as highlighted by the significant interaction of condition×area ($F(4, 861) = 3.393$; $p = .009$). Areas are also conditioned by hemisphere, as the area×hemisphere shows ($F(4, 861) = 3.797$; $p = .004$).

However, all the other interactions of factors at two, three, and four levels do not show significance.

***Beta TRP.*** The analysis reveals a significant main effect for all examined factors: condition ($F(1, 864) = 154.635$; $p < .001$), background ($F(1, 864) = 67.792$; $p < .001$), area ($F(4, 861) = 10.526$; $p < .001$), and hemisphere ($F(1, 864) = 32.689$; $p < .001$). Figure 8 visually represents the key findings of this analysis.

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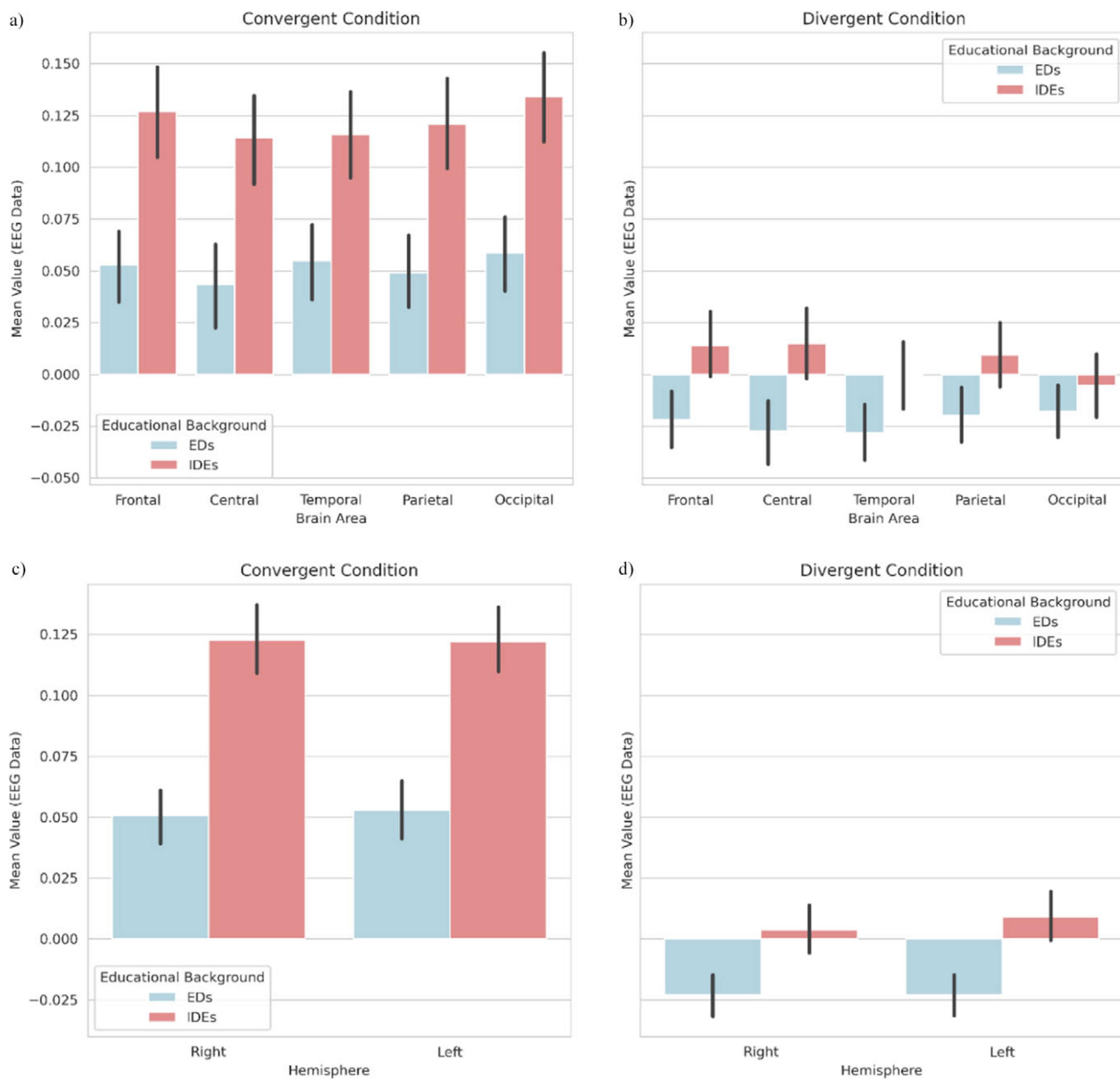


**Figure 9. (a)** Gamma TRPs per brain region, grouped by educational background during CT; **(b)** Gamma TRPs per brain region, grouped by educational background during DT; **(c)** Gamma TRPs per hemisphere, grouped by educational background during CT; **(d)** Gamma TRPs per hemisphere, grouped by educational background during DT.

The highly significant interaction of condition and background ($F(1, 864) = 103.649$; $p < .001$) indicates that CT shows greater beta TRP values than DT, and this discrepancy is more evident in IDEs. However, the other three-level and four-level interactions are not significant.

***Gamma TRP.*** The analysis reveals significant main effects for the main explored factors condition ($F(1, 864) = 563.124$; $p < .001$), background ($F(1, 864) = 151.57$; $p < .001$), while the localization over the brain regions (area: $F(4, 861) = 0.564$; $p = .069$) and the lateralization (hemisphere: $F(1, 864) = .0169$; $p = .068$) exhibit only weak significance for gamma TRPs. The interaction of condition with the educational background ($F(1, 864) = 27.413$; $p < .001$) shows high significance. All the other interactions are detected as non-significant.

