Investigation into Neurological Foundation of Synthesis and Evaluation Activities in Conceptual Design

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Abstract

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Lixin Liu

The objective of this thesis is to use principal component analysis (PCA) to explore the relationship between neurological brain power and activities in conceptual design. This thesis provides an objective method to measure and understand designer's activities with respect to brain signal patterns. Understanding designer's activities may help us develop powerful tools to improve designer's performance. This thesis is based on the cognitive experiments consisting of 6 design tasks conducted at the Concordia Design Lab (Nguyen & Zeng, 2016).

First, we observed the electroencephalogram (EEG) data of closed eyes rest states and design activities (synthesis and evaluation) using statistical methods. We found that the 7 bands of subjects' EEG power are normally distributed. Then we averaged the 32 subjects' relative EEG band power, we found that alpha band power negatively correlated to the other band powers.

Second, we applied PCA to the data. We found that there are three principal components (PCs) that account for most of the variance (97%) of the EEG band power. With respect to the results of 3 PCs, we found that the rest segments are significantly different from the design activity segments, synthesis segments have greater variance than evaluating solution segments, and they are not significantly related. From the results of 3PC, we may observe the EEG data as the baseline of design activities.

Third, by comparing the differences of the subjects on the PCs, we might infer or evaluate the subject's design behavior. By optimizing the model, ultimately it may help us improve the performance of design.

Acknowledgements

I'd like specially thank Professor Yong Zeng who introduced the "life changing curve" to me. He changed my life, and he is still inspiring me to apply it in all aspects of my life. I believe it will also affect my future. I could hardly imagine that Professor Zeng accepted me as a master's student 20 years after of my graduation. He has not only supported me financially, but also has directed and helped me. During this study, there were many challenges and uncertainties for me. Fortunately, I received valuable instructions and directions from Professor Zeng. Throughout this MA, I had the chances to improve my capability in terms of the model of knowledge, skills and affect (Nguyen & Zeng, 2012).

I thank Dr. Thanh An Nguyen for instructing and helping me with research methods, Matlab skills and the process of writing and publishing research. I also want to express my thanks to Philon Nguyen, Suo Tan, Ronaldo Gutierrez, Xiaoying Wang for giving me endless guidance formatting papers, presentations, and projects. I had a good time with Shahriar Taheri, Dalvir Singh, Wenjun Jia, and other colleagues in our lab discussing and cooperating on projects and research. I'd like to thank people in CIISE office. They are Kim Adams, (Department Administrator), Lilia Pernatozzi, (Assistant to the Director), Silvie Pasquarelli (Graduate Program Coordinator), Mireille Wahba, (Graduate Program Coordinator). They are patient and kind, and they helped me during my courses application, registration, and in the process of submitting this thesis. I should also thank our Concordia University and our ENSC department offering me this amazing environment in which to study.

Above all, I appreciate my family, especially my dear wife, who has supported and encouraged me.

I enjoy the whole journey throughout my studies, and it will be a shining light in my life.

Contribution of Authors

This thesis is directed by my supervisor Dr. Yong Zeng. All the experimental data of this thesis are from Design Lab of Concordia University. As the founder of our lab, Dr.Zeng has designed all the experiments during the last ten years. He also directed and deployed the whole process of the research.

As the co-supervisor, Dr. Thanh An Nguyen implemented all the experiments and guided this research. She also reviewed the data analysis. Many programs are based on her original design. During the publication process, she reviewed the thesis and made many corrections.

Philon Nguyen provided comments and corrections related to this thesis, and he also provided feedback on the research methodology and interpretation of the data.

Wenjun Jia provided the program to generate the EEG topographic map for the experimental data and gave valuable feedback regarding the validation of the data analysis.

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1 Introduction

1.1 Background

There are physiological reactions of human behaviors, and the biosignals may represent the behaviors (Andreassi, 2013). Based on the model of the object of design we know that design is a recursive process of the subjective world and objective world. The subjective world is the designer and objective world is the environment and product (Y. Zeng & Cheng, 1991). Our design study is about the relationships between the subjective world and the objective world. The present research question is: what is the relationship between the brain power and the design activity? As we know design activity is related to brain behavior and there are brain signals associated with these activities. To find the relationship between mental behavior and these biosignals, we proposed to study the output pattern of these signals. Studying the brain power rhythm may help us understand the mental behavior (Andreassi, 2013). This study is based on the EEG band classification. From these patterns, we intend to generalize specific models of bio signals corresponding to the mental behaviors involved in design activities. Studying EEG signals associated with design activities from the experimental data helps us build the model. Based on the experiment data, we applied statistical methods to study the pattern of the data, and applied PCA to analyze the principal components of the EEG band power related to design activities. The main question is: What is the relationship between brain power and design activity? The hypothesis is: The brain power is related to the design activity. To test of the hypothesis, this thesis presents the result of correlation between PC1 and the subjective rating of the design activity. The PC1 score represents the first principle component of the composition of the 7 bands' normalized relative EEG power. It may be related to the level of relaxation. The subjective rating is the self-assessment by the subjects of the 6 tasks during the experiment. The self-assessment features include: mental effort, mental workload, performance, mental stress, time demand, and total workload, the method is using NASA TLX to evaluate the result (Nguyen & Zeng, 2016).

1.2 Abbreviation:

- EEG: Electroencephalogram
- Brain power: EEG power (PSD)
- PCA: principal component analysis (PCs: principal components)

- REST 1: the closing-eye rest state before the tasks
- REST 2: the closing-eye rest state after the tasks
- P: Generating the solution for the task (Synthesis)
- E: Evaluating the solutions for the tasks (Evaluation)
- CEV: Accumulative Explained Variance

1.3 Method

This thesis is based on the 6 design tasks experiments of 32 subjects conducted at the Concordia Design Lab (Nguyen & Zeng, 2016). Regarding the collecting of EEG data and transforming EEG data to EEG power data, they have been investigated in the previous research (Nguyen & Zeng, 2016). The main contribution of this thesis is the analysis of the data. Based on the experimental data, we applied statistical methods to study the pattern of the EEG band power, and we applied PCA to analyze the principal components of the EEG band power related to design activities. We intended to derive the PC patterns of design activities. Then we illustrated the figure according to the data of the subjective rating from the 6 tasks experiment. After that we compared the patterns between them. At last we used statistical correlation algorithm to test the result.

The analysis included:

1) Observation of the distribution of the relative EEG band power of the subject's design activities.

2) Analyzed the correlations among the 7 bands of 32 individual's average EEG band powers associated with the design activities.

3) Performed a Principal Components Analysis (PCA) of the average EEG band power for the design activities.

4) Analyzed the PCA results of subjects' design activities.

5) Analyzed the correlation between the Principal Component 1 (PC1) and subjective rating.

1.4 Result

We found that there are different brain power rhythms associated with the rest states, generating the solution and evaluating the solution in the design activities. The outcomes of the analysis are:

1. The subjects' EEG band power data are distributed normally. Based on this result we could use the mean value of the 32 subjects' EEG data to represent the average behavior of the subjects.

2. Alpha band relative power negatively correlated to that of the other bands (theta band, beta bands, gamma bands). (based on the average data from the 32 subjects). Therefore we used PCA to transform the correlated EEG data to the uncorrelated and orthogonal data.

3. There are three Principal Components (3PC) of the 7 band relative EEG power which accounts for that of 97% of the total variance. PC1 accounts for that of 77% of the total variance of the 7 band. Based on this result, we may use the 3PC model to observe the relations between EEG bands and design activities.

4. According to the observations from the 3PC model, we found that the rest states presented high scores for PC1, therefore the PC1 score is related to the relaxation level. Rest 1 (the rest state before the tasks) is different from Rest 2 (the rest state of after the tasks). From the PCA (in section 3.3) we know that the main component is PC1 and is related to alpha band. This result justified that the rest state is related to alpha band power (Sörnmo & Laguna, 2005) (Andreassi, 2013). However we also found that there is a difference between the Rest 1 and Rest 2, Rest 2 is higher than Rest 1 on PC1 score. This may imply that the subjects may be nervous in the beginning and they are less relax than that of the end of the tasks.

5. Based on the observation of PC1, we found that the score of generating solutions has greater variance than that of evaluating solutions and they are not significantly related. This may imply that generating solutions includes more mental strategies than that of evaluating solutions.

6. Everyone thinks and acts differently, and this is related to the structure of brain and the thinking strategy (Kanai & Rees, 2011). We projected the 32 subjects' EEG data on the 3PC model. By comparing the differences and variance of the data on the model, we may infer or evaluate the subject's design behavior. In order to verify the model, we studied the cases of the four subject's generating solutions of the six design tasks. From the observation of the patterns, we intend to explore the designers' behaviors related to them. For example, did they relax during the closing-eye rest? How hard the designers worked (compared with closing eye state)? Did they concentrate

on the work? If we could measure and evaluate the designers' behavior, it would help us develop powerful tools or methods to improve the performance of the design process.

7. At last we compared the subjective rating results with the PC1 results using statistical correlation function. There are some features significantly related to them. As there were only four subjects' data in this analysis, there will be further investigating.

The importance of this thesis is that our research provided an objective method to measure designer's behavior. The originality of this thesis is using Principal Component Analysis (PCA) to study the brain power pattern used during the process of conceptual design. The research is a preliminary investigation of signal pattern related brain neurological activity of a whole process (conceptual design). The result may be used as a prototype (foundation) for future study and improvement. And it can be applied to improve the quality of brain activity. It has a great application of cognitive activities in industrial design, education and administration fields. The following discussing includes literature review, empirical study, conclusion and future work.

2 Literature review

There are three critical questions related to this thesis. They are: how to improve the performance of design? what are the relations between EEG power and design activities? why we use PCA to analyze designers' EEG power?

2.1 How to improve the performance of design?

The goal of our research is to improve the performance of the design process based on the model of the object of design (Y. Zeng & Cheng, 1991) (Yong Zeng, 2001). We know that design is a recursive process of the subjective world and the objective world. Subjective world is the designer and objective world is the environment and product. This is shown in Figure 1.

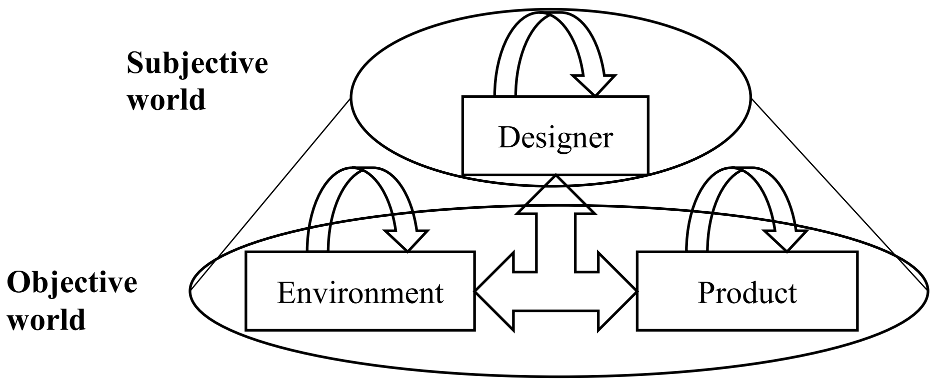


Figure 1. The object of design (Y. Zeng & Cheng, 1991) (Yong Zeng, 2001)

Our study of the design process researches the relationship between the subjective world and the objective world. The object of design is based on two postulates: "*Postulate 1: Design reasoning follows the recursive logic. Postulate 2: Design creativity is related to designer's mental stress through an inverse U-shaped curve"*(Nguyen & Zeng, 2012). As we can see from the Figure 2 that design is the recursive process of the subjective world with the objective world. The designer is the subject and determiner of the process. Therefore, to improve the performance of design, the key factor is the designer's behavior during the process. Based on the performance of creativity theory (Figure 2), we know that the creativity level during the process of design is related to mental stress. And the mental stress is related to the designer's mental effort and mental capability. Thus, to improve the performance of design, the mental stress is the critical factor.

Figure 2. Relationship between design creativity and mental stress follows the inverse u-shaped curve (Nguyen & Zeng, 2012)

The source of brain activity is the neurons which "are always active when we are asleep or awake, active or passive, during meditation or hypnosis" (Sörnmo & Laguna, 2005). To understand the function of the brain objectively, researchers have been studying the responses of physiological signals and their patterns for more than one hundred years. The mental behavior is related to the brain. As we know the subjective world is related to the brain and the activities during the process of design are associated with brain signals. To find the relationship between brain activities and these biosignals, we may study the output patterns of these signals. These bio signals include the responses of EEG, heart rate (ECG), respiration, skin conductance (GSR), eye movement, body movement, etc. (Figure 3). There are many researchers who discuss the relationship between these biosignals and design activities. Analysis of heart rate variability (HRV) was considered by (Nguyen, Xu, & Zeng, 2013), and analysis of body movement was considered by (Tang, 2011). Jin, Zeng, & Wang discussed using eye movement to evaluate the advertising effectiveness (Jin, Zeng, & Wang, 2010). This thesis focuses on EEG signals.

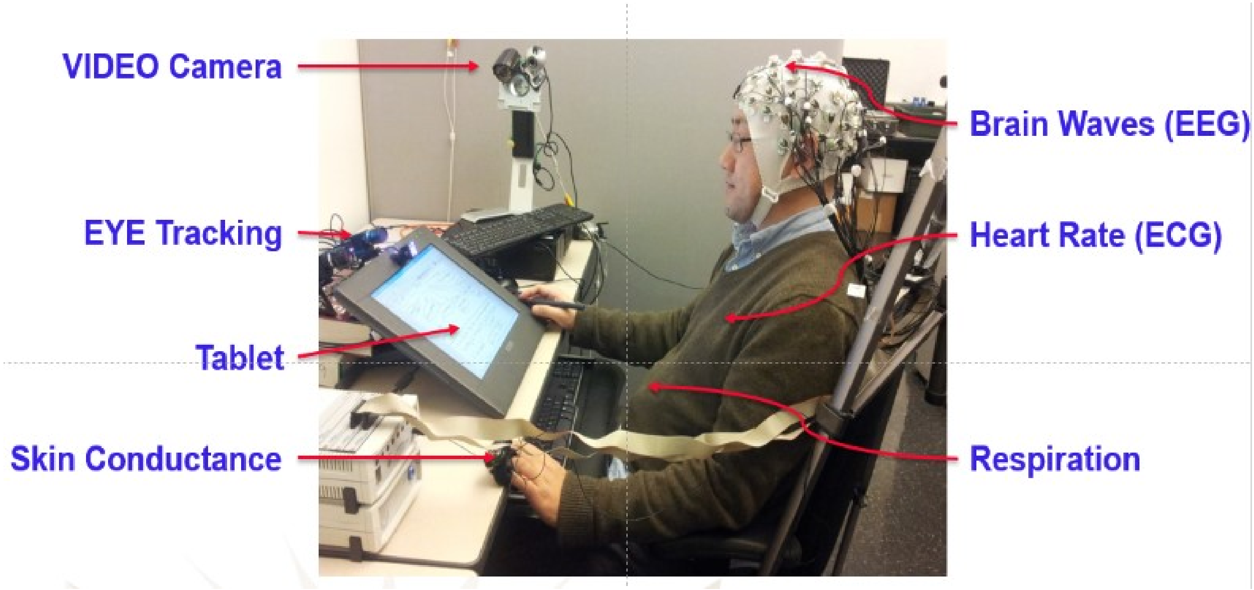


Figure 3. Cognitive experiment of conceptual design ("Design Lab," n.d.)

2.2 What is the relationship between EEG power and design activities?

EEG (electroencephalogram) is the signal captured by electronic devices. EEG records the brain wave patterns. Hans Berger (Haas, 2003) was the first one recorded the EEG "brain waves" by attaching electrodes to the human scalp. He observed there are different EEG waves related to the mental state of the subject, such as the states of attention, relaxation, or sleep (Sörnmo & Laguna, 2005). There are many literature on the relationship between EEG band and cognitive states. Theta band is related to inhibition (Kirmizi-Alsan et al., 2006), certain stages of sleep, and memory and attention (Klimesch, 1999). The alpha band is related to the closing-eye state (Andreassi, 2013) and memory (Klimesch, 1997). Hans Berger found that the beta band was associated with focused attention (Kropotov, 2010). The gamma band is related to task difficulty and mental effort (Mulert et al., 2007) . The study of EEG for designer's activities has elicited many valuable findings (Niedermeyer & Silva, 2005). As EEG is a signal from the brain, researchers try to find the relationship between EEG and a mental behavior according to the patterns of the EEG data using techniques such as classification of EEG (Lotte, Congedo, Lécuyer, Lamarche, & Arnaldi, 2007), assessing emotional states using EEG pattern (Wioleta, 2013) (Koelstra et al., 2012). Studying the patterns of EEG band power may help us understand mental behavior. There are also many researchers studying the relationship between EEG signals and design activities: producing many meaningful findings such as using EEG and Eye Gaze system to assess designer's mental stress

(Petkar, Dande, Yadav, Zeng, & Nguyen, 2009), using EEG band power to measure different brain area of the designer (Nguyen & Zeng, 2010) and using EEG beta power to measure designer's mental effort (Nguyen & Zeng, 2014). This thesis is based on the EEG frequency band classification of design activities using EEG evoked potentials. Studying the EEG signals patterns associated with design activities helps us build a model to measure and evaluate designers' behavior. From the observed patterns, we intend to generalize models of EEG corresponding to the brain activities during design process. According to the experiment data, we applied statistical methods to study the pattern of the EEG data. We found that the distributions of the designer's EEG bands are normally distributed, and the EEG bands are correlated. It is obvious, that these bands are associated with some cognitive states, but they are not independent or directly related to specific design activities. In order to better interpret the EEG data, we tried to find a method to transform the EEG band data to uncorrelated and reduced dimensions data. This lead to our research method of using PCA to transform the data and explore the relationship between EEG band data and design activities.

2.3 Why we use PCA to analyze designers' EEG power?

First, based on EEG waves, it is difficult to identify and evaluate designer's behavior, because of the *diversity of EEG patterns* (Barlow, 1993). Second, based on EEG bands, even though many observations revealed some relationship between EEG bands and mental behavior (Andreassi, 2013), it is hard to identify behavior according to the bands. Third, it helps us to find the patterns of brain power by applying PCA model to quantify mental activities associated with EEG bands (Wilson & Fisher, 1995). Based on the PCA of EEG band, we may help identify and evaluate designer's behavior. Finally, we could verify the model based on the experiment results and collect the constraints to improve the future study.

Principal component analysis (PCA) is a statistical method which might reduce the complexity of multidimensional data using a linear model (Hotelling, 1933). The objective of PCA is simplify the data and find the relations and patterns in the data. Based on the linear correlation model, PCA is a transformation of the original data to uncorrelated and orthogonal data which contains eigenvectors of the original data, and this transformation can be geometrically described as a rotation of the multivariate data to the new coordinate in which it is easy to interpret (Montgomery, 2007). The objective of PCA includes: simplifying data, identifying the relations of the variables, and observing the patterns of the units (Montgomery, 2007).

There are many papers discussing about the use PCA to transform EEG data. Wilson discussed the classifying tasks using PCA (Wilson & Fisher, 1995). Wallstorm investigated the correction of ocular artifacts using PCA (Wallstrom, Kass, Miller, Cohn, & Fox, 2004). Valdés "the spatial PCA of qEEG data" (Valdés et al., 1992). Subasi studied PCA for segmenting signals (Subasi & Ismail Gursoy, 2010). The main difference between the previous study and present research study is that of the event related potentials (ERPs). The ERP of our research is the design activity, such as designing a birthday cake, which is not repeatable during one experiment. As the observation (related to ERP) of PCA is different from that of other studies, this leads to the different result of PCA.

The essence of the PCA of EEG bands is the composition of different EEG bands. This provides us a dynamic bands model for the observation of the design activities. Based on this PCA perspective, we analyzed designers' general and individual behavior. The analysis included 1. we analyzed the patterns of design activities on the PCs to identify the average characteristics of designers' behavior. 2. We also analyzed the variance of the designers' activities on PCs to explore the behaviors of individual characters. The features of the statistical analysis included the difference, the mean, the standard deviation, the ANOVA table, and the control chart.

3 Empirical Study

The research method should be based on a scientific method which consists six to eight stages (Leong, Heah, & Ong, 2015). Based on "Design Research Methodology (DRM)" (Blessing & Chakrabarti, 2009), the procedure of this empirical study includes collecting the EEG raw data from experiments, processing, and segmenting raw data, observing the rhythm of EEG band power, modeling EEG band power, and verify the EEG band model for design activity. To refine and optimize the model, we may go back to collect data, process data, analyze data, model data and verify the result again. This comprises a cycle for EEG data analysis. (Figure 4)

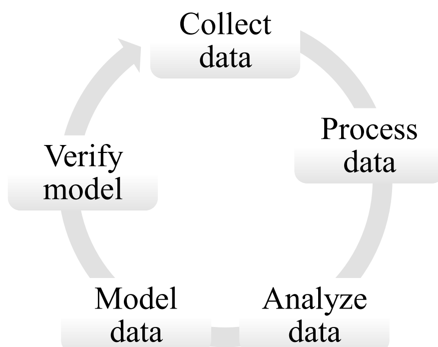


Figure 4. Procedure of the EEG data analysis

3.1 Collect data

The first step of the study is collecting data and preprocessing the EEG raw data.

3.1.1 Experiment setting

The EEG data was collected from the experiments at the Concordia University design Lab. There were 40 master's students from Concordia University participating in the six design tasks experiments. Each experiment lasted two to three hours. During the experiment, the subject was asked to complete the designated open-ended task using a tablet. The physiological signals were captured synchronously. Due to technical reasons, the 32 subjects' EEG data was used for this analysis. Regarding the details of the experiment, please refer to (Nguyen & Zeng, 2016).

3.1.2 Experiment process

There were six design tasks composed of 6 experiments for each subject. Before the experiment and after completing all six tasks, the subject was asked to close his/her eyes for three minutes (closing-eye rest state). We use Rest 1 and Rest 2 represent the rest states of before and after experiment respectively. Every task includes five stages (Figure 5)

1. Read the design task from the given program.
2. Generate the solution for the given task on the tablet.
3. Rate the workload of generating a solution for the task using NASA task load index.
4. Evaluate other subject's solution of the task.
5. Rate the workload of evaluating other subject's solution for the task.

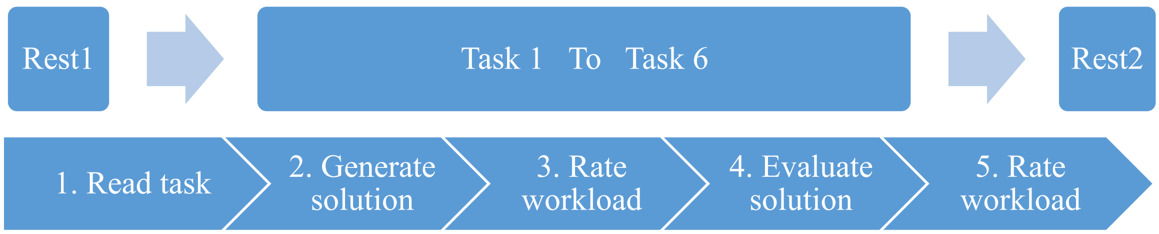


Figure 5. The experiment process

Figure 6 shows the six design tasks of the experiment.

Task1

- **Make a birthday cake** for a five year old kid. How should it look like?

Task2

- Sometimes, we don't know which items should be recycled. **Create a recycle bin** that helps people recycle correctly.

Task3

- **Create a tooth-brush** that incorporates toothpaste.

Task4

- In Montreal, people on wheelchair cannot use the metro safely because most metros only **have stairs** or **escalators**. **Elevators** are not an option because they are costly. You are asked to create an efficient solution to solve this problem.

Task5

- Employees in IT companies sit too much. The company wants their employees to stay healthy and work efficiently at the same time. You are asked to **create a work-space** that can help employees to work and exercise at the same time.

Task6

- There are two problems with standard **drinking fountains**: a) filling up water bottles is not easy, b) people too short cannot use the fountain and people too tall have to bend over. Create a **new drinking fountain** that solves these problems.

Figure 6. The 6 design tasks of the experiments

3.1.3 Preprocess data

After collecting the EEG raw dataset, as the collected EEG raw dataset contains noises, it should be filtered with bandpass and preprocessed with artifact removal. Then the preprocessed EEG dataset (clean data) was separated into EEG segments associated with the design tasks stages. The procedure and functions of preprocessing EEG data follow:(Nguyen & Zeng, 2016)

1) EEG data filter: bandpass 0.3-70 Hz
2) EEG Artifact correction (eye blink removal)
    a. HEOG Amplitude: 150 (μv)

b. VEOG/Blink Threshold: 250 (μv)

3) EEG Segment: Segment EEG data per EEG marker file.

4) Create index matrix for EEG segment data associated with design tasks stages.

3.2 Process data

The second step is process data which includes transforming and observing the EEG data. After collecting the EEG raw data and preprocessing the raw data, the clean EEG data matrix was created for the rhythm analysis. The procedure is shown in Figure 7.

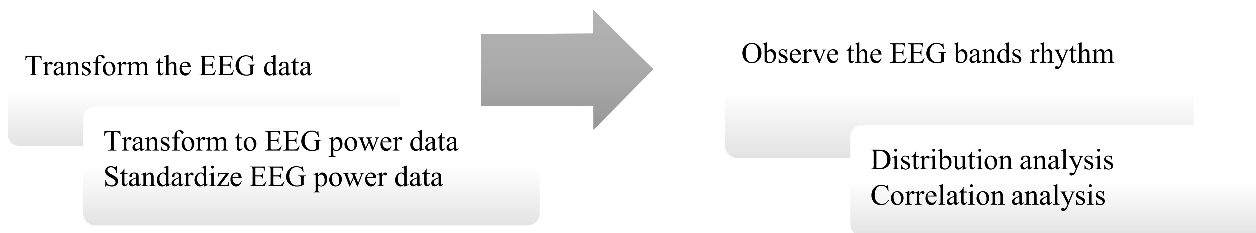


Figure 7. Transform and observe the EEG data

3.2.1 Transform the EEG data

Transformation of the EEG data includes transformation of EEG data to EEG power data, and standardizing the brain power data. We transform EEG data to brain power data for design activities based on the experiments of the 32 subjects. The input data included EEG segment data and index matrix. The algorithm for this transformation is Hamming window on 2-second epochs with 50% overlap. The output data is the accumulated power spectral density (PSD) of seven frequency band EEG data. It is the brain power data matrix. The variables are the bands, design activities, and subjects. The observation is the brain power data.

1) Input Data: EEG signal data of 32 subjects, EEG Segment index matrix based on 14 design activities
2) Output Data: EEG PSD data matrix: 32 subjects, 7 bands, and 14 activities
3) Algorithm: Hamming window on 2-second epochs with 50% overlap
4) EEG channel: Fz Channel of frontal lobe cortex (related to thinking, working memory, and calculating (Nguyen & Zeng, 2016)).

5) Variables (7 bands): theta, alpha, beta1, beta2, gamma(g)1, gamma 2, and gamma 3

6) 14 activities: Rest 1, Rest 2; P1 to P6; E1 to E6

Table 1 represents the experiment variables.

Table 1. Experiment variables

Variables	**Range**
Subject (#)	32
Experiment time (minute)	120~180
EEG channel (#)	64
EEG band (#)	7
EEG power (dB/Hz)	-20~20
Solution generation	P1 to P6
Solution evaluation	E1 to E6
Rest	Res1, Rest 2

7) Rest 1: Closing-eye before the tasks (3 minutes)

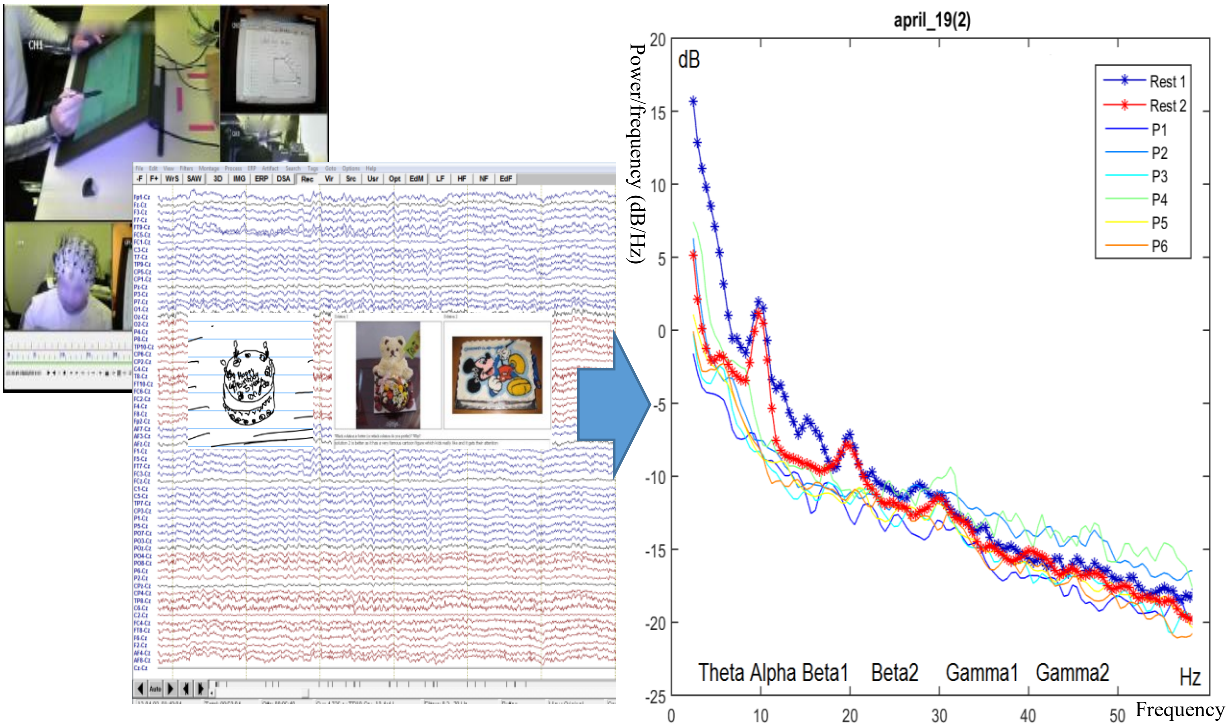
8) Rest 2: Closing-eye after the tasks (3 minutes)

Table 2 is the list of the EEG band breakdown of the experiment.

