ANALYSIS ON VIDEO GAMES DESIGN STYLES BASED ON NEURO-AFFECTIVE COMPUTATIONAL MODEL

BY

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ABSTRACT

Visual elements in video games contribute to a huge factor in design decision of the production. This research explores the science behind the psychology of design styles in video games via quantitative analysis. Previous works studying design styles and their influence over the human mind lack quantitative analysis. Their approach of using subjective experiments do not accurately provide a clear picture of the design-psyche relationship. Current guidelines for designers to decide design style is vague, relying on traditional formula of using shapes as symbols for psychological influences. In particular, affective responses towards particular Design Styles were never understood. Thus, an analysis of Design Styles using Electroencephalogram (EEG) to study its effect on the human emotions is proposed. Classifying EEG data via machine learning allows accurate numerical analysis of Design Styles and their affectivity. The findings enable the understanding of the cause and effect between design and emotions. It can help designers exploit their design potential and the research framework will be a significant contribution in the field of computer science. Subjects play 2 video games of distinct design styles – abstract and realistic - following a strict research protocol for EEG experiments. EEG data sets collected include brain's cognitive functions, stimulated emotional responses, resting state, game playing sessions, and post-experiment state. These numerical measurements are classified using machine learning by applying a known computational model that was constructed from stimulated emotional responses. IAPS serves as the instrument for emotional stimulation. Computer models of valence and arousal are generated through PSD feature extraction while MLP algorithm is applied for the machine learning classification process. Tables and spreadsheets are then laid out for statistical analysis to correlate design and the human psyche. Results from these analysis show evidences of designs styles influences over the subjects' brain activity. Indeed, specific cognitive functions such as memory, literacy, and reasoning are present within the game playing session, indicating a sub-conscious activity from the game that was not purposely designed to stimulate them. While the emotional state never changed between the two different games, the intensity and mood certainly show some distinctions. It seems that arousal intensity are more responsive towards abstract than realistic design. Positive valency also showed its association with abstract design. On the other hand, realism seems to be associated with stable and sustained mood. Deviation of arousal responses reveals that 'appeal' of the design styles depend on the person, not an influence resulted from the design styles. It points out that in the end, design styles may influence certain specific cognitive activity, but they are not substitutes for the designer's artistic ability to make good design.

ملخص البحث

تساهم العناصر المرئية في ألعاب الفيديو كعامل كبير في قرار تصميم الإنتاج. يستكشف هذا البحث علم نفس أساليب التصميم في ألعاب الفيديو من خلال التحليل الكمي. حيث تفتقر الأعمال السابقة التي تدرس أساليب التصميم وتأثيرها على العقل البشري إلى التحليل الكمي ويستخدمون نهج التجارب الذاتية الذي لا يوفر بدقة صورة واضحة للعلاقة بين التصميم والنفسية. الإرشادات الحالية للمصممين لتحديد أسلوب التصميم غامضة، وتعتمد على الصيغة التقليدية لاستخدام الأشكال كرموز للتأثيرات النفسية. ولم يتم فهم الاستجابات العاطفية تجاه أنماط تصميم معينة على وجه الخصوص. وبالتالي، يُقترح تحليل أنماط التصميم باستخدام مخطط كهربية الدماغ (EEG) لدراسة تأثيره على المشاعر البشرية. يسمح تصنيف بيانات EEG عبر التعلم الآلي بتحليل رقمي دقيق لأنماط التصميم وتأثيرها. حيث تمكن النتائج فهم السبب والنتيجة بين التصميم والعواطف. ويمكن أن يساعد المصممين على استغلال إمكاناتهم التصميمية وسيكون إطار البحث مساهمة كبيرة في مجال علوم الكمبيوتر. يلعب المشاركون لعبتي فيديو بأنماط تصميم مميزة –تجريدية وواقعية– ويتم اتباع بروتوكول بحث صارم لتجارب EEG . تتضمن مجموعات بيانات EEG التي تم جمعها الوظائف الإدراكية للدماغ، والاستجابات العاطفية المحفزة، وحالة الراحة، وجلسات اللعب، وحالة ما بعد التجربة. يتم تصنيف هذه القياسات العددية باستخدام التعلم الآلي من خلال تطبيق نموذج حسابي معروف تم إنشاؤه من الاستجابات العاطفية المحفزة. يعمل نظام الصور العاطفية الدولي IAPS كأداة للتحفيز العاطفي. ثم تم إنشاء نماذج الكمبيوتر للتكافؤ والإثارة من خلال استخراج ميزة الكثافة الطيفية للقدرة PSD ، بينما يتم تطبيق خوارزمية متعدد طبقات المستقبلات MLP لعملية تصنيف التعلم الآلي. ثم تم وضع الجداول وجداول البيانات للتحليل الإحصائي لربط التصميم والنفسية البشرية. تظهر نتائج هذا التحليل أدلة على تأثير أنماط التصاميم على نشاط دماغ الأشخاص. في الواقع، توجد وظائف معرفية محددة مثل الذاكرة ومعرفة القراءة والكتابة والتفكير داخل جلسة اللعب، مما يشير إلى نشاط غير واع من اللعبة لم يتم تصميمه عن قصد لتحفيزهم. في حين أن الحالة العاطفية لم تتغير أبدًا بين اللعبتين المختلفتين، إلا أن الشدة والمزاج يظهران بالتأكيد بعض الفروق. ويبدو أن شدة الإثارة أكثر استجابة تجاه التصميم التجريدي من الواقعي. أظهر التكافؤ الإيجابي أيضًا ارتباطه بالتصميم المجرد. من ناحية أخرى، يبدو أن الواقعية مرتبطة بمزاج مستقر ومستدام. ويكشف انحراف استجابات الإثارة أن "جاذبية" أنماط التصميم تعتمد على الشخص، وليس التأثير الناتج عن أنماط التصميم. ويشير إلى أنه في النهاية، قد تؤثر أنماط التصميم على نشاط معرفي معين، لكنها ليست بدائل لقدرة المصمم الفنية على تصميم جيد.

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DECLARATION

I hereby declare that this thesis is the result of my own investigations, except where otherwise stated. I also declare that it has not been previously or concurrently submitted as a whole for any other degrees at IIUM or other institutions.

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This thesis is dedicated to my late father for his dedication in raising his children to be the best among the Ummah. It is also dedicated to my mother who is fighting Parkinson's Disease but never stopped encouraging me to fulfill my dream.

May Allah bless their souls.

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DEFINITION OF TERMS

1. Design Style is defined by the level of realism in the rendering of the virtual world in video games. Sometimes it can also be termed as Graphical Style (Carter, 2016). Throughout this research, the context of Design Style is video games visual design. This is to contrast the term Design Style used by architects and interior designers.
2. Machine Learning is an automated process of complex tasks in analyzing data. It can also be referred to as Artificial Intelligence (AI). However, the term AI may mislead to the idea of computational awareness that is usually associated with robotic design. This is not the case for this research. The Machine Learning process used in this experiment is a classification process of interpreting and predicting data.
3. Valence is an emotional dimension that refers to the positive and negative acceptance.
4. Arousal is an emotional dimension that refers to the intensity of the emotions.
5. Neuro-Affective is the emotional valence and arousal responses emitted by the brain through pulses of small electrical signals. This is a natural phenomenon. The signals can be detected and recorded, thus providing data for numerical analysis
6. Electroencephalogram (EEG) is a technology that allows brain signals to be recorded, measured, and analyzed.
7. Computational Model is the numerical and algorithmic references of a known data that serves as the baseline to predict unknown data. It is important to have a computational model to translate raw data into something meaningful for analysis. Computational Model can be obtained through the process of Feature Extraction.
8. Feature Extraction is an algorithm to acquire computational model of stimulated data. It is one of the key components to allow classification process to work.
9. Cognitive Functions are the many aspects of the human brain functions to perform cognition tasks.

CHAPTER 1

INTRODUCTION AND RESEARCH BACKGROUND

1.0 INTRODUCTION & BACKGROUND INFORMATION

In the age of the Fourth Industrial Revolution (IR4.0), video games have become one of the most popular and profitable business. According to the statistic portal, Statista (statista.com), in the Apple App Store alone, 12.68% of the most downloaded apps by 3rd Quarter of 2022 are games. This figure is significant, because the next most downloaded apps are in the business category, which is only 10.35% of total downloads. While parents may have concerns over the effects of games on their children's growth, they are so common that no one can ignore. It is thus important to understand the effects of video games design on the players.