These results are depicted in Figure 9.

## Behavioral response

The behavioral analyses concentrate on direct observations of participants, considering RT and the number of words. They are subject to a two-way ANOVA, incorporating the Background and Condition factors.

***The number of words and RT.*** For ideation time, participants' RT is explored in the CT and DT conditions, considering the two educational backgrounds through a two-way ANOVA. Condition displays a significant main effect ($F(1, 864) = 1385.11$; $p < .001$), emphasizing substantial differences in RT between CT and DT. While RT values are relatively low during CT (Mean = 3.87; St. Dev. = 3.78), RT is approximately five times longer during DT

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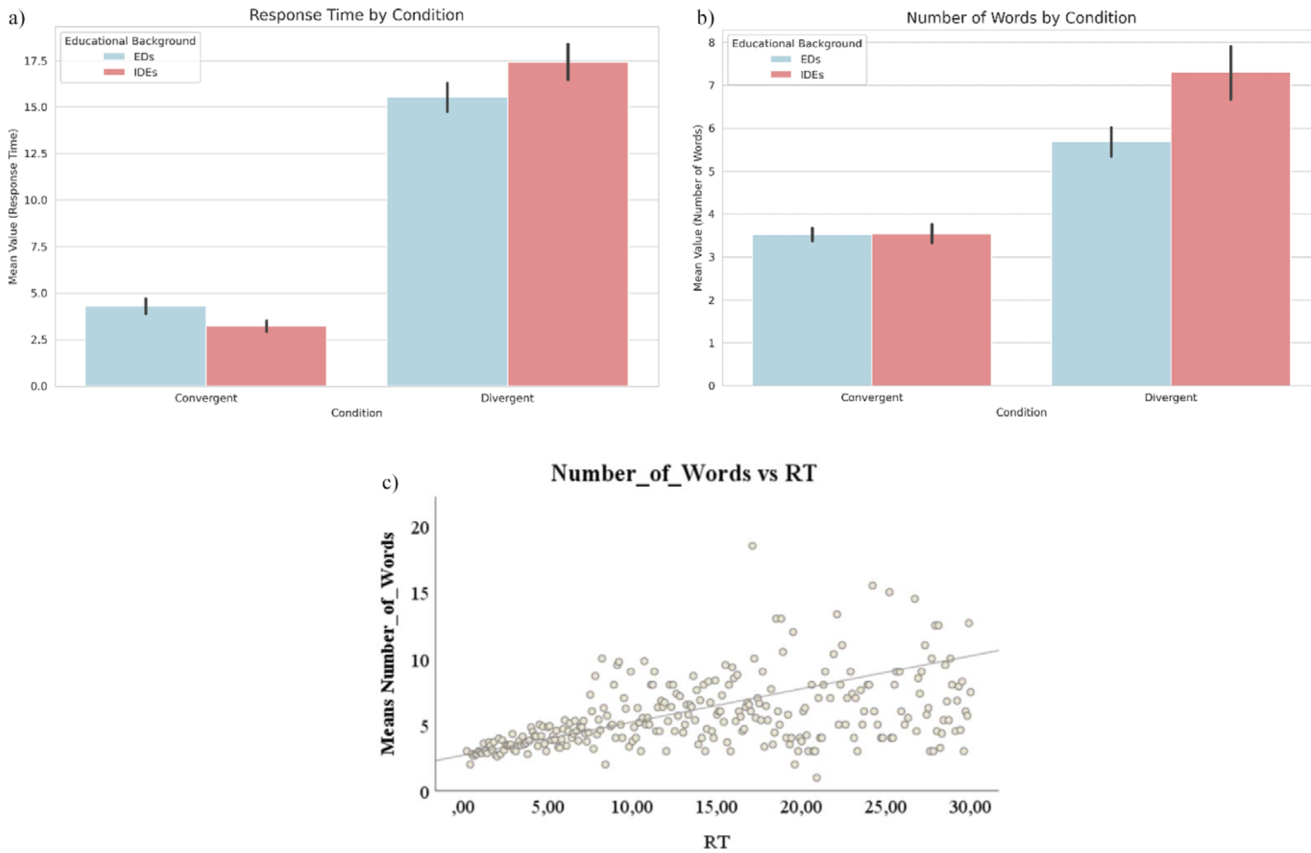


**Figure 10.** **(a)** RT by condition and background; **(b)** Number of words by condition and background; **(c)** Correlation RT vs number of words.

(Mean = 16.30; St. Dev. = 8.33). Background as a sole factor is not statistically significant (F (1, 864) = 1.189; p = .276), with a moderate difference between EDs (Mean = 9.68; St. Dev. = 8.50) and IDEs (Mean = 10.17; St. Dev. = 9.51). However, the interaction background×condition is strongly significant (F (1, 864) = 18.942; $p < .001$), indicating that different educational backgrounds lead to diverse approaches to the task conditions behaviorally. In CT, EDs (Mean = 4.73; St. Dev. = 4.36) tend to spend more time on idea generation than IDEs (Mean = 4.42; St. Dev. = 2.54). Conversely, during DT, IDEs (Mean = 17.43; St. Dev. = 8.66) have higher values than EDs (Mean = 15.93; St. Dev. = 8.01), with a more pronounced difference, as illustrated in Figure 9.a.