Table 2. EEG band breakdown of the experiment

Band	**Frequency (Hz)**
Theta	4—8
Alpha	8—13
Beta 1	13—20
Beta 2	20—30
Gamma 1 (G1)	30—40
Gamma 2 (G2)	40—50
Gamma 3 (G3)	50—60

We transformed the EEG time domain data to frequency domain EEG power data associated with design activity segments. From the accumulated Power Spectral Density (PSD) (Figure 8) of one subject, we can see in the curves of two closed eyes rests states (Rest 1, Rest 2), there are two peak values on the 10 Hz and around 18 Hz, these two points are associated with the alpha band and beta1 band. The transformation input is EEG data and the output is EEG brain power data.



64 channels EEG

Brain (EEG) Power

Figure 8. Transform EEG time domain data to frequency domain EEG power data associated with design activity segments

After transforming EEG data to EEG band power data, we computed the **relative EEG band power** by calculating the percentage of the specific frequency band power of the total frequency band power. In the following analysis, **we use EEG band power** to represent the **relative EEG band power.**

3.2.2 Observe the EEG band rhythm

3.2.2.1 Distribution observation

After EEG data is transformed to EEG band power data, we observed the distribution of subjects' brain power of design activities for 7 bands. The features include mean, low-end and high-end value of rest states, generating solution (P) states and evaluating solution (E) states.

Theta power:

Theta band is found to be related to inhibition of elicited responses (Kirmizi-Alsan et al., 2006), theta band is also related to drowsiness and certain stages of sleep (Sörnmo & Laguna, 2005). From the distribution of the 32 subjects' relative theta power (Figure 9), we know that the average rest states (Resr1 and Rest 2) power lower than the average of P and E (generating a solution and evaluating the solution). The subjects 2 and 4 have a relatively high value of E, The subjects 8, 20, 27, 28, 29 and 31 have a relatively low value E. The subjects of 14, 19 have a relatively high value P and subjects 8 and 31 have a relatively low value P.

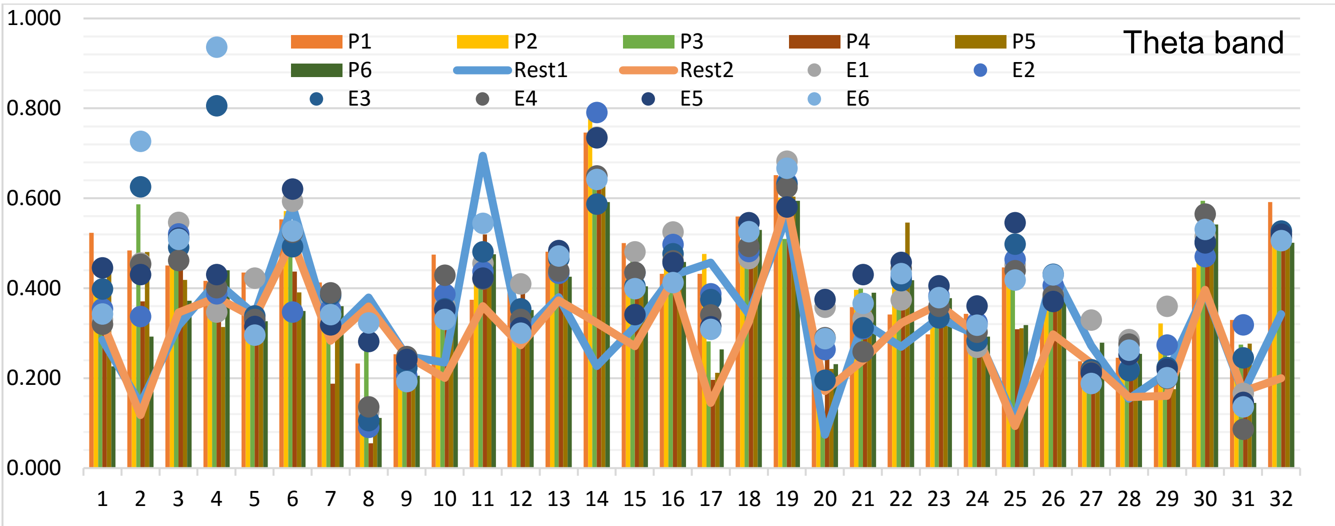


Figure 9. Observation of the relative theta power of the 32 subjects

Alpha power:

The alpha band is related to the closing-eye state (Andreassi, 2013) and memory (Klimesch, 1997). According to the observation of the 32 subjects' alpha power Figure 10, we found that the average of Rest 1 and Rest 2 are greater than P and E, subject 6, 8, 14, and 24 are relatively low in P and E, subjects 25, 27, and 28 are relatively high P and E; subjects 4, 9, 24 are relatively low Rest 1 and Rest 2. Subjects 15, 25, 27, and 28 are relatively high Rest 1 and Rest 2.

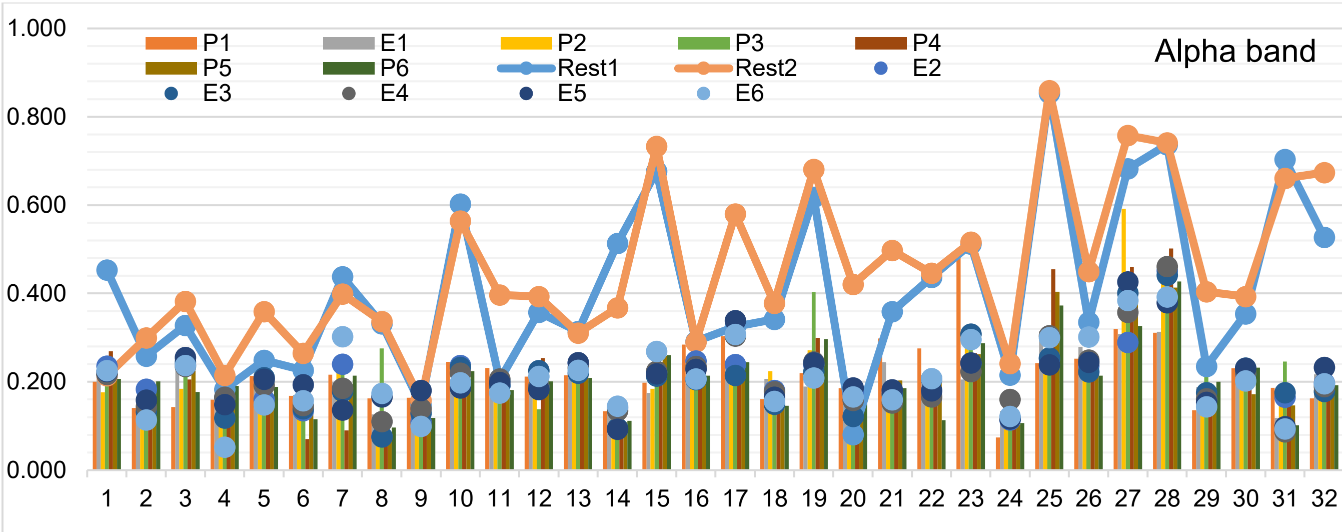


Figure 10. Observation of the relative alpha power of the 32 subjects

Beta power:

Hans Berger found that the beta band was associated with focused attention (Kropotov, 2010). In order reduce the complexity of the EEG data, we observed the beta2 power for the selected design activities of P2, P4 and E1, E3 (Figure 11). We found that the average of P and E was higher than those of Rest 1 and Rest 2. The subjects 10, 11, 15, 22, 23, 26, 29, and 32 were more likely working with similar average mental effort. The subjects 9 and 20 presented more power (mental effort) than other subjects. Subject 14 and 19 presented the lowest mental effort on P2 and P4 than others. Subject 14 presented the lowest mental effort on E1 and subject 4 presented the lowest mental effect on E3.

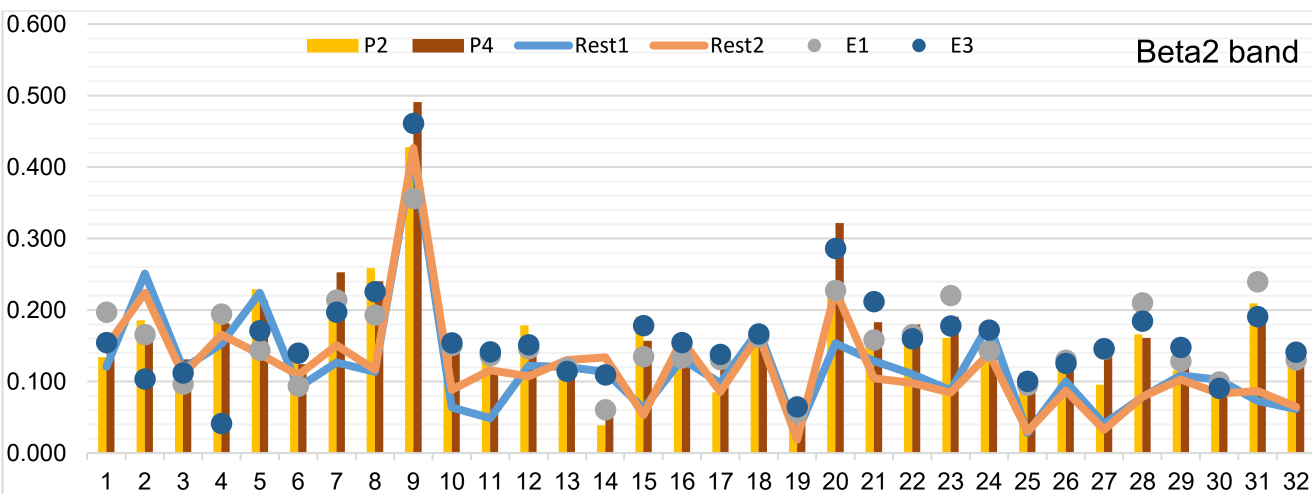


Figure 11. Observation of the relative beta2 power for the selected design activities

Gamma power:

The gamma band rhythm is related to a state of active information processing, such as during finger movements (Andrew & Pfurtscheller, 1996). Gamma power is related to task difficulty and mental effort in anterior cingulate cortex (ACC) (Mulert et al., 2007). From the observation of Gamma2 power of the 32 subjects of Figure 12, we found that the amplitude was lower than that of other low-frequency bands. The average power of rest states was lower than that of E and P. The subjects 8, 20, 24, and 31 had a relatively high value of E, and subjects 18, 19, and 32 had a relatively low value of E and P. Subjects 8, 24, and 32 had relatively high value of P.

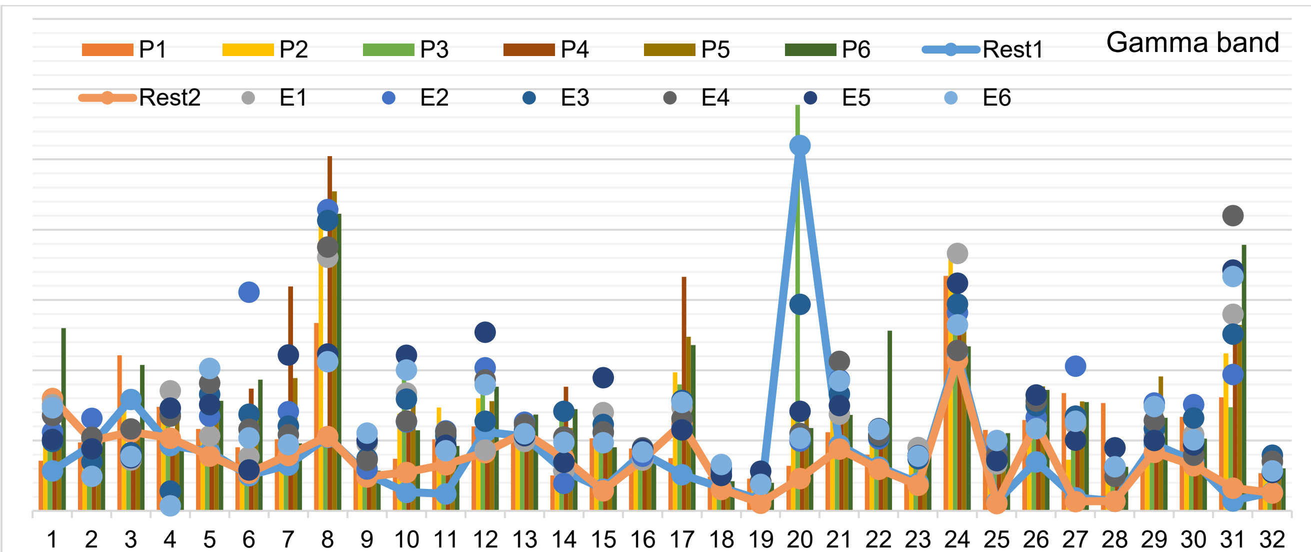


Figure 12. Observation of the relative Gamma2 power of the 32 subjects

3.2.2.2 Summary

Besides the above observation, we also observed the subjects' distribution of the other bands relative EEG power. We found that there are different patterns related to them. Regarding the alpha power, the Rest 1 and Rest 2 have higher scores than the design activities (synthesis and evaluation). This may imply that the closing-eye rest state is related to the alpha band which we have already mentioned in previous discussion. Regarding the other six frequency bands, there is not very clear pattern associated with the design activities. As the observation is based on the three categories of variables including seven EEG bands, 14 design activities and 32 subjects, the analysis of the relations among them becomes complicated. Therefore we used PCA method to simplify and analyze the EEG data.

3.2.3 Variance observation

The following is the variance observation of the 32 subjects' EEG band power associated with the design activities. From the ANOVA table (Table 3) of the 7 bands design activities vs. 32 subjects, we found that:

- The p values of EEG power for theta band, alpha, gamma1, gamma2 are under 1%. This implies that there are significant variances of the 32 subjects in these bands for design activities.
- The p values of EEG power for beta2, beta1 and gamma3 are 9.05%, 26.31%, and 47.39%. This implies that the EEG power of the 32 subjects in these bands is not significantly different.
- Gamma3 power and theta band power has the highest variance within the design activities.
- Alpha band power had the highest variance between the other design activities.

Table 3: ANOVA table for the 7 EEG bands

Bands	**SS-between**	**SS-E**	**F**	**P**
Theta	0.54	7.76	2.30	0.59%
Alpha	2.64	4.48	19.68	0.00%
Beta1	0.02	0.58	1.22	26.31%
Beta2	0.10	2.22	1.57	9.05%
G1	0.06	0.78	2.52	0.25%
G2	0.05	0.71	2.46	0.31%
G3	0.03	1.00	0.98	47.39%

Normalization observation: band power distribution for activities

We observed the normalization of band power distribution for activities. From the normal probability plot of the EEG band power, we found the subjects' EEG data follows a normal distribution. Figure 13 shows the normal probability plot of the 32 subjects in Rest 1 state of theta band EEG power.

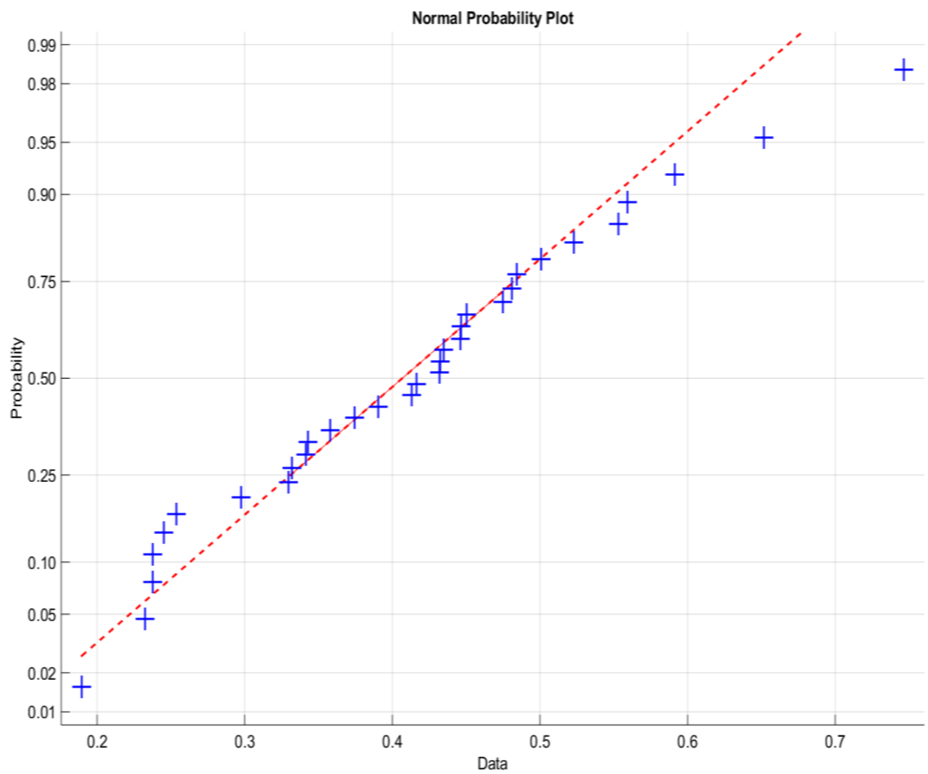


Figure 13. Normal probability plot of the 32 subjects of Rest 1 state of theta band EEG power

3.2.4 Correlation analysis: EEG band Correlation

EEG band is a breakdown from a range of frequencies, and each band has some connection to other bands with respect to the design activities. Therefore, we observed the correlations of bands for subjects' brain power of design activities. As the subjects' data are normally distributed, we could average the 32 subjects' dataset as the sample mean to observe the average behavior of designers in terms of the 7 bands. From the correlation table (Figure 14) of the average EEG data of the 32 subjects, we found that the alpha band negatively correlated to the other bands (theta band, beta bands, gamma bands), and the other bands are positively correlated. Theta band is more related to beta2, G1, G2, G3 bands than the beta1 band. And beta2, G1, and G2 are significantly correlated.

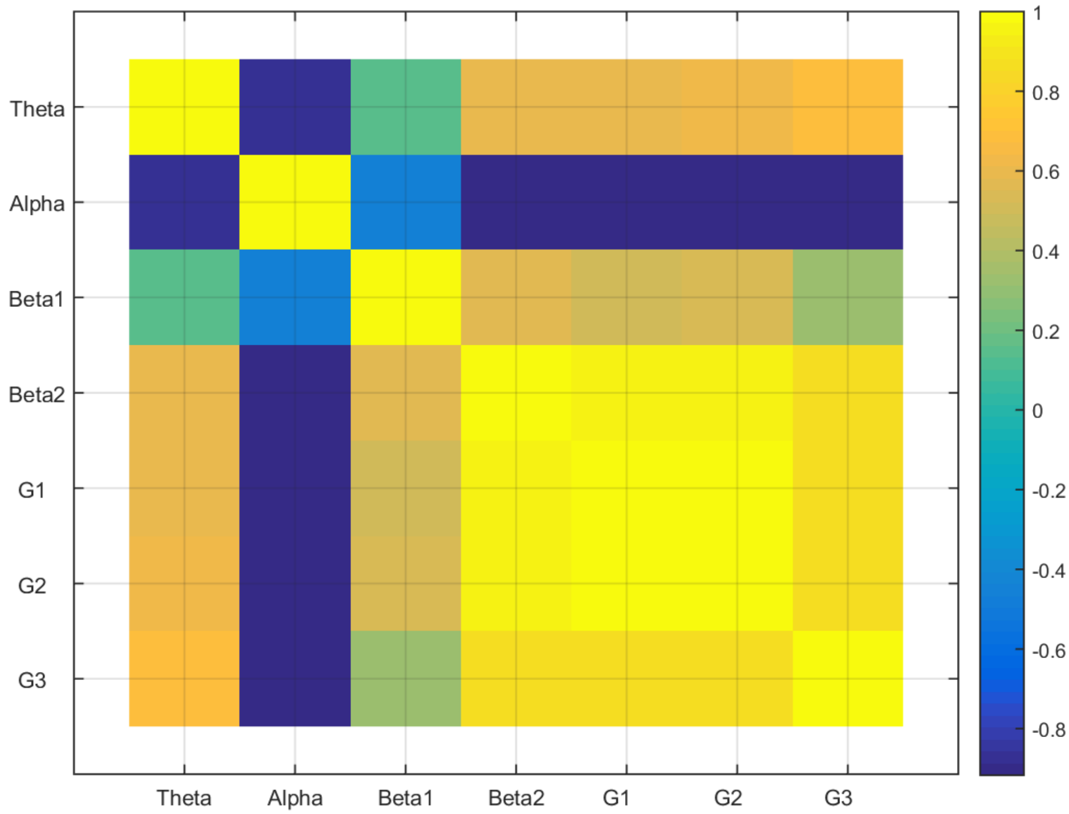


Figure 14. Correlation table of the average EEG data

3.3 Analyze Data

The third step is analyzing data. We analyze the patterns of designers' behavior based on PCA. As the subjects' data are normally distributed, we used the sample mean of the 32 subject's EEG data as the point estimator (Montgomery, 2007) to explore the general behavior of the designers. To simplify the EEG data, identify the relations of the EEG bands, and observe the patterns of the design activities, we apply PCA to the dataset. The procedure is as follows (Figure 15). We applied the PCA matrix A (Table 6) to transform the 32 subject's normalized relative EEG bands power (Table 4) to the 3 PCs (Table 5) to observe the patterns of the subject's design activities associated with the principal components and bands.

Figure 15. PCA of EEG band vs. design activities

3.3.1 Apply PCA algorithm

We applied PCA to analyze the principal components of the EEG band power related to the design activities. First, to find the general behavior of designers, we averaged the 32-subject's data as the point of estimation. And, we analyzed the relations of EEG band power associated with design activities and PCs. Based on the PCA results, we projected the 32 subjects' data on the PCA average EEG data model, in which we observed and analyzed the patterns related to the designers' activities.

In a previous paper (Liu, Nguyen, Zeng, & Hamza, 2016) concerned with the identification of the relationship between EEG bands and design activities, we did the preliminary principal analysis. We found that there are some relations between them. Based on the results, we can see that different bands of EEG power contribute to different design activities, and the bands are correlated. That is why we cannot easily identify the design activities (which are related to behavior) using a single EEG band, as they are correlated. PCA is a method to transfer multi-components data to principal component data which contains most of the information of the original data. We break down EEG frequency signal into different bands according to the traditional method (Theta, Alpha, Beta, and Gamma band) and treat them as multi components. Then, we apply PCA to transfer the multi-components EEG band power to three principal components EEG band power. Regarding our present research with the 6 design tasks experiment, the transformation is meaningful, because the Accumulative Explained Variance (AEV) is above 97%. This implies that the three main factors (3PC) include almost all the EEG band power information.

We applied PCA algorithm to the averaged of the 32 subjects' relative EEG band power during the design activities. Applying PCA algorithm includes:

1) Average the 32 subjects' brain power.

2) Normalize the relative band power (Z-score).

3) PCA input data matrix X (Table 4) is the normalized average EEG power of the 32 subjects. Variables are the 7 bands, and observations are the 14 activities.

4) PCA output data matrix Z (Table 5) is the transformed data of three principal components (3PC) vs. the 14 design activities.

5) The transformation matrix A (Table 6) contains 3 eigenvectors.

6) Verify the PCA result using Cumulative Explained Variance (CEV) (Table 6)

Table 4. Matrix X

X	Theta	Alpha	Beta1	Beta2	G1	G2	G3
Rest 1	-1.56	2.05	-1.49	-2.19	-1.98	-1.98	-1.73
P1	0.95	-0.29	0.30	-0.43	-0.61	-0.54	0.68
E1	0.87	-0.44	0.81	0.09	0.33	0.03	-0.59
P2	0.42	-0.36	0.40	0.36	0.16	0.14	0.09
E2	0.18	-0.43	1.16	0.51	0.56	0.50	0.06
P3	0.21	-0.30	1.23	0.21	-0.03	0.51	-0.11
E3	0.73	-0.49	-0.71	0.35	0.25	0.38	0.14
P4	-0.49	-0.28	0.87	0.73	0.67	0.95	0.46
E4	0.10	-0.42	-0.33	1.00	0.52	0.41	0.59
P5	-0.17	-0.41	0.72	0.58	0.61	0.63	1.08
E5	0.72	-0.39	-1.49	-0.12	0.36	0.36	0.71
P6	-0.52	-0.45	0.68	1.04	1.37	1.04	0.85
E6	1.00	-0.43	-1.36	-0.01	0.05	-0.10	0.25
Rest 2	-2.46	2.63	-0.78	-2.12	-2.25	-2.33	-2.48

Matrix Z is the transformed data of the three principal components (3PC) vs. 14 design activities.

Table 5. Matrix Z

Z	PC1	PC2	PC3
Rest 1	4.93	-0.34	-0.21
P1	-0.11	-0.58	1.10

E1	-0.60	0.26	1.09
P2	-0.69	0.10	0.37
E2	-1.18	0.90	0.38
P3	-0.72	0.92	0.69
E3	-0.74	-0.96	-0.06
P4	-1.31	1.05	-0.53
E4	-1.16	-0.29	-0.65
P5	-1.46	0.58	-0.39
E5	-0.58	-1.71	-0.55
P6	-1.94	0.92	-1.01
E6	-0.26	-1.73	0.00
Rest 2	5.82	0.88	-0.

Transformation matrix A contains 3 eigenvectors: PC1, PC2, and PC3.

Table 6. Matrix A

A	**PC1**	**PC2**	**PC3**
Theta	-0.32	-0.52	0.66
Alpha	0.42	0.16	-0.19
Beta1	-0.23	0.80	0.51
Beta2	-0.41	0.12	-0.23
G1	-0.41	0.07	-0.31
G2	-0.42	0.10	-0.24
G3	-0.39	-0.18	-0.23

The CEV table shows the Cumulative Explained Variance (CEV) of the 3 PCs. From Table 7 and Figure 16 we can see that the Cumulative Explained Variance (CEV) of the 3PC accounts 97% percent of the total variance of the EEG bands. And the PC1 accounts 78% of the total variance of the EEG bands. This means that the 7 bands EEG power is transformed to the 3 unrelated components, which keep the most information of the original EEG data. The 3 PCs contain the combination of different bands. This transformation simplifies the EEG data and provides us with a new perspective for the EEG data. Based on the new perspective for EEG data, we tried to find the patterns of the EEG data which associated with the design activities. We explored the relations of the EEG bands, PCs, and design activities, then we analyzed the statistical features of the EEG data to associate them with the design behavior.

Table 7. Cumulative Explained Variance (CEV)

%	**PC1**	**PC2**	**PC3**
EV	77.84	13.35	5.96
CEV	77.84	91.19	97.16

The Cumulative Explained Variance (CEV) of 3 PC rhythms chart follows.

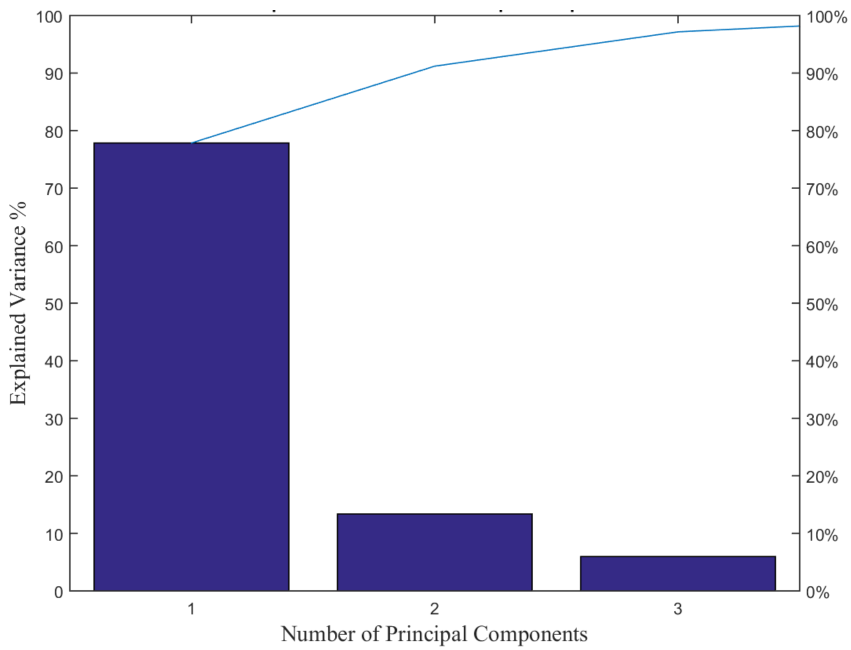


Figure 16. Cumulative Explained Variance (CEV) of 3 PC rhythms

3.3.2 Identify Principal Components (PCs)

After applying PCA algorithm of EEG band power, we tried to identify Principal Components (PCs) of EEG band power for the design activities. First, we observed the relations of PCs, bands, and design activities based on the biplot of the data. Then we projected the EEG data on the PCs to observe the features of the data.

3.3.2.1 Relationship of PCs, bands, and design activities

Based on matrix data A and matrix data Z, we illustrated the band's coefficients and the design activities' scores on the PCs' coordinate to find the relationship of bands, the design activities and PCs. We found the following results.

Based on the biplot of PC1 vs. PC2 (Figure 17), the two rest states (Rest 1 and Rest 2) are far from the points (P1 to P2 and E1 to E6) which represent the design activities; the two rest states (Rest 1 and Rest 2) scores are positive and the design activities' score are negative on PC1; there is a difference from Rest 1 and Rest 2. The loading of the alpha band is negative to other bands. The loading of the beta1 band is greatly positive on PC2 and the loading of theta band is greatly negative to PC2.

