Designing-related neural processes: Higher alpha, theta and beta bands' key roles in distinguishing designing from problem-solving

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Author Institution, Country in Times italics 11 pt
Corresponding author email address in Times italics 11 pt

This paper presents results from an experiment studying differences between designing and problem-solving in professional industrial designers, using EEG to measure neurophysiological activations. We compare neurophysiological activation and frequency bands power between three prototypical tasks, a problem-solving layout task, an open design layout task and an open design free-hand sketching task. The study draws on the neurophysiological results from 18 experiment sessions with professional designers. Results indicate significant differences in activations between the problem-solving task and the design tasks, in terms of aggregate, temporal and frequency bands power across participants. Higher alpha and beta frequency band values play a key role in the open design sketching task when compared to the layout tasks.

Introduction

Creativity related neural processes have been widely investigated [1], however, designing related neural processes are still in the early stages of study. Distinguishing designing from creativity, specifically through measuring the brain networks during designing and when being creative can have an impact in the unfolding of the neuroscience of designing and creativity research. With this ultimate aim in mind, we report research in this paper that aims to distinguish designing from problem-solving. The

Design Computing and Cognition DCC'20. J.S. Gero (ed), pp. xx-yy. © Springer 2020

commensurability of measurements of neurophysiological studies in design research makes for a robust approach for studying brain activity during designing.

Design studies based on functional magnetic resonance imaging (fMRI) started a decade ago [2] with a controlled experiment reporting preliminary results on the distinction between designing and problem-solving. The present experiment extends this study. However, through the use of the electroencephalography technique (EEG) we aim at results based on frequency bands of brain waves to distinguish designing from problem-solving tasks. Studies using EEG commenced more than 40 years ago [3] investigating cortical activation during multiple tasks. Some 20 years later a study on categorization tasks of experts and novices [4] made use of EEG in design research. In the last 10 years, single domain-related EEG design studies [5, 6, 7, 8], functional near-infrared spectroscopy (fNIRS) design studies [9] and fMRI studies focused on sustainability judgments [10], design ideation and inspirational stimuli [11] of mechanical engineers, graphic designers [12] and architects [13] have been used to understand acts of designing from a neurophysiological perspective. As designing is a temporal activity EEG has started to play a role in design research because of its high temporal resolution, readily available software, reduction in the cost of portable equipment and relatively little need for specialized training.

EEG Studies

Electroencephalography records electrical brain activity with electrodes placed along the scalp. Neurons transmit signals down the axon and the dendrites via an electrical impulse. EEG activity reflects the summation of the synchronous activity of thousands or millions of neurons that by having similar spatial orientation their ions line up and create waves to be detected. Pyramidal neurons of the cortex are thought to produce the most EEG signal because they are well-aligned and fire together [14, 15]. EEG measures electromagnetic fields generated by this neural activity. Activity from deep sources of the brain is more difficult to detect than currents near the skull, thus EEG is more sensitive to cortical activity [16, 15]. Despite EEG's limited spatial resolution, it offers high temporal resolution in the order of milliseconds in a portable device which makes it a highly suitable tool to investigate designing as a temporal activity.

The present study uses a low-cost EEG device, which has some limitations when compared to medical grade systems. These limitations of physical stability and serial measurement of electrodes are not significant for what we are measuring: the unfolding neurophysiological activations during tasks of the experiment session. Although the low-cost EEG equipment have higher signal to noise ratio potentially resulting in a higher variability of the results and higher standard deviation, the statistical approach we describe, compensates for these potential effects. Low-cost, noninvasive portable EEG equipment becomes a viable tool for the level of resolution we are interested in and for achieving preliminary results and tentative evidence that can support more advanced research [17, 18].

In design research, frequency bands results derived from EEG signals have been widely used as a measurement tool. They have been used to compare visual thinking spent during solution generation with solution evaluation of a layout task [8], EEG bands have been associated with the design activities, namely beta 2, gamma 1 and gamma 2 [7], higher alpha power has been found to be associated with open ended tasks and divergent thinking, theta and beta power has been found to be associated to convergent thinking in decision-making and constraints tasks [6], and they have been used in the study of visual attention and association in expert designers [5].

Aim

This paper describes a study that forms part of a larger research project whose goal is to investigate neurophysiological activation of designers across multiple design domains [19]. The study reported in this paper is based on the analysis of industrial designers' neurophysiological activations using an EEG headset in the context of performing problem-solving and design tasks in a laboratory setting. The aim of the study is to:

- investigate the neurophysiological activation differences and frequency bands of industrial designers when performing designing and problem-solving tasks.

We explore the differences between a problem-solving task and two open design tasks, one based on layout design with constraints and the other an open-ended task that uses free hand sketching. The analysis focuses on the neurophysiological activation differences observed and their frequency bands, along the execution of the tasks, distinguishing activations between brain regions . We investigate the following research questions:

- What are the differences in the neurophysiological activations of industrial designers' frequency bands when problem-solving and designing?
- What brain regions show differences in the neurophysiological

activations of the frequency bands of industrial designers when problem-solving and designing?
- What are the differences in the neurophysiological activations of industrial designers' frequency bands and brain regions when addressing an open design task?