Design styles are one of many important decision factors faced by video games designers. It is a form of visual language to communicate the player what kind of video game he or she is playing. However, the psychological impact of design styles goes beyond what the eyes see. In animation production – a less interactive form of the same media – a phenomenon known as the 'uncanny valley' subconsciously caused the viewer to feel contempt towards realistic design styles (Mori, 2012). On the other hand, exaggerated proportion of the stylized design styles may be attractive to younger audience such as cartoons for children (Ben-Zvi et al., 2016). Clearly, different design styles has different psychological effects to the audience.

Since design styles can influence the mind and emotion (Khairuddin et al., 2014), learning acquisition skills are also affected. It is the effects on the learning aptitude that this research is focused on. While there exist video games designed to be 'educational' from the ground-up, the interest here is whether the 'non-educational' games has any effects on the learning aptitude at all. After all, around 95% of the games available in the market today are purely designed for entertainment rather than educational.

1.1 HISTORY AND DEVELOPMENT OF DESIGN STYLES.

The history of design styles started during the days of traditional animation. In the 1930s, animators (mostly by Disney) made animated films and cartoons by hand drawing. To achieve the effects of "persistence of vision" – thus creating the illusion that the drawings are moving and acting – animators had to draw a lot of drawings (Johnston & Thomas, 1981). A one second motion would take around 12 to 24 drawings (Williams, 2009). An hour feature film would take 86,400 drawings and that is just for one moving elements/character in the scene. A scene may contain more than one characters to be animated.

To simplify the drawing process, Disney animators designed their characters to be easy to replicate and hand drawn over and over again (Bancroft, 2006; Boot & Hommel, 2015). Their technique is part of the twelve principles of animation, known as 'solid drawings'(Johnston & Thomas, 1981). This concept forces the animators to draw characters in volumes and consistent geometric structure underneath a detailed design. All of the iconic characters by Disney were designed like this: Mickey Mouse, Donald Duck, Goofy, etc. Thus, an abstract design was born. For years (and even now) animators adopted this technique including those by Warner Bros. who created Bugs Bunny and Daffy Duck.

However, cartoons characters with realistic proportions and forms made their appearance with the invention of a new technique called Rotoscoping. During these times, films were cheap enough to be made so that real life actors can be traced over and animation characters can take the form of realistic human shape.

Rotoscoping made animation production a little easier but it has major flaws. First, it cannot be made appealing due to the realistic movements in which it was traced over. Drawings, even when traced over a real sample, cannot be detailed enough to convey realistic motions. Cartoons with abstract design often has exaggerated movements to make it more interesting and attractive. This is the first sign of the 'uncanny valley' effect which will be discussed later in this thesis. Second, the rotoscoping technique cannot adapt the twelve principles of animation which creates the illusion of life (Johnston & Thomas, 1981). Principles such as exaggerated movements, squash and stretch, and staging are very hard to be adopted to rotoscoping technique. Finally, rotoscoping technique simply does not have the freedom of creativity that abstract design allows.

Over the years, technology and techniques evolve. They also merge, adapting Rotoscope with the animation principles as the main structure. Design also evolve, and a style between abstract and realistic was conceived. For instance, in Asia the most popular and appealing stylized character design is the Japanese anime. Somewhere between a simplified geometric shapes and realistic human proportions (particularly female characters), anime has fans all over the world.

Primarily, design styles evolve and developed side by side with techniques and technologies to make them. Abstract design has always been a starting point and the realistic design has always been the goal. Current technologies no longer pose any limits to character designs. Similar milestone also happened to other art medium such as puppeteering and 3D "virtual reality" video games. However, today, the technology to digitally 'sculpt' any 3D shapes in virtual space is so advanced and intuitive, designers are no longer constrained to limit their ideas. They instead use design styles based on conceptual needs. For instance, designers of the game *Team Fortress 2* adopted stylized characters so that their characters are instantly identifiable even in silhouette (McMahan et al., 2015). It is at this point that the awareness of design styles' effect to the player's mind, emotions, and other behaviors are not fully understood.

1.2 SIGNIFICANCE AND BENEFITS OF RESEARCH FOR GAME DEVELOPERS, DESIGNERS, AND THE INDUSTRY AS A WHOLE

In principle, when conceiving video games with specific target audience, design styles should function as one of the important visual elements that stimulate the player's mood to tune-in to the proper mind set for the game's intended concept. For instance, colorfully stylized characters suggests children related content. Alternatively, desaturated realism hints at horror themed genre. Design styles communicate to the consumer well before they play the game. Apart from visual communication, the pursuit of realism to attract as many audience as possible is also major factor in the video games industry. The technological advancement of these top rated games such as *Grand Theft Auto V, Metal Gear Solid V: Phantom Pain, Call of Duty: Modern Warfare,* and *Cyberpunk 2077* is so high that it is difficult for the untrained eye to distinguish between computer generated image (CGI) and image of reality.

However, these design styles can be mis-matched on purpose to create a new breed of content. Adult oriented content can also be made to look stylized and colorful, and children's content consists of realistic looking characters. There are also top tier games that did not recreate realism for attraction – games such as *Fortnite, Team Fortress,* and *Loadout.* Those games could have taken advantage of the powerful graphic technology to achieve realism. Instead, they had gone to the stylized route to create fun and enjoyable images of their products. In fact, in the case of *Team Fortress,* the designers purposely use stylized design to create highly memorable characters (Mitchel, 2007). They made it so that the players instantly recognize the characters in any angles, even in silhouette.

While design styles cue the consumer about the content of the video games, it can sometime be misleading (Carter, 2016). Parents may mistake games for children for games for adults. Games that are interesting at the few rounds of play may lose replay value and therefore its shelf life. Some games simply look outdated and dull. Not to mention the cost of creating realistic games may take a huge amount of money and designers' skills – only to find out that the pursuit of realism may not be worth it.

Realism in video games graphics also has a big problem. Historically, and studied by other researches (Mori, 2012; Geller, 2008; Schneider, 2007), realistic renderings of computer generated human (or human-like characters) has the tendency for giving a repulsive reaction to the audience. This reaction is known as the "uncanny valley phenomenon". The uncanny valley refers to the valley-like curve of the likeness or pleasantness of the viewer when looking at a realistic looking artificial characters. It shows that as the character is closer to looking like a human, the interest and arousal increases until at a certain point where the curve suddenly drops. Having the game designed within the uncanny valley would be catastrophic, since no one wants to even look at the game. Let alone plays and buys it.

As a consequence, the full potential of the video game may not be exploited and benefited by the design styles they used. Contents may be misled by the wrong visual themes. Interesting and challenging games may lose their worth because they simply do not look promising. Those top tier games invested a lot to reach ultimate realism in graphics may not achieve the ultimate gaming experience as the design suggests – and lose money in making them as well. Losing audience, high costs, and misunderstood contents are some of the issues that contribute to the failure of a production that, at concept stage, may have high potential.

The problem, then, stems from the lack of understanding of design styles and how it affects the players (Lee, 2018). In the context of video games, it is usually the correlation with emotion of playing the game that is important. Emotional responses helps make the game more enjoyable and motivates the player to grind and overcome the challenges. In particular, the emotional valence and arousal are the two quantitative constructs that can be measured for research. Thus far, there are no studies that relates design styles with emotional valence and arousal.

The biggest concern of this research is how it is going to contribute to the growth and development of the video game industry. It is also to be highlighted that the body of knowledge that this research discusses has a high significance in the design community. Most importantly, the contribution of this research can be a valuable asset for designers, developers, researchers, and the video games economy.

1. Significance
    a. Quantitative analysis and understanding via machine learning of the effects of design styles on video game players. This approach has the advantage of obtaining emotional information directly from the brain, eliminating misinterpretation from the subject’s verbal feedback.
    b. Correlation of design and brain activity, specifically the cognitive functions. Since the data obtained is quantifiable data, correlation between Design Styles and brain activities extracted from EEG is possible.
    c. Emotional responses affected by different Design Styles, thus allowing the study of design-player relationship through neuro-affective model. By understanding this relationship, designers have the potential of being empowered to enhance the effectiveness and value of their design.

2. Benefits
    a. Adding factors to design decisions enabling developers to evaluate their projects effectively. The most gain can be obtained by channeling the right

amount of resources (budget, skills, and hardware capabilities) to the right direction. Indirectly, this may potentially increases profit.

b. Provides insights as to what is 'perfect' and what is 'good enough' when pursuing realism in game design, effectively manages resources accordingly. Sometimes being perfect is not important. Being excellent at delivering high-quality design is a higher priority.