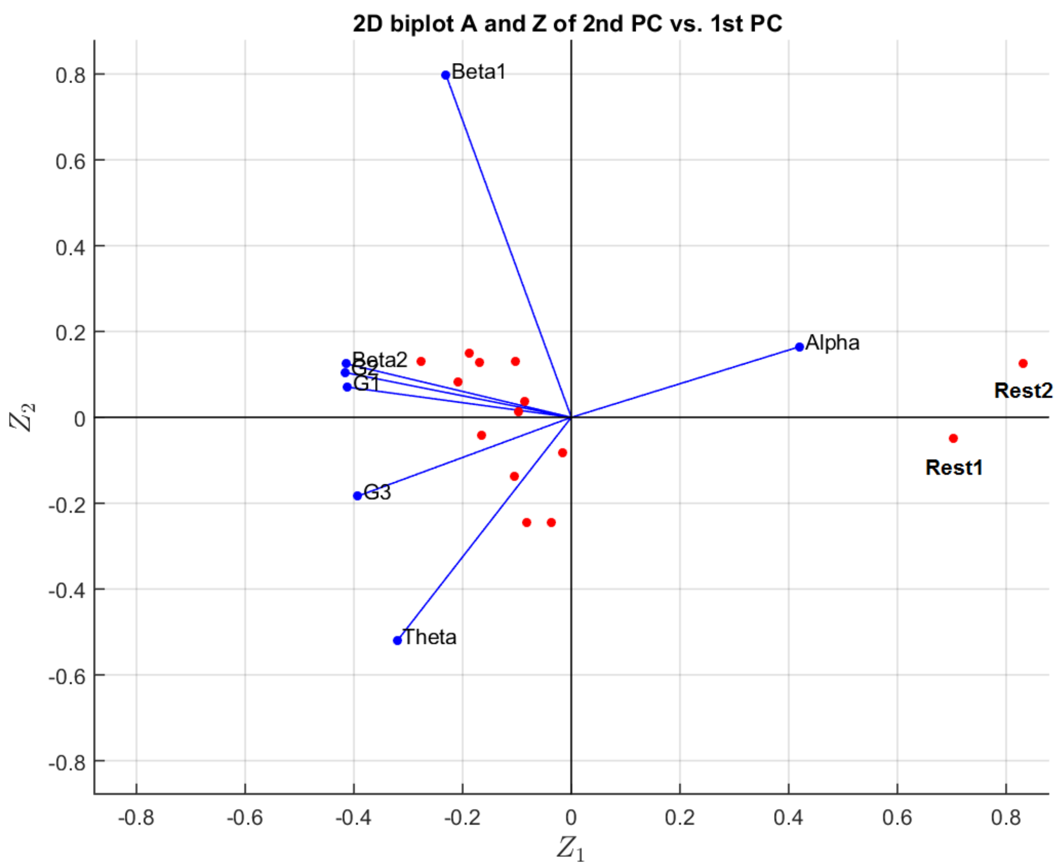


Figure 17. Biplot of PC1 vs. PC2

On the biplot of PC2 vs. PC3 (Figure 18), the score of Rest 2 is positive and the score of Rest 1 is negative PC2; P2 to P6 are positive on PC2 and P1 are negative to PC2; P1 to P3 are positive on PC3 and P4 to P6 are negative to PC3. Beta1 loading is greatly positive PC2 and Theta loading is greatly negative to PC2; Beta1 and Theta loadings are positive to PC3; other band loadings are negative to PC3.

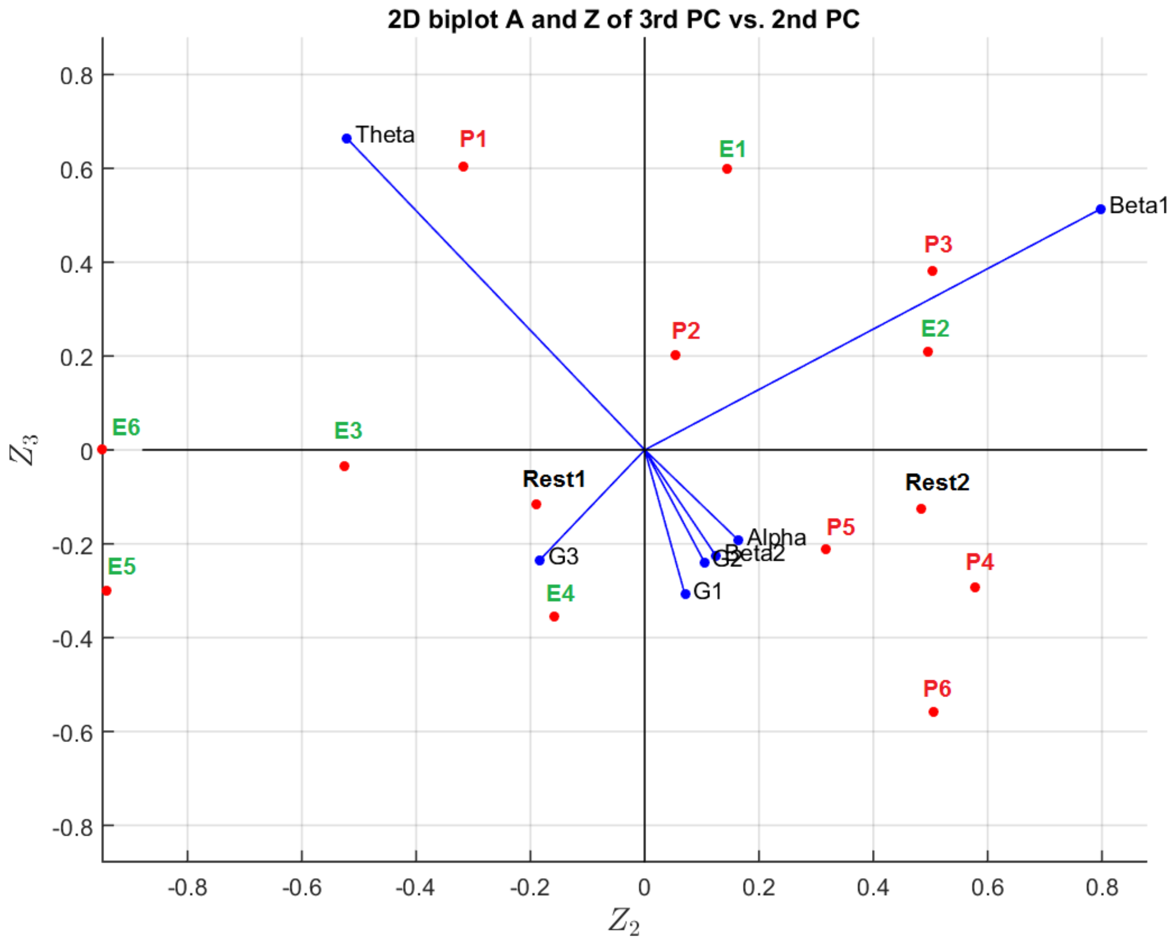


Figure 18. Biplot of PC2 vs. PC3

3.3.2.2 PCs vs. bands

Based on the PCA transformation matrix A, which contains the coefficients of PCs, we used a bar chart and simulation curve to plot the data of the 3 PCs and bands. From **Figure 19** we found the relationship between the PCs and the EEG bands as following.

- **PC1** combines positive alpha band and negative other bands (theta, beta1, beta2, gamma1, gamma2, and gamma3). *This implies PC1 is like a bandpass of the alpha band.*

- **PC2** combines negative theta band and gamma3 band, positive other bands. This implies *PC2 is like the positive bandpass of the beta1 band and a negative bandpass of theta band.*
- **PC3** combines positive theta band and beta1 band, negative other bands. This implies *PC3 is like band passes of theta and beta1 band.*

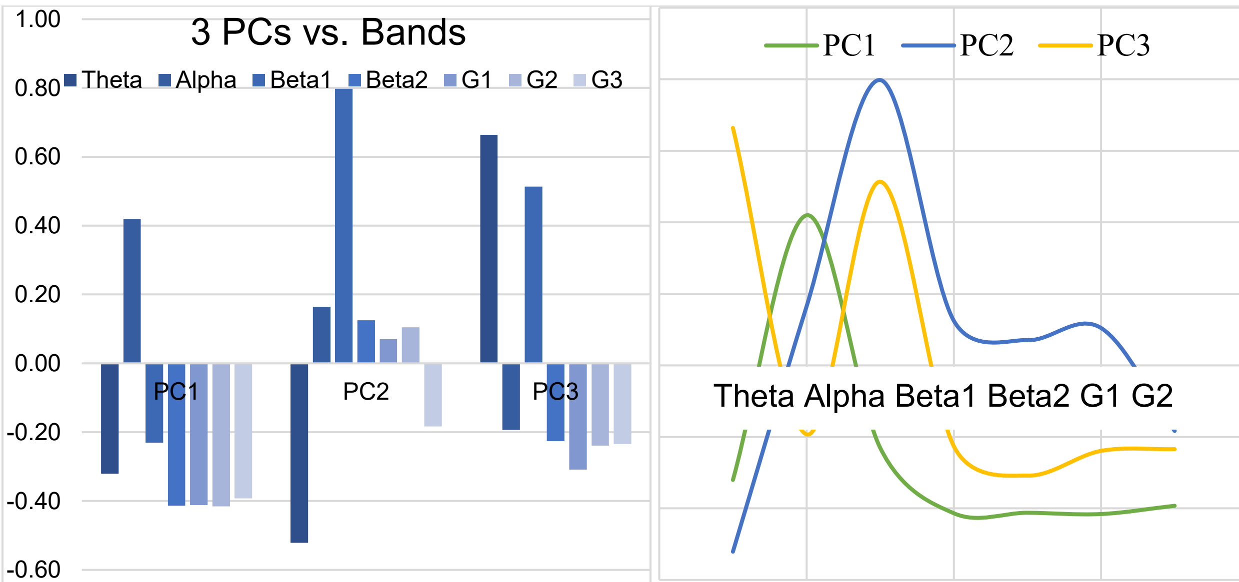


Figure 19. 3PC vs. EEG Bands and bandpass simulation

3.3.2.3 PCs vs. design activities

To find patterns of EEG band power associated with the design activities, we analyzed the relationship between the design activities and the PCs based om the PCA-transformed matrix data Z. Matrix Z contains 3 PCs transformed data from the standardized relative EEG power data X. We projected the design activities data on PCs to explore the relation between them based on Matrix Z.

Rest states vs. PCs (Figure 20**)**

Rest 1 and Rest 2 represent the normalized relative EEG power of the closing-eye rest state before and after the tasks. 1. Rest 1 and Rest 2 on PC1 are much high than other activities on PC2 and PC3; Rest 2 is higher than Rest 1. 2. Rest 1 is negative PC1 and Rest 2 is positive PC2. 3. Rest 1 and Rest 2 are similar negative PC3.

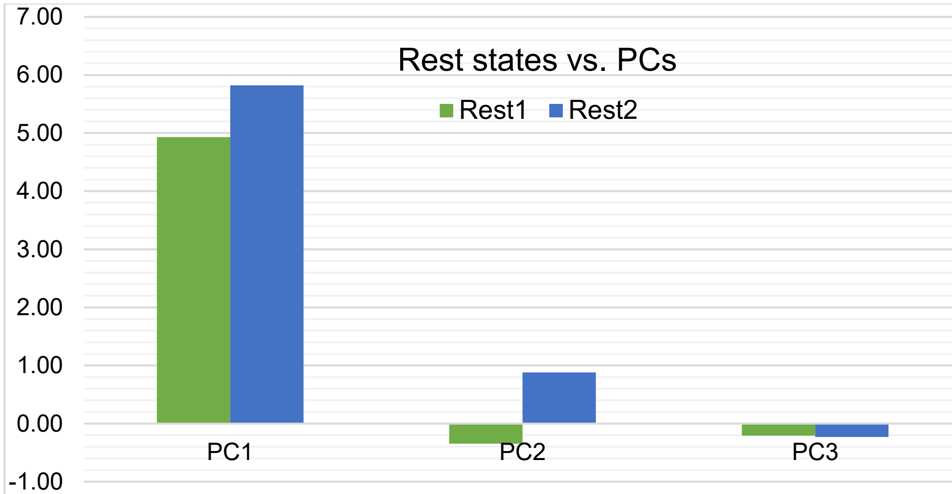


Figure 20. Rest states vs. PCs

Generating solutions (P) vs. PCs (Figure 21**)**

P1 to P6 represent the normalized relative EEG power of generating solutions of the 6 tasks. 1. P1 to P6 are a negative increase on PC1. This phenomenon may imply the increasing efforts of generating the solutions of the 6 tasks. 2. P1 is negative on PC2 and P2 to P6 are positive PC2. P2 is much lower than P3 to P6. 3. P1 to P3 are positive PC3 and P4 to P6 are negative PC3.

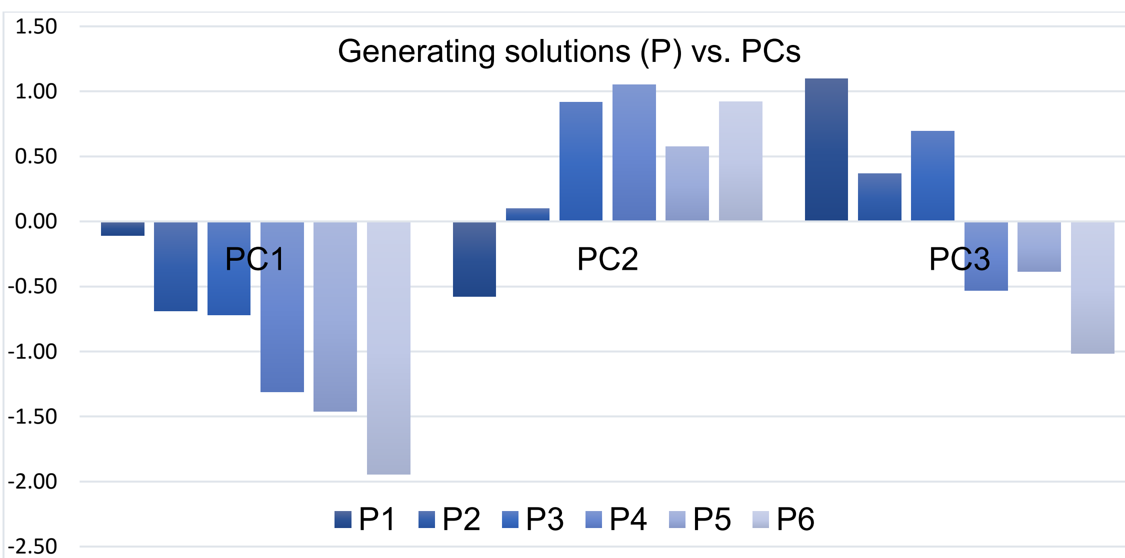


Figure 21. Generating solutions (P) vs. PCs

Evaluating solutions (E) vs. PCs (Figure 22 **)**

E1 to E6 represent the normalized relative EEG power of evaluating the 6 tasks. 1. E1 to E6 are negative PC1; E2 and E4 are the lowest on PC1; E6 is the highest PC1. *This may imply that subjects work harder on E2 and E4 than on other task. The subjects could be tired at the end of E6 and worked with less mental effort*. Other related patterns need to be studied. 2. E1 and E2 are positive PC2; E3 to E6 are negative to PC2; E2 is highest PC2; E5 and E6 are lowest PC2. 3. E1 and E2 are positive PC3; E3 to E5 are negative PC3; E6 is near zero on PC3; E1 is the highest PC3 and E4 is the lowest PC3.

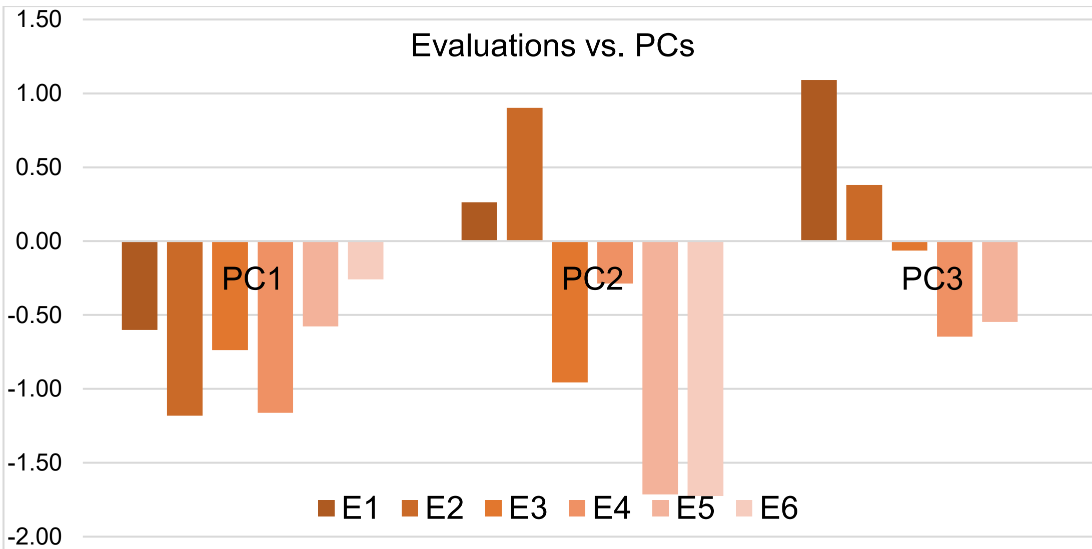


Figure 22. Evaluations vs. PCs

3.3.3 Analyze the PCs pattern

To find the pattern of the EEG power associated with design activities, based on the transformed data matrix Z, we compare the design activities and rest states in relation to 3 PCs. We plot the bar charts based on the matrix Z to explore the relationship between the design activities in relation to PCs.

3.3.3.1 Comparison between the rest states and design activities

Rest represents the average relative EEG power (standardized) of Rest 1 and Rest 2. P represents the average relative EEG power (standardized) of generating solutions (P1 to P6). E represents the average relative EEG power (standardized) of evaluating solutions (E1 to E6).

Comparisons of Rest vs. P and Rest vs. E (Figure 23**)**

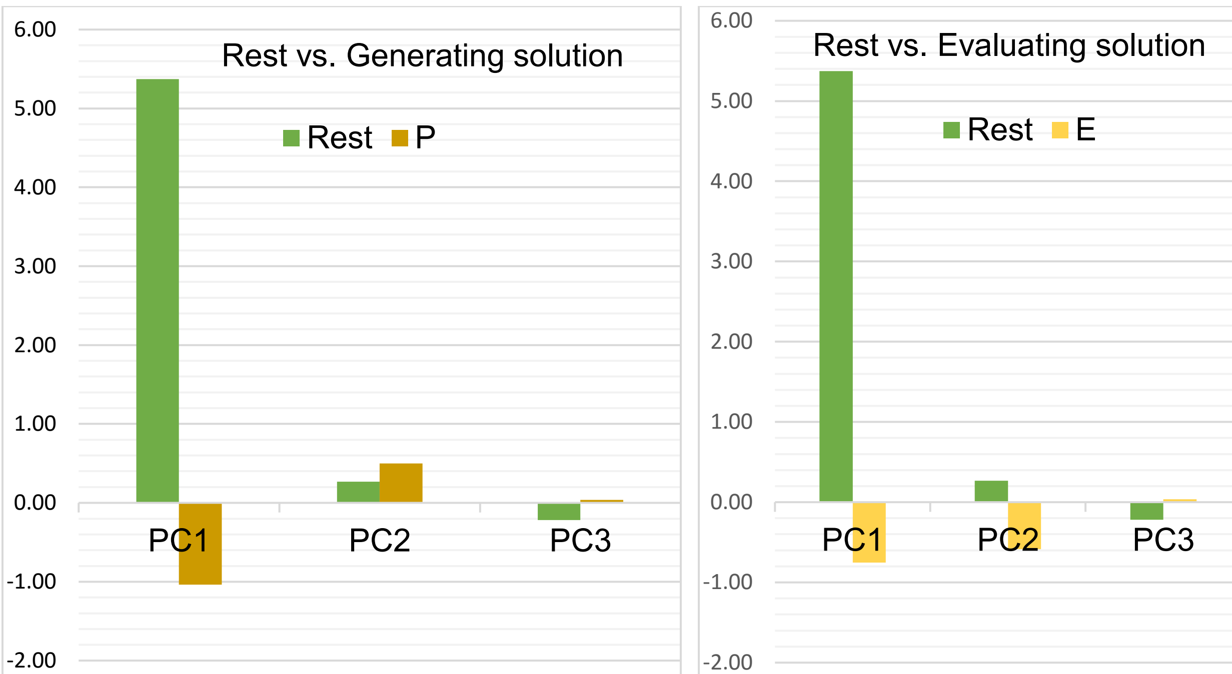


Figure 23. Rest vs. Generating solutions (P) and Evaluating solutions (E)

- Rest vs. Generating solution (P):

For PC1, Rest is positive, P is negative, and Rest has a high score. For PC2, P is higher than Rest and they are both positive. For PC3 Rest is negative and P is close to zero.

- Rest vs. Evaluating solutions (E):

For PC1, Rest is high positive and E is low negative. For PC2, Rest is positive and E is negative. For PC3 Rest is negative and E is close to zero.

- Summary

*From above observation, we found that rest state is mainly related to **positive** PC1, design activities of generating solution (P) and evaluating solution (E) are mainly related to **negative** PC1. This implies PC1 may represent the level of relaxation.*

3.3.3.2 Comparison between generating solution (P) and evaluating solution (E)

- **Generating solution (P) vs. evaluating solution (E) (**Figure 24**)**

For PC1, generating solution (P) and evaluating solution (E) are both negative, and P is more negative than E. For PC2, P is positive and E is negative. For PC3, P and E are both close to zero.

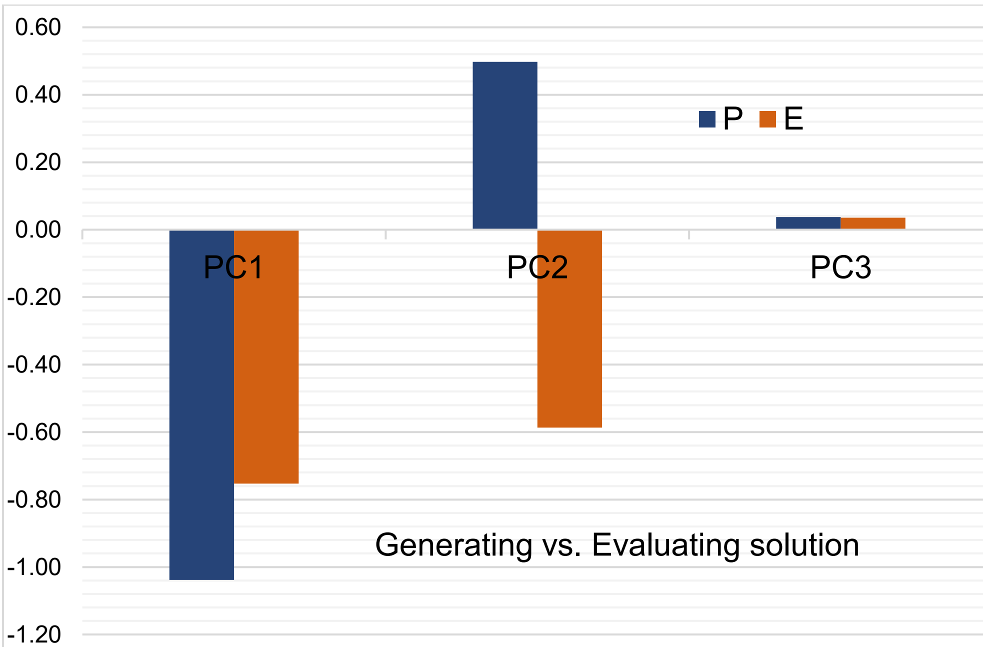


Figure 24. Generating solution (P) vs. evaluating solution (E)

- **Generating solutions vs. 3PC (**Figure 25**)**

P1 to P6 negative increase for PC1.This pattern may imply that the subject put more and more mental efforts as the task became more and more complicate. P1 is negative PC2 and P2 to P6 are positive PC2. P2 is lower than P3 to P6. P1 to P3 are positive PC3 and P4 to P6 are negative PC3.

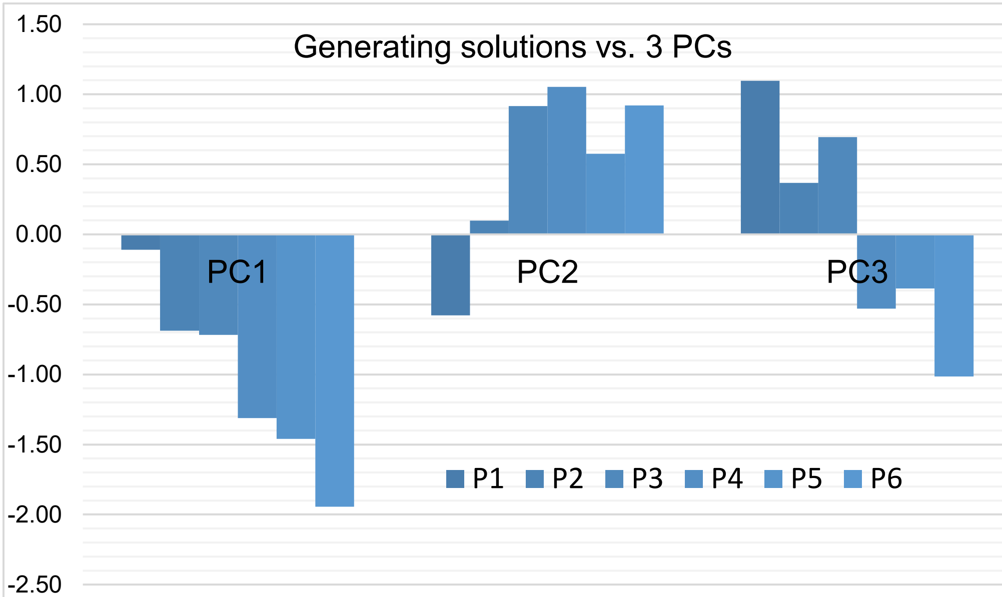


Figure 25. Generating solutions vs. 3PC

- **Evaluating solutions vs. 3PC (**Figure 26**)**

E1 to E6 are negative PC1. E2 and E4 are the lowest on PC1. E6 is the highest on PC1. This may suggest that subjects worked harder on E2 and E4 than other tasks. The subjects could be tired at the end of E6. E1 and E2 are positive PC2. E3 to E6 are negative to PC2. E2 is highest PC2. E5 and E6 are lowest PC2. E1 and E2 are positive PC3. E3 to E5 are negative PC3. E6 is near zero PC3. E1 is the highest PC3 and E4 is the lowest PC3.

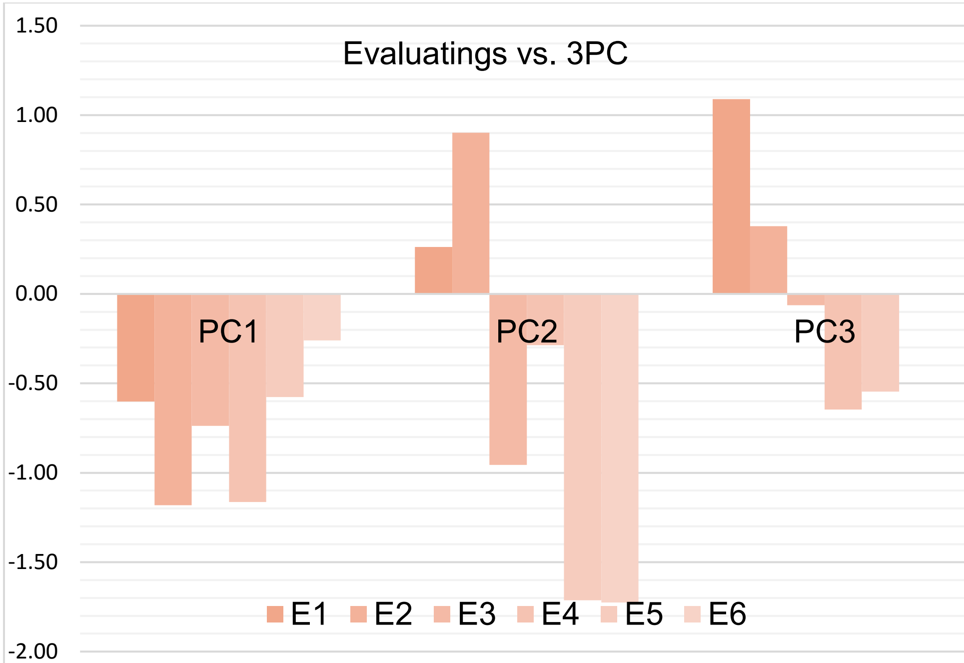


Figure 26. Evaluations vs. 3PC

3.3.3.3 Statistical analysis of generating solutions (P) vs. evaluating solutions (E) for PC1

We applied statistical analysis of generating solutions (P) and evaluating solutions (E) for PC1 to find out the relationship between them. First, it is a regression analysis of generating solutions (P) vs. evaluating solutions (E) for PC1. From Table 8 we found that the regression of P vs. E is not significant (F=0.5) which means *generating solutions (P) and evaluating solutions (E) are not significant related*. Then, from Table 9 and Table 10 we can see that P and E are different, but not significant (p=0.37). However, the variance of P (0.43) is bigger than that of E (0.13). *This may suggest that there is a similarity related to generating and evaluating solutions, and generating solutions have more variance than that of evaluating solutions.*

Table 8. Regression table of P and E

P and E	df	SS	MS	F	Significance F
Regression	1.00	0.08	0.08	0.56	**0.50**
Residual	4.00	0.57	0.14		

Total	5.00	0.65

Table 9. Variance table of P vs. E

Groups	Count	Sum	Average	Variance
E	6.00	-4.52	-0.75	**0.13**
P	6.00	-6.23	-1.04	**0.43**

Table 10. ANOVA table of P and E

P and E	SS	df	MS	F	p-value
Between Groups	0.24	1.00	0.24	0.87	**0.37**
Within Groups	2.81	10.00	0.28		
Total	3.05	11.00			

Figure 27 is the boxplot of generating solutions (P) and evaluating solutions (E) for PC1. It shows the variance of P is bigger than that of E and the average of P is lower than that of E (based on PC1)

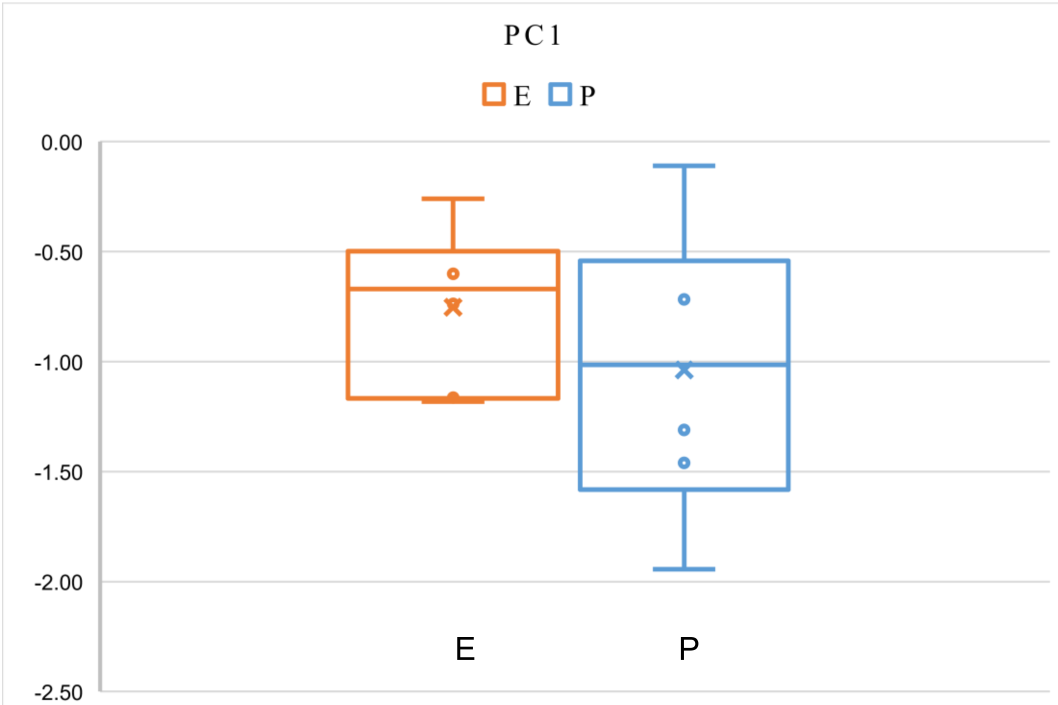


Figure 27. Boxplot of P vs. E of PC1

3.3.4 Summary

Based on above observation, we may infer that PC1 is like a bandpass of the alpha band. PC2 is like the positive bandpass of the beta1 band and a negative bandpass of theta band. PC3 is like band passes of theta and beta1 band.