Methods

The hypotheses are tested by using the problem-solving task as the reference and statistically comparing the design tasks with the reference task. We compare absolute values known as transformed power (POW), for total signal and frequency bands, and task-related power (TRP), where the problem-solving neurophysiological activation is the base for comparison. For the present study the analysis focused on a subset of the experiment sessions.

The tasks and experimental procedure were piloted prior to the full study, through five different sessions which produced changes resulting in the final experiment. The research team of this study consisted of seven researchers including design scientists, a data analyst, a statistician, a cognitive psychologist and a neurophysiologist.

Participants

The participants comprised 29 industrial designers, results from eleven of them were not used due to measurement problems. Results are based on 18 right-handed participants, all professional, aged 25-43 (M = 31.7, SD = 7.3), 10 men (age M = 35.1, SD = 7.2) and 8 women (age M = 27.5, SD = 5.1). The participants are all professionals (experience M = 7.8, SD = 5.6). This study was approved by the local ethics committee of the University of XXX.

Experiment Tasks Design

We adopted and replicated the problem-solving and layout design tasks described in the Alexiou *et al.* [2] fMRI-based study. We matched Tasks 1 with the problem-solving task [2] in terms of requests, number of constraints, stimuli and number of instructions. Task 1 is considered a problem-solving task as the problem itself is well-defined and highly constrained, and the set of equivalent solutions is unique [2].

By adding an open layout design task to the previous experiment, we produced a block experiment in order to determine whether the open layout design task produces different results. The open layout design Task 3 has no predetermined final state and the task is open-ended. The block experiment consisting of a sequence of 3 tasks was previously reported [19].

We added a fourth completely open design task that uses free-hand sketching after Task 3. Task 4 is an ill-defined and fully unconstrained task unrelated to formal problem-solving, Table 1. Each participant was given two sheets of paper (A3 size) and three instruments, a pencil, graphite and a pen. The design tasks (3 and 4) although of a different nature both require defining the problem and the solution spaces.

We expect that a neurophysiological subtraction between the problem-solving Task 1 and the design tasks reveals brain magnetic fields more strongly involved in designing. The complete tasks sequence is described elsewhere Vieira et al. [19]. For this paper the focus is on Task 1, Task 3 and Task 4, neurophysiological activations of total and bands frequency, Figure 1.

Table 1 Description of the problem-solving, basic design and open design tasks.

Task 1 Problem-solving	**Task 3** Open layout design	**Task 4** Open sketching design
In Task 1 the design of a set of furniture is available and three conditions are given as requirements. The task consists of placing the magnetic pieces inside a given area of a room with a door, a window and a balcony.	In Task 3 the same design available is complemented with a second board of movable pieces that comprise all the fixed elements of the previous tasks, namely, the walls, the door, the window and the balcony. The participant is told to arrange a space.	In the free-hand sketching Task 4, the participants are asked to: propose and represent an outline design for a future personal entertainment system

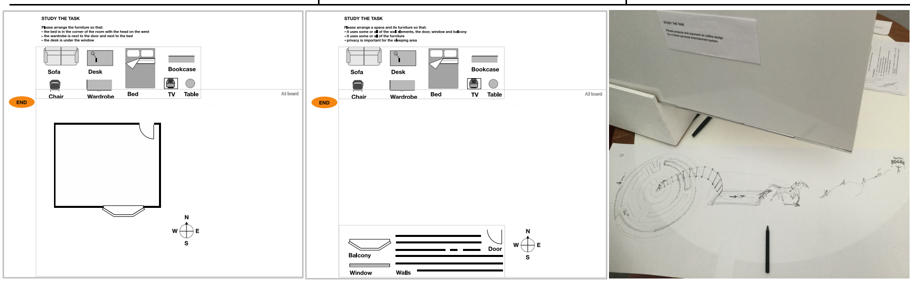

Fig. 1 Depiction of the problem-solving Task 1, open layout design Task 3 and open free hand sketching design Task 4.

Setup and Procedure

A tangible interface for individual task performance was built based on magnetic material for easy handling, Figure 2. Differently from the original tasks [2], the magnetic pieces were placed at the top of the vertical magnetic board to prevent signal noise due to eye and head horizontal movements. A pre-task was designed so that participants could familiarize themselves with the use of the EEG headset and with maneuvering the magnetic pieces that make up the physical interface [19].