3. Contribution
    a. Research methods to apply EEG and machine learning to analyze design styles and the human psyche. In this research, the context and scope are cognitive functions and emotional responses. Opportunities for other contexts and scopes can apply the same methodology as done by this research.
    b. Body of knowledge about design styles and their effects on the human mind. Designers can exploit the findings of this research for their own advantage to maximize their work potential.
    c. Adding value to the video games content. Apart from target audience filters – such as adult rated contents and parental guidance recommendations – video games can now be valued by how it affects the cognitive functions of the brain and/or emotions. Educational values for educational video games can be rated more effectively and therefore it is hoped that such qualities can take the video games industry to a higher level.

1.3 PROBLEM STATEMENTS

Ideally, every visual components such as colour schemes, themes, and design styles should have a clear purpose to the overall renderings of any video games design. These components are what makes the game visually attractive and pulls people to play and engage.

However, the effects of Design Styles were never really understood in designing a video game better or worse (Lee, 2018; Carter, 2016). Current approach simply depends on the design team's preferences, market trends, or resource limitations. In particular, how Design Styles affect the minds of the player is still vague, especially in terms of quantitative correlations.

As a consequences, maximum design potential of a particular game concepts is left unexploited. Due to the mis-match of Design Styles, visual communications are less efficient to compliment the game genre, play-mechanics, and narratives. Budgeting is also affected, as the expenditure of high skills and advanced technology to make the game inclined towards Realistic Design Style is obviously very high (Keo, 2017). In fact, realism may sometimes does not have any benefits to the game experience at all and it is better to be made with a more stylised approach.

This research proposes the correlation between design styles and affective valence and arousal (i.e. emotions) via Electroencephalogram (EEG). While there are other researches that study design styles, their approach lacks numerical and statistical analysis with measured data collection. EEG is the solution to measure human emotion while playing video games. A stimuli for emotions can serve as the control data to generate a neuro-affective model – which in this case is the valence and arousal model. This model can then be applied to classify the game playing EEG data for analysis using machine learning.

EEG data, machine learning classifications, and neuro-affective model are the key ingredients to open up opportunities to explore new studies on how design styles affects gamers. The gaps in questions are:

1. Analysis on design styles - *abstract, stylised, realistic* - affecting the human mind has never been explored using EEG.
2. Previous works that analysed Design Styles and the brain cognitive functions lacked quantitative evidences.
3. There are no detailed study on the correlation of design styles with emotional responses.
4. Classification of design styles with brain activities via machine learning requires a new framework. This research hopes to contribute its methodology by conceiving a new framework based on an existing one.

At the end of this research, it is hoped that the insights of the research findings can be exploited by designers and developers to enhance their production value as well as making the right decisions on making a video game.

1.4 RESEARCH QUESTIONS

In order for this research to be of important value, it has to answer some very important research questions. Otherwise, it has no reason for being. This research is thus aimed to answer these questions:

1. What is the quantitative and measurable connection between Design Styles and affective (emotional) responses of the brain?
   Since Design Styles are quantifiable as a spectrum of realism, they can be correlated with emotions detected from the brain signals using EEG. The task to gain an answer to this question requires a working framework of using EEG and machine learning classifier.
2. What are the effects of Design Styles on the brain's cognitive functions?
   Prior to conducting this research's experiment, a literature review may provide a little insight of the effects of Design Styles over cognition. EEG and machine learning can thus explore a more in-depth look at the connection between these two analysis constructs.
3. Why do emotional responses in video games matter when playing video games?
   Even without doing research, no one could have ignored the importance of emotions in video games design. However, in this research, it is the minute changes of emotional activity that matters more. Affective dynamics can have an impact in the video games narrative.
4. How can the understanding of Design Styles – emotions relationship help designers to maximize their design potential?
   The ultimate goal of this research is to improve the design process of creating the best video games in the market. By providing answers to aid designers achieve extraordinary results, it is hoped that this research can contribute to the future of video games design.

1.5 RESEARCH OBJECTIVES

To gain answers to the Research Questions, several Research Objectives have been conceived:

1. To develop a Design Styles Neuro-Affective Classification (DSNAC) framework for classifying game playing EEG data with neuro-affective model.
   The concept of classifying emotions while playing games of two different Design Styles is a novelty. A new working framework has to be developed.
2. To verify that the conceived framework works.
   Following the development of the new framework, a verification is needed to validate that it works.
3. To analyse emotional responses from two different Design Styles.
   Obtaining emotional data while playing video games via EEG allows analytical investigation of emotional dynamics in conjunction to different Design Styles.
4. To understand the effects of Design Styles over valence and arousal.
   As in the above objective, however at a closer perspective of breaking down emotions into two-dimensional space model. The findings of this research analysis will ultimately conclude into the understanding of the effects of Design Styles over emotional valence and arousal.

Table 1.1 is the summary of research questions with their corresponding research objectives. Answers will be obtained when the objectives are achieved. The methodology towards reaching the research objectives are also shown, as well as the contribution of this research.

Table 1.1: Research Questions and Research Objectives.

Research Questions	**Research Objectives**	**Methodology**	**Contribution**
1. What is the quantitative and measurable connection between Design Styles and affective (emotional) responses of the brain?	1. To develop a framework for classifying game playing EEG data with neuro-affective model 2. To verify that the conceived framework works	- Literature Review - EEG & Machine Learning	A New Framework for classifying video games Design Styles based on neuro-affective computational model
2. What are the effects of Design Styles on the brain's cognitive functions?	3. To analyse emotional responses from two different Design Styles	- Brain Performance Test - Scatter Plot Analysis - Statistical Analysis	Findings of the relationship between Design Styles and Emotions
3. Why do emotional responses in video games matter when playing video games?	4. To understand the effects of Design Styles over valence and arousal	- Scatter Plot Analysis - Statistical Analysis - Data Distribution Analysis	Understanding emotional behaviour under different Design Styles while playing video games
4. How can the understanding of Design Styles – emotions relationship help designers to maximize their design potential?			A new body of knowledge for the Video Games Industry and Neuro-Affective researches

1.6 CONCEPTUAL FRAMEWORK

In order to observe and analyze emotional responses over different Design Styles, a working framework needs to be developed. The proposed EEG instruments to capture affective signatures from the brain only shows raw signals. For obtaining any meaningful data from these EEG signals, they must be classified using machine learning. The framework, therefore, is conceived around the concept of classifying unknown data with a known computational model.

Unknown data can only be classified if the known reference is accurately reproduced as a computational model. Here, there are two challenges to overcome. First, known data has to come from a reliable source that can give accurate sampling of the right emotional responses. Second, the known data must be turned into a reliable affective computational model to allow accurate predictions of the unknown data source.

The solution to the first issue requires an established instrument that can stimulate specific emotions to a subject. Ideally for this research, the stimuli should be via visual exposures, in line with the need to classify emotional responses from the visual exposure of two different design styles.

The second issue calls for an accurate method to convert raw EEG data from stimulated subject into numerical model. There are several solutions available, and the method chosen for this research will be based on the highest accuracy possible as well as accessibility to that technology. It is usually comprised in two parts. One is the feature extraction process where the raw data will be analyzed for unique signatures in their signals. The other is the classifier where the signals data are classified into their proper categories – which in this case are emotions. The combination of different many feature extractions and classifier yields different levels of accuracy. Each has its own traits and characteristics. The ideal solution for this research is the one that has the highest accuracy for visual stimulation data. Detailed investigations in this matter will be discussed in chapter 2 and chapter 3.

Results from these classification processes are then collected and collated for statistical analysis to investigate the effects of Design Styles to the player. Apart from the emphasis on quantitative analysis, qualitative analysis is also being considered for inclusion in the study. A detailed procedure of conducting this research is discussed in chapter 3, Research Design and Methodology.

The huge advantage and also the novelty of this conceptual framework is that the study is analyzing measurable and candid responses. Accurate analysis can be achieved from this approach since the data collected are free from the influence of human error. Traditional survey and exam-like experiments are prone to inaccuracy, inconsistency, and unreliable due to the human tendency for doubt, mis-understanding, and lack of comprehension. Thus, EEG methodology is the key to unlocking the numerical classification of Design Styles with the human emotions.

1.7 SCOPE AND DELIMITATION

It is important for this research to define its scope and limits od research. Such a broad topic covering video games design and human psyche can get astray easily if they are not planned with boundaries. The main focus here is to learn about design styles as deep as possible, in the most objective way possible.