A positive PC1 score is related to the level of relaxation (related to rest state). The subjects may be less relaxed before the tasks than after the tasks during their closing-eyes rests. The negative PC1 score is most likely related to the level of mental effort of work hardness (related to generating and evaluating solutions). Scores on PC2 may also be related to the mental effort of design activities. PC3 is to be studied based on PC1 and PC2.

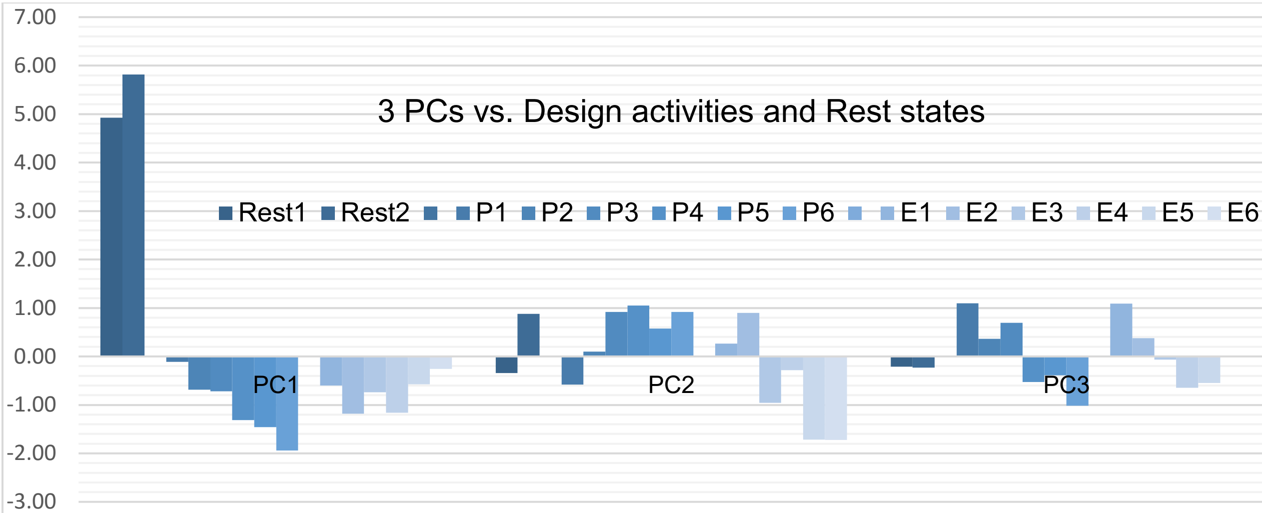


Figure 28. 3 PCs vs. Design activities and Rest states

3.4 Model Data

The fourth step is modeling the data. "A pattern in data modeling can be described as a template that can serve as a guide for developing data models." (Silverston & Agnew, 2009). We may use the average of the 32 subjects PCA data as the baseline of the design activities. The transformation patterns include 1. Relative EEG band power. 2. Average relative EEG band power of 32 subjects. 3. The PCs transformed average relative EEG band power. This model may represent the average characteristics of designer's behavior. Based on this PCA model, we analyzed the data features which relate to designers' behavior. We projected the 32 subjects' EEG data on this model to observe the features related to the data. The Matrix A is used to multiply the subjects' EEG band data. The outcome is the PCA-transformed data from the subjects. We analyzed the features including statistical difference, variance, and correlation of the EEG data to infer the designers' behavior.

3.4.1 Difference analysis

The following is the analysis of the statistical difference of the rest states and design activities based on the 32 subjects' PCA transformed EEG data (see appendix). To analyze the difference between the design activities of the subjects, we applied statistical variance function to the PCA-transformed EEG data, then we constructed the p values table of all the design activities. From the p values of the rest states and design activities, we found there are significant ($p<0.05$) differences between some states. The p values of Rest 1 and Rest 2 with P and E are zero on PC1, which means there are significant differences between the rest state and design activities states.

1. Regarding of Rest 1 and Rest 2, the p values of Rest 1 and Rest 2 for PC1 to PC3 is 0.243, 0.201 and 0.397. This implies that the Rest 1 state is different from the Rest 2 state greatly for PC2. However, the difference is not significant.
2. For PC1 (Table 11), P1 and P6 are significantly different from the other five design activities. (P1 and E2, E4, P5, P6; P6 and P1, E1, P2, P3, E5)
3. For PC2 (Table 12), Rest 2 is significantly different from the seven other states. There are significant difference between P1, E5, E6 and the other states.
4. For PC3 (Table 13), P1 and E1 are significantly different from the other states.

We may conclude that it is possible to identify rest state from other design activities as they are significantly different. However, for the design activities generating solutions (P) and evaluating solutions (E), there are some differences between the activities, but these differences are not significant enough to identify them on PCA model.

Table 11. p-value table on PC1

PC1	**Rest 1**	**P1**	**E1**	**P2**	**E2**	**P3**	**E3**	**P4**	**E4**	**P5**	**E5**	**P6**	**E6**	**Rest 2**
Rest 1	1.000	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.243
P1		1.000	0.260	0.171	**0.037**	0.186	0.100	0.061	**0.023**	**0.025**	0.289	**0.004**	0.368	**0.000**
E1			1.000	0.801	0.250	0.826	0.550	0.363	0.178	0.186	0.957	**0.032**	0.853	**0.000**
P2				1.000	0.343	0.978	0.715	0.483	0.251	0.260	0.763	**0.044**	0.673	**0.000**
E2					1.000	0.343	0.560	0.841	0.898	0.899	0.241	0.251	0.217	**0.000**
P3						1.000	0.702	0.478	0.255	0.264	0.789	**0.047**	0.698	**0.000**
E3							1.000	0.724	0.451	0.459	0.525	0.093	0.462	**0.000**
P4								1.000	0.737	0.741	0.348	0.201	0.310	**0.000**
E4									1.000	0.999	0.174	0.267	0.159	**0.000**
P5										1.000	0.181	0.276	0.165	**0.000**
E5											1.000	**0.032**	0.895	**0.000**
P6												1.000	**0.032**	**0.000**
E6													1.000	**0.000**
Rest 2														1.000

Table 12. p-value table on PC2

PC2	**Rest 1**	**P1**	**E1**	**P2**	**E2**	**P3**	**E3**	**P4**	**E4**	**P5**	**E5**	**P6**	**E6**	**Rest 2**
Rest 1	1	0.280	0.497	0.663	0.660	0.534	0.366	0.459	0.607	0.737	0.027	0.477	0.141	0.201
P1		1	0.609	0.348	0.038	0.040	0.732	0.021	0.381	0.076	0.192	0.018	0.664	0.009

E1			1	0.699	0.116	0.108	0.818	0.064	0.760	0.192	0.056	0.057	0.325	0.024
P2				1	0.157	0.149	0.477	0.082	0.912	0.275	0.010	0.069	0.135	0.031
E2					1	0.734	0.035	0.597	0.108	0.910	0.000	0.625	0.007	0.203
P3						1	0.044	0.910	0.113	0.696	0.000	0.968	0.010	0.386
E3							1	0.018	0.527	0.088	0.058	0.013	0.390	0.008
P4								1	0.055	0.582	0.000	0.926	0.004	0.405
E4									1	0.218	0.010	0.043	0.148	0.022
P5										1	0.001	0.610	0.020	0.217
E5											1	0.000	0.369	0.000
P6												1	0.003	0.343
E6													1	0.002
Rest 2														1

Table 13. p-value table on PC3

PC3	Rest 1	P1	E1	P2	E2	P3	E3	P4	E4	P5	E5	P6	E6	Rest 2
Rest 1	1	0.185	0.149	0.806	0.938	0.806	0.854	0.410	0.284	0.561	0.499	0.189	0.873	0.397
P1		1	0.968	0.165	0.131	0.210	0.070	0.016	0.005	0.024	0.031	0.004	0.125	0.013
E1			1	0.114	0.090	0.160	0.042	0.008	0.002	0.012	0.019	0.002	0.094	0.006
P2				1	0.834	0.984	0.578	0.179	0.081	0.278	0.269	0.054	0.653	0.163
E2					1	0.835	0.743	0.272	0.147	0.408	0.373	0.095	0.788	0.255
P3						1	0.603	0.215	0.114	0.321	0.300	0.075	0.664	0.200
E3							1	0.423	0.258	0.614	0.540	0.163	1.000	0.405
P4								1	0.811	0.738	0.904	0.549	0.503	0.994
E4									1	0.532	0.727	0.676	0.358	0.811
P5										1	0.856	0.339	0.680	0.724
E5											1	0.499	0.600	0.896
P6												1	0.238	0.543
E6													1	0.490
Rest 2														1

3.4.2 Variance analysis

The following is the statistical variance analysis of the design activities for PC1 based on the model of the 32 subject's PCA transformed EEG data (see appendix).

Everybody thinks and acts differently, and human behaviors are related to our brain structure and the cognitive strategies the brain uses (Kanai & Rees, 2011). The strategy of thinking is connected with the brain circuit caused by neurons, and the individual differences of brain activity during task performance can be predicted by brain image (MRI) (Tavor et al., 2016). The behaviors are either related to the brain structure or related to the way of thinking. To observe the behaviors related to the individuals' design activities, we applied statistical analysis to the distribution and variance of the 32 subject's PCA data.

3.4.2.1 Rest states and design activities

From the boxplot (Figure 29), we can see the distributions of the subject's rest states (Rest 1 and Rest 2) on PC1 are normal. There is one outlier in Rest 2. Rest 2 state (mean=3.3) is higher than Rest 1 state (mean=2.8). The variance of Rest 1 (SD =1.8) is bigger than Rest 2 (SD =1.7) for PC1. *This may imply that before the tasks the subjects were facing uncertainty and they were nervous. Thus, even when they were closing their eyes, their minds were still working which could vary from person to person. After the tasks, the subjects were more relaxed than that of before the tasks when they closed their eyes, as there was less uncertainty, and the variation of the subjects states is less than before the tasks.*

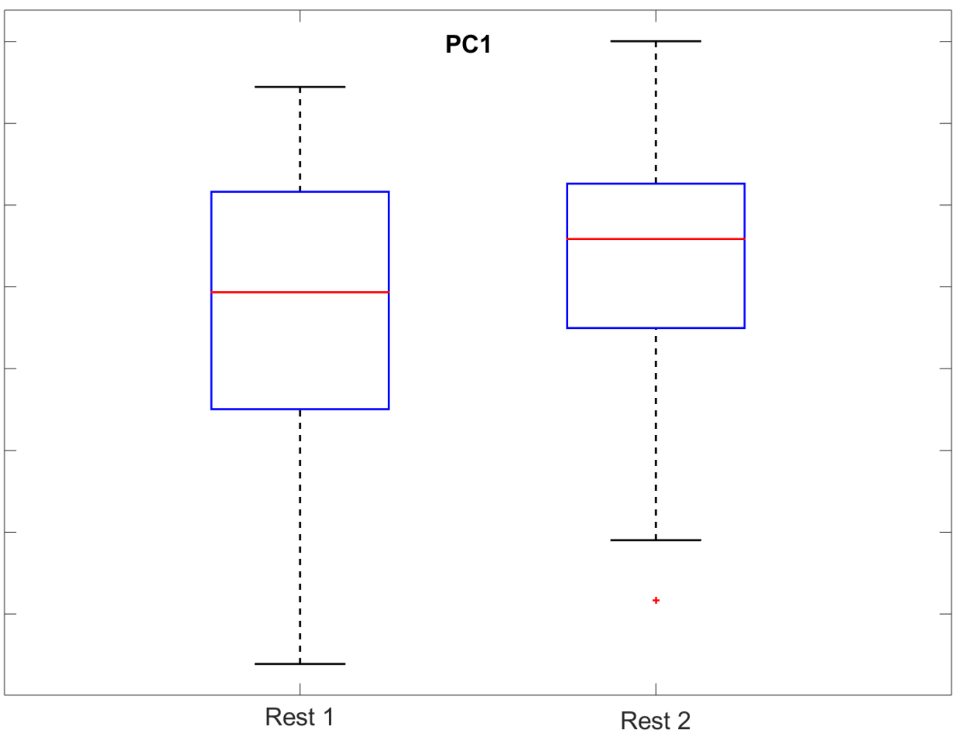


Figure 29. Boxplot of Rest 1 and Rest 2

A control chart is used to assess and control the quality of the observed processes. There are two features to investigate during the process: Mean and Standard Deviation (SD) (Montgomery, 2007) We treat the design activities as the stages of the design process and treat the subjects' EEG band power as the trails of the observations. The mean values of the subjects' data represents the average characteristics of the design activities, and the Standard Deviation (SD) relates to the individuals' variances. Thus, the mean value represents the subject's average behavior and the variance value represents the difference of individuals' behavior. From the control chart (Figure 30) for the design activities and rest states for PC1, we can see the average (XBAR) and variance (SD) values of the rest states are much higher than the design activities, and the variance values of the states at beginning and at the end are higher than those in the middle. *This may imply that the subjects concentrated their minds on the design activities more than on the rest states. And they were less concentrated at the beginning and at the end. One explanation is that at the beginning they were facing uncertainty and at the end, they were tired and sleepy*. Regarding the closing-eye state, there are many papers about using EEG band power to measure sleepiness (Torsvall & Åkerstedt, 1988) (Åkerstedt & Gillberg, 1990). There is also literature about the closed-eye hallucinations and closed-eye visualizations. Meditative relaxation techniques are related to the closed eyes states. There are many different levels of mental activities even when one's eyes are closed (Ladd, 1903) (Lilly, 1977). This can be seen from the great variance value of the Rest 1 and Rest 2.

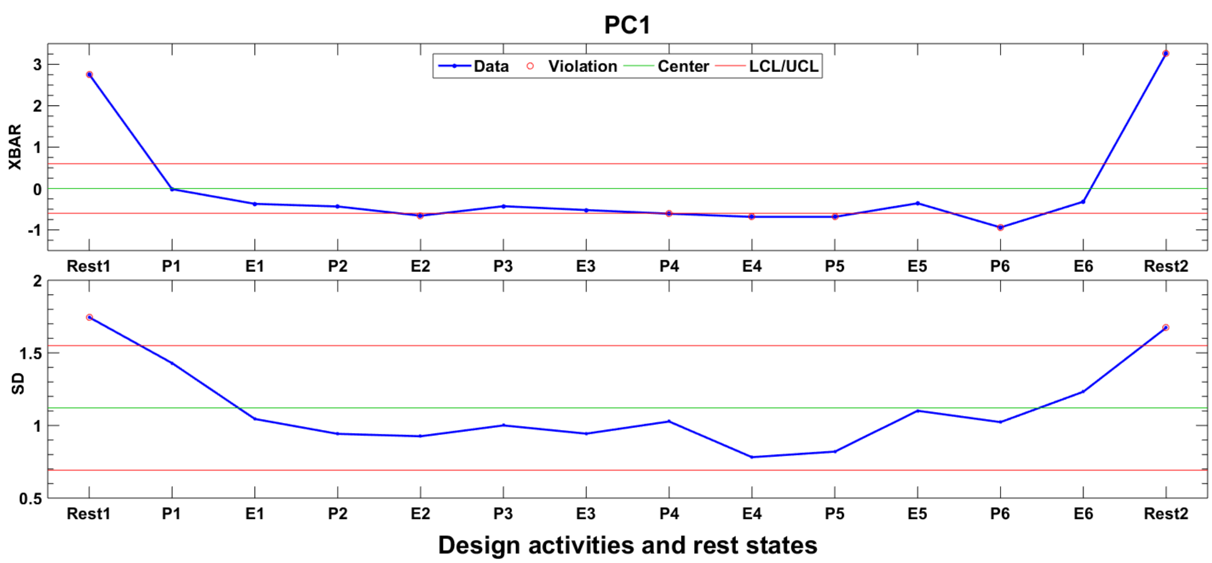


Figure 30. The control chart of the design activities and rest states

3.4.2.2 Solution generation

From the boxplot of solution generation (P), we found that the distributions of generating solutions (P1 to P6) are normally distributed. There is one outlier in P1 and P4, and two outliers in P2. From the XBAR control chart in Figure 31, we can see that P1 to P3 are above the average (mean=-0.5), P4 to P6 are below average, and the trend is in decline. From the SD control chart, we can see the value of P1 is the highest (sd=1.5), P5 is the lowest (sd=0.7). *This may imply that the subjects spent more and more mental effort as the tasks became more and more difficult, and they became less relaxed. In task 1 (P1) the subjects were not concentrated and in task 5 (P5) they were greatly concentrated.*

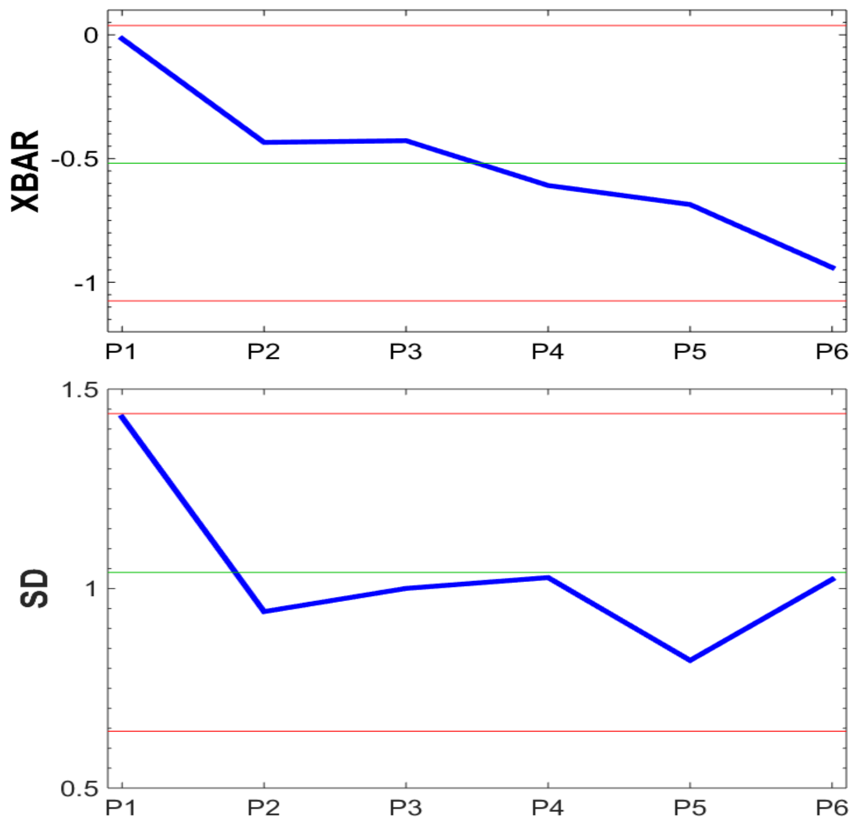


Figure 31. The control chart of solution generation (P)

3.4.2.3 Solution evaluation

From the boxplot for solution evaluation (E), we found that the distributions of evaluating solutions (E1 to E6) are normally distributed. There is one outlier in E2 and E4, and two outliers in E3 and E6. From the XBAR control chart in Figure 32, we can see that E1, E5, and E6 are above the average (-0.5), the trend from E1 to E6 is zigzag. From the SD control chart, we can see the value of E6 is the highest (sd=1.2), E4 is the lowest (sd=0.8). *This may imply that the subjects spent more mental effort on the tasks 2, 3, 4 than 1,5,6 and they became less concentrated at the end.*

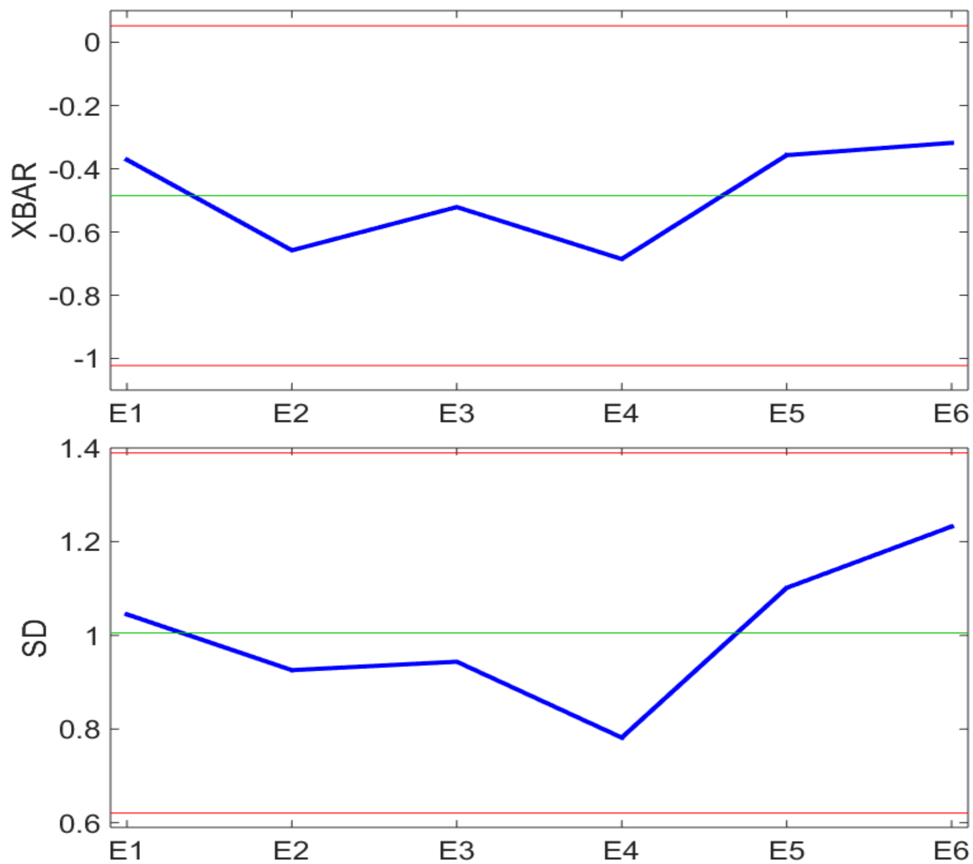


Figure 32. The control chart of solution evaluation (E)

Comparing generating solutions to evaluating solutions, we found that the range of generating solutions is bigger than that of evaluating solutions in the average and variance values. *This may imply that generating solutions includes more mental strategies than that of evaluating solutions.*

3.4.3 Correlation analysis

To explore the relationship of the design activities, we applied statistical correlation function to the 32 subjects' PCA transformed EEG data. From the results of correlation table, we found the following observations.

3.4.3.1 PC1 correlations (Figure 33)

- Rest 1 and Rest 2 are greatly correlated (0.59)
- Rest states are negatively related to the design activities, except P6 with Rest 2 (0.07)
- E3 and E6 (0.51), P4 and P5 (0.51), E1 and E5 (0.45), are strongly related (0.5)

- E5 and P6 are greatly negatively related (-0.53)
- P1 and E4 (-0.4), P2 and P5 (-0.3) are strong negatively related.

	Rest1	P1	E1	P2	E2	P3	E3	P4	E4	P5	E5	P6	E6	Rest2
Rest1	1.000	-0.150	-0.452	-0.110	-0.162	-0.146	-0.318	-0.028	-0.216	-0.240	-0.430	-0.178	-0.242	0.591
P1	-0.150	1.000	0.193	0.165	0.013	-0.268	-0.182	-0.351	-0.404	-0.079	0.199	0.023	-0.144	-0.252
E1	-0.452	0.193	1.000	0.043	0.238	-0.103	-0.142	-0.242	-0.064	-0.192	0.454	-0.293	0.059	-0.223
P2	-0.110	0.165	0.043	1.000	0.029	-0.103	-0.280	-0.239	0.099	-0.343	0.302	-0.204	-0.181	-0.086
E2	-0.162	0.013	0.238	0.029	1.000	-0.046	-0.214	-0.123	0.145	0.007	-0.042	-0.105	0.034	-0.341
P3	-0.146	-0.268	-0.103	-0.103	-0.046	1.000	-0.036	-0.177	0.012	0.172	0.012	0.125	0.065	-0.162
E3	-0.318	-0.182	-0.142	-0.280	-0.214	-0.036	1.000	0.264	0.179	0.137	0.107	-0.060	0.510	-0.413
P4	-0.028	-0.351	-0.242	-0.239	-0.123	-0.177	0.264	1.000	-0.061	0.509	-0.204	0.247	-0.255	-0.024
E4	-0.216	-0.404	-0.064	0.099	0.145	0.012	0.179	-0.061	1.000	-0.152	0.159	-0.060	0.146	-0.165
P5	-0.240	-0.079	-0.192	-0.343	0.007	0.172	0.137	0.509	-0.152	1.000	-0.231	0.309	-0.164	-0.200
E5	-0.430	0.199	0.454	0.302	-0.042	0.012	0.107	-0.204	0.159	-0.231	1.000	-0.529	0.023	-0.407
P6	-0.178	0.023	-0.293	-0.204	-0.105	0.125	-0.060	0.247	-0.060	0.309	-0.529	1.000	-0.174	0.070
E6	-0.242	-0.144	0.059	-0.181	0.034	0.065	0.510	-0.255	0.146	-0.164	0.023	-0.174	1.000	-0.382
Rest2	0.591	-0.252	-0.223	-0.086	-0.341	-0.162	-0.413	-0.024	-0.165	-0.200	-0.407	0.070	-0.382	1.000

Figure 33. PC1 correlations

3.4.3.2 PC2 correlations (Figure 34)

- Rest 1 and Rest 2 are greatly correlated (0.58)
- Rest states are negatively related to the design activities, except Rest 1 and P2 (0.05) and E1(0.18), and Rest 2 and P2 (0.2) and P6 (0.1)
- E3 and E6 are greatly related (0.67), P4 and E2, P5 and P6 are strongly related (0.4)
- P2 and E6, E1 and E6, E1 and P6 are strongly negatively related (-0.4)

	Rest1	P1	E1	P2	E2	P3	E3	P4	E4	P5	E5	P6	E6	Rest2
Rest1	1.000	-0.325	0.046	0.185	-0.313	-0.424	-0.212	-0.232	-0.211	-0.289	-0.327	-0.103	-0.234	0.575
P1	-0.325	1.000	0.165	-0.189	-0.007	0.070	-0.170	-0.241	-0.108	-0.121	0.095	-0.313	0.023	-0.101
E1	0.046	0.165	1.000	0.073	0.098	-0.205	-0.049	-0.107	0.094	-0.204	-0.269	-0.411	-0.393	-0.036
P2	0.185	-0.189	0.073	1.000	0.130	-0.167	-0.274	0.076	-0.281	-0.169	-0.147	0.033	-0.433	0.205
E2	-0.313	-0.007	0.098	0.130	1.000	-0.296	-0.103	0.431	-0.201	0.114	-0.023	0.104	-0.097	-0.198
P3	-0.424	0.070	-0.205	-0.167	-0.296	1.000	0.065	-0.022	0.258	0.046	0.175	-0.064	0.171	-0.384
E3	-0.212	-0.170	-0.049	-0.274	-0.103	0.065	1.000	-0.075	0.272	-0.052	-0.138	-0.126	0.669	-0.516
P4	-0.232	-0.241	-0.107	0.076	0.431	-0.022	-0.075	1.000	-0.042	0.032	0.033	0.170	-0.126	-0.276
E4	-0.211	-0.108	0.094	-0.281	-0.201	0.258	0.272	-0.042	1.000	-0.236	0.020	0.026	0.071	-0.308
P5	-0.289	-0.121	-0.204	-0.169	0.114	0.046	-0.052	0.032	-0.236	1.000	-0.016	0.396	-0.033	-0.112
E5	-0.327	0.095	-0.269	-0.147	-0.023	0.175	-0.138	0.033	0.020	-0.016	1.000	-0.035	0.114	-0.267
P6	-0.103	-0.313	-0.411	0.033	0.104	-0.064	-0.126	0.170	0.026	0.396	-0.035	1.000	-0.245	0.106
E6	-0.234	0.023	-0.393	-0.433	-0.097	0.171	0.669	-0.126	0.071	-0.033	0.114	-0.245	1.000	-0.408
Rest2	0.575	-0.101	-0.036	0.205	-0.198	-0.384	-0.516	-0.276	-0.308	-0.112	-0.267	0.106	-0.408	1.000

Figure 34. PC2 correlations

3.4.3.3 PC3 correlations (Figure 35)

- Rest 1 and Rest 2 are somewhat correlated (0.324)
- Rest states are negatively related to solution evaluation (E) of the design activities
- E3 and E6 are greatly related (0.45), P4 and P5 are strongly related (0.48)
- E5 and P6, E6 and P1, E6 and P2 are strongly negatively related (-0.48, -043, -0.45)

	Rest1	P1	E1	P2	E2	P3	E3	P4	E4	P5	E5	P6	E6	Rest2
Rest1	1.000	0.213	-0.293	-0.307	-0.314	0.269	-0.099	-0.275	-0.306	-0.307	-0.346	0.070	-0.091	0.324
P1	0.213	1.000	-0.049	0.210	0.060	0.070	-0.113	-0.131	-0.337	-0.170	-0.249	-0.145	-0.430	0.034
E1	-0.293	-0.049	1.000	0.301	-0.083	-0.218	-0.144	-0.025	0.071	-0.308	0.097	0.084	-0.117	-0.112
P2	-0.307	0.210	0.301	1.000	0.265	-0.174	-0.306	-0.038	-0.135	-0.102	0.023	0.177	-0.451	-0.119
E2	-0.314	0.060	-0.083	0.265	1.000	-0.261	0.098	-0.010	-0.024	0.080	-0.050	-0.008	-0.157	-0.320
P3	0.269	0.070	-0.218	-0.174	-0.261	1.000	0.010	-0.363	-0.207	0.029	-0.097	-0.197	-0.122	0.122
E3	-0.099	-0.113	-0.144	-0.306	0.098	0.010	1.000	-0.119	0.053	-0.050	-0.085	-0.357	0.447	-0.338
P4	-0.275	-0.131	-0.025	-0.038	-0.010	-0.363	-0.119	1.000	-0.131	0.475	-0.064	0.106	-0.250	0.003
E4	-0.306	-0.337	0.071	-0.135	-0.024	-0.207	0.053	-0.131	1.000	-0.093	0.248	-0.137	0.328	-0.187
P5	-0.307	-0.170	-0.308	-0.102	0.080	0.029	-0.050	0.475	-0.093	1.000	-0.073	0.077	-0.180	-0.164
E5	-0.346	-0.249	0.097	0.023	-0.050	-0.097	-0.085	-0.064	0.248	-0.073	1.000	-0.483	0.267	-0.220
P6	0.070	-0.145	0.084	0.177	-0.008	-0.197	-0.357	0.106	-0.137	0.077	-0.483	1.000	-0.248	0.110
E6	-0.091	-0.430	-0.117	-0.451	-0.157	-0.122	0.447	-0.250	0.328	-0.180	0.267	-0.248	1.000	-0.248
Rest2	0.324	0.034	-0.112	-0.119	-0.320	0.122	-0.338	0.003	-0.187	-0.164	-0.220	0.110	-0.248	1.000

Figure 35. PC3 correlations

From the PCs correlation analysis, we found that rest states are negatively related the design activities in PC1 and PC2, and negatively related to solution evaluation in all 3PC. E3 and E6, P5 and P6 are greatly related to all the design activities. *This may imply the relaxation level of the closing-eye rest state affects the mental effort level of the design activities, it especially affects the level of solution evaluation activity. And there may be some relationship between design tasks of P5 and P6; and E3 and E6.*

3.4.4 Summary

According to the variance analysis of the subjects based on PCA, we may infer the behaviors related the design activities as following.