One researcher was present in each experiment session to instruct the participant and to check for recording issues. A period of 10 minutes for setting up and a few minutes for a short introduction are necessary for informing each participant, reading and signing of the consent agreement and set the room temperature. A complete description of the procedure is reported [19]. The researcher followed a script to conduct the experiment so that each participant was presented with the same information and stimuli. The participants were asked to stay silent during the tasks and use the breaks for talking and clarifying doubts. The participants performed the sequence of tasks. If needed, extra time was given to the participants, in particular in Tasks 3 and 4, so they could find a satisfactory solution.

Data Collection Methods

EEG activity was recorded using a portable 14-channel system Emotiv Epoc+. Electrodes are arranged according to the 10-10 I.S, Figure 2.

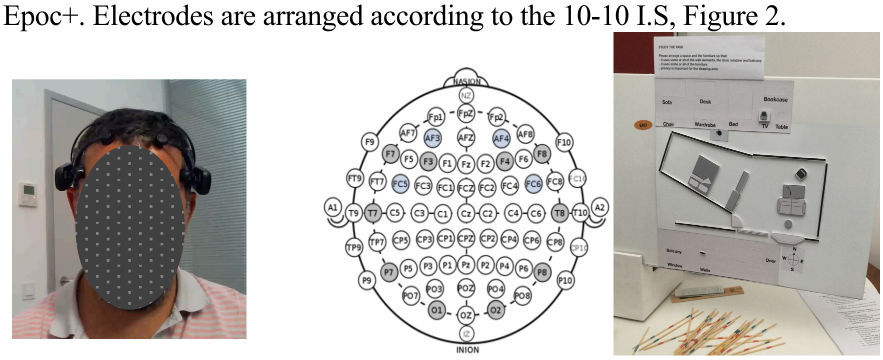

Fig. 2 Emotiv Epoc+ electrodes arrangement (10-10 I.S.) and experiment setup using the headset.

Electromagnetic interference of the room was checked for frequencies below 60Hz. Each of the Emotiv Epoc+ channel collects continuous signals of electrical activity at their location. The participants performed the tasks on the physical magnetic board, with two video cameras capturing the participant face and activity and an audio recorder, Figure 3. All the data captures were streamed using Panopto software (https://www.panopto.com/).

The experimental sessions took place at the University of Porto, between March and July of 2017, and June and September of 2018, and in the Design Hub of Mouraria, Lisbon, during August 2018 in rooms with the necessary conditions for the experiment, such as natural lighting sufficient for performing experiments between 9:00 and 15:00 and no electromagnetic interference.

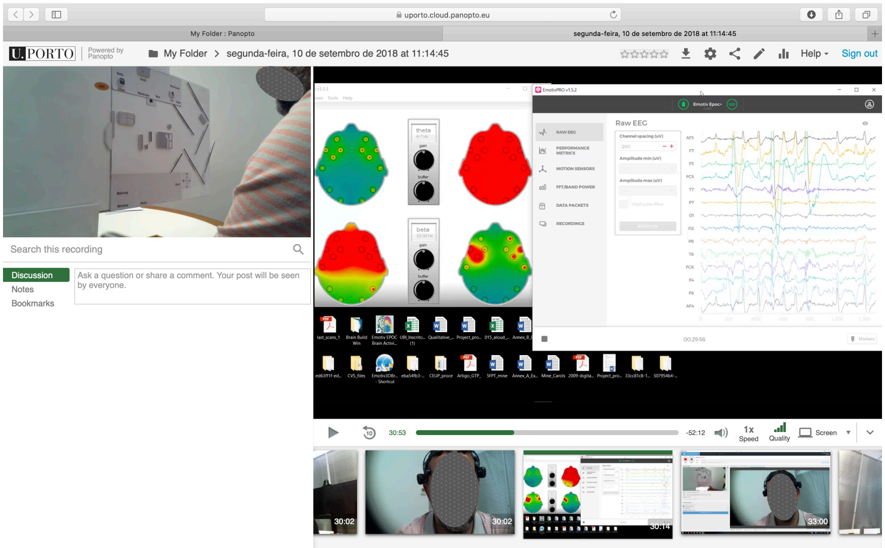

Fig. 3 Screen capture depicting audio, video and screen captures streaming in Panopto.

Data Processing Methods

The fourteen electrodes were disposed according to the 10-10 I.S, Figure 2, 256 Hz sampling rate, low cutoff 0.1 Hz, high cutoff 50 Hz. We adopted the blind source separation (BSS) technique based on canonical correlation analysis (CCA) for the removal of muscle artifacts from EEG recordings [21, 22] adapted to remove the short EMG bursts due to articulation of spoken language, attenuating the muscle artifacts contamination on the EEG recordings [23]. The BSS-CCA algorithm, by using correlation as a criterion to measure independence of signals, takes into account temporal correlation. By establishing an ordering system of the separated singular valued components of the signal, the outputted components are sorted so that the highest correlated sources represent EEG sources and the lowest correlated sources represent noise. By systematically eliminating a subset of the bottom sources, the EEG signal from all subjects used in this study were cleaned. Thus, data processing includes the removal of Emotiv specific DC offset with the Infinite Impulse Response (IIR) filter and BSS-CCA. Data analysis included total and band power values on individual and aggregate levels using MatLab and EEGLab open source software. All the EEG segments of the recorded data were used for averaging throughout the entire tasks. Unpublished results testing the BSS-CCA procedure efficacy on EEG signals from participants performing sketching tasks in three conditions including pen and paper confirm its efficacy. The statistical approach we describe, compensates the potential effects on the procedure due to the limitations of the equipment. A more detailed description is reported here [24]. The motor actions involved in the tasks using the tangible interface versus the free hand sketching and their corresponding EEG signals are of the same source, thus we claim that the BSS-CCA procedure filters the signal of both from artifacts. The EEG data analysis pipeline is shown in Figure 4.