1. The focus of this study is the Design Styles.

   While it is interesting to learn what the effects of design styles can induce, the attention is to learn about them, rather than attempting to profile subjects or correlating design with a set number of population. This is the reason why subject population in this research is not as important as a those that seek out to profile their data with the subjects.
2. Design styles on video games, rather than cinematic animation.

   There are studies regarding design styles in the context of cinematic animation. Apart from the lack of quantitative analysis in the previous works, there are few on which the topic centered on video games. To close this gap, this research takes the opportunity to focus the topic on video games.
3. Referring to the uncanny valley curve, user interaction with the design styles has more agitation than static viewing.

The effects of realistic design style in cinematic animation often discusses its relation with the *uncanny valley phenomenon*. Video games, on the other hand, has more depth to it because of the interaction involved with the player. According to the study by Mori (2012), moving animation has steeper response rate to the *uncanny valley* than still images. Thus, it is reckoned that interacting with it provokes a more agitated response than moving footages.

4. Non-educational video games: for relevance in the mass market dominated by non-educational video games.

   The interest in finding out how video games design affect the players must not be confused with the game genre that is designed to affect them. Educational games are of course designed to stimulate the mind for learning in their game level design as well as their game mechanics. To learn more about how design styles affect the players, games that are purely designed for entertainment purposes are selected. This is the element in choosing the game titles used for this research's experiment (i.e. the EEG recording session).

5. Commercially available video games.

   It is imperative that the research studies the effects of game design based on the games that people are playing. In no way what so ever that the research should involve in creating a dedicated game specific for this experiment. In that respect, commercially available games are used. In chapter 3, the selection of video games for this experiment and the criteria to which the games must meet are discussed in detail.

6. Study on design styles data, not on subject population.

   The statistical analysis in this research studies the emotional reaction of the brain towards playing video games of two design styles. The population samples are the data instances rather than the number of subjects playing the game. In such context, one subject would be sufficient, but additional number of subjects can contribute to a stronger validation of findings. Furthermore any discrepancies in the analysis results can provide a deeper understanding of the relationship between design styles and brain/emotion activity.

1.8 SUMMARY

Abstract, Stylized, and Realistic Design Styles of video game characters each has its own way of affecting and influencing the player’s mind in terms of psychology and emotion. Different players with different emotional responses and cognitive behavior in their brains may have a particular response to a particular Design Style. The brain naturally emits neuro signals that correspond to the player’s affectivity – the emotional valence and arousal. It can be captured by an EEG device, thus providing quantitative data of actual neuro-affective responses to allow analysis between two different Design Styles. By understanding how Design Styles influence the dynamics of affective responses, developers can exploit their design to deliver more effective video games for their intended target audiences. In addition to the findings that add to the body of knowledge, this research will also provide a gateway to new researches from its EEG machine learning framework. The framework, which functions as the classifier of EEG signals into affective data, can be adapted for other research context.

CHAPTER 2

LITERATURE REVIEW

2.0 INTRODUCTION

The purpose of this literature review is to gain acquainted with the topic of this research before it is being carried out. It is also one of the methods to gather insights and information that can assist the research as well as to obtain some answers to the research questions.

There are two important pre-requisite requirements for this research. One is terminology definitions with background information to explain the significance of certain components that are a part of this research. The other is identifying associated technologies and other developments to be applied in the design of this research. The first is carried out by investigating current and previous works that have been done. The latter is by investigating the works that may contribute to the research design.

It is imperative that the review of literature be carried out systematically and remained focused to this research topic. Most important of all is that some of the research questions and objectives laid out in chapter 1 needs to be answered by reviewing past researches. Ultimately, the review of literature should provide the following:

1. Clear definitions and insights of important terms used in this research.
2. Information regarding the influence of Design Styles over emotions (Research question 1b)
3. Knowledge on the importance of emotional responses in video games (Research question 2).
4. Understanding of the existing technologies, methods, and models needed to carry out this research using EEG and machine learning.

2.1. DEFINITION AND THE SIGNIFICANCE OF DESIGN STYLES IN VIDEO GAMES

Keo (2017) defined Design Style as an artistic interpretation of a design based on its likeness to reality. The input that is provided in the study describes what are Abstract, Stylised, and Realistic Design Styles. Titled *Graphical Styles in Video Games*, Keo (2017) defined each three styles as follows:

Abstract:

> *Abstractionism is one of the graphical style categories that focuses on representing the game in geometric shapes and forms instead of directly depicting characters, objects or distinct places (Järvinen 2009).*

Stylised:

> *In his paper, Järvinen (2009) describes stylized graphics as caricaturism. A caricature is a picture or a representation of an object that is simplified down to its most defining features. In computer graphics, style can also be referred to as non-photorealistic rendering (NPR) which means graphics that focus on visualizing the content with specific digital art styles (Winkenbach & Salesin 1994).*

Realistic:

> *Realism emulates game characters, objects and environments with as much likeness to reality as possible. Realism became a major trend in the 1990s when three-dimensional visualization became the new standard for game graphics. Since then, realism is still arguably the most desired look for modern games.*

Visual elements in video games contribute to a huge factor in design decision of the production. What is displayed to the player influences them to play longer, make purchases, create a fan base of the game title, and thus generate continuous profit for the company. This research explores the science behind the psychology of design styles in video games to uncover the recipe for good game design.

Design styles are the major visual theme for the overall look of the video game. They create the mood of the play and set the consistency of the game's design functions. Whether the production is meant for children, education, entertainment, or simulation, the game's design becomes fully effective for their intended purposes when the right design styles is applied.

Until now, there are no framework or methods that measures the connection between design styles and their influence over the human mind. Current guidelines for designers to decide design style is vague, relying on traditional formula of using shapes as symbols for psychological influences. For instance, stylized caricature are applied to appeal to children audiences using symbolic basic shapes to influence certain psychological connection - round shapes for cute but unstable characters, whilst triangular and pointy design represents villainy. While this approach had been used for ages, modern artistic works sometimes exploit the other way around.

Adult oriented contents are now communicated visually with cartoon-like visuals that contradicts the original understanding of how design styles are applied. What seemed like cute graphics for children, may contain violence and sexual contents that only adults can understand. The idea of specific design styles are only intended for specific audience are not clearly defined. Moreover, with the advent of computer-generated images (CGI) for video games that has become easier to make surreal images, there are more and more crossover between design styles and the targeted audiences. Specific styles for specific audience simply no longer applies.

Yet, it is still obvious to which design style appeals to children whenever their parents switch on the TV or when going to the toy store. To conclude design style is irrelevant to the human mind is unfounded, but to simply relate it to the psychological aspect of the human mind is not valid without deep understanding of how design styles affect the audience. At least, sub-consciously everyone kind of know what visuals go well with specific group of audience such as what design language is suitable for teenage girls, or small children, or serious adults seeking for horror entertainment, etc. The only problem is the scientific and measured understanding of how design styles engage the human interest is not yet known.

Such a body of knowledge is important to video games developers. The decision to select which design style can really make or break the game production. It is not a simple matter of 'taste' by the producer of the game, rather it involves many aspect of the development. Cost, time management, market first impression, target audience, programming, technical complexity to achieve the desired design styles, and other factors are all affected by the design style chosen.

Design styles are actually a degree of realism within a linear spectrum. On one end there is an abstract design while on the other end is the realistic design. Abstract design consists of simpler and unrealistic looking shapes that represents the real world. Realistic design is the design that try to immerse the audience with simulated reality. In between them lies what is known as the stylized design, a hybrid that combines abstract and realistic design. Figure 2.1 shows an example of each of these design styles.

Figure 2.1: Design Styles Examples. Chameleon Run (Noodelcake Studios 2016), Team Fortress II (Valve Corp 2007), Cyberpunk 2077 (CD Projekt 2020).

Unlike in the animation industry, video games are deeply rooted to the technological developments of the graphics technology. Chronologically, of course, video games started with an abstract shapes that represent the real object in the real world. Figure 2.2a shows the early *shoot'em-up* video game called *Space Invader* the used flat pixelated shapes to represent an aircraft shooting on incoming alien UFOs. Contrast to the video games available today, Figure 2.2b demonstrates how photo-realistic a game can be. As technology progresses, games have becoming more and more realistic.