1. For the rest state, before the tasks the subjects were facing uncertainty and they were nervous. Thus, even when they were closing their eyes as a, their minds were still working. And the level of rest state might vary from person to person. After the tasks, the subjects were more relaxed when they closed their eyes, as there was less uncertainty, and the variation after the tasks is less than the variance before the tasks.

2. For the synthesis behavior, the subjects spent more and more mental effort as the tasks became more and more difficult, and they became less relax. In task 1 (P1) the subjects were not concentrated and in task 5 (P5) they were greatly concentrated.

3. For the evaluation behavior, subjects spent more mental effort in the middle of the experiment (tasks 2, 3, 4) than the beginning and end (tasks 1, 5, and 6), and they became less concentrated at the end.

4. The relaxation level of the rest states affects the mental effort level of the design activities, it especially affects the level of effect during the evaluation activity. And there may be some strong relationship between the design tasks of P4 and P5; and E3 and E6.

As the correlational analysis may just conduct the relationship between the variables and observations, it could hardly identify the cause of the behavior because of the “directionality problem” and “third variable problem” (Martin, 2008). To verify the above explanation, we should investigate the psychology mechanism of the human cognitive behavior. We should also test the result by comparing the objective method (EEG PCA patterns) with subjective method (NASA TLX) (Nguyen & Zeng, 2016).

3.5 Preliminary case study

To verify the PCA EEG model, we proposed a preliminary case study. Four subjects’ solutions were randomly chosen to study the relationship between the brain power and design activity based on transformed experimental data.

3.5.1 Overview

We overviewed the four subjects' EEG power of the rest states and design activities. The following represent the EEG topographic map (64 channels) and EEG PC1 power (Chanel Fz) of the four subjects (subject04 of Figure 36, subject06 of Figure 37, subject 10 of Figure 38, subject 14 of Figure 39).These figures help us visualize the patterns related subjects' design behaviors. Based on the observations we try to find the relationship between the subject's EEG power and design activities. From the transformed EEG data, we proposed a hypothesis and applied a statistical method to validate the hypothesis.

Subject 04

EEG topographic map and PC1 power of subject 04 (April 08, 2013)

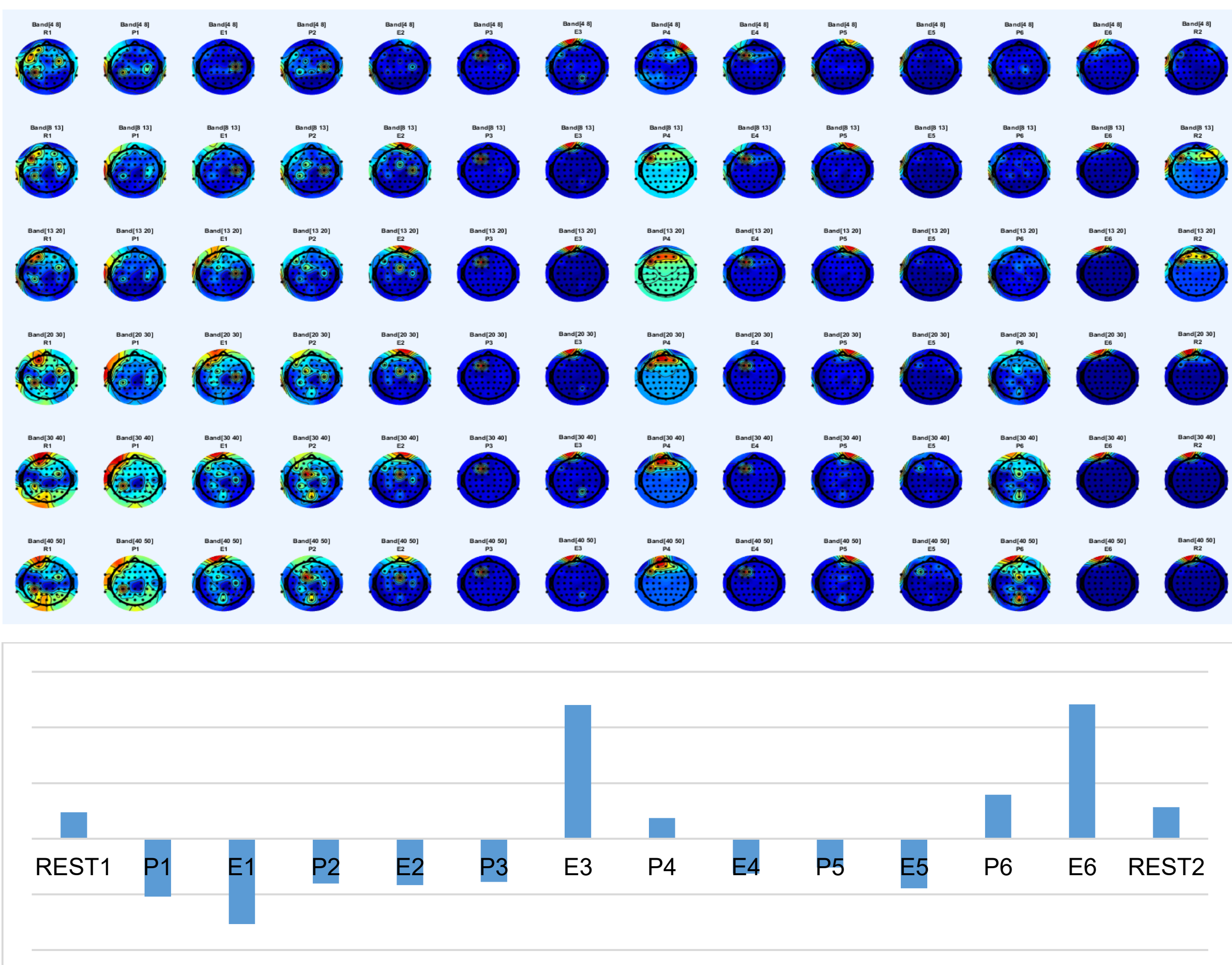


Figure 36. EEG topographic map and PC1 of subject 04

Subject 06

EEG topographic map and PC1 power of subject 06 (April 16(1), 2013)

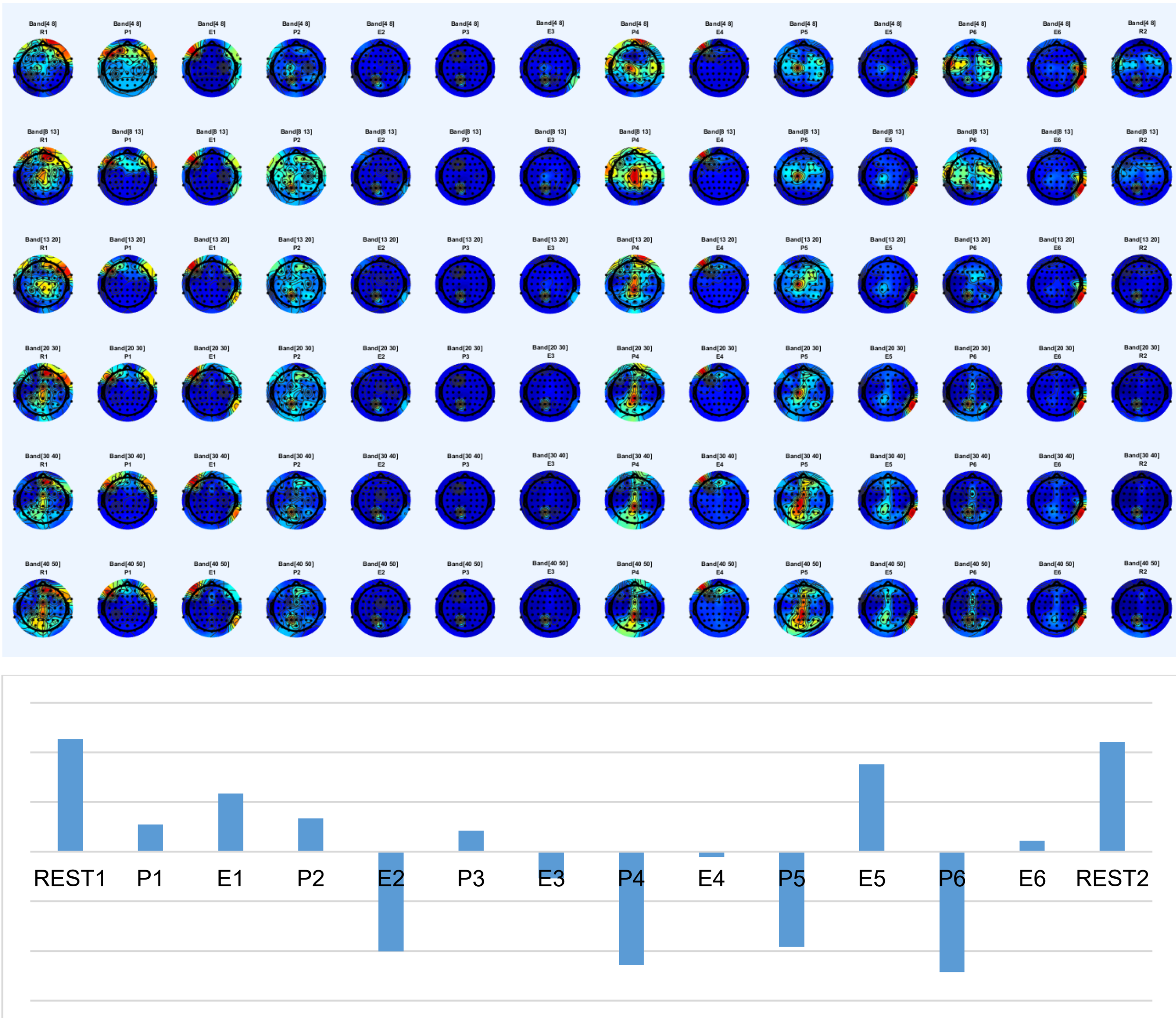


Figure 37. EEG topographic map and PC1 of subject 06

Subject 10

EEG topographic map and PC1 power of subject 10 (April_18(2), 2013)

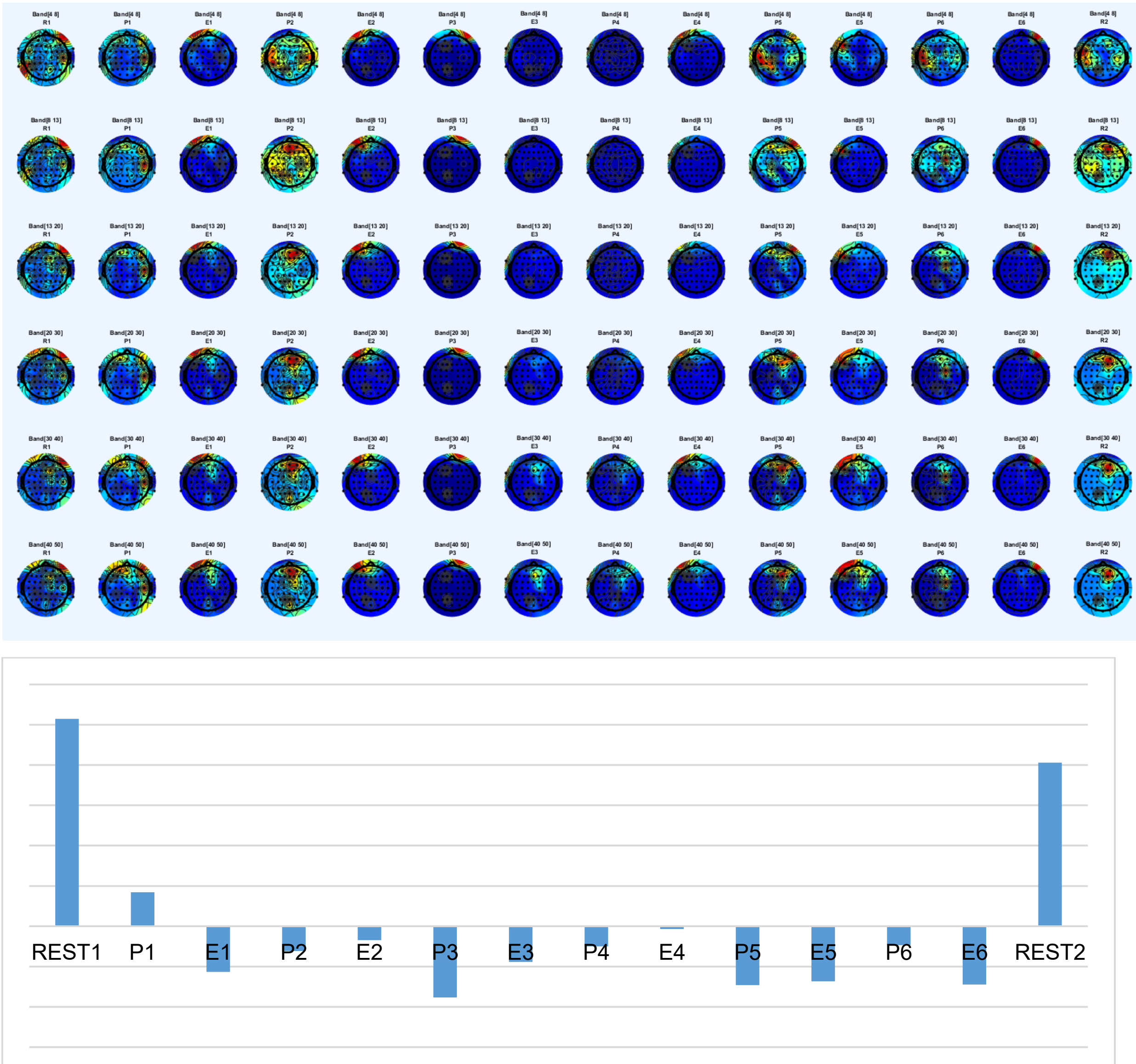


Figure 38. EEG topographic map and PC1 of subject 10

Subject 14

EEG topographic map and PC1 power of subject14 (April 24, 2013)

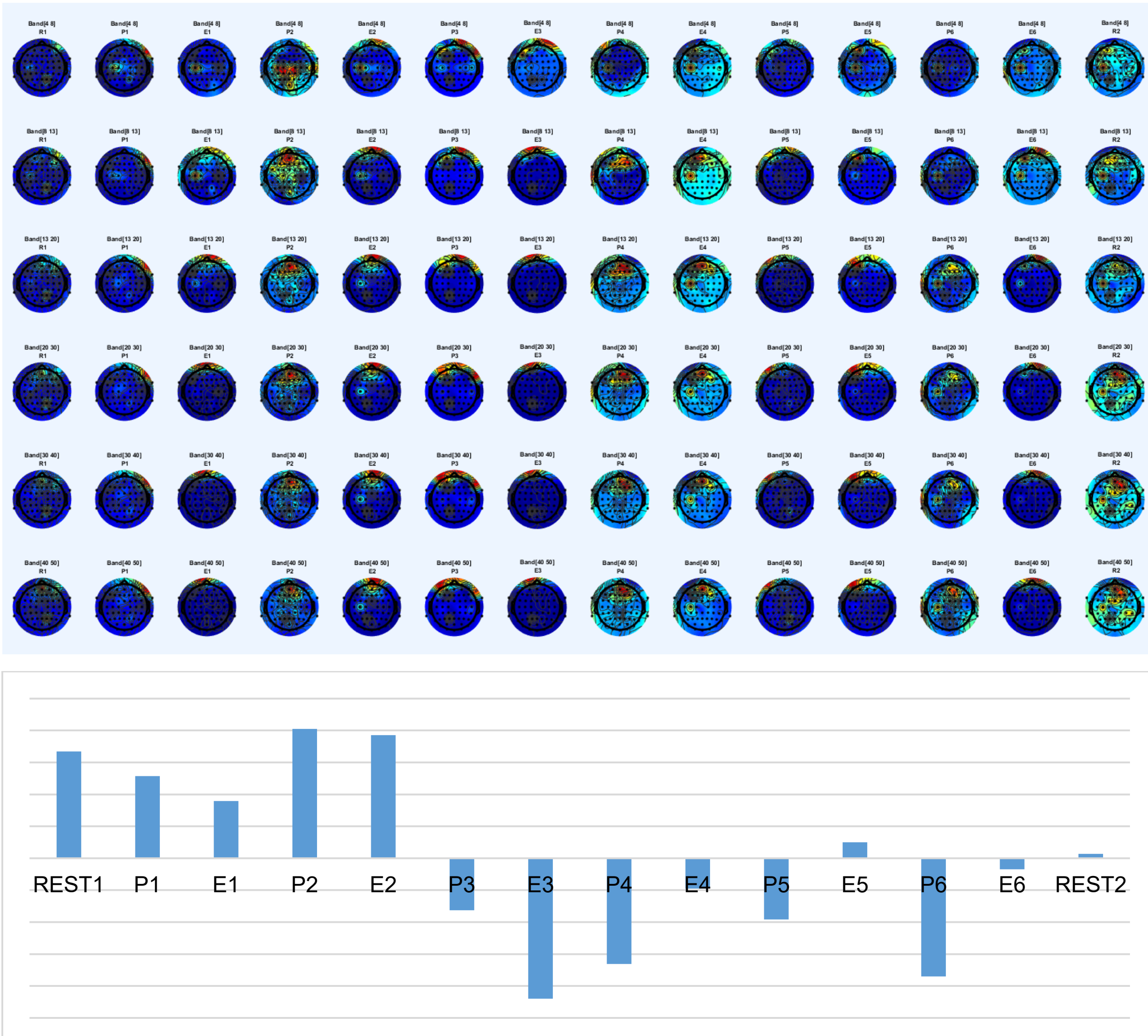


Figure 39. EEG topographic map and PC1 of subject 14

From the overview of the subject's EEG topographic map, we can see subject04 has a high score on E3 and E6 and has relative low rest score. Subject 06 has high rest score and low score of E2, P4, P5, and P6. Subject 10 has very high rest score, and low sore of P3, P5, E5 and E6. Subject 14 has high Rest 1 score but low Rest 2 score and has low scores of E3, P4, P5, and P6.

3.5.2 Observation

After we visualized the EEG topographic map and PCA EEG pattern, we observed the 6 tasks' design activities (P) vs. brain power and their solutions. We explored the subject's behavior based on the PC1 brain power pattern and the subjects' results during the experiments. And we compared the features of the subjects' solutions and their self-assessments (subjective ratings) with the EEG power pattern.

3.5.2.1 Case 1

Subject 04 (female, left-hand, not enough rest, total time was 850 seconds) (Figure 40)

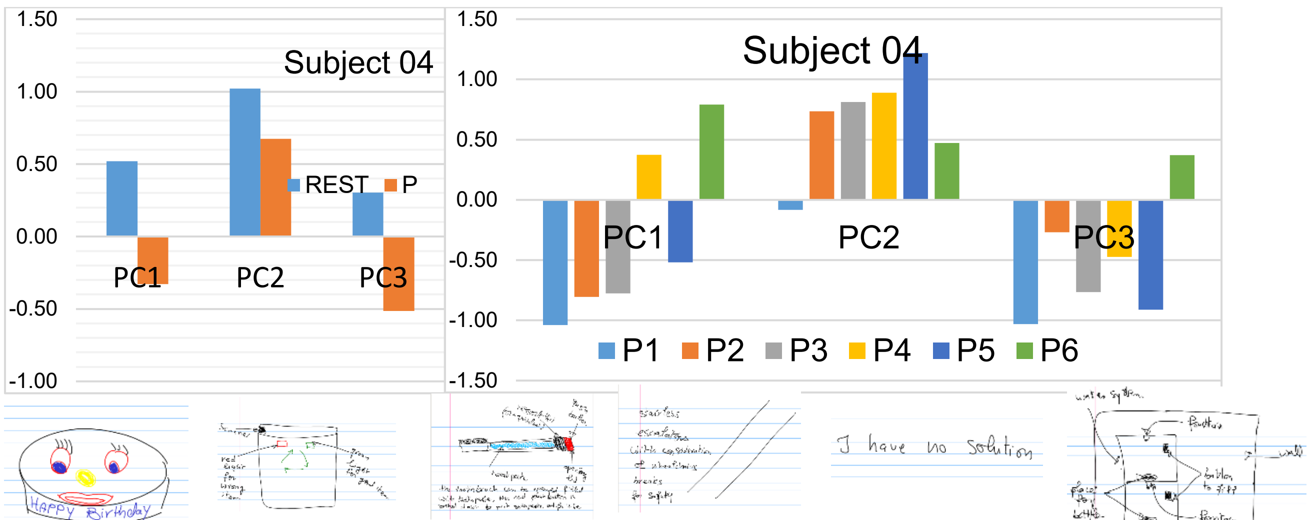


Figure 40. PC1 and solutions of subject 04

The subject was a left-hand female (born in 1984) with electronics and electricity background. During her closing-eye rest state, she was not relaxing enough from her expression of the video. The total time she spent generating solutions for the 6 tasks was 850 seconds. The result of self-rating performance was (30, 70, 50, 30, 0, 45).

From the PC1 REST vs. P (generating solutions) figure we can see the REST score is positive (0.52) and P score is negative (-0.32). However, the amplitude is relatively low.

From the PC1 power, we can see the P1, P2, P3, and P5 are negative, P4 and P6 are positive. The value of P is increasing except P5.

Based on the result we may infer that the subject put less metal effort of the last three tasks than the first three tasks. We also can see the results that she used colors for the first three tasks and did not use color in the last three tasks, and she did not give the solution to the fifth task, she rated the highest stress value (50) to the other tasks (10-40). As the subject is a left-hand designer, the pattern of PC rhythms may be different from right-hand designers.

As the subject was not relaxing enough during the closing-eye rest, it could affect her performance.

3.5.2.2 Case 2

Subject 06 (female, right-hand, enough rest, total time was 814 seconds) Figure 41

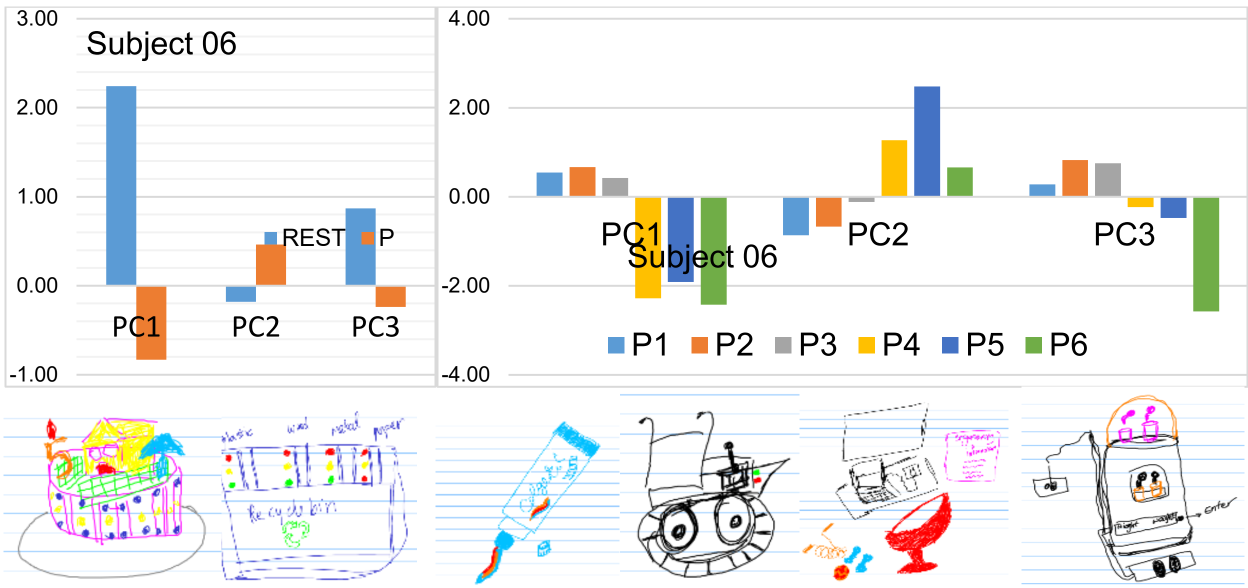


Figure 41. PC1 and solutions of subject 06

The subject was female (born in 1979) with software engineering background. During her closing-eye rest, she was relaxing enough from her expression on the video. The total time she spent for generating solutions of the 6 tasks was 814 seconds. The result of self-rating performance was (35, 40, 30, 82, 39, 83).

From the PC1 rest vs. generating solutions figure we can see the Rest value is positive (2.24) and P value (-0.83) is negative. The amplitude is relatively high.

From the PC1, we can see the P1, P2, P3 are positive, and P4, P5, and P6 are negative. The zigzag trend of the P scores is the same as the result of self-rating performance.

Based on the result we may infer that the subject put more metal effort into the last three tasks than the first three tasks. We also can see the results that she used colors for all the tasks, and she self-rated the mental stress levels of the six tasks as (94, 90, 80, 39, 91, 30). This could infer that at first three tasks she felt stressed uncertainty. After the three tasks, she could manage her stress, then she put more effort into the last three tasks, and she was satisfied with her performances on task 4 (82) and task 6 (83).

As the subject was relaxing enough during the closing-eye rest, it could have affected her performance.

3.5.2.3 Case 3

Subject 10 (male, right-hand, relax rest, total time was 1559 seconds) (Figure 42)

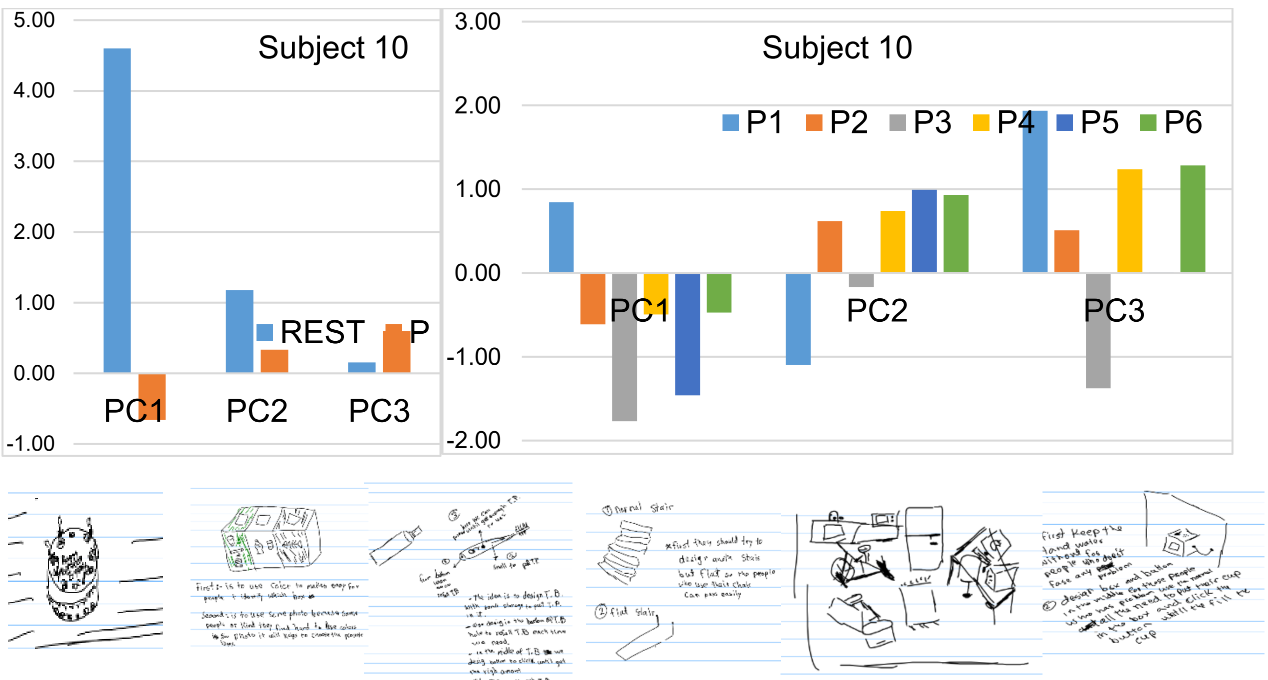


Figure 42. PC1 and solutions of subject 10

The subject was male (born in 1985) with an engineering background. During his closing-eye rest, he was relaxing enough from expression video. The total time he spent generating solutions for the 6 tasks was 1559 seconds. The result of self-rating performance was (50, 50, 55, 70, 40, 70). The stress was (55, 70, 55, 50, 75, 30)

From the PC1 rest vs. generating solutions figure we can see the Rest value is positive (4.6) and P value (-0.66) is negative. The amplitude is relatively high.

From the PC1 power, we can see the P1 is positive, and P2 to P6 are negative. The P3 and P5 have the highest amplitude scores, and P2, P4, P6 have the lowest amplitude scores.