Each of the Emotiv Epoc+ channels continuous electrical signal were processed to produce multiple measures. Here we report on three measurements: task-related power (TRP), and total signal and bands frequency transformed power (Pow). The Pow is the transformed power, more specifically the mean of the squared values of microvolts per second (μV/s) for each electrode processed signal per task. This measure tells us about the amplitude of the signal per channel and per participant magnified to absolute values. We present Pow values on aggregates of participants' individual results, per total task and for each task deciles for the temporal analysis of. The TRP is the task-related power, typically calculated taking the resting state as the reference period per individual [23, 25, 15]. This method, normally time-locked to fractions of seconds, is used across sessions that take minutes to allow for the design activity to unfold. We consider our experiment locked for the complete unfolding of the cognitive activities involved in each task.

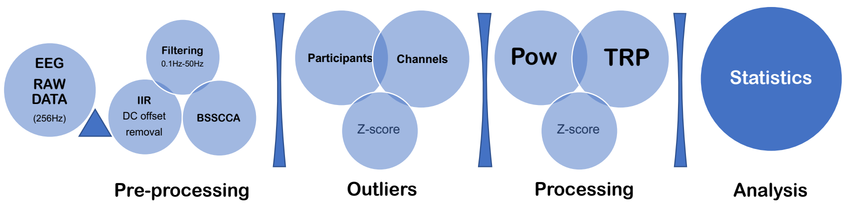

Fig. 4 EEG Data Analysis Pipeline

We processed the Pow and the TRP measurements for each participant per total task and temporal deciles. After a z-transform was conducted in the analysis of Pow across tasks per participant data to determine outliers, the criteria for excluding participants were based on the evidence of 6 or more threshold z-score values above 1.96 or below -1.96 and individual measurements above 2.81 or below -2.81. After determining the outliers, we calculated the mean and standard deviation of each measure for each cohort. After the division of the Pow into time deciles (which provides the basis for the analysis of temporal stages) amplitude leading to two and a half standard deviations from the mean as threshold values were excluded per channel. In this process 11 experiments were further excluded leaving 18. The same procedure was applied to the frequency bands, Figure 4. This approach involves the decomposition of the EEG signal into component frequency bands. We used the typical frequency bands and their approximate spectral boundaries, delta (0.1–4 Hz), theta (4–7 Hz), alpha 1 (7–10 Hz), alpha 2 (7–13 Hz), beta 1 (13–16 Hz), beta 2 (16–20 Hz) and beta 3 (20–28 Hz). By the adoption of lower and upper alpha boundaries, and the beta waves in three sections, we expect to find and unfold results that can be related to the literature.

Data Analysis Methods

We take the problem-solving Task 1 as the control/reference period for the TRP calculations. Thus, for each electrode, the following formula was applied taking the log of the Pow of the corresponding electrode $_i$ (of 14), in Task 1 as the reference period. By subtracting the log-transformed power of the reference period (Pow_i, reference) from the activation period (Pow_i, activation) for each trial $_j$ (each one of the five tasks per participant), according to the formula:

$$TRP_i = \log(Pow_i, \text{activation})_j - \log(Pow_i, \text{reference})_j$$

By doing this, negative values indicate a decrease of task-related power from the reference (problem-solving Task 1) for the activation period, while positive values indicate a power increase [27] (power and activation refer to brain wave amplitude).

Statistical approach

We performed standard analyses based on the design of the experiment: always a repeated-measures design with pairwise comparisons to follow up on specific differences with task, hemisphere, electrode and decile as within-subject factors. These analyses were performed for the dependent variable of

Pow and for all the within-subject variables. The threshold for significance in all the analyses is p≤.05. We further describe each statistical comparison performed in relation to the research questions and the methods used. To compare the Pow of the three tasks we performed an analysis by running a 5x2x7 repeated-measurement ANOVA, with the within-subject factors of task, hemisphere and electrode. We then compare the three tasks, two by two.

We perform pairwise comparisons of the seven frequency bands Pow by running for each of them a 2x2x7 ANOVA, with the within-subject factors of task, hemisphere and electrode. We then compare the frequency bands Pow across temporal deciles for the two open design tasks. We performed an analysis by running a 2x2x7x10 ANOVA, with the within-subject factors of task, hemisphere, electrode and decile.