Examining the number of words, condition manifests a significant main effect (F (1, 864) = 282.586; $p < .001$), showcasing a considerable disparity in the number of words used by participants. During DT (Mean = 6.43; St. Dev. = 4.32), participants generated almost twice as many words as in CT (Mean = 3.53; St. Dev. = 1.67). Background also exhibits a highly significant main effect (F (1, 864) = 22.260; $p < .001$), where IDEs (Mean = 5.38; St. Dev. = 4.33) tend to use more words compared to EDs (Mean = 4.63; St. Dev. = 2.88). The interaction background×condition is highly significant (F (1, 864) = 21.997; $p < .001$). In CT, educational backgrounds do not significantly impact IDEs (Mean = 3.75; St. Dev. = 1.79) and EDs (Mean = 3.71; St. Dev. = 1.61). Both groups demonstrate larger averages in DT, but the effect for IDEs (Mean = 7.29; St. Dev. = 5.29) is significantly greater than for EDs (Mean = 5.85; St. Dev. = 3.42). These differences are evident in Figure 9.b.

The two variables, RT and the number of words, also exhibit a highly significant correlation ($\rho = 0.41$; $p < .001$), as depicted in Figure 10.c.

***Perceived stress.*** The analysis of perceived stress refers to the entire task without exploring the two conditions differently. It was analyzed using a t-test to examine the differences between the two educational backgrounds.

As mentioned earlier, stress is a noteworthy variable in Design Research, and as such, participants' perceived stress was systematically investigated. Stress data were aggregated for the entire experiment rather than being segmented for each condition. Subsequently, a t-test was conducted based on participants' educational background. The results reveal a significant impact of educational background on the perceived stress of participants (t (1, 32) = 14.797; $p < .001$). Specifically, IDEs report higher stress levels (Mean = 2.99; St. Dev. = .83) than EDs (Mean = 2.42; St. Dev. = .88). This difference is visually represented in Figure 11.

Additionally, since the perceived stress does not exhibit any significant correlation with RT or the number of words, they are not reported.

## *Correlations between neural and behavioral measures*

The relationships between neural and behavioral measures are elucidated across various brain regions, hemispheres, RT, number of words, and perceived stress. Corresponding correlations are detailed in Table 2, where brain regions are presented as rows and conditions, educational background, RT, number of words, and perceived stress serve as columns, reiterated for each brain band. The correlations refer to each trial, characterized by different TRPs (for each band), RT, and NW, while stress levels are constant per participant.

Regarding alpha TRPs, RT, and the number of words do not exhibit any significant correlations. However, perceived stress

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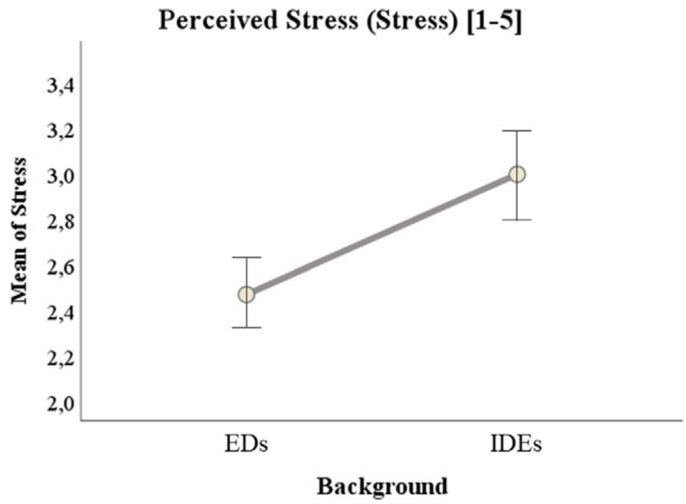


**Figure 11.** Participants' perceived stress by educational background.

demonstrates highly significant negative correlations with all brain regions and hemispheres. Therefore, elevated perceived stress levels significantly diminish alpha power across the entire brain.

Contrastingly, beta and gamma bands yield similar outcomes. Beta TRPs display significant correlations with RT and perceived stress across the whole brain on a per-region and per-hemisphere analysis. Increased response time and heightened perceived stress levels are associated with reduced beta power throughout the brain. Notably, the number of words demonstrates a significant negative correlation with right hemisphere beta power in frontal, central, and temporal regions. Frontal and temporal beta in the left regions also exhibit a significant negative correlation with the number of words. The negative correlations of TRPs with RT and the number of words suggest that the behavioral measurements adopted might be a good proxy of cognitive effort (Kyllonen and Zu, 2016), coherently with the perceived stress.

Gamma TRPs exhibit highly significant negative correlations across all brain areas and hemispheres concerning RT, the number of words, and perceived stress. RT, more than others, appears to affect gamma power.

Given that RT, the number of words, and perceived stress are influenced by educational background, these correlations underscore the significance of these findings and their corresponding effects on both neural and behavioral measures.

However, these analyses should consider that the small range of TRPs ($-0.2, +0.2$) might also suggest that, while the correlations are weak, the variability in TRPs is limited. This can potentially impact the strength of the correlation, as restricted variability often limits the ability to detect stronger relationships.

## Discussion

The results presented the answers to the research questions mentioned above on (1) *the educational backgrounds influencing neural and behavioral measurements during DT and CT*, and (2) *the correlation between neural and behavioral measurements in designers with different educational backgrounds during DT and CT*.