Based on the result we may infer that the subject put more metal effort into task 3 and 5 than other tasks. We also can see the results that he did not use color for the tasks, and he gave descriptions for the tasks of 2, 3, 4, and 6. He was not satisfied with the performance (40) of task 5, and he felt that the last task was the lowest stress (30).

As the subject was relaxing enough during the closing-eye rest, it could have affected his performance.

3.5.2.4 Case 4

Subject 14 (male, right-hand, enough rest, total time was 811 seconds) (Figure 43)

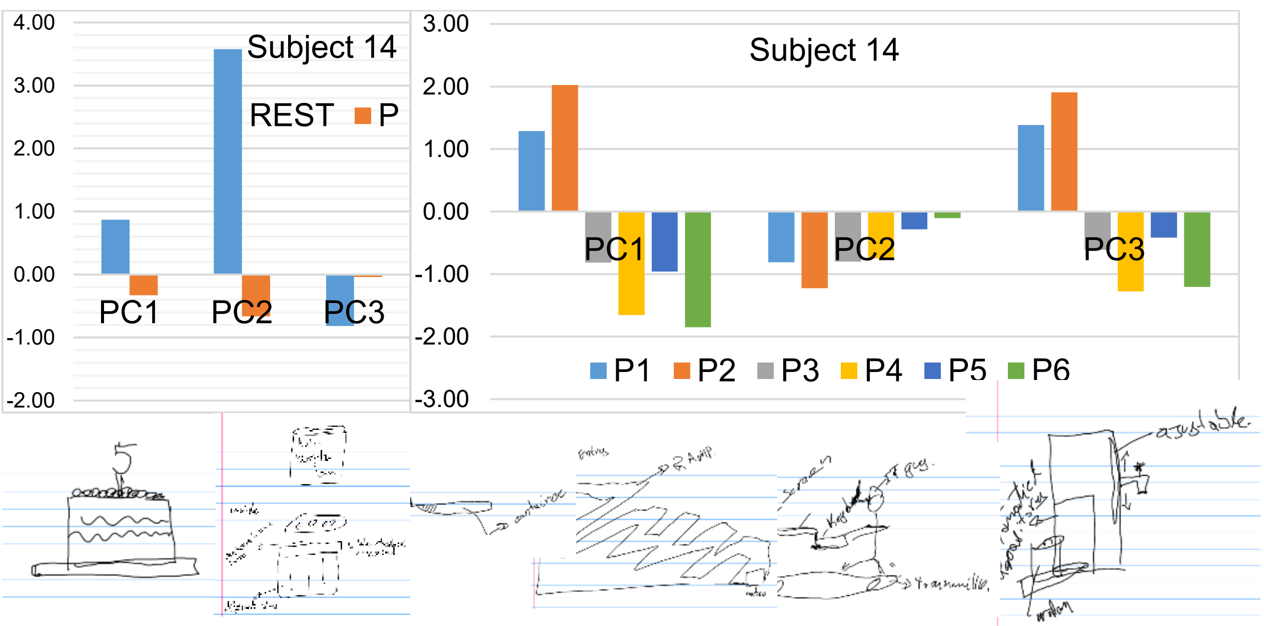


Figure 43. PC1 and solutions of subject 14

The subject was male (born in 1977) with a quality engineering background. During his closing-eye rest, he was relaxing enough from the expression of the video. The total time he spent for generating solutions of the 6 tasks was 811 seconds. The result of self-rating performance was (35, 37, 45, 40, 29, 18). The stress was (75, 28, 24, 40, 84, 40)

From the PC1 rest vs. generating solutions figure we can see the Rest value is positive (0.87) and P value (-0.33) is negative. The amplitude is relatively low.

From the PC1 power, we can see the P1 is positive, P2 to P6 are negative. The P3 and P5 have the highest amplitude scores, and P2, P4, P6 have the lowest amplitude scores.

Based on the result we may infer that the subject put more metal effort on task 3 and 5 than other tasks. We can also see the results that he did not use color for the tasks, and he gave descriptions for the tasks of 2, 3, 4, and 6. He was not satisfied with the performance (40) of task 5, and he felt that the last task was the lowest stress (30).

The subject could be not relaxing enough during the closing-eye rest; it could affect his performance.

3.5.3 Comparison analysis

The following is the comparison of PC1 brain power pattern with subjects' design results.

3.5.3.1 The pattern of the subjects' ratings

The following is the observation of the 4 subjects' self-assessments. The assessment is the subjective rating based on NASA TLX (Nguyen & Zeng, 2016) of the 6 tasks' solutions. We collected the data from the experiments of the 4 subjects. To compare the result in the same scale, we computed the relative score of the subjects' rating data. Then, we plotted the stacked lines based on the data to observe the patterns related to design activities. The features included mental effort, mental workload, performance, mental stress, time demand, time spent, and total workload. Cake, Bin, Brush, Metro, Exercise and Fountain represent the six design tasks.

Mental effort

Table 14. Mental effort

Subject	Cake	Bin	Brush	Metro	Exercise	Fountain
04	0.13	0.75	0.38	0.13	0.00	1.00
06	0.79	0.67	0.00	1.00	0.65	0.07
10	0.00	0.33	0.67	1.00	1.00	0.56
14	0.00	0.29	0.36	0.71	0.93	1.00

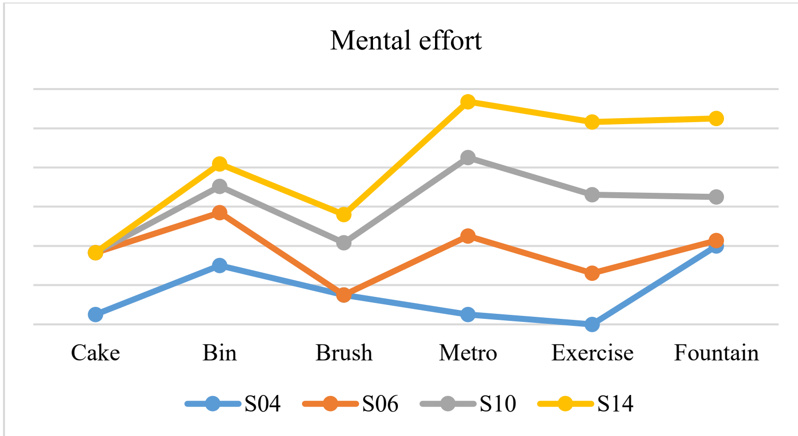


Figure 44. Mental effort

Mental workload

Table 15. Mental workload

Subject	Cake	Bin	Brush	Metro	Exercise	Fountain
04	0.00	0.40	0.47	0.60	1.00	0.87
06	0.00	0.83	1.00	0.80	1.00	0.17
10	0.00	0.67	0.58	0.58	1.00	0.58
14	0.13	0.23	0.00	0.38	1.00	0.74

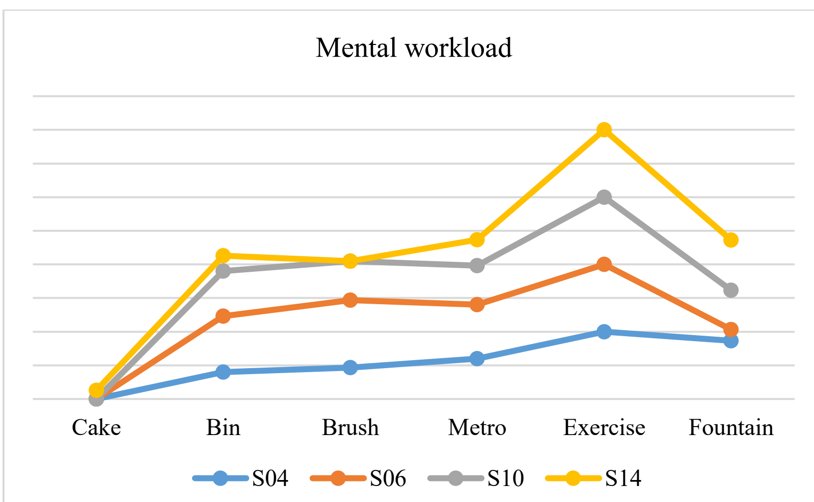


Figure 45. Mental workload

Performance

Table 16. Performance

Subject	Cake	Bin	Brush	Metro	Exercise	Fountain

04	0.43	1.00	0.71	0.43	0.00	0.64
06	0.09	0.19	0.00	0.98	0.17	1.00
10	0.33	0.33	0.50	1.00	0.00	1.00
14	0.63	0.70	1.00	0.81	0.41	0.00

Figure 46. Performance

Mental stress

Table 17. Mental stress

Subject	Cake	Bin	Brush	Metro	Exercise	Fountain
04	0.00	0.25	0.00	0.50	1.00	0.75
06	1.00	0.94	0.78	0.14	0.95	0.00
10	0.56	0.89	0.56	0.44	1.00	0.00
14	0.85	0.07	0.00	0.27	1.00	0.27

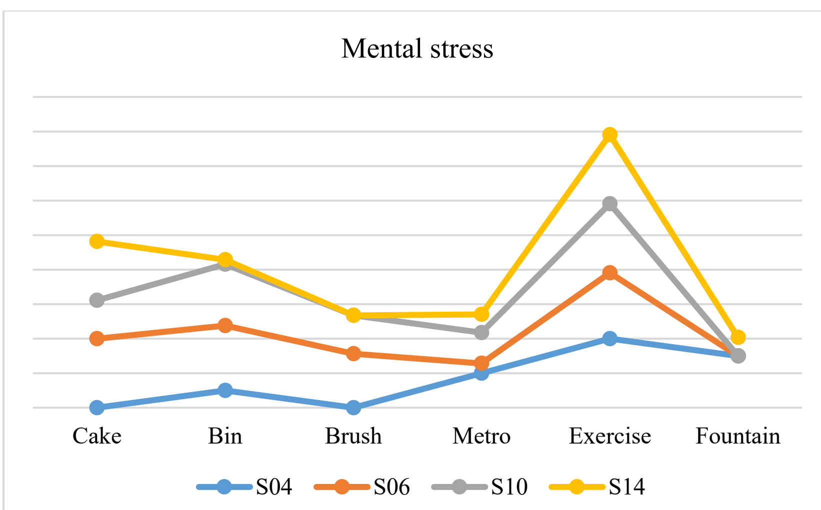


Figure 47. Mental stress

Time demand

Table 18. Time demand

Subject	Cake	Bin	Brush	Metro	Exercise	Fountain
04	0.00	0.50	0.38	0.31	1.00	0.75
06	0.40	0.80	0.56	0.00	0.56	1.00
10	0.00	0.00	0.67	0.33	1.00	0.33
14	0.00	0.32	0.28	0.70	1.00	0.76

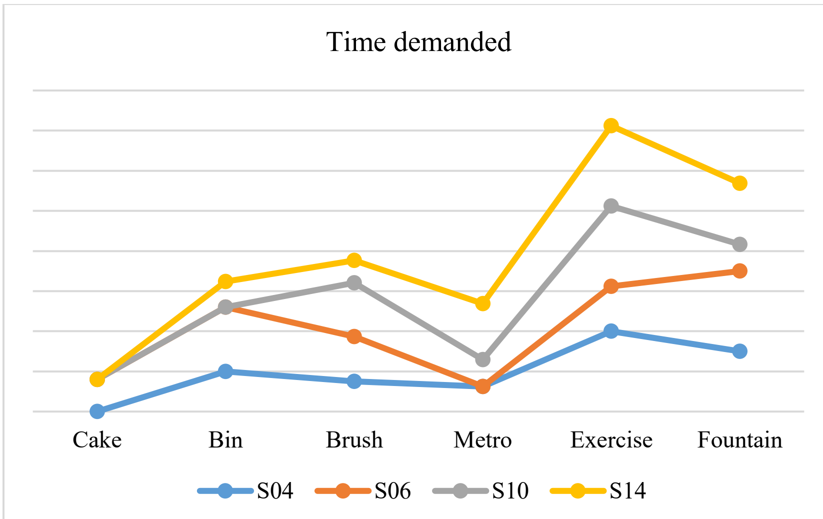


Figure 48. Time demand

Time consumed

Table 19. Time consumed

Subject	Cake	Bin	Brush	Metro	Exercise	Fountain
04	0.45	0.72	0.84	0.23	0.00	1.00
06	0.58	0.36	0.35	0.00	1.00	0.15
10	0.66	0.03	0.30	0.44	1.00	0.00
14	0.59	1.00	0.00	0.22	0.55	0.36

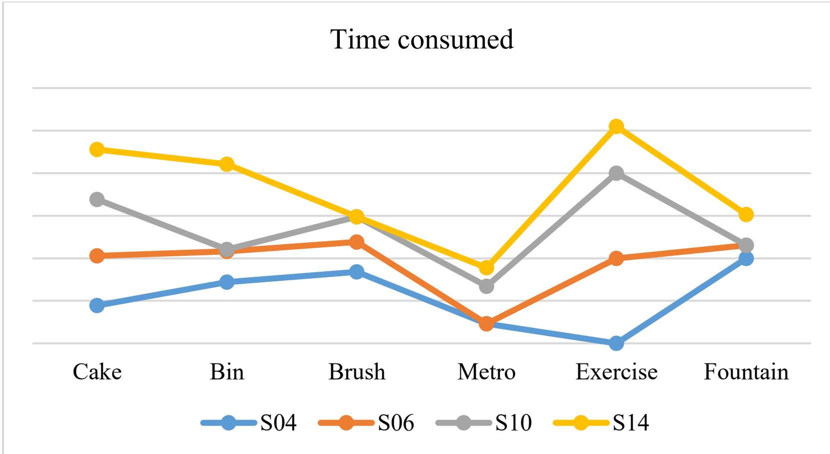


Figure 49. Time consumed

Total workload

Table 20. Total workload

Subject	Cake	Bin	Brush	Metro	Exercise	Fountain
04	0.00	0.71	0.46	0.44	0.78	1.00
06	0.47	1.00	0.14	0.72	0.97	0.00
10	0.00	0.48	0.62	0.72	1.00	0.45
14	0.21	0.05	0.00	0.41	1.00	0.40

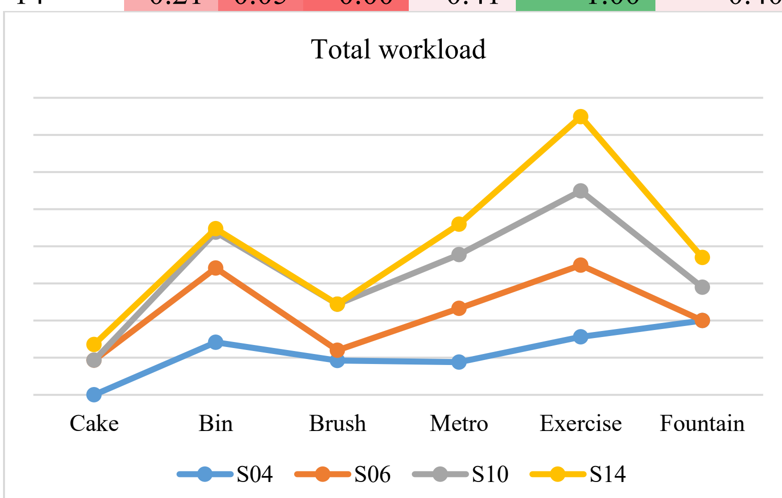


Figure 50. Total workload

3.5.3.2 The pattern of the PC1 of the subjects

PC1 pattern of the 4 subjects follows:

Table 21. PC1 of the 4 subjects

	Rest 1	Cake	Bin	Brush	Metro	Exercise	Fountain	Rest 2
S04	0.47	-1.04	-0.81	-0.78	0.37	-0.52	0.79	0.57

S06	2.27	0.54	0.67	0.42	-2.28	-1.92	-2.42	2.22
S10	5.14	0.85	-0.61	-1.77	-0.50	-1.46	-0.47	4.06
S14	1.67	1.28	2.02	-0.82	-1.66	-0.96	-1.85	0.07

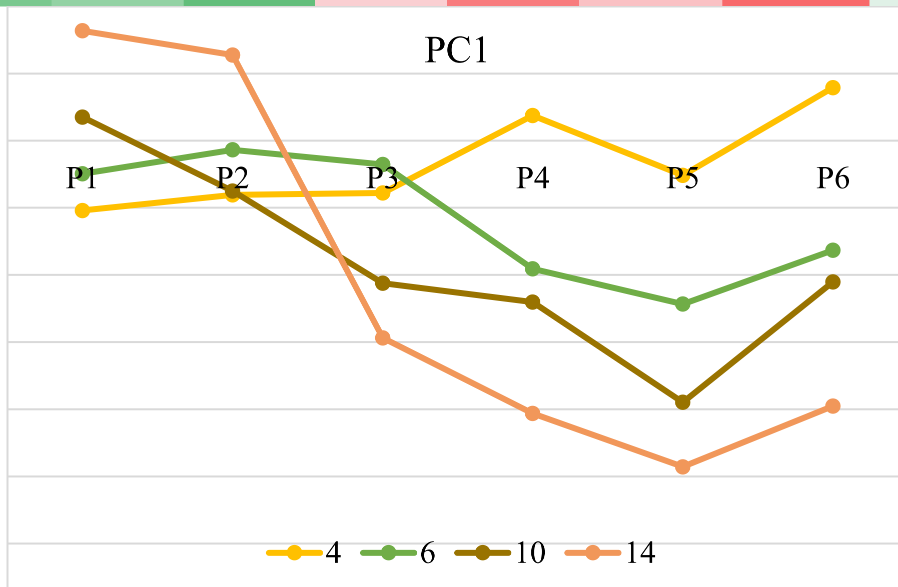


Figure 51. PC1 of the 4 subjects

3.5.3.3 Correlation analysis

After we compared the patterns of the 4 subjects' self-assessment rating results with the patterns of their EEG principal component power, we found there are similar trends among the features. Therefore, we apply statistical correlation analysis to test the relationship of these features. From the correlation table of the features (Table 22), we infer the behavior related to the design activities. The results may give us clues be able to generate an optimized model to evaluate or quantify the designer's behavior. From the correlation table, we found there are some significant relations of these features.

- Subject04: the mental load has a significant relation between stress and time demanded. PC1 is greatly related mental load and mental stress (0.6).
- Subject 06: the performance and stress, time and effort are significantly negatively related (-0.96). PC1 is greatly related to stress and performance.
- Subject 10: The total workload is significantly related to effort and mental load (0.94). PC1 is greatly related to mental load, time demanded, and total workload.

- Subject 14: the time demanded is significantly related to effort and mental load. PC1 is greatly related to effort and time.
- The performance is negatively related to the stress
- PC1 is mainly related to mental load or mental effort except subject 06.

Table 22. Correlation of the features

S04	*Effort*	*Mental load*	*Performance*	*Stress*	*Time demanded*	*Time*	*Total workload*	*PC1*
Effort	1.00							
Mental load	0.14	1.00						
Performance	0.74	-0.40	1.00					
Stress	0.01	0.91	-0.57	1.00				
Time demanded	0.20	0.93	-0.32	0.87	1.00			
Time	0.86	-0.17	0.80	-0.39	-0.13	1.00		
Total workload	0.60	0.85	0.09	0.73	0.88	0.26	1.00	
PC1	0.40	0.61	-0.06	0.59	0.36	0.17	0.58	1.00
Effort (S06)	1.00							
Mental load	0.01	1.00						
Performance	0.08	-0.26	1.00					
Stress	0.18	0.22	-0.96	1.00				
Time demanded	-0.68	-0.20	-0.08	0.02	1.00			
Time	0.09	0.17	-0.68	0.76	0.13	1.00		
Total workload	0.76	0.47	-0.24	0.47	-0.30	0.41	1.00	
PC1	-0.06	0.00	-0.80	0.74	0.10	0.17	0.07	1.00
Effort **(S10)**	1.00							
Mental load	0.79	1.00						
Performance	0.16	-0.19	1.00					
Stress	0.10	0.38	-0.87	1.00				
Time demanded	0.77	0.71	-0.30	0.26	1.00			
Time	0.28	0.11	-0.60	0.53	0.54	1.00		
Total workload	0.94	0.94	-0.13	0.36	0.82	0.30	1.00	
PC1	-0.70	-0.82	0.17	-0.28	-0.80	-0.03	-0.83	1.00
Effort **(S14)**	1.00							
Mental load	0.86	1.00						
Performance	-0.62	-0.76	1.00					
Stress	0.08	0.51	-0.34	1.00				
Time demanded	0.96	0.90	-0.51	0.21	1.00			
Time	-0.26	0.12	-0.22	0.22	-0.14	1.00		
Total workload	0.70	0.91	-0.50	0.73	0.82	0.03	1.00	
PC1	-0.81	-0.49	0.30	0.04	-0.71	0.77	-0.46	1.00

3.5.4 Summary

Based on the observation above, we did the preliminary study of the subjective features of design activities associated with the EEG PC power. First, we reviewed the EEG topographic and PC1 power of the four subjects' design activities. Then we observed the subjective and objective patterns associated with the solutions. From the solutions we found some phenomena related to results. For example, the female subjects used colors for their designs solutions whereas male subjects did not, and the rest states may affect the design activities. We also found there are some similar trends among the features. Finally, we applied statistical correlation analysis of the features to test the relations among the features. The results demonstrated that there are some significant relationship among some subjective rating features, such as time demanded, mental workload and etc. PC1 power has different relationship with the features of the 4 subjects. The subjective rating of performance and stress is negatively related. As the correlation is the linear analysis, the results may not reflect the real relations of the features. We may analyze more data to test the inverse shape relation of mental stress and mental effort. As a next step we may observe and analyze more subjects' brain power data. We will try to model and evaluate subjects' behavior during design process.

4 Conclusion

Based on the results of the analysis and case study we conclude that there is a relationship between the brain power and design activity. PCA is a method which may significantly simplify the 7 bands EEG data to the three principal components (3PC) in the context of the conceptual design activities (Synthesis and Evaluation).

From the PCA results, we found that PC1 represents the level of the relaxation. There is a difference between the Rest 1 and Rest 2 which may imply that the subjects are nervous in the beginning and they are less relax at beginning of the tasks than at the end of the tasks. We also found that generating solutions has greater variance than evaluating solutions, and they are not significant related. This suggests that there are more strategies of the synthesis than evaluation. Furthermore, from the observation of EEG data on the PCA model, we found different patterns for the rest states before and after the tasks, and different patterns for generating and evaluating solutions associated the EEG bands and PCs. Therefore, we may consider the 3PC patterns as the relative average model of brain (EEG) power for the design activities.

As every designer has different behavior, to observe the variance of designers' behavior, the 32 subject's EEG data were projected on the model. By comparing the differences of the subjects' data on the model, we may infer or evaluate the designers' behaviors. From the observation and statistical analysis, we found that even when the subjects were closing their eyes, their minds were working. Subjects were less concentrated at the beginning and the end of the design process.

To validate the results, we studied the data from four specific subjects. We observed the EEG topographic and PC EEG map of their solutions for the tasks. Then we observed the subjects' self-assessments of the six tasks and the PCs EEG power patterns. We found there are some similar patterns between the data of subjective rating and the PC EEG. Therefore, we applied correlation analysis. We found there are some significant relationship of subjective ratings, such as mental load and time load. PC1 has different relationship with the subjective ratings. To find the relationship between PC1 and subjective rating, the data gathered from the other subjects should be studied in the same way. By optimizing the model, ultimately it may help us improve the design.

5 Future work

Discussion

In this study, we analyzed the general and individual characteristics of designers' behavior based on the EEG PCA model (Averaged Relative Z-score EEG power). The data was from our experiments of the six design tasks.

- Regarding the average of the subjects' EEG data, we observed the patterns of design activities on the PCs to identify the average characteristics of the designers' behaviors. We used the mean value as the estimator of the sample data. There are conditions for the method that could result in bias. Therefore, we may investigate the sample data distribution and the error of different situation.
- Regarding the relative EEG power, the advantage is that it reduces the variance of the measurement of EEG data which may be caused by the device. However, the disadvantage is that it cannot compare the subjects' amplitude states based on the scale of the frequency band. Thus, the results of the analysis have some limitations.
- Regarding the PCA model, as we know there are many different methods to reduce the complexity of the data, to identify the independent factors within the EEG data, such as ICA, PCA, LDA etc. (Gursoy & Subast, 2008). Regarding the PCA algorithm, there are many variables related to the function and changing parameters might also cause different results. Therefore, we may also have a further study of the factor analysis for the EEG data.
- When we analyze the relation of the design activities and EEG power, there are some key questions to be addressed, such as: what features to analyze? Why we applied the statistical analysis of the difference, the mean, the standard deviation, ANOVA, and the control chart of design activities? How to analyze the relationship? As the PCA and correlation analysis are based on the linear model, and we know the EEG signals are related to nonlinear and multiple processing layers of the neural system. What are the multiple linear and non-linear transformations used to create these relationships? Thus, we may consider the deep machine learning method for the artificial neural network and the EEG analysis.

Challenge

This study is the preliminary investigating of the neurological foundation of design activities, even though we found there are some relations between the EEG band power and design activities, there are still many challenges regarding of the further study of EEG band and design behavior. For example,

- The data collecting process: When collecting the EEG signal from the experiments, there are always a lot of noise of the data. To remove the noise, there are different methods of data processing and transformation. This may cause the loss of information. During every experiment, there was a manual process for recording all the activities associated with the EEG segments. And the accuracy of the recording directly affects the results of analysis.
- There is also a challenge of the EEG band breakdown. As the band breakdown is based on the traditional EEG frequency recognition. It may not represent the basic features of the EEG frequency.
- This study is based on one channel (Fz) of the EEG data for the whole design process, there may be a limitation related to the interpretation of the patterns. It is possible that there are maybe different features of the same EEG channel for different subjects, and the pattern may be different in different time segments. Therefore we may consider the future analysis on EEG band and channels together.

Future study

- To validate the model of the analysis, we could apply validation method for the EEG PCA model. We should investigate the average model by using cross validation approach.
- We cloud analyze the EEG power together with the channels and bands of the design activities.
- To improve the accuracy of the analysis, we cloud analyze the correlation of the EEG data with other biosignals data.
- We could apply deep machine learning skills to identify or evaluate the design behavior based on the patterns of the EEG model.
- We could design different experiments to study the design behavior and bio signals.
- To improve and verify the results of the research, it is very important to study the applications of the research. We are trying to apply our research in aerospace industry to improve the conceptual design. And we could apply the research in the field of cognition to develop powerful tools for human intelligence.

To investigate the neurological foundation for conceptual design, there are some critical factors to study, such as the variance and uncertainty of behavior related to brain power. The artificial neural network has been developed to model the neural system. It may help us recognize the mechanism of neural system related to conceptual design. Questions to be addressed in the future might be: Are there different behaviors between male and female during the design process? Is left-hand behavior different from right-hand behavior? What are the best time intervals for design? What is the order of the tasks regarding the difficulty? There are always challenge and possibilities in research. The study will never stop.

Publication

Liu, L., Nguyen, T. A., Zeng, Y., & Hamza, A. B. (2016). Identification of Relationships between Electroencephalography (EEG) Bands and Design Activities. In ASME 2016 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (p. V007T06A019–V007T06A019). American Society of Mechanical Engineers.