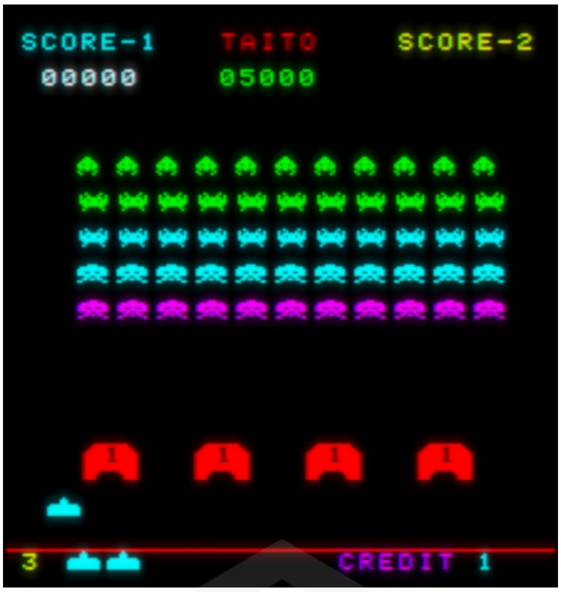

Figure 2.2a: Abstract design of the classic Space Invaders game. (Taito, 1979)

Figure 2.2b: Sky Force (Infinite Dreams, 2014)

The technology behind the realism in video games are very complex. However, the main categories that become the main technological driving force to create realism are 3D modelling, lighting, shading, rendering, texturing, motion capture, and AI game engines. Obviously, the more realistic a game is, the more complex and painstakingly hard it is to make.

The pursue of realism has become the evolution of the video game technology development. Computer Scientists push boundaries to bring artificial world to life, immersing players in the virtual world with believable visual candy. Currently the technology is still imperfect to recreate the real world inside a virtual environment, but the results are now as impressive as ever.

Interestingly, as the evolution of game engineering steps forward, artistic visions look both directions. Some designers are now using the high tech to actually recreate abstract visuals in a new way. While designers are no longer handicapped by the technology to realize their imagination, abstract design styles can now be made into what is known as the surreal environment. Surrealism are abstract in design, but represented in a believable way. Figure 2.3 is just one example. The virtual world may be obviously artificial, but one would have believed such a place exists.

Figure 2.3:"A cut-scene from the Final Fantasy XVI". Square Enix (2023)

Benefits of such surrealism approach in design is the freedom of creativity and the breadth of expressions available for designers to explore. Less obvious advantage is the option to reduce complexity of the development process – at least not as complex as realistic design. It seems at this point that realistic and abstract are both appealing in their own way. But, how they affects the human mind is still not clearly understood.

This is when deciding design styles become critical. Pushing realism to new heights – and therefore the limits of the hardware – may cost more than the game is worth. Realism may also not be able to deliver a better game experience. Furthermore, pursuing realism would lead to overlooking opportunities of developing surreal design with less sophistication and thus less resources. Then there is a matter of cost, skills required to produce, and debugging issues.

2.2 THE SIGNIFICANCE AND EFFECTS OF DESIGN STYLES TO THE AUDIENCE

The factors determining design styles are now beyond a matter of ‘taste’ or trends. Although trend is what pushed cel-shading technology forward within the 2003 and 2008 periods, selecting which design styles can be more complicated if the developers really want to fully maximize their design potential. Especially when the game is intended to have some kind of educational value to it, which in this case sub-conscious mind stimulating effects are desirable.

It does not mean, however, that video games should have a mind altering attributes. Although it would be a dream come true for a concept of playing video games can suddenly improve the player’s literacy and numeracy competency, such a science-fiction idea must not be confused with the notion of the player being brain-washed or implanted with fake memory. The interest in mind stimulating effects here is the ability to deliver the deepest immersive experience in playing the video game. It is also desirable if the game is able to ‘pre-set’ the mood of the player to always be ready for whatever activity the game is designed for. This could make the game more enjoyable and thus have added intangible value to its tangible content. Think of it as the vitamins and minerals of the game content.

Design styles have been known to be the default design aspect in the context of tackling specific age group, gender, and genre. But the understanding of these choices were based on traditional/past experiences that is common throughout the game chronology (Carter, 2016). How design style actually correlate to the human mind is still not fully understood. Nevertheless, they are mostly quantitative analysis and some of the methods used have gaps that can still be improved upon. Design – mind classification can be the key to unlock unexplored territory of immersive gaming. Educational games, for instance, can be made more effective when they are precisely designed to stimulate specific aspect of the mind for learning a specific topic or to train specific cognitive function (Lee, 2018).

Table 2.1 summarizes the previous works that had been done to understand this matter along with their methodology. Alongside them are the gaps that can potentially be filled by this research to contribute in the pool of knowledge in understanding the effects of Design Styles to the game players.

Table 2.1: Summary of Literature Review on previous works.

Author, Year	**Design Related Insights**	**Psychological & Emotional Effects**	**Methodology**	**Gaps**
Poirier-poulin, 2020	Genre	Empathy Effects through immersive environment	Survey	Lack of quantitative analysis, Design Styles are not in focus.
Hölttä, 2018	Design Styles	Narrative Mood Effects	Survey	Lack of quantitative analysis
Altunoz, 2018	Design Styles	Role and Personality	Systematic Literature Review	Lack of quantitative analysis
Naumann, 2018	Level Design	Cognitive Workload	EEG	Design Styles are not the area of study
Lee, 2018	Design Styles	Cognitive and Preferences	Questionnaire	Lack of quantitative analysis
Bartsch, 2017	Immersive Design	Cognitive and Affective Challenges	2 x 2 Experiment	Lack of quantitative analysis
Keo, 2017	Design Styles	N/A	Case Study	Effects of Design Styles are not discussed
Balducci, 2017	Game Level Design	Affective Stimulation	EEG	Design Styles are not discussed
Thibault, 2016	Retrospective Influences	Preferences	Systematic Literature Review	Lack of quantitative analysis
Ben-Zvi, 2016	Design Styles Technology	N/A	Tech development	Effects of Design Styles are not discussed
Carter, 2016	Design Styles	Age related preferences	Experimental observations	Lack of quantitative analysis
Imhof, 2015	Design Styles Rendering Technology	N/A	Rendering solutions	Effects of Design Styles are not discussed
Zell, 2015	Shapes and Materials	Effects of Perception on CGI	Experiments	Lack of quantitative analysis

Khairuddin, 2015	2D & 3D	Topographical activity	EEG	Psychological effects are not discussed
Kaplan, 2014	Design Process	N/A	Technical Observations	Effects of Design Styles are not discussed
Sharan, 2013	Motion Blur	Player Experience	Questionnaire Experiemnts	Lack of quantitative analysis
Mori, 2012	Level of Realism	Uncanny Valley Phenomenon	EEG	Affective activities during game play for video games are not discussed. Other psychological and affective stimulations are not studied
Rapeepisarn, 2008	Genre	Cognitive Performance	Learning Techniques in Gaming	Lack of quantitative analysis. Design Styles are not discussed
Geller, 2008	Level of Realism	Overcoming Uncanny Valley	Experimental observations	Lack of quantitative analysis
Schneider, 2007	Japanese Anime	Exploration of Uncanny Valley Effects		Lack of quantitative analysis
Mitchel, 2007	Design Styles	Memorable Identification of Characters	Illustrative Renderings Technique	This is a technical discussion. It does not investigate Design – Psyche relationship
Järvinen, 2002	Audiovisual Elements and Styles	N/A	Systematic Literature Review	Effects of Design Styles are not discussed

From the table above, there are apparently quite a number of studies regarding Design Styles. This signifies the importance of the topic. But most importantly, the attempt to understand Design and psychology relationship lacks quantitative analysis. While these researches validated their findings by large sampling population, results that were outcomes of human performance may still have errors and inaccuracy. These being influenced by the fact that a person can be misunderstood during the data collection, confused, interrupted, forgotten, or simply made a mistake. On the other hand, a device that can capture the required data out of the subject without them even knowing it is far more precise and accurate. This is why this research proposes EEG methodology.

EEG methodology did indeed being used in several other researches regarding similar topic. However, they either study Design Styles on a different context or Emotions on a different context. None of them looked into Design Styles affecting emotions. The closest similarity in terms of topic is the study made by Lee (2018) who investigated the effects of Design Styles on educational games. However, Lee's research did not investigate brain signals for quantitative studies. It also lacks emotional response analysis as well as an observation on a phenomenon known as the Uncanny Valley. Mori (2012), who first coined the term 'Uncanny Valley' in the 80s, also made design investigations using EEG. Although he explored the spectrum of realism, it was not in the context of emotional responses entirely – instead, it was a look into the Uncanny Valley in more depth. In addition, Mori is more focused in robotic designs rather than video games characters.