### *Educational background in convergent and divergent thinking*

To answer the first research question, we start by analyzing the differences between the different types of thinking. This allows us to validate the robustness of the dataset and the reliability of further findings.

Analyzing the alpha band, the results affirm the primary findings in the literature: the main effect of the task condition (Hu et al., 2022a; Li et al., 2024) and, in general, a monotonic decrease in alpha TRPs from frontal to posterior regions (Jauk et al., 2012), but a particular significant and relevant effect of educational background (Vieira; 2020b). This observed increase in alpha power during DT aligns with the assumption that participants followed different reasoning in the two task conditions. This finding supports the internal attention hypothesis related to DT (Klimesch et al., 2007), aligning with the top-down control over cognition (Fink and Benedek, 2014), raising the relevance of the dual-process theory in design ideation (Gonçalves and Cash, 2021). This is essential for internally redirecting attention focus during goal-directed idea generation (Benedek, 2018; Goucher-Lambert et al., 2019; Li et al., 2024). However, while alpha synchronization is consistent with divergent ideation, it does not provide a direct measure of creativity without considering task context and behavioral output.

On the other hand, highly significant lateralization (related to hemisphere) and localization (related to brain regions) were found, emphasizing the critical role of different brain regions in the alpha band during CT and DT (Jauk et al., 2012). Frontal regions record larger alpha TRPs than occipital areas, showing an intricate relationship between brain regions and conditions. This relationship is also conditioned by the hemisphere and the educational background observed: higher alpha TRPs are found in frontal, central, and temporal areas in the right hemisphere, particularly in DT, and they are more consistent for IDE. This observed pattern is typically associated with creative idea generation sub-processes, including external stimuli inhibition, memory retrieval, and mental imagery (Benedek et al., 2014). The different activation of the hemispheres aligns with the literature, suggesting that hemispheric contributions to cognitive processing tend to be distinct, even in design (Vieira et al., 2022). This increases the relevance of the triple significant interaction, showing that different educational backgrounds affect the activation of the hemispheres in relation to different thinking tasks.

**Table 2.** Correlations between neurocognitive and behavioral measures

| ρ (p-value) | TRPs | Alpha | *RT* | *NW* | *Stress* | Beta | *RT* | *NW* | *Stress* | Gamma | *RT* | *NW* | *Stress* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Hemisphere** | | | | | | | | | | | | | |
| Left | | | .020 (.493) | .009 (.767) | **−.148** (< .001)** | | **−.118** (<.001)** | .053¬ (.067) | **−.148** (<.001)** | | **−.229** (<.001)** | **−.106** (<.001)** | **−.109** (<.001)** |
| Right | | | −.014 (.627) | −.021 (487) | **−.118** (< .001)** | | **−.140** (<.001)** | **−.061* (.038)** | **−.127** (<.001)** | | **−.248** (<.001)** | **−.105** (<.001)** | **−.115** (<.001)** |
| **Area** | **Hemisphere×Area** | | | | | | | | | | | | |
| F | | | −.011 (.707) | −.030 (.306) | **−.125** (< .001)** | | **−.143** (<.001)** | **−.082** (.005)** | **−.112** (<.001)** | | **−0.228** (<.001)** | **−0.100** (<.001)** | **−0.101** (<.001)** |
| | F_Left | | −.004 (.899) | −.020 (.491) | **−.129** (<.001)** | | **−.130** (<.001)** | **−.076** (.009)** | **−.110** (<.001)** | | **−.218** (<.001)** | **−.105** (<.001)** | **−.109** (<.001)** |
| | F_Right | | −.018 (.552) | −.038 (.199) | **−.128** (<.001)** | | **−.150** (<.001)** | **−.085** (.003)** | **−.108** (<.001)** | | **−.232** (<.001)** | **−.093** (.001)** | **−.090** (.002)** |
| C | | | .005 (.868) | −.015 (.605) | **−.148** (<.001)** | | **−.117** (<.001)** | −.050¬ (.085) | **−.133** (<.001)** | | **−.210** (<.001)** | **−.067* (.021)** | **−.091** (.002)** |
| | C_Left | | .016 (.593) | .005 (.877) | **−.150** (<.001)** | | **−.092** (.002)** | −.035 (.231) | **−.135** (<.001)** | | **−.183** (<.001)** | **−.062* (.035)** | **−.087** (.002)** |
| | C_Right | | −.006 (.830) | −.032 (.279) | **−.123** (<.001)** | | **−.130** (<.001)** | **−.060* (.038)** | **−.119** (<.001)** | | **−.223** (<.001)** | **−.068* (.019)** | **−.089** (.002)** |
| T | | | −.019 (.523) | −.027 (.353) | **−0.134** (<.001)** | | **−.136** (<.001)** | **−.063* (.030)** | **−.152** (<.001)** | | **−.250** (<.001)** | **.108** (<.001)** | **−.115** (<.001)** |
| | T_Left | | .005 (.860) | −0.10 (.731) | **−.145** (<.001)** | | **−.128** (<.001)** | **−.062* (.034)** | **−.154** (<.001)** | | **−.244** (<.001)** | **−.105** (<.001)** | **−.104** (<.001)** |
| | T_Right | | −.038 (.196) | −.039 (.186) | **−.102** (<.001)** | | **−.131** (<.001)** | **−.058* (.048)** | **−.133** (<.001)** | | **−.245** (<.001)** | **−.106** (<.001)** | **−.121** (<.001)** |
| P | | | .029 (.324) | .017 (.576) | **−.116** (<.001)** | | **−.079** (.007)** | .032 (.267) | **−.134** (<.001)** | | **−.225** (<.001)** | **−.107** (<.001)** | **−.123** (<.001)** |
| | P_Left | | .040 (.171) | .025 (.401) | **−.121** (<.001)** | | **−.071* (.015)** | −.033 (.251) | **−.147** (<.001)** | | **−.214** (<.001)** | **−.105** (<.001)** | **−.116** (<.001)** |
| | P_Right | | .016 (.595) | .007 (.811) | **−.101** (<.001)** | | **−.083** (.004)** | −.029 (.316) | **−.113** (<.001)** | | **−.229** (<.001)** | **−.106** (<.001)** | **−.128** (<.001)** |
| O | | | .004 (.905) | .019 (.528) | **−.109** (<.001)** | | **−.154** (<.001)** | −.051¬ (.080) | **−.138** (<.001)** | | **−.267** (<.001)** | **−.142** (<.001)** | **−.126** (<.001)** |
| | O_Left | | .028 (.352) | .032 (.278) | **−.117** (<.001)** | | **−.134** (<.001)** | −.046 (.116) | **−.147** (<.001)** | | **−.250** (<.001)** | **−.137** (<.001)** | **−.114** (<.001)** |
| | O_Right | | −.022 (.467) | .003 (.932) | **−.088** (.003)** | | **−.158** (<.001)** | −.051¬ (.080) | **−.115** (<.001)** | | **−.271** (<.001)** | **−.137** (<.001)** | **−.134** (<.001)** |