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Appendixes

Appendix1. Relative EEG band Power of the experiment

(Theta, Alpha, Beta 1, Beta 2, Gamma 1, Gamma 2 and Gamma 3)

Theta	Rest1	P1	E1	P2	E2	P3	E3	P4	E4	P5	E5	P6	E6	Rest2
april_02(3).xlsx	0.29	0.52	0.33	0.40	0.35	0.35	0.40	0.38	0.32	0.44	0.45	0.23	0.34	0.33
april_04(1).xlsx	0.14	0.48	0.46	0.35	0.34	0.59	0.63	0.37	0.45	0.48	0.43	0.29	0.73	0.12
Apri_04(2).xlsx	0.32	0.45	0.55	0.45	0.52	0.47	0.49	0.45	0.46	0.42	0.51	0.37	0.51	0.35
april_08.xlsx	0.41	0.42	0.35	0.37	0.39	0.37	0.81	0.36	0.40	0.31	0.43	0.44	0.94	0.38
April_15.xlsx	0.34	0.43	0.42	0.34	0.33	0.33	0.34	0.34	0.33	0.36	0.32	0.33	0.30	0.33
April_16(1).xlsx	0.58	0.55	0.59	0.57	0.35	0.54	0.49	0.44	0.52	0.39	0.62	0.35	0.53	0.51
april_16(3).xlsx	0.30	0.41	0.38	0.36	0.35	0.38	0.39	0.19	0.39	0.30	0.32	0.36	0.34	0.28
april_18(1).xlsx	0.38	0.23	0.13	0.08	0.09	0.31	0.11	0.06	0.14	0.08	0.28	0.11	0.32	0.36
april_18(2).xlsx	0.25	0.25	0.25	0.24	0.21	0.25	0.22	0.22	0.25	0.18	0.24	0.21	0.19	0.25
april_19(1).xlsx	0.23	0.47	0.36	0.37	0.39	0.33	0.35	0.40	0.43	0.34	0.35	0.39	0.33	0.20
April_19(2).xlsx	0.69	0.37	0.46	0.42	0.44	0.44	0.48	0.52	0.42	0.46	0.42	0.48	0.54	0.36
April_2(1).xlsx	0.30	0.39	0.41	0.31	0.32	0.29	0.35	0.39	0.33	0.32	0.31	0.35	0.30	0.27
april_22.xlsx	0.38	0.48	0.48	0.44	0.43	0.45	0.47	0.43	0.44	0.45	0.48	0.43	0.47	0.37
april_24.xlsx	0.23	0.75	0.74	0.79	0.79	0.66	0.59	0.62	0.65	0.65	0.74	0.59	0.64	0.32
aug_05.xlsx	0.31	0.50	0.48	0.44	0.44	0.47	0.41	0.38	0.44	0.44	0.34	0.40	0.40	0.27
august_01.xlsx	0.43	0.43	0.53	0.48	0.50	0.44	0.48	0.49	0.46	0.48	0.46	0.46	0.41	0.42
July_29.xlsx	0.46	0.43	0.38	0.48	0.39	0.28	0.38	0.20	0.34	0.21	0.31	0.26	0.31	0.15
July_30.xlsx	0.34	0.56	0.47	0.47	0.48	0.50	0.55	0.47	0.49	0.52	0.55	0.53	0.53	0.32
June_25.xlsx	0.56	0.65	0.68	0.60	0.63	0.51	0.63	0.59	0.62	0.60	0.58	0.59	0.67	0.59
Sep_12(2).xlsx	0.07	0.24	0.36	0.30	0.26	0.12	0.20	0.24	0.29	0.22	0.38	0.23	0.29	0.17
Sep_12(1).xlsx	0.32	0.36	0.33	0.40	0.31	0.40	0.31	0.31	0.26	0.37	0.43	0.39	0.37	0.24
Sep_13(2).xlsx	0.27	0.34	0.37	0.40	0.43	0.36	0.42	0.37	0.44	0.55	0.46	0.42	0.43	0.32
Sep_13(1).xlsx	0.33	0.30	0.34	0.35	0.38	0.32	0.33	0.35	0.36	0.35	0.41	0.38	0.38	0.36
Sep_18.xlsx	0.30	0.34	0.27	0.27	0.32	0.34	0.28	0.33	0.30	0.30	0.36	0.29	0.32	0.30
Feb_18(2)_2014	0.11	0.45	0.45	0.45	0.46	0.46	0.50	0.31	0.44	0.31	0.55	0.32	0.42	0.09
Feb_19(2)_2014	0.44	0.33	0.39	0.40	0.41	0.35	0.43	0.40	0.38	0.36	0.37	0.38	0.43	0.30
Mar_14(2)_2014	0.27	0.24	0.33	0.23	0.21	0.23	0.22	0.19	0.21	0.23	0.21	0.28	0.19	0.23
Feb_28(2)_2014	0.15	0.25	0.29	0.22	0.22	0.20	0.22	0.23	0.28	0.24	0.25	0.25	0.26	0.16
Feb_28(1)_2014	0.21	0.19	0.36	0.32	0.27	0.25	0.22	0.24	0.20	0.18	0.22	0.21	0.20	0.16
Feb_20(2)_2014	0.39	0.45	0.52	0.52	0.47	0.59	0.50	0.54	0.57	0.57	0.50	0.54	0.53	0.40
Feb_07(1)_2014	0.17	0.33	0.17	0.25	0.32	0.27	0.25	0.23	0.09	0.28	0.15	0.15	0.14	0.17
April_30_2014.xl	0.34	0.59	0.53	0.53	0.51	0.52	0.53	0.53	0.51	0.51	0.52	0.50	0.51	0.20

Alpha	Rest1	P1	E1	P2	E2	P3	E3	P4	E4	P5	E5	P6	E6	Rest2	
april_02(3).xlsx	0.45	0.20	0.21	0.18	0.24	0.24	0.22	0.27	0.22	0.22	0.22	0.21	0.23	0.21	
april_04(1).xlsx	0.26	0.14	0.13	0.16	0.18	0.13	0.13	0.20	0.14	0.18	0.16	0.20	0.11	0.30	
Apri_04(2).xlsx	0.33	0.14	0.24	0.18	0.24	0.27	0.25	0.21	0.23	0.23	0.25	0.18	0.24	0.38	
april_08.xlsx	0.18	0.16	0.16	0.15	0.16	0.18	0.12	0.22	0.17	0.21	0.15	0.19	0.05	0.21	
April_15.xlsx	0.25	0.21	0.24	0.18	0.16	0.20	0.21	0.19	0.19	0.17	0.21	0.19	0.15	0.36	
April_16(1).xlsx	0.23	0.17	0.17	0.16	0.13	0.16	0.14	0.07	0.15	0.13	0.19	0.12	0.16	0.26	
april_16(3).xlsx	0.44	0.22	0.20	0.23	0.24	0.22	0.18	0.09	0.19	0.18	0.14	0.21	0.30	0.40	
april_18(1).xlsx	0.33	0.16	0.13	0.08	0.08	0.28	0.08	0.06	0.11	0.07	0.17	0.10	0.17	0.34	
april_18(2).xlsx	0.15	0.16	0.16	0.12	0.11	0.13	0.13	0.12	0.14	0.12	0.18	0.12	0.10	0.16	
april_19(1).xlsx	0.60	0.25	0.20	0.23	0.24	0.18	0.23	0.22	0.22	0.19	0.19	0.22	0.20	0.56	
April_19(2).xlsx	0.20	0.23	0.20	0.18	0.19	0.18	0.19	0.19	0.21	0.19	0.20	0.18	0.18	0.40	
April_2(1).xlsx	0.36	0.21	0.22	0.18	0.19	0.14	0.23	0.25	0.19	0.23	0.18	0.20	0.21	0.39	
april_22.xlsx	0.31	0.21	0.21	0.23	0.24	0.22	0.22	0.23	0.23	0.21	0.24	0.21	0.23	0.31	
april_24.xlsx	0.51	0.13	0.13	0.13	0.14	0.12	0.09	0.11	0.14	0.11	0.09	0.11	0.14	0.37	
aug_05.xlsx	0.68	0.20	0.17	0.18	0.22	0.22	0.21	0.24	0.22	0.26	0.22	0.26	0.27	0.73	
august_01.xlsx	0.29	0.28	0.22	0.22	0.25	0.21	0.21	0.25	0.23	0.24	0.23	0.21	0.21	0.29	
July_29.xlsx	0.32	0.30	0.24	0.21	0.24	0.21	0.21	0.26	0.30	0.21	0.34	0.24	0.31	0.58	
July_30.xlsx	0.34	0.16	0.21	0.22	0.18	0.16	0.15	0.19	0.18	0.17	0.17	0.15	0.16	0.38	
June_25.xlsx	0.62	0.22	0.19	0.27	0.24	0.40	0.22	0.30	0.25	0.25	0.24	0.30	0.21	0.68	
Sep_12(2).xlsx	0.08	0.19	0.19	0.16	0.17	0.09	0.12	0.13	0.16	0.15	0.19	0.15	0.17	0.42	
Sep_12(1).xlsx	0.36	0.30	0.24	0.19	0.18	0.20	0.17	0.18	0.15	0.20	0.18	0.19	0.16	0.50	
Sep_13(2).xlsx	0.44	0.28	0.21	0.17	0.21	0.22	0.21	0.20	0.17	0.21	0.18	0.11	0.21	0.45	
Sep_13(1).xlsx	0.51	0.49	0.20	0.31	0.24	0.29	0.31	0.26	0.22	0.26	0.24	0.29	0.30	0.52	
Sep_18.xlsx	0.22	0.07	0.13	0.11	0.11	0.09	0.12	0.10	0.16	0.10	0.12	0.11	0.12	0.24	
Feb_18(2)_2014	0.85	0.24	0.32	0.27	0.25	0.24	0.25	0.45	0.30	0.40	0.24	0.37	0.30	0.86	
Feb_19(2)_2014	0.33	0.25	0.28	0.22	0.24	0.25	0.22	0.22	0.25	0.24	0.24	0.21	0.30	0.45	
Mar_14(2)_2014	0.68	0.32	0.31	0.59	0.29	0.39	0.40	0.46	0.36	0.41	0.43	0.33	0.38	0.76	
Feb_28(2)_2014	0.74	0.31	0.31	0.47	0.45	0.45	0.44	0.50	0.46	0.41	0.38	0.43	0.39	0.74	
Feb_28(1)_2014	0.24	0.14	0.19	0.18	0.16	0.22	0.18	0.20	0.16	0.16	0.15	0.20	0.14	0.40	
Feb_20(2)_2014	0.35	0.23	0.20	0.20	0.22	0.18	0.23	0.21	0.22	0.17	0.23	0.23	0.20	0.39	
Feb_07(1)_2014	0.70	0.19	0.12	0.15	0.17	0.25	0.18	0.18	0.09	0.15	0.10	0.10	0.09	0.66	
April_30_2014.x	0.53	0.16	0.22	0.21	0.20	0.21	0.18	0.18	0.19	0.18	0.23	0.19	0.20	0.67	

Beta1	Rest1	P1	E1	P2	E2	P3	E3	P4	E4	P5	E5	P6	E6	Rest2	
april_02(3).xlsx	0.15	0.12	0.12	0.11	0.17	0.17	0.19	0.16	0.18	0.15	0.14	0.14	0.16	0.12	
april_04(1).xlsx	0.22	0.12	0.14	0.18	0.16	0.10	0.08	0.17	0.13	0.13	0.13	0.17	0.06	0.22	
Apri_04(2).xlsx	0.10	0.10	0.12	0.12	0.12	0.13	0.13	0.12	0.13	0.15	0.14	0.12	0.13	0.10	
april_08.xlsx	0.20	0.13	0.17	0.18	0.16	0.18	0.05	0.17	0.13	0.19	0.14	0.17	0.02	0.20	
April_15.xlsx	0.13	0.14	0.12	0.19	0.18	0.14	0.13	0.17	0.13	0.15	0.16	0.16	0.13	0.17	
April_16(1).xlsx	0.11	0.12	0.10	0.12	0.14	0.14	0.12	0.16	0.13	0.17	0.11	0.13	0.13	0.14	
april_16(3).xlsx	0.11	0.14	0.13	0.13	0.14	0.14	0.15	0.13	0.12	0.13	0.11	0.14	0.13	0.12	
april_18(1).xlsx	0.12	0.18	0.16	0.13	0.11	0.22	0.13	0.11	0.13	0.10	0.13	0.09	0.15	0.13	
april_18(2).xlsx	0.24	0.24	0.25	0.22	0.23	0.22	0.20	0.18	0.15	0.27	0.12	0.23	0.19	0.23	
april_19(1).xlsx	0.16	0.16	0.16	0.17	0.16	0.15	0.16	0.17	0.15	0.17	0.14	0.18	0.15	0.16	
April_19(2).xlsx	0.07	0.17	0.16	0.12	0.14	0.14	0.13	0.11	0.15	0.14	0.15	0.14	0.11	0.13	
April_2(1).xlsx	0.17	0.17	0.18	0.17	0.16	0.21	0.18	0.18	0.16	0.18	0.14	0.16	0.18	0.21	
april_22.xlsx	0.13	0.14	0.14	0.14	0.14	0.14	0.13	0.14	0.14	0.13	0.12	0.14	0.13	0.13	
april_24.xlsx	0.15	0.06	0.05	0.05	0.04	0.04	0.06	0.04	0.07	0.06	0.05	0.06	0.07	0.15	
aug_05.xlsx	0.08	0.14	0.12	0.13	0.13	0.11	0.13	0.15	0.13	0.13	0.12	0.15	0.13	0.07	
august_01.xlsx	0.13	0.12	0.11	0.13	0.11	0.14	0.12	0.12	0.13	0.13	0.11	0.13	0.12	0.12	
July_29.xlsx	0.11	0.14	0.16	0.10	0.14	0.17	0.13	0.13	0.14	0.15	0.16	0.13	0.14	0.09	
July_30.xlsx	0.18	0.15	0.19	0.18	0.18	0.18	0.13	0.19	0.16	0.17	0.16	0.17	0.14	0.18	
June_25.xlsx	0.06	0.09	0.09	0.11	0.10	0.10	0.11	0.13	0.10	0.12	0.12	0.10	0.09	0.04	
Sep_12(2).xlsx	0.07	0.17	0.15	0.17	0.18	0.11	0.13	0.21	0.15	0.16	0.16	0.18	0.16	0.19	
Sep_12(1).xlsx	0.14	0.16	0.17	0.15	0.16	0.12	0.15	0.17	0.13	0.16	0.12	0.15	0.13	0.11	
Sep_13(2).xlsx	0.13	0.16	0.16	0.16	0.16	0.16	0.15	0.19	0.16	0.10	0.15	0.10	0.16	0.12	
Sep_13(1).xlsx	0.11	0.12	0.17	0.14	0.16	0.15	0.14	0.14	0.15	0.14	0.13	0.14	0.14	0.10	
Sep_18.xlsx	0.15	0.08	0.13	0.12	0.09	0.08	0.11	0.08	0.12	0.08	0.06	0.09	0.08	0.12	
Feb_18(2)_2014.x	0.05	0.14	0.17	0.15	0.16	0.14	0.15	0.13	0.15	0.12	0.12	0.12	0.14	0.06	
Feb_19(2)_2014.x	0.14	0.21	0.14	0.13	0.15	0.16	0.13	0.14	0.12	0.14	0.11	0.15	0.13	0.15	
Mar_14(2)_2014.x	0.10	0.21	0.16	0.11	0.17	0.20	0.15	0.16	0.18	0.14	0.16	0.18	0.18	0.08	
Feb_28(2)_2014.x	0.10	0.16	0.18	0.17	0.18	0.17	0.17	0.17	0.15	0.19	0.18	0.18	0.19	0.10	
Feb_28(1)_2014.x	0.16	0.12	0.18	0.21	0.17	0.21	0.18	0.19	0.19	0.16	0.16	0.24	0.13	0.19	
Feb_20(2)_2014.x	0.15	0.13	0.12	0.11	0.12	0.10	0.11	0.10	0.10	0.12	0.12	0.11	0.12	0.13	
Feb_07(1)_2014.x	0.12	0.15	0.12	0.14	0.17	0.19	0.15	0.14	0.09	0.15	0.11	0.13	0.10	0.12	
April_30_2014.xls	0.10	0.13	0.14	0.13	0.15	0.14	0.12	0.14	0.14	0.14	0.12	0.15	0.14	0.11	

Beta2	Rest1	P1	E1	P2	E2	P3	E3	P4	E4	P5	E5	P6	E6	Rest2	
april_02(3).xl	0.12	0.14	0.20	0.13	0.16	0.17	0.15	0.14	0.20	0.16	0.14	0.16	0.17	0.15	
april_04(1).xl	0.25	0.14	0.17	0.19	0.17	0.10	0.10	0.16	0.16	0.12	0.17	0.19	0.07	0.22	
Apri_04(2).xl	0.12	0.12	0.10	0.13	0.10	0.12	0.11	0.13	0.12	0.13	0.10	0.15	0.12	0.11	
april_08.xlsx	0.15	0.16	0.19	0.20	0.19	0.19	0.04	0.18	0.19	0.19	0.16	0.17	0.01	0.17	
April_15.xlsx	0.22	0.14	0.14	0.23	0.19	0.21	0.17	0.21	0.18	0.21	0.20	0.20	0.19	0.14	
April_16(1).x	0.09	0.12	0.09	0.13	0.13	0.10	0.14	0.12	0.14	0.19	0.09	0.15	0.13	0.11	
april_16(3).xl	0.13	0.17	0.21	0.20	0.17	0.18	0.20	0.25	0.22	0.20	0.19	0.22	0.15	0.15	
april_18(1).xl	0.11	0.19	0.19	0.26	0.24	0.15	0.23	0.24	0.22	0.20	0.20	0.19	0.16	0.12	
april_18(2).xl	0.42	0.39	0.36	0.43	0.49	0.43	0.46	0.49	0.47	0.48	0.43	0.47	0.47	0.43	
april_19(1).xl	0.06	0.13	0.15	0.16	0.15	0.15	0.15	0.15	0.13	0.15	0.14	0.15	0.14	0.09	
April_19(2).x	0.05	0.15	0.14	0.15	0.16	0.16	0.14	0.12	0.16	0.15	0.16	0.15	0.12	0.12	
April_2(1).xls	0.12	0.14	0.15	0.18	0.16	0.17	0.15	0.14	0.15	0.16	0.17	0.15	0.16	0.11	
april_22.xlsx	0.12	0.11	0.12	0.13	0.12	0.12	0.11	0.13	0.13	0.13	0.11	0.14	0.12	0.13	
april_24.xlsx	0.11	0.05	0.06	0.04	0.04	0.07	0.11	0.07	0.08	0.09	0.07	0.09	0.08	0.13	
aug_05.xlsx	0.06	0.13	0.14	0.19	0.15	0.15	0.18	0.16	0.16	0.15	0.17	0.18	0.15	0.05	
august_01.xls	0.13	0.12	0.13	0.14	0.12	0.20	0.15	0.13	0.14	0.13	0.16	0.20	0.22	0.16	
July_29.xlsx	0.10	0.12	0.13	0.08	0.13	0.16	0.14	0.14	0.13	0.15	0.13	0.15	0.13	0.09	
July_30.xlsx	0.17	0.14	0.16	0.16	0.15	0.15	0.17	0.16	0.17	0.16	0.14	0.17	0.14	0.17	
June_25.xlsx	0.03	0.07	0.06	0.07	0.06	0.06	0.06	0.07	0.06	0.07	0.07	0.06	0.06	0.02	
Sep_12(2).xls	0.15	0.37	0.23	0.24	0.30	0.21	0.29	0.32	0.31	0.32	0.20	0.35	0.31	0.23	
Sep_12(1).xls	0.13	0.16	0.16	0.17	0.18	0.17	0.21	0.18	0.24	0.15	0.15	0.16	0.18	0.10	
Sep_13(2).xls	0.11	0.13	0.17	0.16	0.15	0.18	0.16	0.18	0.16	0.07	0.14	0.11	0.14	0.10	
Sep_13(1).xls	0.09	0.11	0.22	0.16	0.18	0.17	0.18	0.19	0.21	0.18	0.17	0.15	0.16	0.08	
Sep_18.xlsx	0.18	0.14	0.14	0.14	0.15	0.15	0.17	0.14	0.17	0.20	0.12	0.15	0.15	0.14	
Feb_18(2)_20	0.03	0.11	0.10	0.11	0.10	0.11	0.10	0.09	0.10	0.10	0.08	0.10	0.11	0.03	
Feb_19(2)_20	0.10	0.16	0.13	0.13	0.13	0.14	0.13	0.13	0.14	0.14	0.13	0.16	0.11	0.09	
Mar_14(2)_20	0.04	0.16	0.15	0.10	0.18	0.15	0.15	0.15	0.17	0.13	0.16	0.17	0.17	0.03	
Feb_28(2)_20	0.08	0.20	0.21	0.17	0.17	0.18	0.18	0.16	0.15	0.18	0.17	0.18	0.18	0.08	
Feb_28(1)_20	0.11	0.09	0.13	0.12	0.15	0.15	0.15	0.14	0.15	0.13	0.11	0.13	0.12	0.10	
Feb_20(2)_20	0.10	0.10	0.10	0.10	0.10	0.08	0.09	0.09	0.10	0.09	0.10	0.09	0.10	0.08	
Feb_07(1)_20	0.07	0.16	0.24	0.21	0.17	0.16	0.19	0.18	0.21	0.15	0.20	0.21	0.25	0.09	
April_30_201	0.06	0.12	0.13	0.15	0.16	0.14	0.14	0.15	0.14	0.16	0.14	0.16	0.16	0.06	

Gamma1	Rest1	P1	E1	P2	E2	P3	E3	P4	E4	P5	E5	P6	E6	Rest2	
april_02(3)	0.04	0.05	0.08	0.14	0.07	0.07	0.06	0.07	0.08	0.06	0.07	0.14	0.09	0.14	
april_04(1)	0.19	0.13	0.13	0.14	0.16	0.09	0.08	0.13	0.13	0.11	0.16	0.17	0.07	0.21	
Apri_04(2).	0.08	0.09	0.06	0.08	0.06	0.07	0.06	0.08	0.08	0.09	0.06	0.12	0.06	0.07	
april_08.xls	0.07	0.13	0.11	0.08	0.09	0.11	0.02	0.08	0.09	0.09	0.10	0.06	0.01	0.07	
April_15.xl	0.09	0.09	0.09	0.09	0.14	0.11	0.11	0.10	0.12	0.10	0.10	0.11	0.14	0.08	
April_16(1)	0.04	0.06	0.06	0.05	0.13	0.06	0.08	0.12	0.06	0.08	0.04	0.14	0.07	0.04	
april_16(3)	0.06	0.09	0.09	0.09	0.09	0.10	0.10	0.17	0.09	0.13	0.15	0.10	0.08	0.07	
april_18(1)	0.07	0.15	0.24	0.25	0.25	0.09	0.24	0.26	0.21	0.29	0.13	0.26	0.13	0.07	
april_18(2)	0.05	0.05	0.07	0.06	0.05	0.04	0.05	0.05	0.05	0.05	0.06	0.05	0.06	0.04	
april_19(1)	0.02	0.06	0.11	0.09	0.08	0.11	0.10	0.08	0.08	0.11	0.12	0.08	0.13	0.04	
April_19(2)	0.02	0.09	0.09	0.11	0.10	0.09	0.08	0.09	0.09	0.09	0.08	0.08	0.07	0.06	
April_2(1).:	0.06	0.08	0.07	0.10	0.10	0.11	0.09	0.07	0.11	0.08	0.09	0.09	0.09	0.05	
april_22.xls	0.07	0.08	0.08	0.08	0.08	0.08	0.08	0.09	0.08	0.09	0.08	0.09	0.08	0.08	
april_24.xls	0.05	0.03	0.05	0.02	0.03	0.06	0.09	0.07	0.06	0.07	0.06	0.08	0.06	0.07	
aug_05.xlsx	0.02	0.07	0.07	0.06	0.07	0.07	0.08	0.07	0.07	0.06	0.10	0.07	0.07	0.02	
august_01.:	0.07	0.07	0.06	0.07	0.06	0.06	0.07	0.06	0.07	0.06	0.07	0.05	0.06	0.06	
July_29.xls:	0.05	0.06	0.09	0.08	0.09	0.12	0.10	0.15	0.08	0.14	0.07	0.11	0.09	0.06	
July_30.xls:	0.03	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.06	0.03	
June_25.xls	0.01	0.03	0.03	0.03	0.03	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.01	
Sep_12(2).:	0.29	0.09	0.10	0.13	0.11	0.12	0.14	0.11	0.11	0.12	0.09	0.11	0.10	0.06	
Sep_12(1).:	0.07	0.07	0.09	0.09	0.11	0.09	0.12	0.12	0.14	0.10	0.10	0.10	0.11	0.06	
Sep_13(2).:	0.05	0.08	0.08	0.08	0.08	0.09	0.08	0.08	0.08	0.05	0.08	0.16	0.08	0.04	
Sep_13(1).:	0.05	0.07	0.10	0.09	0.09	0.11	0.08	0.10	0.10	0.10	0.10	0.09	0.09	0.04	
Sep_18.xls:	0.11	0.11	0.15	0.15	0.15	0.16	0.16	0.16	0.15	0.15	0.18	0.21	0.19	0.13	
Feb_18(2)_	0.01	0.08	0.05	0.06	0.06	0.07	0.05	0.05	0.05	0.07	0.05	0.09	0.06	0.01	
Feb_19(2)_	0.06	0.07	0.09	0.09	0.08	0.08	0.10	0.09	0.09	0.08	0.11	0.09	0.07	0.07	
Mar_14(2)_	0.02	0.10	0.09	0.05	0.11	0.08	0.10	0.08	0.08	0.09	0.08	0.09	0.11	0.01	
Feb_28(2)_	0.02	0.10	0.08	0.05	0.05	0.06	0.05	0.04	0.05	0.06	0.07	0.05	0.06	0.02	
Feb_28(1)_	0.06	0.05	0.08	0.06	0.08	0.08	0.07	0.08	0.08	0.09	0.06	0.08	0.08	0.05	
Feb_20(2)_	0.05	0.07	0.07	0.07	0.08	0.05	0.07	0.07	0.05	0.05	0.06	0.06	0.07	0.04	
Feb_07(1)_	0.02	0.09	0.18	0.12	0.11	0.11	0.11	0.12	0.20	0.13	0.18	0.16	0.20	0.03	
April_30_2(	0.02	0.05	0.05	0.05	0.05	0.05	0.06	0.05	0.06	0.05	0.05	0.05	0.05	0.02	

G2	Rest1	P1	E1	P2	E2	P3	E3	P4	E4	P5	E5	P6	E6	Rest2	
april_02(3).xls	0.029	0.036	0.076	0.058	0.056	0.058	0.050	0.057	0.068	0.045	0.051	0.130	0.073	0.080	
april_04(1).xls	0.047	0.049	0.052	0.059	0.066	0.041	0.035	0.051	0.053	0.045	0.044	0.053	0.025	0.050	
Apri_04(2).xls:	0.079	0.111	0.036	0.071	0.040	0.047	0.042	0.061	0.058	0.056	0.038	0.104	0.039	0.056	
april_08.xlsx	0.047	0.074	0.086	0.064	0.069	0.068	0.014	0.058	0.068	0.072	0.073	0.045	0.004	0.052	
April_15.xlsx	0.042	0.058	0.053	0.051	0.068	0.075	0.083	0.058	0.091	0.067	0.076	0.078	0.102	0.039	
April_16(1).xls	0.025	0.045	0.039	0.040	0.156	0.056	0.069	0.087	0.058	0.069	0.029	0.093	0.052	0.027	
april_16(3).xls	0.033	0.051	0.061	0.062	0.071	0.057	0.061	0.160	0.054	0.095	0.111	0.048	0.047	0.040	
april_18(1).xls	0.053	0.134	0.181	0.205	0.215	0.051	0.207	0.252	0.188	0.227	0.112	0.211	0.106	0.053	
april_18(2).xls	0.026	0.030	0.048	0.036	0.030	0.029	0.038	0.044	0.036	0.034	0.050	0.029	0.056	0.024	
april_19(1).xls	0.013	0.037	0.084	0.069	0.064	0.105	0.080	0.060	0.064	0.084	0.111	0.057	0.100	0.028	
April_19(2).xls	0.012	0.051	0.050	0.074	0.057	0.052	0.054	0.057	0.056	0.049	0.047	0.046	0.043	0.033	
April_2(1).xlsx	0.056	0.060	0.043	0.080	0.102	0.106	0.064	0.050	0.093	0.078	0.127	0.088	0.090	0.042	
april_22.xlsx	0.053	0.051	0.050	0.055	0.063	0.067	0.057	0.059	0.062	0.060	0.054	0.069	0.055	0.056	
april_24.xlsx	0.029	0.025	0.029	0.018	0.020	0.071	0.071	0.088	0.053	0.059	0.035	0.072	0.049	0.037	
aug_05.xlsx	0.016	0.052	0.070	0.057	0.056	0.049	0.062	0.059	0.056	0.047	0.095	0.045	0.049	0.014	
august_01.xlsx	0.041	0.044	0.036	0.042	0.039	0.039	0.045	0.037	0.045	0.040	0.044	0.037	0.042	0.036	
July_29.xlsx	0.026	0.038	0.074	0.099	0.059	0.090	0.079	0.166	0.066	0.124	0.058	0.118	0.077	0.062	
July_30.xlsx	0.017	0.024	0.029	0.019	0.029	0.025	0.030	0.022	0.025	0.020	0.025	0.021	0.033	0.015	
June_25.xlsx	0.008	0.023	0.020	0.021	0.020	0.018	0.021	0.020	0.021	0.022	0.028	0.020	0.019	0.006	
Sep_12(2).xlsx	0.260	0.032	0.051	0.075	0.050	0.289	0.147	0.055	0.055	0.069	0.071	0.059	0.052	0.023	
Sep_12(1).xlsx	0.047	0.056	0.069	0.067	0.094	0.071	0.083	0.090	0.107	0.073	0.075	0.068	0.093	0.044	
Sep_13(2).xlsx	0.031	0.040	0.054	0.061	0.051	0.061	0.053	0.062	0.054	0.063	0.059	0.128	0.058	0.030	
Sep_13(1).xlsx	0.020	0.026	0.045	0.045	0.039	0.050	0.037	0.043	0.039	0.041	0.040	0.043	0.039	0.018	
Sep_18.xlsx	0.111	0.167	0.183	0.187	0.141	0.157	0.147	0.153	0.114	0.129	0.162	0.117	0.133	0.107	
Feb_18(2)_201	0.007	0.058	0.034	0.046	0.045	0.053	0.038	0.043	0.040	0.050	0.036	0.055	0.050	0.005	
Feb_19(2)_201	0.035	0.065	0.063	0.076	0.067	0.077	0.075	0.075	0.078	0.089	0.083	0.086	0.059	0.062	
Mar_14(2)_201	0.010	0.084	0.062	0.036	0.103	0.062	0.068	0.053	0.064	0.078	0.051	0.077	0.064	0.007	
Feb_28(2)_201	0.007	0.077	0.045	0.031	0.031	0.032	0.032	0.021	0.025	0.032	0.045	0.031	0.032	0.007	
Feb_28(1)_201	0.048	0.031	0.053	0.046	0.077	0.079	0.059	0.064	0.064	0.096	0.050	0.066	0.074	0.042	
Feb_20(2)_201	0.036	0.067	0.055	0.055	0.076	0.043	0.066	0.056	0.040	0.044	0.047	0.051	0.051	0.032	
Feb_07(1)_201	0.007	0.081	0.140	0.112	0.097	0.074	0.126	0.141	0.210	0.132	0.171	0.189	0.167	0.016	
April_30_2014	0.013	0.027	0.034	0.028	0.028	0.029	0.040	0.032	0.035	0.032	0.027	0.030	0.029	0.013	