Analysis of Results

Results of total task-related power (TRP) across the 18 participants, indicate that the tasks can be distinguished from each other, Figure 5. The radar diagram plot simulates the two hemispheres by distributing the electrodes (10-10 IS) symmetrically around a vertical axis.

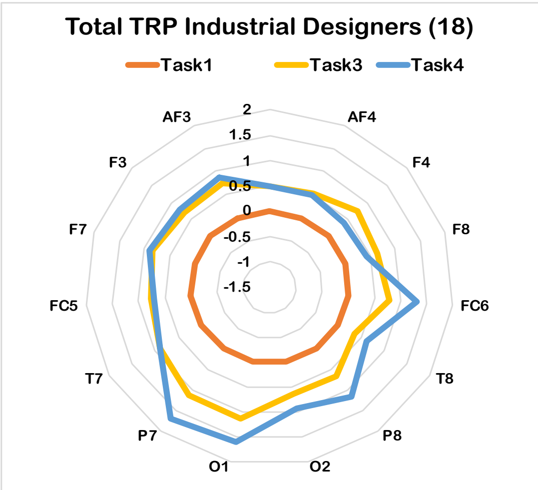

Fig. 5 Task-related power (TRP) for the 14 electrodes by taking problem-solving Task 1 as the reference period for the open design tasks.

Total TRP scores per electrode can be considered by comparing with the vertical scale and across the three tasks. Once the problem-solving Task 1 (reference task) is subtracted from itself to produce the reference, it shows up as an orange circle with a value of zero for all electrode measurements. The difference is shown as higher or lower activation of the electrodes/regions per task within or beyond the orange circle border. The open design tasks (3 and 4) show expanded amplitude from the problem-solving Task 1, Figure 5.

Analysis of Transformed Power across Tasks

Total transformed power (Pow), for each task across the 14 channels are depicted, Figure 6. The plot simulates the two hemispheres by distributing the electrodes (10-10 IS) symmetrically around a vertical axis. Pow scores per electrode (average of entire task) can be considered by comparing with the vertical scale and across the three tasks. Results from running the 5x2x7 ANOVA, are described.

The open design sketching Task 4 shows higher neurophysiological activation than Task 1 and is followed in amplitude by the open layout design Task 3. Below we report on statistically significant ($p \leq .05$) differences between tasks, shown as solid circles channel by channel.

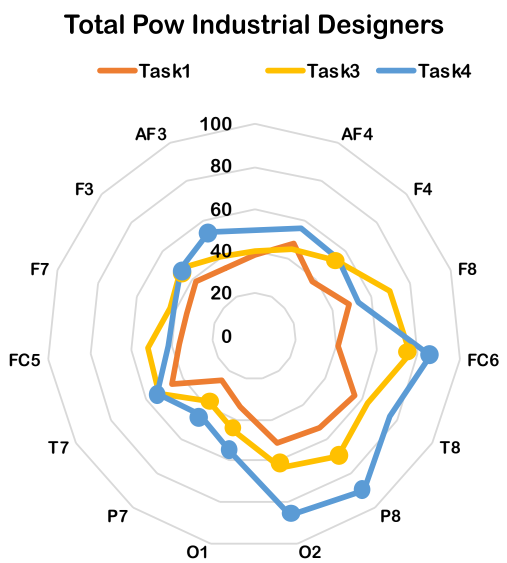

Fig. 6 Transformed power (Pow) and channels of statistically significant differences between Task 1 -Task 3, and Task 1 - Task 4 highlighted with a solid circle.

The pairwise comparisons revealed that the problem-solving Task 1 differs significantly from:

- Open layout design Task 3 ($p<.01$).
- open design sketching Task 4 ($p<.001$).

The significant main effects are presented in Table 2.

Table 2 Significant main effects from the repeated-measurement ANOVA.

task ($p<.001$)
hemisphere ($p<.001$)
electrode ($p<.001$)

Analysis of Transformed Power of Frequency Bands

Total transformed power (Pow) of each frequency band for the three tasks, across the 14 channels are depicted in Figures 7 and 8. Pow scores per electrode (average of entire task) can be considered by comparing with the vertical scale and across the different bands. Delta band Pow values are of a different scale, and do not show significant differences between the three tasks, possibly due to the low quality of the signal in the lower frequencies and are therefore not represented.

The pairwise comparisons revealed that the problem-solving Task 1 differs significantly from the open design sketching Task 4 for all the within-subject factors and frequency bands. As differences cannot be discriminated, we report only the comparisons between Task 1 and Task 3, Task 3 and Task 4.