In Bold all the values linked to significant p-values: ¬ low significance ($p<.10$); * significance ($p<.05$); ** strong significance ($p<.01$)

On the contrary, beta activity is typically linked to active reasoning and maintaining an alert state (Engel and Fries, 2010). While alpha activity is often associated with the inhibition of brain activity, beta activity is instead connected with activating specific areas (Klimesch et al., 2007). The attribution of the beta band to DT is quite ambiguous in the literature, and the discordance of results is often linked to the specific tasks adopted by different studies (Shemyakina et al., 2007).

Regarding different task conditions, results indicate that beta waves are more prevalent in CT than in DT. In both conditions, beta waves appear to be more prominent in the posterior areas than in the anterior ones. In DT, beta TRPs exhibit a monotonic decrease in designers' activations from frontal to occipital regions, particularly noticeable for EDs. This finding aligns with the literature associating beta with analytical problem-solving (Erickson et al., 2018), where attention should be focused on the external world. Other findings connect higher values of beta power to creative ideation (Liu et al., 2018). This discrepancy may be attributed to the different types of tasks adopted and the selected individuals. Indeed, more engaged participants could activate a sort of "divergent mindset," resulting in high levels of beta in the baseline and, then, lower beta TRPs.

These results offer a detailed overview of beta TRPs across brain regions and hemispheres, categorized by educational background during both CT and DT, aligning with existing literature (e.g., Vieira, 2022).

In the literature, the activity of the gamma band in ideation is poorly investigated, where, similarly to beta, gamma TRPs play an opposite role to alpha, contrasting with attention to the internal world. This similarity is consistent with the present findings. Generally, gamma activations are related to immediate close associations, alertness, and object recognition (Horan, 2009). However, some studies suggest that gamma could be related to creative

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thinking, while others exclude it (Mazza et al., 2023). Gamma band activity, often associated with the binding of perceptual and memory elements into coherent representations (Herrmann et al., 2010) and semantic activities (Mellem et al., 2014), may support convergent reasoning when participants are refining or verifying ideas. These findings are consistent with accounts of gamma involvement in semantic integration (Jauk et al., 2012), though its specific role in creativity remains debated (Mazza et al., 2023). Indeed, the relationship between gamma and decision-making activities (Karch et al., 2016) is coherent with the high values of gamma TRPs in CT. Regarding the effect of the condition, results indicate that gamma waves are more prevalent when a task involves CT rather than creative ideation. The significantly high synchronization in CT could be associated with the use of episodic and working memory, as suggested in the literature (Benussi et al., 2022), which could be a way to think about a common use for an object.

In conclusion, the external validity of AUT for real-world design ideation is debated. While AUT captures DT processes relevant to early conceptual phases (where open-ended exploration and reinterpretation of object functions are essential), it simplifies the complexity of design tasks, which often involve multiple constraints, characterized by CT (e.g., technical feasibility, stakeholder needs, market considerations), often linked to iteration. Therefore, AUT can be seen as a controlled proxy that isolates the basic cognitive construct of ideation, providing valuable but partial insights into real-world design performance. DT tasks can be training for or an initial activity in design ideation without specific boundaries, as some methods require, enhancing creative outcomes (König et al., 2023). AUT aligns with specific design challenges, such as defining secondary uses for objects, extending their life cycles (Liao and MacDonald, 2021), or studying product affordance in usability design (Fiodorova and Shu, 2023).

### Educational background and neurocognitive measurements

In addressing the **first research question**, the noteworthy impacts of educational background underscore and extend previous findings concerning the role of knowledge in tasks within the domain of Design Research (Vieira et al., 2022). Educational background may also be correlated with varying levels of contextual experience and skills, which can detrimentally influence mental states associated with ideation (Hu and Reid, 2018; Vieira et al., 2022). On the behavioral standpoint, despite participants exhibiting similar RTs overall, the interaction with the different task conditions indicates an additional correlation between specific educational backgrounds and performances in both CT and DT. These differences manifest in ideation time and the quantity of words employed. On the effect of educational background on neural aspects, participants' brain activations may be influenced by their distinct design approaches, reflecting a potentially different mindset when facing problems.