G3	Rest1	P1	E1	P2	E2	P3	E3	P4	E4	P5	E5	P6	E6	Rest2	
april_02(3).xl	0.026	0.029	0.087	0.074	0.064	0.040	0.031	0.031	0.042	0.032	0.034	0.079	0.055	0.065	
april_04(1).xl	0.025	0.030	0.025	0.032	0.036	0.025	0.019	0.026	0.033	0.032	0.028	0.030	0.012	0.026	
Apri_04(2).xls	0.075	0.068	0.022	0.068	0.023	0.028	0.029	0.059	0.037	0.049	0.020	0.073	0.020	0.038	
april_08.xlsx	0.030	0.043	0.051	0.040	0.045	0.042	0.009	0.034	0.040	0.046	0.044	0.025	0.002	0.034	
April_15.xlsx	0.028	0.040	0.035	0.025	0.051	0.057	0.059	0.038	0.075	0.049	0.055	0.047	0.079	0.026	
April_16(1).xl	0.014	0.035	0.032	0.025	0.068	0.037	0.047	0.077	0.035	0.063	0.021	0.112	0.031	0.016	
april_16(3).xl	0.021	0.036	0.038	0.039	0.045	0.037	0.037	0.115	0.038	0.073	0.078	0.032	0.029	0.026	
april_18(1).xl	0.033	0.068	0.089	0.120	0.120	0.034	0.118	0.132	0.101	0.129	0.073	0.134	0.062	0.037	
april_18(2).xl	0.013	0.016	0.030	0.016	0.016	0.015	0.020	0.023	0.018	0.016	0.027	0.014	0.038	0.013	
april_19(1).xl	0.008	0.022	0.057	0.041	0.045	0.077	0.060	0.042	0.052	0.062	0.067	0.040	0.077	0.017	
April_19(2).xl	0.009	0.043	0.032	0.050	0.038	0.033	0.030	0.039	0.034	0.032	0.030	0.028	0.028	0.019	
April_2(1).xls	0.041	0.048	0.034	0.089	0.077	0.083	0.057	0.038	0.071	0.064	0.084	0.074	0.071	0.032	
april_22.xlsx	0.034	0.037	0.028	0.039	0.043	0.039	0.039	0.043	0.044	0.042	0.034	0.045	0.038	0.033	
april_24.xlsx	0.018	0.018	0.017	0.010	0.013	0.046	0.052	0.062	0.033	0.040	0.021	0.059	0.029	0.022	
aug_05.xlsx	0.011	0.036	0.046	0.041	0.038	0.035	0.039	0.038	0.036	0.032	0.074	0.032	0.033	0.009	
august_01.xls	0.025	0.027	0.024	0.027	0.025	0.024	0.028	0.026	0.030	0.025	0.030	0.021	0.029	0.021	
July_29.xlsx	0.014	0.026	0.046	0.054	0.057	0.080	0.061	0.070	0.052	0.117	0.039	0.096	0.053	0.055	
July_30.xlsx	0.016	0.014	0.016	0.014	0.020	0.021	0.022	0.014	0.016	0.014	0.014	0.012	0.028	0.008	
June_25.xlsx	0.006	0.015	0.015	0.014	0.013	0.012	0.014	0.012	0.016	0.013	0.024	0.014	0.011	0.006	
Sep_12(2).xls	0.176	0.016	0.034	0.043	0.031	0.148	0.075	0.030	0.031	0.048	0.037	0.031	0.027	0.013	
Sep_12(1).xls	0.029	0.039	0.041	0.046	0.065	0.047	0.057	0.060	0.078	0.050	0.046	0.046	0.063	0.031	
Sep_13(2).xls	0.064	0.077	0.073	0.070	0.047	0.065	0.043	0.051	0.047	0.025	0.047	0.052	0.043	0.022	
Sep_13(1).xls	0.011	0.014	0.024	0.025	0.023	0.029	0.020	0.025	0.026	0.024	0.022	0.021	0.020	0.010	
Sep_18.xlsx	0.048	0.157	0.090	0.119	0.132	0.111	0.109	0.119	0.091	0.140	0.100	0.128	0.106	0.072	
Feb_18(2)_20	0.004	0.039	0.021	0.032	0.044	0.037	0.025	0.032	0.028	0.050	0.026	0.052	0.033	0.003	
Feb_19(2)_20	0.021	0.035	0.039	0.054	0.043	0.062	0.046	0.056	0.060	0.059	0.073	0.047	0.034	0.048	
Mar_14(2)_20	0.006	0.054	0.037	0.022	0.055	0.035	0.034	0.031	0.039	0.057	0.034	0.053	0.034	0.005	
Feb_28(2)_20	0.004	0.040	0.024	0.017	0.016	0.018	0.019	0.013	0.013	0.017	0.021	0.018	0.016	0.004	
Feb_28(1)_20	0.263	0.452	0.113	0.164	0.173	0.117	0.236	0.193	0.254	0.287	0.331	0.174	0.331	0.157	
Feb_20(2)_20	0.022	0.048	0.034	0.035	0.036	0.026	0.037	0.033	0.027	0.029	0.031	0.031	0.033	0.019	
Feb_07(1)_20	0.005	0.115	0.141	0.133	0.071	0.064	0.109	0.111	0.208	0.118	0.174	0.158	0.153	0.013	
April_30_2014	0.008	0.020	0.020	0.018	0.019	0.020	0.029	0.022	0.026	0.027	0.023	0.022	0.021	0.009	

Appendix 2. Average of 32 subjects' relative EEG band power

EEG	Theta	Alpha	Beta1	Beta2	G1	G2	G3	
Rest1	0.32	0.40	0.13	0.12	0.06	0.04	0.03	
P1	0.41	0.22	0.14	0.15	0.08	0.06	0.05	
E1	0.41	0.20	0.15	0.16	0.09	0.06	0.04	
P2	0.39	0.21	0.14	0.16	0.09	0.06	0.05	
E2	0.39	0.21	0.15	0.16	0.09	0.07	0.05	
P3	0.39	0.22	0.15	0.16	0.08	0.07	0.05	
E3	0.40	0.20	0.13	0.16	0.09	0.07	0.05	
P4	0.36	0.22	0.15	0.17	0.09	0.07	0.05	
E4	0.38	0.21	0.14	0.17	0.09	0.07	0.05	
P5	0.37	0.21	0.15	0.16	0.09	0.07	0.06	
E5	0.40	0.21	0.13	0.15	0.09	0.07	0.06	
P6	0.36	0.20	0.14	0.17	0.10	0.07	0.06	
E6	0.41	0.21	0.13	0.15	0.08	0.06	0.05	
Rest2	0.29	0.45	0.13	0.12	0.06	0.04	0.03	

Appendix 3. Z-score of average of 32 subjects' relative EEG band power

X	Theta	Alpha	Beta1	Beta2	G1	G2	G3
Rest1	-1.56	2.05	-1.49	-2.19	-1.98	-1.98	-1.73
P1	0.95	-0.29	0.30	-0.43	-0.61	-0.54	0.68
E1	0.87	-0.44	0.81	0.09	0.33	0.03	-0.59
P2	0.42	-0.36	0.40	0.36	0.16	0.14	0.09
E2	0.18	-0.43	1.16	0.51	0.56	0.50	0.06
P3	0.21	-0.30	1.23	0.21	-0.03	0.51	-0.11
E3	0.73	-0.49	-0.71	0.35	0.25	0.38	0.14
P4	-0.49	-0.28	0.87	0.73	0.67	0.95	0.46
E4	0.10	-0.42	-0.33	1.00	0.52	0.41	0.59
P5	-0.17	-0.41	0.72	0.58	0.61	0.63	1.08
E5	0.72	-0.39	-1.49	-0.12	0.36	0.36	0.71
P6	-0.52	-0.45	0.68	1.04	1.37	1.04	0.85
E6	1.00	-0.43	-1.36	-0.01	0.05	-0.10	0.25
Rest2	-2.46	2.63	-0.78	-2.12	-2.25	-2.33	-2.48

Appendix 4. PCA transformed average EEG data

Z	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Rest 1	4.93	-0.34	-0.21	0.11	-0.15	0.01	-0.02
Rest 2	5.82	0.88	-0.23	-0.10	0.13	0.02	0.01
P1	-0.11	-0.58	1.10	0.91	0.10	0.06	0.01
P2	-0.69	0.10	0.37	-0.09	0.16	0.00	-0.01
P3	-0.72	0.92	0.69	-0.04	-0.14	-0.32	0.00
P4	-1.31	1.05	-0.53	0.03	-0.11	-0.17	0.00
P5	-1.46	0.58	-0.39	0.61	-0.03	0.05	-0.01
P6	-1.94	0.92	-1.01	0.00	-0.08	0.24	0.00
E1	-0.60	0.26	1.09	-0.62	-0.08	0.23	0.01
E2	-1.18	0.90	0.38	-0.18	-0.04	0.07	-0.01
E3	-0.74	-0.96	-0.06	-0.38	0.04	-0.16	0.00

E4	-1.16	-0.29	-0.65	-0.09	0.47	-0.05	0.01
E5	-0.58	-1.71	-0.55	0.05	-0.33	0.00	0.02
E6	-0.26	-1.73	0.00	-0.20	0.07	0.03	-0.02

Appendix 5. 32 Subjects PCA transformed EEG data

Subject	Rest1	P1	E1	P2	E2	P3	E3	P4	E4	P5	E5	P6	E6	Rest2	
1	3.87	0.92	-1.43	-0.82	-0.19	0.09	0.20	0.91	-0.98	0.43	0.58	-2.05	-0.69	-0.83	
2	-0.40	-0.25	-0.45	-1.15	-1.56	0.83	1.64	0.09	-0.78	0.39	-0.32	-0.70	2.77	-0.10	
3	0.60	-2.15	1.54	-1.30	1.16	0.52	0.78	-1.13	-0.17	-1.22	1.33	-3.15	0.65	2.55	
4	0.47	-1.04	-1.54	-0.81	-0.83	-0.78	2.40	0.37	-0.63	-0.52	-0.89	0.79	2.42	0.57	
5	1.33	0.87	1.47	0.11	-1.41	-0.68	-0.14	-0.21	-1.03	-0.73	-0.21	-0.71	-2.19	3.54	
6	2.27	0.54	1.17	0.67	-2.01	0.42	-0.54	-2.28	-0.11	-1.92	1.76	-2.42	0.22	2.22	
7	3.65	0.20	-0.26	0.06	-0.01	0.01	-0.70	-3.66	-0.26	-1.42	-1.61	-0.31	1.44	2.86	
8	2.92	0.18	-0.50	-1.51	-1.27	1.73	-1.24	-1.65	-0.74	-1.22	0.49	-0.90	0.83	2.88	
9	1.29	1.19	-0.95	-0.34	-0.11	0.96	-0.33	-0.99	-0.07	-0.11	0.00	0.35	-2.55	1.68	
10	5.14	0.85	-1.13	-0.61	-0.34	-1.77	-0.89	-0.50	-0.07	-1.46	-1.36	-0.47	-1.44	4.06	
11	4.03	-0.69	-0.51	-2.08	-1.15	-0.92	-0.30	-0.45	-0.87	-0.45	-0.32	-0.25	0.33	3.63	
12	3.04	0.42	0.73	-1.64	-1.24	-2.58	0.06	1.17	-1.02	-0.13	-1.35	-0.66	-0.77	3.97	
13	3.06	0.89	0.95	-0.23	-0.53	-1.32	-0.02	-1.26	-1.03	-1.66	1.92	-3.26	0.24	2.25	
14	1.67	1.28	0.89	2.02	1.93	-0.82	-2.20	-1.66	-0.47	-0.96	0.25	-1.85	-0.17	0.07	
15	4.93	-0.77	-1.22	-1.19	-0.72	-0.34	-1.15	-0.80	-0.74	-0.17	-2.68	-0.52	-0.19	5.57	
16	1.12	0.29	0.82	-1.14	0.81	-0.10	-1.89	0.97	-1.90	0.37	-1.23	1.04	-1.59	2.44	
17	2.38	1.25	-0.35	0.44	-0.20	-1.84	-0.81	-1.84	0.40	-2.56	0.70	-1.52	0.16	3.81	
18	1.84	1.06	-0.79	0.36	-0.94	-0.75	-1.58	-0.03	-0.57	0.34	0.39	-0.26	-2.13	3.06	
19	4.68	-1.31	-1.13	-0.83	-0.62	1.33	-1.27	-0.48	-1.09	-0.91	-2.65	-0.48	-0.65	5.40	
20	-1.61	0.20	0.55	-0.04	0.13	-1.04	-0.64	-0.39	0.01	-0.27	0.46	-0.24	0.07	2.80	
21	2.95	1.34	0.36	-0.05	-1.59	0.15	-1.58	-1.57	-2.94	-0.29	-0.10	-0.21	-1.44	4.96	
22	2.72	0.29	-0.94	-1.18	-0.25	-1.08	-0.28	-0.94	-0.68	1.41	-0.38	-2.34	-0.17	3.83	
23	4.30	3.45	-2.12	-0.55	-1.44	-1.53	0.08	-1.24	-1.83	-1.11	-1.30	-0.74	-0.29	4.31	
24	1.94	-0.83	0.08	-0.39	-0.31	-0.90	-0.48	-0.48	0.70	-0.97	-0.29	-0.55	-0.17	2.64	
25	5.44	-1.99	-0.09	-1.19	-1.34	-1.70	-0.57	0.33	-0.51	-1.02	-0.12	-1.61	-1.07	5.45	
26	3.37	-0.02	0.51	-0.97	-0.11	-0.93	-0.91	-0.79	-0.86	-1.02	-1.58	-1.66	1.66	3.32	
27	3.85	-2.03	-1.54	2.19	-2.37	-0.57	-0.40	0.45	-0.79	-0.91	0.02	-2.01	-0.66	4.76	
28	4.89	-3.91	-2.64	0.07	-0.12	-0.18	-0.36	0.83	0.29	-0.75	-1.53	-0.55	-0.89	4.83	
29	1.27	1.68	-0.43	0.42	-1.58	-0.90	-0.65	-0.53	-0.97	-1.28	0.49	-0.48	-0.70	3.67	
30	1.74	-2.16	-1.07	-1.13	-1.87	1.17	-0.54	-0.23	0.90	0.29	-0.44	0.08	-0.97	4.21	
31	4.46	0.00	-1.15	-0.69	-0.29	0.18	-0.41	-0.39	-1.52	-0.48	-1.12	-1.25	-1.37	4.04	
32	5.13	-0.25	-0.74	-0.42	-0.69	-0.35	-1.95	-1.12	-1.63	-1.60	-0.34	-1.19	-0.86	6.00	
Average	**2.76**	**-0.02**	**-0.37**	**-0.43**	**-0.66**	**-0.43**	**-0.52**	**-0.61**	**-0.69**	**-0.69**	**-0.36**	**-0.94**	**-0.32**	**3.26**	
SD	**1.72**	**1.41**	**1.03**	**0.93**	**0.91**	**0.98**	**0.93**	**1.01**	**0.77**	**0.81**	**1.08**	**1.01**	**1.21**	**1.65**	

Appendix 6. Matlab code for computing relative EEG band power

```
function eegpower2016liu()
%script to merge segments and compute power for EEG data
    %output is a matrix
    %read xls file
```

```
    %fname_xls = 'F:\Data\six-
problem\GSR_six_problem\Data\gsr_segments.xlsx';
    [FileName,PathName] = uigetfile('C:\Users\LIU LIXIN\Google
Drive\proj\PAPER2016\experimentdata\exdata\*.xlsx','Select the
eeg_segments.xlsx file');
    Segment_ID=[PathName,FileName];
    eegfolder =uigetdir('C:\Users\LIU
LIXIN\Documents\EEGA\eegsegment\','Select the eeg folder with *.mul');

    freqmax=60;% ta=[0.3 8]; %liu
    delta=[0.3 4];
    theta=[4 8];
    alpha = [8 13]; %LIU ALPHA FREQ
    beta1 = [13 20]; %beta 1 freq
    beta2 = [20 30];%beta 2 freq
    gamma1=[30 40];
    gamma2=[40 50];
    gamma3=[50 60]; %liu:
    totalband = [4 60]; %total freq



    fs = 500;
    nfft = 1024;
    winlength = 512;
    overlap= 256;

 [~, ~, alldata] = xlsread(Segment_ID);%LLX: Read  segments from excel file
subjects = alldata(2:end,1);
activities = alldata(1,2:end);
segments = alldata(2:end,2:end); %ignore headers
clear alldata;

    subjects = lower(subjects); %vector contains eeg file name % Liu:why
change to lowcase

    row = size(segments,1);
    col = size(segments,2);

     DELTA = zeros(row,col);
     THETA = zeros(row,col);
     ALPHA= zeros(row,col);
     BETA1 = zeros(row,col);
     BETA2 = zeros(row,col);
     GAMMA1 = zeros(row,col);
     GAMMA2 = zeros(row,col);
     GAMMA3 = zeros(row,col);

    TOTALPOWER = zeros(row,col);

   cc = jet(14) ; %list of colors

    calib = 1; %difference between eeg marker and segment xlsx

    %read all the eeg files
    d = dir(eegfolder);
```

```
    isub = [d(:).isdir]; %# returns logical vector
    nameFolds = {d(isub).name}';
    nameFolds(ismember(nameFolds,{'.','..'})) = [];
    nameFolds = lower(nameFolds);

    %for each eeg folder
    for i=1:length(nameFolds)
        %search corresponding name
        %make sure the name is different
        tmp = strfind(subjects, nameFolds{i});

        idx = find(~cellfun(@isempty,tmp));
        %if exists the file
        if (length(idx)==1)
            %  if (~isnan(seg_dur{idx,1}))
            if ((segments{idx,1})>0) %LIU Liu

               f = figure; %draw figure

                for c=1:col
                    %for each condition, merge the segments
                    if (ischar(segments{idx,c}))
                        %col_idx  = strsplit(segments{idx,j},',');
                        col_idx = str2num(segments{idx,c});
                    else
                        col_idx = segments{idx,c};
                    end

                    %sort the index
                    col_idx = sort(col_idx)+calib;

                    %read and merge the eeg data
                    %get into the eeg folder
                    subeeglist = dir([eegfolder,'\',nameFolds{i},'\*.mul']);
                    subeeglist = struct2cell(subeeglist);
                    %find the segments
                    for k=1:length(col_idx)
                        tmp = strfind(subeeglist(1,:), ['Mk',
num2str(col_idx(k)),'.mul']);
                        fileidx = find(~cellfun(@isempty,tmp));
                        tmp = load([eegfolder,'\',nameFolds{i},'\',
subeeglist{1,fileidx}]);
                        if (k==1)
                            data = tmp;
                        else
                            data = [data; tmp];
                        end
                    end
                    tmp = strfind(subeeglist(1,:), ['Mk',
num2str(col_idx(1)),'.mul']);
                    fileidx = find(~cellfun(@isempty,tmp));
                    data = load([eegfolder,'\',nameFolds{i},'\',
subeeglist{1,fileidx}]);

                    %compute power
```

```
                    [eegfolder,'\',nameFolds{i},'\', subeeglist{1,fileidx}]

                 if (length(data)<winlength)  pxx=0; %liu
                    else
                    [pxx, freq] = pwelch(data, winlength,overlap,nfft,fs);
                    fmin = find(freq>2,1);fmax = find(freq>freqmax,1);


                    if ((c==1)||(c==col)) %if rest
                        plot(freq(fmin:fmax),10*log10(pxx(fmin:fmax)),
'color', cc(c,:),  'Marker', '*');
                        %plot(freq(fmin:fmax),10*log10(pxx(fmin:fmax)),
'Marker', '*');
                    elseif (mod(c,2)==1) % LIU Plot the 6 activities of
EVALUATION(mod(c,2)==0).
                            plot(freq(fmin:fmax),10*log10(pxx(fmin:fmax)),
'color', cc(c,:));
                            %plot(freq(fmin:fmax),10*log10(pxx(fmin:fmax)));
                    end
                    hold on;

                    pdelta = bandpower(pxx, freq, delta, 'psd'); %LIU
                    ptheta = bandpower(pxx, freq, theta, 'psd'); %LIU

                    palpha = bandpower(pxx, freq, alpha, 'psd'); %LIU
                    pbeta1 = bandpower(pxx, freq, beta1, 'psd');
                    pbeta2 = bandpower(pxx, freq, beta2, 'psd');

                    pgamma1 = bandpower(pxx, freq, gamma1, 'psd');
                    pgamma2 = bandpower(pxx, freq, gamma2, 'psd');
                    pgamma3 = bandpower(pxx, freq, gamma3, 'psd');

                    ptotalband = bandpower(pxx, freq, totalband, 'psd');
%
                    %result
                    DELTA(idx,c) = pdelta;%LIU
                    THETA(idx,c) = ptheta;
                    ALPHA(idx,c) = palpha; %LIU
                    BETA1(idx,c) = pbeta1;
                    BETA2(idx,c) = pbeta2;
                    GAMMA1(idx,c) =pgamma1;
                    GAMMA2(idx,c) =pgamma2;
                    GAMMA3(idx,c) =pgamma3;

                    TOTALPOWER(idx,c) = ptotalband;
%                     output_total02(idx,c) = total_power2;

                    %clear variables
                    clear ratio tmp data;
                 end  %liu
                end
                   EEGPOWER_rel={THETA./TOTALPOWER...
                       ALPHA./TOTALPOWER BETA1./TOTALPOWER
BETA2./TOTALPOWER...
```

```
                       GAMMA1./TOTALPOWER GAMMA2./TOTALPOWER
GAMMA3./TOTALPOWER};  % LIU Caculate the relative beta2 power

                %all about the figure
                t = title(nameFolds{i});
                set(t,'Interpreter','none');
                lh = legend('Rest 1', 'E1', ...
                               'E2',  ...
                               'E3', ...
                               'E4',...
                               'E5',...
                               'E6',...
                                'Rest 2');
%                 set(lh,'location','northeastoutside');
                set(lh,'location','northeast'); %LIU
                saveas(f, [nameFolds{i},'.png']);

            end
            %   %             close all; %close figure;
        elseif (~isempty(idx))
            sprintf('there is a problem with file name');
            break;
        end

    end


  EEGPOWER_ave = zeros(col, size(EEGPOWER_rel,2));
    for i1=1:size(EEGPOWER_rel,2);
        EEGPOWER_ave(:, i1)=(mean(EEGPOWER_rel{i1}))';
    end

 save('eegpower2016.mat');

figure
boxplot(EEGPOWER_ave);
  title('Average EEG relative power');%Liu
    xlabel('Frequency Band');%Liu
    ylabel('Averge Power'); %Liu
savefig(gcf,'eeg_design_boxplot');

figure
bar(EEGPOWER_rel{4},'DisplayName','EEGPOWER_rel')%Liu
title('Relative beta2 power');
savefig(gcf,'output_relb2')%Liu

figure
boxplot(EEGPOWER_rel{4}); %Liu
    title('Rel beta2 power');%Liu
    xlabel('Activities');%Liu
    ylabel('Relative power'); %Liu
    savefig(gcf,'eeg_powerb2_boxA');
end
```

Appendix 7. Matlab code for computing PCA of average EEG power

```
% Select the file to Analyze
[FileName,PathName] = uigetfile('C:\Users\LIU LIXIN\Google
Drive\proj\PAPER2016\experimentdata\eegscdata01\EEG\eegdesigns\eegdesignREL\*
.xlsx','Select the *.xlsx file to Analyze');
nfile=([PathName,FileName]);
[X1, txt, alldata] = xlsread(nfile);
var_liu = char(txt(1,2:end));
observations = char(txt(2:end,1));

npl=normplot(X1);  %0
title('normplot(X1)');
saveas(gcf,'f00.png');
savefig('f00');


%Plotting of covariance matrix of waferdata using plottable.m (Q4b)
[n,p]=size(X1);
%The data for many of the variables are strongly skewed to the right.
%scatterplot matrix of the data
[ha,ax,bigax,P]=plotmatrix(X1);  %1
axes(bigax);
title('plotmatrix(X1)');
saveas(gcf,'f01.png');
savefig('f01');
delete(P); %delete the histograms

boxplot(X1,var_liu);
saveas(gcf,'f02.png');
savefig('f02');

% Center X by subtracting off column means
X0 = bsxfun(@minus,X1,mean(X1,1));
S = X0'*X0./(n-1); %Covariance matrix

xbar = mean(X1,1);
[R,sigma] = corrcov(S);
corrmat = corrcoef(X1);
figure; imagesc(corrmat); %3
set(gca,'XTick',1:p); set(gca,'YTick',1:p);
set(gca,'XTickLabel',var_liu); set(gca,'YTickLabel',var_liu);
axis([0 p+1 0 p+1]); grid; colorbar;
saveas(gcf,'f03.png');
savefig('f03');

figure; displaytable(corrmat,var_liu); %4
saveas(gcf,'f04.png');
savefig('f04');


figure('Name','Component Correlation Matrix'); %4a
plottable(corrmat,'%.2f');
set(gca,'LineWidth',1.2);
```

```
set(gca,'FontSize',12);
set(gca,'color',[.95 .95 .95],'XColor','white', 'YColor','white');
set(gcf,'color','white'); %camzoom(1.1);
set(gcf,'InvertHardCopy','off');
set(gcf,'PaperPositionMode','auto');
title('Component Correlation Matrix')
saveas(gcf,'f4a.png');
savefig('f04a');

%Applying PCA:
% [A,Z,variance,Tsquare]=princomp(X) performs PCA on the n-by-p data matrix
X, and returns the
% principal component coefficients, also known as loadings. Rows of X
correspond to observations,
% columns to variables. A is a p-by-p matrix, each column containing
coefficients for one principal
% component. The columns are in order of decreasing component variance.
% Z=the principal component matrix scores; that is, the representation of X
in the principal component space.
% Rows of Z correspond to observations, columns to components.
% Variance= a vector containing the eigenvalues of the covariance matrix of
X.
% Tsquare= contains Hotelling's T2 statistic for each data point.
% princomp centers X by subtracting off column means, but does not rescale
the columns of X.
% To perform principal components analysis with standardized variables, that
is, based on correlations,
% use princomp(zscore(X))
%ZSCORE X

X=zscore(X1);
X=X1;
[A,Z,variance,Tsquare]=pca(X);

% PC2 coef vs. PC1 coef
figure; %5
scatter(A(:,1),A(:,2),15,'ko','MarkerFaceColor',[.49 1 .63],'LineWidth',1);
title('Scatter plot of 2nd PC vs. 1st PC');
xlabel('PC1 coefficient','fontsize',14,'fontname','times');
ylabel('PC2 coefficient','fontsize',14,'fontname','times');
centeraxes(gca); %Center the axis
gname(var_liu)
saveas(gcf,'f05.png');
savefig('f05');

%PC3 coef vs. PC2 coef
figure;%5a
scatter(A(:,2),A(:,3),15,'ko','MarkerFaceColor',[.49 1 .63],'LineWidth',1);
title('Scatter plot of 2nd PC vs. 3rd PC');
xlabel('PC2 coefficient','fontsize',14,'fontname','times');
ylabel('PC3 coefficient','fontsize',14,'fontname','times');

centeraxes(gca); %Center the axis

gname(var_liu); %press the Enter or Escape key to stop labeling.
saveas(gcf,'f05a.png');
```

```
savefig('f05a');

%PC3 coef vs. PC1 coef
figure;%5a
scatter(A(:,1),A(:,3),15,'ko','MarkerFaceColor',[.49 1 .63],'LineWidth',1);
title('Scatter plot of 1st PC vs. 3rd PC');
xlabel('PC1 coefficient','fontsize',14,'fontname','times');
ylabel('PC3 coefficient','fontsize',14,'fontname','times');
centeraxes(gca); %Center the axis
gname(var_liu); %press the Enter or Escape key to stop labeling.
saveas(gcf,'f05b.png');
savefig('f05b');

%Plotting Explained variance vs number of Principal Components (Q4d)
%using Plot and Pareto commands
expvar=100*variance/sum(variance);%percent of the total variability explained
by each principal component.
figure;%6
plot(expvar,'ko-','MarkerFaceColor',[.49 1 .63],'LineWidth',1);
xlabel('Number of Principal Components','fontsize',14,'fontname','times');
ylabel('Explained Variance %','fontsize',14,'fontname','times');
title('Scree Plot: Explained variance vs. Principal Component Number');
% gname(expvar)
saveas(gcf,'f06.png');
savefig('f06');

figure;%7
pareto(expvar);
xlabel('Number of Principal Components','fontsize',14,'fontname','times');
ylabel('Explained Variance %','fontsize',14,'fontname','times');
title('Pareto of Explained variance vs. Principal Component Number');
saveas(gcf,'f07.png');
savefig('f07');


% PC2 score vs. PC1 score  (Q4f)
figure;%8
scatter(Z(:,1),Z(:,2),15,'ko','MarkerFaceColor',[.49 1 .63],'LineWidth',1);
title('Scatter plot of 2nd PC vs. 1st PC');
xlabel('PC1 score','fontsize',14,'fontname','times');
ylabel('PC2 score','fontsize',14,'fontname','times');
centeraxes(gca); %Center the axis
gname(observations)
saveas(gcf,'f08.png');
savefig('f08');

% PC3 score vs. PC2 score
figure;%8a
scatter(Z(:,2),Z(:,3),15,'ko','MarkerFaceColor',[.49 1 .63],'LineWidth',1);
title('Scatter plot of 3rd PC vs. 2nd PC');
xlabel('PC2 score','fontsize',14,'fontname','times');
ylabel('PC3 score','fontsize',14,'fontname','times');
centeraxes(gca); %Center the axis
gname(observations)
saveas(gcf,'f08a.png');
savefig('f08a');
```

```
% PC3 score vs. PC1 score
figure;%8b
scatter(Z(:,1),Z(:,3),15,'ko','MarkerFaceColor',[.49 1 .63],'LineWidth',1);
title('Scatter plot of 3rd PC vs. 1st PC');
xlabel('PC1 score','fontsize',14,'fontname','times');
ylabel('PC3 score','fontsize',14,'fontname','times');
centeraxes(gca); %Center the axis
gname(observations)
saveas(gcf,'f08b.png');
savefig('f08b');


%The following command and plot show that two components account for 98% of
the variance:

cumsum(variance)/sum(variance);
figure;%9
%Biploy helps visualize both the principal component coefficients for each
variable and the principal
%component scores for each observation in a single plot.
biplot(A(:,1:2),'Scores',Z(:,1:2),'VarLabels',var_liu,'MarkerSize',15)
xlabel('$Z_1$','fontsize',14,'fontname','times','Interpreter','LaTex');
ylabel('$Z_2$','fontsize',14,'fontname','times','Interpreter','LaTex');
title('2D biplot A and Z of 2nd PC vs. 1st PC ');

text(Z(:,1),Z(:,2),observations)

axis tight;
saveas(gcf,'f09.png');
savefig('f09');

figure;%9a
biplot(A(:,2:3),'Scores',Z(:,2:3),'VarLabels',var_liu,'MarkerSize',15)
xlabel('$Z_2$','fontsize',14,'fontname','times','Interpreter','LaTex');
ylabel('$Z_3$','fontsize',14,'fontname','times','Interpreter','LaTex');
title('2D biplot A and Z of 3rd PC vs. 2nd PC');
axis tight;
saveas(gcf,'f09a.png');
savefig('f09a');

figure;%9b
biplot(A(:,[1,3]),'Scores',Z(:,[1,3]),'VarLabels',var_liu,'ObsLabels',observa
tions,'MarkerSize',15)
xlabel('$Z_2$','fontsize',14,'fontname','times','Interpreter','LaTex');
ylabel('$Z_3$','fontsize',14,'fontname','times','Interpreter','LaTex');
title('2D biplot A and Z of 3rd PC vs. 1st PC');
axis tight;
saveas(gcf,'f09b.png');
savefig('f09b');


figure('Name','3D biplot A and Z');%10
biplot(A(:,1:3),'Scores',Z(:,1:3),'ObsLabels',observations,'VarLabels',var_li
u,'MarkerSize',15)
```

```
 xlabel('$Z_1$','fontsize',14,'fontname','times','Interpreter','LaTex');
 ylabel('$Z_2$','fontsize',14,'fontname','times','Interpreter','LaTex');
 zlabel('$Z_3$','fontsize',14,'fontname','times','Interpreter','LaTex');
 title('3D biplot A and Z');
axis tight;
saveas(gcf,'f10.png');
savefig('f10');

figure;%11
alpha = 0.05;
[outliers1, h1] = tsquarechart(X,alpha); %T^2 chart
title('tsquarechart(X,alpha)');
saveas(gcf,'f11.png');
savefig('f11');

figure;%12
k=1;
[outliers2, h2] = pcachart(X,k); %1st PCA control chart
ylabel('$Z_1$','fontsize',14,'fontname','times','Interpreter','LaTex');
title('PCA control chart');
saveas(gcf,'f12.png');
savefig('f12');

save([FileName,'pca.mat']);
```