In contrast to what traditionally has been the practice for many animation/cartoon character designers – particularly Disney, the world's most renown animation production studio – from Disney's own research lab, found out that Design Styles is irrelevant to the audience's age (Carter, 2016). It is a contradictory since stylized and exaggerated proportions of the human forms (in most cases it is, in fact, an abstract) are usually made for young children and vice versa. Perhaps there are more towards Design Styles and age relationship. Perhaps the more accurate assessment is to look into how emotions are agitated towards different Design Styles at different ages. Alas, this research will not attempt to observe such large age groups. Instead, it is hoped that this research will open up paths to explore other such topics and beyond.

Final important mention from the table is the work by Mitchel (2007). This is actually an article of a technical discussion of the design process of one of the most played game around the globe, *Team Fortress 2*. The significance of this discussion is that it shows how designers really care about the fine details in picking up which design styles most suitable to their production objectives. In this case, the team that developed *Team Fortress 2* was given a no-compromised goal of achieving the most memorable character design possible. It had led to the converging of highly exaggerated stylized design with distinct silhouette that can be identified almost instantly and so memorable that anything resembles similar shapes would remind the person of that game. And they had achieved that goal. Such is the amazing significance Design Styles in a video game production.

2.3 EMOTIONAL AND PSYCHOLOGICAL INFLUENCE OF VIDEO GAMES

Psychological studies on emotions influenced by Design Styles have never been done before. This research attempts to fill that gap. However, there are other studies that examined the relationship between emotions and video games. There are also researches that looked into the effects of video games and the psychological performance of the human mind. The objective of reviewing these topics is to find the connections between Design Styles, emotions, and human psychology – namely, the cognitive functions of the brain.

2.3.1 RELATIONSHIP BETWEEN DESIGN STYLES AND PSYCHOLOGICAL PERFORMANCE OF THE HUMAN MIND

The idea to analyze design styles for best use in the context of educational games are already being studied by Lilian Lee (2018). The method used was questionnaire surveys where the students choose graphical elements that they prefer. Lee's findings reveals that students of secondary schools prefer realistic design styles. However, the results do not reflect true psychological effects to the brain. While students' preference hints at the appropriate design style to use in educational games, it does not mean that it is the best for them.

One significant research that proves abstract design has educational benefits is the one did by Franceschini et al (2017). Their claim of dyslexic children can be cured and prevented by playing action video games are very bold indeed. Surely, this is a fact that no one can ignore. A video game that has not just entertainment value, but a healing property as well. Their findings may sound like it was taken out of science fiction movie, but their evidences, facts, and figures are real.

Their work proves action genre video games can stimulate the brain – specifically, curing dyslexic children. An unassuming reader might think that the games they used are something like a scrabble or word-related activity. Surprisingly, that is not the case. The game was a shoot-'em up type titled *Space Invader 2.* The game mechanic has nothing to do with reading. The game activities has no word related elements. In fact, the graphics are retro-designed bare and simple. Interestingly, *Space Invader 2* is of abstract design. But why? For a research made in 2017, Franceschini et al could have chosen a game with a better (and more interesting, more realistic) graphics.

The reason *Space Invader 2* was used was not discussed in the context of design. Their selection focuses on action genres rather than visual elements. Could the design elements contribute to the brain stimulation as much as the action genre's game mechanics? Perhaps the fact that *Space Invader 2* is a simple abstract design played a role in the brain activity.

Evidences of graphical elements influence the brain can be found in Khairuddin's work (Khairuddin et al, 2014) where he did an EEG topographical map of the brain reacting to 2D and 3D games. Although Kharuddin's findings do not have anything to do with learning, the brain activity is clearly apparent. Playing 3D games requires more data processing that involve working memory and attention. 3D games also activate different brain waves (theta and alpha) at different part of the brain (frontal and occipital) compared to 2D games (beta and gamma bands mainly at the temporal lobes). Nowadays, 3D are more realistic than ever. 2D games are usually cartoony and more of an abstract.

The effects of 2D and 3D games upon the brain goes the beyond brainwaves. There are many researches that report the 'Uncanny Valley' effect when encountering designs that are keening towards realism (Schneider, 2007). The 'Uncanny Valley', a term first coined by a robotic researcher Masahiro Mori in 1970, is an effect that puts the viewer at a disturbed and uneasy state. According to Mori (2012), when an artificial appearance is getting closer to realistic, even the tiniest inaccuracy will cause an unsettling feeling. This is also true for video games graphics. Research conducted by Geller, Schneider, and Zell are among those that confirm it so (Geller, 2008; Schneider et al, 2007; Zell et al, 2015).

In other words, the 'Uncanny Valley' is a negative arousal effect. Interestingly, a graph (Figure 2.4) showing positive/negative response to likeness of video game characters to the real human being shows an increase in interest until it reaches the 'Uncanny Valley'. This indicates that stylized character has more appealing potential than realistic ones. The significance of this is that positive arousal events help memory performance to become better. Birkett (2018) stated:

"...high-arousal emotional memories last longer, whereas memories for non-arousing events are more prone to disruption."

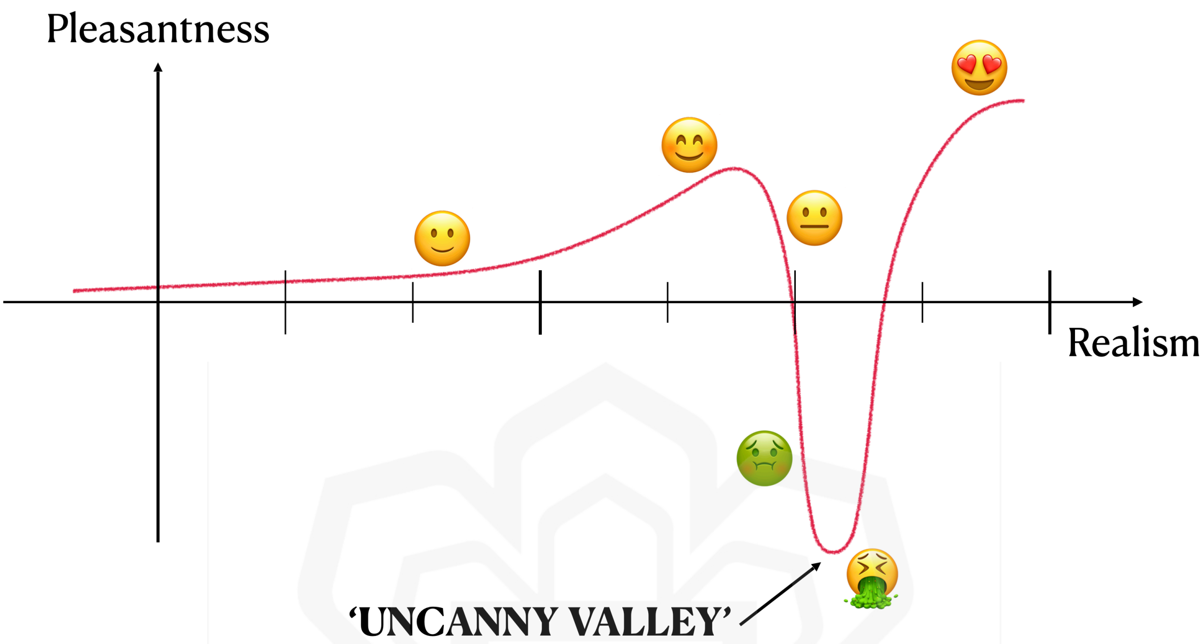

Figure 2.4: The Uncanny Valley visualisation.

The works by Franceschini et al. (2017) were not perfect, either. There are gaps and opportunities that can be further investigated and analysed. For instance, their subjects are dyslexic children. This raises the questions whether the same thing applies to adults, other health issues, or healthy participants. Researches by others suggest that it does. According to Chandra et al (2016), playing action video games enhances cognitive abilities.

Similar to the work by Franceschini et al (2017), Chandra et al (2016) differs by focusing cognitive enhancements on normal adults. Also contrary between the two researches are the design styles of the games they used. Chandra used a game titled 'Tom Clancy's Rainbow Six', a combat fighting game with a realistic rendering of soldiers in a war scenario. As Khairuddin et al (2014) pointed out that 3D realistic graphics required more data processing from the brain, it could have been a contribution to the cognitive enhancement that Chandra's research have discovered. Abstract games enhance reading abilities and realistic games enhance cognitive abilities? (Chandra et al, 2016). This is among the objectives of this research proposal to correlate design styles with learning aptitude.