About alpha, EDs exhibit negative values of alpha TRPs, representing desynchronization, across all brain regions and hemispheres during both CT and DT. The diminished brain activity in the alpha band suggests an approach similar to problem-solving adopted by EDs. Conversely, IDEs display synchronization across all hemispheres and brain regions, except for the occipital region. This specifically implies a potential link between educational expertise and neural engagement in creative ideation. These findings indicate that varying educational backgrounds in creative ideation in a design task can significantly impact DT. This aspect could be crucial in explaining the neurocognitive differences underpinning design problem-solving associated with diverse backgrounds and experiences (Vieira et al., 2022), emphasizing how prior experiences can lead to distinct interpretations of the same task and hold substantial industrial implications (Jackson, 1996).

Since alpha is associated with the inhibition of brain activities, IDEs could be deemed more effective in tackling DT tasks. Experience may elucidate their efficiency in mental activation for such a task (Sun et al., 2014). Alpha desynchronization is often interpreted as an index of cortical activation during task engagement (Klimesch, 2012), suggesting that EDs, by exhibiting alpha desynchronization, may adopt a more structured and attention-demanding approach compared to IDEs.

Concerning beta TRPs, a primary observation is that IDEs exhibit synchronization in the CT and desynchronization in all brain regions and the left hemisphere. Conversely, EDs display both synchronization and desynchronization in the CT, while only desynchronization is evident in the DT. The significance of the educational background is particularly pronounced in the CT, where IDEs manifest significantly larger values across all the areas, hemispheres, and conditions, except for the occipital area in the DT.

In the realm of gamma, the significance of the educational background is notably prominent in CT, with IDEs exhibiting markedly higher values across all brain regions and hemispheres. IDEs consistently demonstrate elevated gamma TRPs in various areas, hemispheres, and conditions. They exclusively show synchronization in gamma, indicating heightened gamma TRPs when engaged in a task compared to their baseline. Consequently, ideation activity can be associated with an increased gamma power for IDEs. On the other hand, EDs exhibit desynchronization in the DT condition across all brain areas and both hemispheres.

Accordingly, our findings align with the neurocognitive framework proposed by Yeo et al. (2024), which emphasizes the role of attentional control in shaping creative outputs. Specifically, participants exposed to more structured or convergent tasks in their educational background (such as EDs) may have relied more heavily on enhancing the usefulness of their ideas. In contrast, IDEs may have fostered undirected attention, promoting greater novelty, albeit sometimes at the expense of immediate applicability. While the cognitive styles associated with different educational backgrounds have long been debated in creativity literature (Kozbelt et al., 2010), our findings reinforce the preliminary findings on how such educational experiences shape neurocognitive responses during design ideation. Specifically, this study can validate the individual differences in creative cognitive styles (Chen et al., 2015), which might be affected as well by the educational background.

Our findings, though preliminary, suggest that there are significant differences among designers with varied educational backgrounds. This highlights the importance of not treating designers as a uniform group. Then, from the neurocognitive viewpoint, we can answer that **significant interactions exist between different types of thinking and the educational background, establishing the different brain activations that may represent a different way of reasoning**. This validates H1.1. Understanding these differences is essential for defining and optimizing team compositions, especially in multidisciplinary design projects.

These findings can be extended to the recruitment processes: neurocognitive can be adopted in future profiling to better understand candidates' cognitive strengths. By identifying whether a candidate exhibits patterns similar to those of EDs or IDEs, employers can better match them to appropriate roles and tasks, improving performance and job satisfaction. Moreover, these differences can be considered in the design of working spaces: promoting concentration may be beneficial for EDs, while environments that encourage free thinking may be better suited for IDEs. Continued research on the neural and cognitive differences between EDs and IDEs can further refine educational and professional practices.

### Educational background and behavioral measurements

In terms of behavioral measurements, it is confirmed that DT necessitates more time for ideation, and it is observed that DT yields a greater number of words compared to CT. CT, which centers on finding a single correct solution, often involves activities related to memory retrieval (Calic et al., 2020).

The positive correlation between RT and the number of words suggests that a longer duration spent on ideation is linked to a greater number of words used to articulate an idea. This correlation implies that participants using more time can develop more complex or elaborated ideas, aligning with analogous findings in the literature derived from semantic analysis (Casakin and Georgiev, 2021).

While literature results concerning the relationship between time and designers' performances are not unequivocal, numerous findings support a positive correlation between these variables and the quality of design outcomes (Mulet et al., 2017; Yang et al., 2023). In the CT condition, word usage is closely tied to objective definition, exhibiting a low standard deviation and a high concentration around the value of 3. This concentration is where the response primarily comprises the ["to" + *verb* + *direct object*] structure, frequently employed as units to conceptualize an idea (Petersson and Lundberg, 2018). In contrast, the DT condition involves a larger number of words, possibly indicative of participants' need to elucidate the unconventional usage they have devised. Consequently, their responses demand more details to be more explicit with a more detailed explanation (Kudrowitz and Dallas, 2011). Moreover, the increased use of words in the DT condition could be linked to a more open state of mind among participants, and this might indicate a more extensive exploration of the design space (Chong et al., 2025).