Frequency Bands in problem-solving and open layout design

The significant main effects across frequency bands is shown in Table 3. The open layout design Task 3 shows higher neurophysiological activation than the problem-solving Task 1 in the right prefrontal and occipitotemporal cortices, Figure 7. Significant differences ($p \leq .05$) were found in theta, alpha 1 and alpha 2 frequency bands, mainly of channels in the left hemisphere. The channels of significant differences across frequency bands are shown highlighted with a solid circle, Figure 7.

Table 3 Significant main effects from the ANOVA between Task 1 and Task 3

	Theta	**Alpha 1**	**Alpha 2**	**Beta 1**	**Beta 2**	**Beta 3**
task	.07	.06	<.01	.19	.08	.13
hemisphere	<.01	<.001	<.01	<.001	<.001	<.001
electrode	.02	<.001	.26	<.01	.02	<.01

The pairwise comparisons revealed that the problem-solving Task 1 differs significantly from the open layout design Task 3 only for alpha 2. For the other within-subject factors: *hemisphere,* significant differences are found across all frequency bands; *electrode,* significant differences are found across all frequency bands with exception to alpha 2.

Task 3 shows higher amplitude than Task 1 except for the channels, AF3, in beta 1 and beta 2, and F8 in beta 3. Although these channels show lower activation (Pow) in the open layout design task than in the problem-solving task, none indicates significant differences.

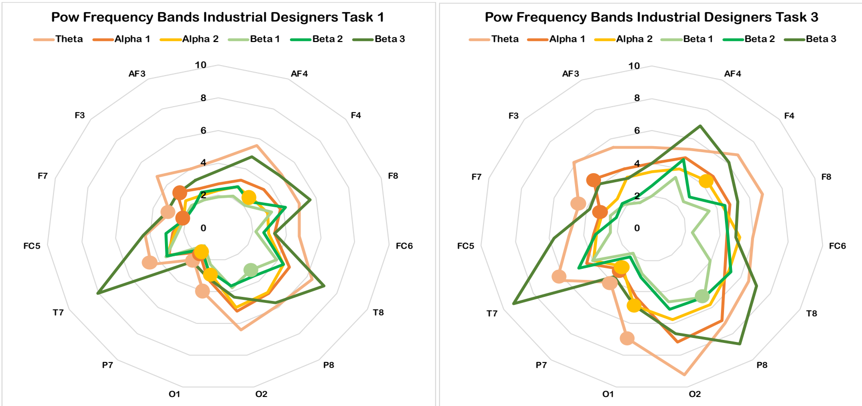

Fig. 7 Transformed power (Pow) of frequency bands and channels of significant differences highlighted with a circle between Task 1 and Task 3.

Frequency Bands in open layout design and open free hand sketching design

Significant differences are found for all the within-subject factors, across bands and between tasks, except for *task* in alpha 1 frequency band, Table 4.

Table 4 Significant main effects from the ANOVA between Task 3 and Task 4

	Theta	**Alpha 1**	**Alpha 2**	**Beta 1**	**Beta 2**	**Beta 3**
task	.02	.21	<.01	.03	<.01	<.001
hemisphere	<.001	<.001	<.001	<.001	<.001	<.001
electrode	.02	<.01	<.001	<.01	.01	.02

The open sketching design Task 4 shows higher neurophysiological activation from the open layout design Task 3. Significant differences ($p \leq .05$) are noticed on both hemispheres with evident higher amplitude for theta, alpha 2 and beta waves in the channels of the right occipitotemporal cortex (FC6, T8, P8, O2). The channels of significant differences are shown highlighted with a circle, Figure 8. Although many channels show lower activation (Pow) in the sketching design task than in the open layout design task, none indicates significant differences.

In Task 4 upper alpha shows higher activation than the lower alpha for the channels T8, P8 and O2, contrary to Task 3. Beta 2 shows expanded activation from beta 1 in Task 4, for the channels, FC6, T8, P8 and O2, while in Task 3 beta 2 and beta 1 have similar activation. Theta band also shows higher amplitude in Task 4, in particular for the channels FC6, T8 and P8.

Frequency Bands across Deciles for the Open design Tasks

The division of each design session's data into temporal deciles allows a more detailed analysis of the temporal dimension stages. Total transformed power (Pow) of each frequency band for the two open design tasks, and the 14 channels were calculated across deciles. Designing is a temporal activity, the division into deciles helps discerning how designing unfolds in time. Different cognitive behaviors exhibited when design sessions are divided into deciles show the temporal activity in designing [27].