Other researches also suggest video games potential as being a boost for the mind to learn. Ashinov (2014) suggests that video games are an ideal platform for pedagogical tool of education. It elevates learning potential as well as motivates better memory performance, social skills, and cognitive behavior. Benlamine (2017) also relates video games with behavior, observing that play styles are influenced by the big 5 personality traits. The way a player approach a game – all-out attack versus strategic planning – reveals the psychological side of the player. This in turn can be made useful for educational approach for learning. Learning aptitudes are different from person to person.

2.3.2 RELATIONSHIP BETWEEN EMOTIONS AND VIDEO GAMES

The “Uncanny Valley” phenomenon that was pointed out by Schneider (2007) and Mori (2012) signifies the link between visual design and emotions. But how important is emotions in the development of a successful video games? Poels (2012) investigated the effects of emotions and found that the feelings and mood of the player have an effect to the play time and various other preferences. Bartsch (2017) explored the affective (emotions and feelings) aspect of game experience and found that emotions, mood, cognitive processes, and game experiences all have connections to each other.

Emotions are important in game design in which it must be attractive enough to the player and the long-term exposure to the game visuals should not wear out the interest too soon. As a consequences, shelf life is affected by emotions. First impression to enter market for a new design is also affected. So does play time, a factor for sales and popularity which influence sales and therefore success of the production studio that makes the game.

2.3.3 RELATIONSHIP BETWEEN EMOTIONS AND COGNITIVE FUNCTIONS

Emotions has a great influence over cognitive performance. Tyng et al (2017). acknowledge this in their study on the influence of emotions on cognition process and memory. In the context of creating the ideal learning environment, emotional valence and arousal have a big impact to the human cognitive functions. Emotions greatly influences the perception, attention, learning, memory, reasoning, and problem solving.

Further studies of emotional interactions and emotional changes through videos by Gartmeier (2017) also reveals their relationship in cognitive ability. Although in his research the context of study is the understanding and control of emotions in a learning environment, the interaction of emotions from videos are apparently influencing certain cognitive functions.

In another research, Faria (2016) proposes the inclusion of emotions in designing a new learning architecture to reduce emotional stains and difficulty that students encounter while interacting with learning platforms. Cognition in workplaces is effected by emotions as well. Benozzo (2012) revealed that emotions and cognitive performance in workplaces are deeply intertwined.

Interestingly, emotions that are originated from the brain can be analysed by neuroscience. Emotional signals from the brain can be recorded and correlated with cognitive functions as has been done by Sasi Kumar (2018). What has not been done, however, is the correlation between game design and learning. But before design and learning can be correlated, learning aptitude must first be measured.

Learning aptitude refers to an individual's capability to acquire knowledge and skills of a specific type of intelligence (Sharan et al, 2013). In other words, it is the measure of the cognitive performance. There are many types of intelligence, as pointed out by Philip Carter (2005), that the general intelligence quotient (IQ) tests do not properly measure one's actual intellectual performance. According to Carter (2005), a professor from Havard University named Howard Gardner, who is the originator of the multiple intelligence theory states that there are 7 types of intelligence:

i. *Verbal*: linguistic, e.g. lexical skills, formal speech, verbal debate, creative writing.
ii. *Body*: kinesthetic (movement), e.g. body language, physical gestures, creative dance, physical exercise, drama.
iii. *Musical*: rhythmic, e.g. music performance, singing, musical composition, rhythmic patterns.

iv. *Logic*: mathematic, e.g. numerical aptitude, problem solving, deciphering codes, abstract symbols and formulae.

v. *Visual*: spatial, e.g. patterns and designs, painting, drawing, active imagination, sculpture, colour schemes.

vi. *Interpersonal*: (relationships with others), e.g. person-to-person communication, empathy practices, group projects, collaboration skills, receiving and giving feedback.

vii. *Intrapersonal*: (self-understanding and insight), e.g. thinking strategies, emotional processing, knowing yourself, higher order reasoning, focusing = concentration.

Carter himself added two more types of intelligence, *creativity* and *memory.* Multiple types of intelligence mean that people can be intelligent in many ways.

It is apparent that there are plenty of opportunities for research in the field of learning skills other than reading abilities (Chandra et al, 2016; Franceschini et al, 2017). The important thing is to how these learning abilities are measured. While there are many variables to measure intelligence, the tools to measure them are also aplenty. Among the widely recognized IQ tests are Stanford-Binet Intelligence Test, the Wechsler Adult Intelligence Scale (WAIS), or the Cattell Culture Fair Intelligence Test. The aptitude tests in Carter's *The Complete Book of Intelligence Tests* provide multi-dimensional assessment and therefore it is the preferred tool for this research.

The measurements in the aptitude tests instrument are not according to intelligent types. Instead, the components are organized into a simpler categories. Due to time and resources constraint (as well as to prevent participants boredom for having to do too many aptitude tests), only some of the aptitudes will be measured for this research. They are:

i. **Logical Reasoning:** the process of using a rational, systematic series of steps based on sound mathematical procedures and given statements to arrive at a conclusion.

ii. **Creativity:** the use of imagination or original ideas to create something; inventiveness.

iii. **Emotional Intelligence:** the capacity to be aware of, control, and express one's emotions, and to handle interpersonal relationships judiciously and empathetically.

iv. **Memory:** the faculty by which the mind stores and remembers information.

Components measurements can be found in the Research Methodology: 3.2 Participants Profiling section of this document.

2.4 EMOTIONAL MODELS AND THEIR ROLE IN THIS RESEARCH

To study the relationship – especially quantitatively – between emotions and Design Style, emotions must be able to be classified in a dimensional model. Several emotional models exist, among them in the Table 2.2, which was provided by Yaacob (2015):

Table 2.2: Emotional Models

MODEL	DIMENSIONS	REFERENCES
Polar Affective Space	Valence - Arousal	Ivonin (2012)
Affective Space Model	Valence - Arousal	N. Kamaruddin & Wahab (2012)
12-Point Affective Circumplex	Valence - Arousal	Yik et al. (2011)
VA Emotion Space	Valence - Arousal	Sun et al. (2009)
3D Circumplex Model	8 - Bipolar Emotions-Intensity	Plutchik (2001)
Tetrahedral Emotional Space	Hedonic Valence, Activation, & Control	Gehm & Scherer (1998)
Vector Model	Pleasantness - Arousal	Bradley (1992)
Circumplex Model Of Affect	Valence - Arousal	Russel (1980)
PAD Emotional State	Pleasantness (Valence), Arousal, & Dominance	Mehrabian & Russel (1974)

These models attempt to conceive human emotions as defined in two or three-dimensional space. According to Posner, Russell, and Peterson (2005), dimensional model of emotions imply that there is a central and interconnecting neurophysiological system responsible for all affective state. Thus, an EEG analysis collected from all regions of the brain is possible to classify emotions and their response behavior.

Model selection is important. To classify emotions out of brain signals coming out from playing video games, the right model can yield better accuracy and/or resolution than the others. While three-dimensional model may sound more sophisticated and allow more depth for analysis, the most prominent models used in researches are the two-dimensional models, namely the Circumplex, Vector, and PANA model (Rubin, Talerico, 2009). This research will not attempt at investigating the most accurate emotions model. The most reliable one will be selected instead.

Circumplex and Vector model is similar in that emotions are classified on a two-dimensional plane. This plane is made of Valence and Arousal axis. PANA model, on the other hand, is slightly different that the Valence-Arousal axis is at a 45 degree angle. Remington (2000) indicated that the Vector model is the most widely used especially for using a picture stimuli. As opposed to other models which respond to other types of stimuli, Vector model can be reliable enough for this research to use the established IAPS stimuli. A more specific version of the vector model chosen for this research is the Affective Space Model (N. Kamaruddin & Wahab, 2012)

IAPS is short for International Affective Picture System. It is a picture system for stimulating particular emotions when exposed to the subjects (volunteers or participants) of a study (Lang, 2008). This instrument to stimulate specific emotions are widely used in psychological research (Bradley, 2007). It was developed by the National Institute of Mental Health Center for Emotion and Attention at the University of Florida, U.S.A. This tool is the perfect stimuli for this research because first it is a well-established stimuli and second it is widely used which means references for it is abundance.