From these perspectives, we can conclude that **no specific educational background is associated with longer response times; instead, differences arise depending on the task**. However, **educational background does influence the number of words used, with IDEs typically using more words. These differences also interact with the type of thinking employed. These findings validate H1.2.**

Looking at the perceived stress, the literature highlights the nonlinearity of design-related cognitive processes, encompassing both CT and DT, as a recognized source of mental load that could generate stress (Yang et al., 2023). In Design, a moderate level of mental stress has been positively correlated with the originality of generated ideas (Nguyen and Zeng, 2013). The **heightened stress perceived by IDEs** addresses the first research question and aligns with their increased experience in DT activities, shaped by their educational background. In Engineering Design, such activities are often closely constrained by system functional and structural limitations (Miller et al., 2021). Furthermore, within this context, an augmented knowledge base increases exposure to stress, leading to creative outcomes only when this stress reaches an optimal level (Yang et al., 2023). These considerations elucidate the generally observed moderate level of stress among participants. An important limitation of these results is related to the perceived stress as a per-participant measurement, neglecting variations of the perceived stress while performing the experimental task.

Previous studies have identified significant correlations between stress and the theta band (e.g., Chikhi et al., 2022). However, in this study, no significant correlations were found. This discrepancy may be due to two key factors. First, we focused on perceived stress rather than actual stress, and these two measures have been shown to differ (Epel et al., 2018). Additionally, there is an inconsistency in how stress is measured across the literature (Blandino et al., 2025). Second, our study examined stress during an idea generation task, where cognitive activities may influence overall activation differently than tasks that primarily generate cognitive load.

By comprehending the impact of stress on cognitive performance, educators, designers, and managers can develop interventions to manage stress and optimize outcomes. This involves identifying individual differences in sensitivity to stress and how they affect cognitive performance. Accordingly, stress management strategies can enhance several benefits for designers, both in terms of performance and mental health. Understanding the interplay between stress and educational backgrounds enables the development of more targeted and effective interventions.

Incorporating cognitive stress into experimental tasks allows researchers to create more realistic scenarios, leading to more accurate assessments of cognitive abilities, considering also individual differences.

### *Interaction of behavioral and neurocognitive measures*

The response to the **second research question** is intricately connected with the preceding findings and better framed with the correlation analysis presented. The diminishing value of alpha corresponding to a heightened perception of stress aligns with the general role of alpha as an indicator of meditation and internally directed attention, aspects that are unrelated to stress. In the literature, it has been observed that alpha TRPs increase when stress levels are low or moderated (Nguyen and Zeng, 2014), a trend consistent with the majority of participants' experiences in the current experiment. This finding is further supported by the observation that, during conceptual design, designers' stress is higher in correspondence to the lower level of mental effort, without any significant effect on the design outcome (Nguyen and Zeng, 2014). The robust relationship between stress and the alpha band has been extensively explored (Berretz et al., 2022), with significant evidence, including during the AUT (Wang et al., 2019). Within this context, the negative correlation between alpha activities and stress appears to be coherent with the different task conditions.

Overall, elevated levels of perceived stress are consistently associated with a global reduction in TRP values across alpha, beta, and gamma bands, suggesting a widespread modulation of neural activity over the entire scalp. This general downregulation of TRP activity in response to stress highlights its pervasive effect on brain function, regardless of specific frequency bands or localized regions. However, the correlations with perceived stress are limited by the fact that perceived stress was measured only once for the entire task, while several TRPs were collected for each trial based on the EEG sampling rate. This means that the correlations reflect an overall mindset associated with the varying levels of perceived stress rather than trial-specific fluctuations.

The significant correlation of perceived stress with overall brain activations (across all the considered bands) is considerable. In particular, the negative association between perceived stress and TRPs supports earlier findings linking increased cognitive load to reductions in alpha and gamma power (Berka et al., 2007), especially under open-ended tasks with ambiguous constraints (Miller et al., 2021). It represents a link between the participants' awareness of mental states and their neural activations, increasing the reliability of self-reported data, also in cognition research (Dunbar et al., 2020). In this domain, creative cognition involves the

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dynamic interplay of various cognitive activities, incorporating network activities that emphasize how stress can impede creativity (Vartanian et al., 2020). This result emphasizes the relevance of the perceived stress with an actual neural activation: higher levels of perceived stress are linked to a decreased level of alpha, beta, and gamma TRPs.

In contrast to stress, RT and the number of words appear to selectively influence beta and gamma activity, with no notable relationship observed in the alpha band. The lack of significant correlations between alpha TRPs and RT, and the number of words underscores that alpha likely does not play a substantial role in articulating or detailing an idea, reinforcing its pronounced correlation with the type of thinking (Jauk et al., 2012). Additionally, a particularly strong negative correlation between RT and gamma TRPs suggests that faster idea generation may involve higher gamma activity, potentially reflecting increased cognitive integration or semantic processing (Karch et al., 2016). Moreover, this relationship between gamma and behavioral measurements aligns with the relevance of the gamma band on semantic priming tasks (Mellem et al., 2014). The elevated gamma synchrony observed in IDEs may indicate greater semantic integration and concept recombination (Maguire et al., 2010), aligning with their performance in ideational fluency and novelty (Beaty et al., 2014).

On the other hand, the literature suggests that beta may be associated with a positive correlation with stress (Abhang et al., 2016), and gamma does not exhibit a clear relationship with stress. Moreover, this discrepancy could be driven by variations in RT and the number of words adopted by participants, suggesting an intricate relationship that is not controlled in the current study. Beta activation has frequently been linked to object recognition (Karch et al., 2016), possibly reflecting responses to stimuli presented as everyday objects, which inherently require mental interpretation from the word to its meaning. This could serve as an additional explanation for the elevated levels of TRPs in the CT condition. Furthermore, CT, characterized by lower RT and number of words, exhibits a significant negative correlation with gamma TRPs throughout the entire brain.