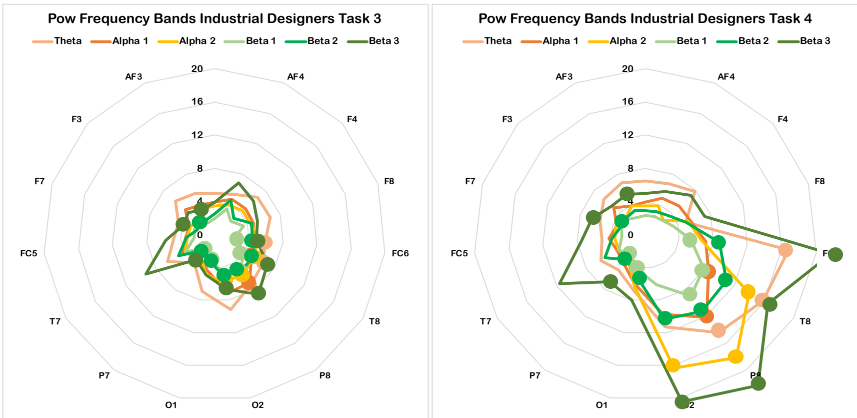

Fig. 8 Transformed power (Pow) of frequency bands and channels of significant differences highlighted with a circle between Task 3 and Task 4.

We expect to derive from the analysis of deciles results that cannot be distinguished at the aggregate level. Below we report on significant ($p \leq .05$) differences from running the 2x2x7x10 ANOVA, Table 5.

Table 5 Significant main effects from the ANOVA between Task 3 and Task 4

	Theta	**Alpha 1**	**Alpha 2**	**Beta 1**	**Beta 2**	**Beta 3**
task	.18	.02	<.01	<.01	<.001	<.001
hemisphere	<.001	<.001	<.001	<.001	<.001	<.001
electrode	<.001	<.001	<.001	<.001	<.01	<.01
decile	<.001	.03	<.001	<.001	<.001	<.001

The pairwise comparisons revealed that the open layout design Task 3 differs significantly from the open sketching design Task 4 for all the within-subject factors, across bands, except for *task* in theta. Significant differences are more accentuated for *task* and *electrode* in the statistical analysis across deciles. The absence of significant difference for *task* in alpha 1 on the aggregate level is not supported across deciles.

Pow scores per electrode (average of each decile) can be considered for Task 4, across deciles by comparing with the vertical scale for the different bands, Figure 9. The channels of significant differences ($p \leq .05$), shown highlighted with a circle are noticed in both hemispheres.

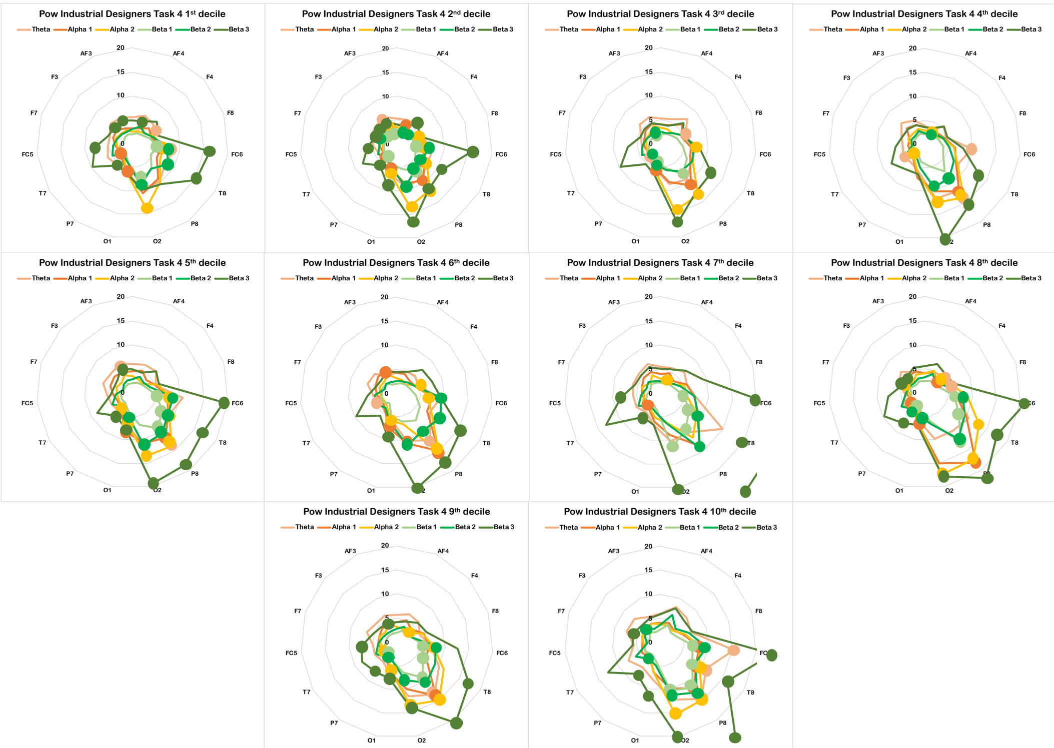

Fig. 9 Transformed power (Pow) of frequency bands of Task 4 and channels of significant differences highlighted with a solid circle between Task 3 and Task 4.