This additional evidence related to the educational background can lead to the development of tailored programs for EDs and IDEs to leverage their unique strengths in ideation. For instance, programs and training for EDs might focus more on problem-solving techniques, while those for IDEs could emphasize creative ideation and innovation. On the other hand, they can also generate some contamination, sharing more activities between the two different educational backgrounds. The same considerations can be extended to design teams to maximize their different abilities. For example, ideation tasks can be led by IDEs, while problem-solving tasks can be led by EDs.

Finally, the impact of timing and wording cannot be overlooked. Given that RT and the number of words show significant negative correlations with beta TRPs, RT and wording are deemed to influence the beta power's intensity.

## Conclusion

This study contributes significantly to bridging the gap between design neurocognition and cognitive neuroscience. Adhering to the rigorous experimental protocol standards in cognitive neuroscience, the study focuses on research gaps derived from design research. Such an approach enhances the reliability and comparability of findings, contributing to the emerging field of design neurocognition. By examining the effects of designers' educational backgrounds on their neural and behavioral measurements during CT and DT, this research offers valuable insights into the neurocognitive processes underpinning design activities.

Designers exhibit distinct activations and performances in CT and DT, especially with higher alpha activities (related to internal attention processes) during DT, while beta and gamma show higher values during CT. Significant differences in behavioral measures corroborate these internal processing disparities in DT. This validates our experiment, allowing us to have a robust understanding of the exploring factors. Accordingly, the educational background magnifies these differences. IDEs display alpha event-related synchronization, longer response times, and a higher number of words, while EDs show the opposite trend with higher beta and gamma event-related synchronization during CT. These findings highlight the impact of education, showing that different approaches to design could affect designers' outcomes. Such mechanisms offer crucial insights into cognition during DT, potentially influencing ideation in design. Moreover, stress also affirms its relevance for designers, with IDEs exhibiting higher stress levels, aligning with their generally longer response time and higher number of words.

These differences underscore the importance of neurocognitive studies in identifying differences that might be overlooked otherwise. For instance, this study highlights how individual interpretations, shaped by prior experience and background, can impact the same task, emphasizing its significance in interdisciplinary working environments. The necessity of further research into the impact of different educational backgrounds on design is required, considering these differences in both theoretical and practical applications, and in team-based design tasks. Some potential practical applications, recognizing the influence of educational background on designers' ideation, can inform the development of customized training programs and collaborative strategies. For instance, IDEs may benefit from stress management interventions and time management training. Conversely, EDs might require support in enhancing DT skills to foster creativity.

Several significant correlations between neural and behavioral data and perceived stress are identified. Perceived stress shows a relevant correlation with all the explored brain areas and hemispheres across different brain bands. These results reveal two distinct neural modulation patterns: a general suppressive effect of stress on overall TRP power across bands and a more targeted modulation of beta and gamma activity by behavioral markers such as RT and the number of words. This discovery represents a pivotal advancement in Cognitive Research, notably enhancing the reliability of self-reported data. On the other hand, perceived stress does not show a clear association with behavioral data. Response time and number of words do not relate to the alpha band, emphasizing its dependence on the type of thinking. Behavioral responses, instead, significantly correlate with beta and gamma bands, revealing their connection with the act of wording. Additionally, the integration of neurocognitive monitoring tools in design education and practice could provide real-time feedback, enabling adaptive learning environments and personalized support to optimize cognitive performance.

While our study offers valuable insights, several limitations must be acknowledged. The use of the AUT captures specific cognitive components related to design ideation, but it does not encompass the full complexity of real-world design processes. When interpreting AUT results, it is important to acknowledge that findings may generalize more directly to unconstrained or exploratory design contexts, rather than to fully constrained industrial design scenarios. Future studies should aim to employ more comprehensive methods to capture the full complexity of design cognition. The potential

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influence of neurophysiological measurement equipment on participants' stress levels and cognitive performance also warrants consideration, as it may introduce confounding variables. This raises important considerations about the effects of investigative instruments on biomedical tools, extending beyond the scope of this paper. However, another key limitation of this study is the mismatch in data granularity between EEG and perceived stress measurements; although this reflects the nature of the constructs being measured, future research should consider using continuous or trial-level stress indicators to enhance temporal alignment. Lastly, the study did not account for gender differences, and the imbalance in educational backgrounds among genders limits the generalizability of the findings.

Further research could investigate whether observed differences in ideation approaches between IDEs and EDs are due to specific training or a self-selection mechanism. Moreover, future studies can examine the neurocognitive processes involved in team-based design activities, how the educational background could influence group creative problem-solving.

Finally, these insights could be leveraged to create adaptive AI tools that support designers in real time. For instance, AI-driven design platforms could monitor cognitive states (e.g., alpha synchronization indicating internal focus during ideation) and provide tailored interventions, such as prompts or visual stimuli, to enhance creativity. Similarly, computational systems could simulate the impact of educational background or stress on cognitive strategies, enabling the design of more personalized and effective training programs for designers.

**Supplementary material.** The supplementary material for this article can be found at http://doi.org/10.1017/S0890060425100188.

**Data availability statement.** The data that support the findings of this study are available from the corresponding author, upon request, because of the sensitive information they include. The derived and aggregated data are reported in this document.

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