Discussion

The neurophysiological activations of these industrial designers when problem-solving and designing was measured and showed to increase in amplitude in both open design tasks across all channels. While the open design tasks show different activation, in particular higher amplitude in the right prefrontal cortex (F8) for the open layout design task, and higher amplitude in both occipital cortices and in the right temporal cortex, for the open free hand sketching design task, both largely increase in amplitude from the problem-solving task, across all channels, except for AF4, in the open layout design task. The largest increase was measured in the right occipitotemporal cortex, for the channels FC6, T8, P8 and O2, specially for the open free hand sketching design task.

The comparison between the frequency bands of problem-solving and the open layout design tasks shows significant differences on the upper alpha band, and marginally significant differences also on theta, alpha 1 and beta 2. The two tasks show significant differences between hemispheres across the six frequency bands. Channels of significant differences were found mostly in the left hemisphere, namely, P7 (theta, alpha 1 and alpha 2), F7 (theta and alpha 1), O1 (theta and alpha 2), T7 (theta) and F3 (alpha 1). In the right hemisphere, channels of significant differences are F4 (alpha 2), and P8 (beta 1).

Results on the frequency bands show significant differences between problem-solving and the open free hand sketching design task across all bands, mostly in the right hemisphere, for the channels, FC6, T8, P8 and O2, and in the left hemisphere for the channels O1 and P7, and partially for the channels AF3, F7 and F3.

Overall when moving from problem-solving to open design tasks, alpha 2 shows decreased activation from alpha 1 in the problem-solving and open layout design tasks, but increased activation in the free hand sketching design task. Similarly, beta 2 has similar activation to beta 1 in the problem-solving and open layout design tasks, and expanded activation from beta 1 in the free hand sketching design task.

More relevant differences for understanding designing emerge when comparing the open layout design task to the open free hand sketching design task. As the task involves sketching activities. Channel P8, shows significant differences across all the six frequency bands. P8 is associated with the cognitive functions activated by sketching. T8 is the only other channel with significant differences across all the bands. This difference in activation might be related to sketching. The right occipitotemporal cortex shows increased amplitude in theta, alpha 2, beta 2 and beta 3. This expansion appears as consistent in all channels of this brain region from beta 2 to beta 3, while a shift in the channels from FC6 to O2 appears from theta to alpha 2.

The channel O2 has significant differences in alpha 2, beta 2 and beta 3. The channel FC6, has significant differences in theta, and Beta waves (1, 2 and 3). The channel F7 has significant differences in Beta 3. In general, all the three beta waves increase in amplitude in the open free hand sketching design task.

From the analysis of deciles, the data shows important differences across time, revealing variability in the task, for hemispheres, bands and channels. As Task 4 is the most prototypical design task in this experiment, increased amplitude of alpha 2 from alpha 1, is evident across deciles except for decile 6. An increase in amplitude of beta 2 compared to beta 1 is also observed across deciles except for decile 3. As upper alpha and beta 2 have similar behavior in the layout tasks (1 and 3), we can infer that alpha 2 and beta 2 play an important role in completely open designing. The analysis of deciles also shows more significant differences between the open design tasks, across deciles for alpha 2, beta 2 and beta 3.

Conclusion

Both alpha and beta bands seem to play a role in the most prototypical design task of this experiment, the open sketching design task, in particular alpha 2 and beta 2. From the problem-solving Task 1 to the open layout design Task 3 only the upper alpha frequency band shows significant differences. We can infer that upper alpha plays a significant role when shifting form problem-solving to design tasks. This shifts also brings significant differences to channels of the left hemisphere, F3, F7 and P7, associated with the interplay of deductive and inductive reasoning, and T7 and O1, mainly on theta, but also on alpha bands. Shifting from a problem-solving to an open layout design task also brings more flexibility in the activation across bands for the channels P7, F7 and FC6 across the bands. This is also visible when shifting from the open layout design task to the sketching design task. At this stage, and in particular from the analysis of deciles, the channels of greater change towards designing as thinking process are FC6, T8, P8 and O2. From the expanded activation of these channels, different time dynamics are visible in the six bands across deciles. The progressive increase of theta activations across time supports the upper alpha [6] and beta waves [7] key role in designing. Design neurocognition research methods must include analysis of the time dimension, to assess the unfolding of designing cognitive activities.

The research reported here aims at using brain activations as the measure to assess differences between problem-solving and designing. In particular, it used those measurements to distinguish between problem-solving and two design tasks. It then proceeded to use those measurements to further distinguish between two classes of design tasks: an open but constrained design task and a fully open design task.

Each of the channels is associated with a Brodmann area [29]. Brodmann areas are brain regions that have been associated with various cognitive functions. It is left to future analysis to correlate measured activations with Brodmann areas and hence to cognitive functions. The increases and decreases in activation would then be increases and decreases in cognitive functions. This would allow us to begin to connect these results directly with design cognition.

The results in this paper demonstrate that low cost EEG devices can be used to measure brain activations of designers. In doing so, it opens an avenue of design research that was previously available only to researchers who had access to medical grade equipment.

Acknowledgments and financial support

To come

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