2.5 BANDWIDTH AND BRAIN ANATOMY

Classifying brain signals into emotions data requires more than the understanding of how machine learning works. The brain itself has a few aspects of its own that can be learned to aid with the data analysis. This research will not go as far as investigating every section of the brain anatomy. Instead, it will focus on the two things that are most commonly associated with EEG analysis and psychological studies. These are the brain anatomy (in the context of human psyche) and brain signals bandwidth.

2.5.1 ANATOMY OF THE BRAIN AND ITS TOPOGRAPHY

The 19 channels from the EEG device were strategically positioned in a specific part of the brain. A review from Balducci (2019), the regions of the brain that are being studied specifically for EEG are shown in Figure 2.7:

a. Frontal lobe – the front part of the brain, associated with reasoning, planning, part of speech, movements, emotions, and problem solving.
b. Occipital lobe – the back part of the brain, associated with visual processing.
c. Parietal lobe – the top part of the brain, associated with movement, orientation, recognition, and perception of stimuli.
d. Temporal lobe – the left and right sides of the brain, associated with perceptions and recognition of auditory stimuli, memory, and speech.

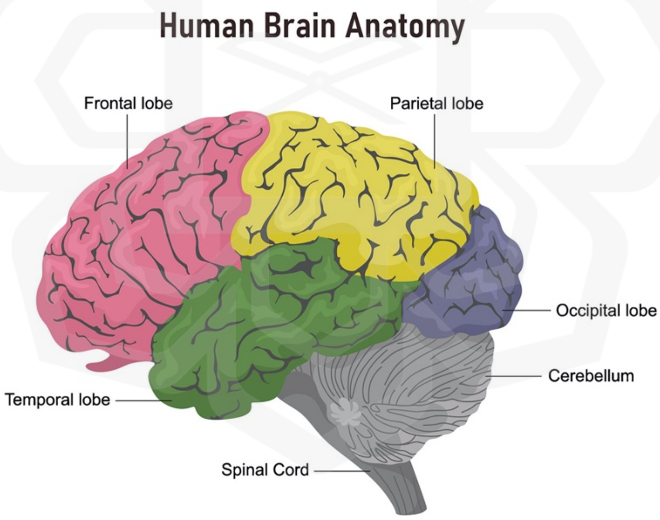

Figure 2.5: “Human Brain Anatomy”, John Hopkins University (2023)

Figure 2.5 shows an illustration of these areas on an actual human brain. These regions, when mapped on a 2-dimensional plane, are known as the brain’s topography. Just like a map on the Atlas, a topography chart can provide a general overview of the brain’s activity in relation to the its anatomy. Figure 2.6 shows an example of a topographical map of the brain, showing the brain in plan-view with the frontal lobe facing up. The color scheme in this sample indicates intensity level from lowest (blue) to the highest (red).

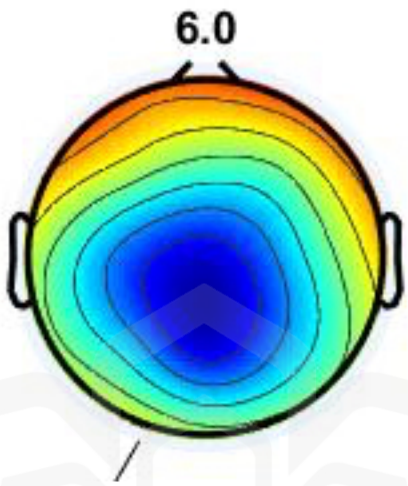

Figure 2.6: An example of a brain topography.

Brain topography allows spatial analysis. Each lobe of the brain in the topographical map can be overlayed with the brain's energy level, for instance, to analyze activity intensity on a specific area.

2.5.2 BRAIN WAVE ANALYSIS ON DIFFERENT FREQUENCY RANGES

The human brain emits signals of different frequencies. According to Balducci (2019), the brain works in different frequencies for different levels of state of mind. Each level is a state of consciousness and attention that are associated to many different functions of everyday life. A bandwidth is a range of frequencies that has unique attributes of its own that distinguish itself from other frequencies. In the context of brain signals, the bandwidths are associated to the consciousness level of the mind. Starting from sub-conscious level all the way to high alertness, the frequency associated with them are from low to high respectively.

There are five main bandwidths of the brain signals that are associated with consciousness and activity. An excerpt from *Affective level design for a role-playing* *videogame evaluated by a brain–computer interface and machine learning methods* (Balducci, 2019):

1. *Gamma Waves have the highest frequency range (30-80 Hz), involved in higher cognitive functioning like memory and information processing; states of anxiety and stress presents high levels of this.*
2. *Beta Waves known as "high frequency-low ampli- tude" waves (13-30 Hz) involves conscious thought, logical and critical thinking and socialization; their activity increases with stimulants, like caffeine.*
3. *Alpha Waves associated to calm and meditation with a regular and synchronized configuration (8-13 Hz); they are also called Berger waves in memory of the inventor of the EEG in 1929.*
4. *Theta Waves involved in daydreaming and REM sleep phase with a low frequency range (3.5-8 Hz); they are connected to deep and raw emotions, in- tuition and creativity with streams of consciousness near an hypnotic state.*
5. *Delta Waves the slowest recorded brainwaves (under 3.5 Hz) associated with deepest levels of sleep; an abnormal activity usually denotes brain injuries and learning problems.*

Each of these conscious level of the mind may react emotionally differently with the two design styles of the video games in this research. Thus, it is of great interest that the EEG data be analyzed with separate bandwidths. It allows the observation of playing video games from sub-consciousness to full alert thereby providing deeper insights to understand how design styles in video games affect the human mind. It is possible that design styles may influence different levels of the mind differently. Referring to the literature review from Khairuddin (2014), where 3D animation medium affects specific bandwidth differently from 2D medium, design styles may have similar effects.

2.6 SUMMARY OF LITERATURE REVIEW

Design Styles are basically levels of realism in visual presentation of a video game that mimics the real world. They have influences over the human mind. In particular, emotions and cognitive functions may change in behavior or performance when playing video games of different Design Style. Cognitive performance, in the other hand are also related to emotions. The three elements – video games, cognitive functions, and emotions – are evidently intertwined in a complex relationship of cause and effect. Previous works relate specific topic on either emotions with video games, cognitive performance with video games, or emotions with cognitive performance. None of them focused on the effects of Design Styles on emotions. However, these researches show pieces of evidence that Design Styles have a direct impact on cognitive functions as well as the human emotions.

Emotion is a major ingredient to make successful video games. It is obvious that if the developer wants their video games to be liked by their target audience, then 'likeness' is the key. Liking something means being aroused and pleased by it. Certainly, a design shouldn't stimulate the feelings of repulsion and unpleasantness. Several theories and emotions model exist, but the one suitable for this research is the Vector Model, which defines emotions in a 2-dimensional space. It is the most prominent model for many research (Rubin, 2009) and the fact that it coincides to be the most suitable for picture based stimuli is a great opportunity for this research. For the stimuli, an IAPS instrument is selected.

To study and understand Design Style in the context of emotions, EEG data need to be classified using machine learning. The classification process yields the highest accuracy when Power Spectral Density feature extraction and Multi-Layer Perceptron classifier are being used.

To sum it up, this literature review provides insights towards the interplay between Design Styles and the human psyche. It also helps finding a working framework in which this research can be based on to develop a new one. In that respect, this chapter provided the answers to which emotional model to use as well as what algorithm combination is best for classifying EEG data. The remaining components of this research could not have been possible without the review of literature.

CHAPTER 3

DESIGN STYLES NEURO-AFFECTIVE CLASSIFICATION (DSNAC) FRAMEWORK

3.0 INTRODUCTION

In this chapter, the design development of a novel framework to classify gameplay data based on neuro-affective computational model is discussed. There are two analysis constructs that serve as the keys to this framework. First is the Design Styles used in video games and second is the brain activity of the player playing the video games. The research aims to quantify both constructs and classify them to figure out their meanings to the player and designer/developer. In this way, relationship between both constructs can therefore be studied and understood. Understanding their correlation adds to the body of knowledge in the video games industry but more importantly it is hoped that the conclusion of this research will be able to open up opportunity for games designers exploit their potential.

The next analysis construct is the brain activity of the subjects. The key to obtain measurable quantitative data from the human psyche is the electroencephalogram (EEG) device. By detecting and measuring the amplitude as well as the frequency of the electrical signal emitted naturally by the brain, cognitive functions and emotional responses can be acquired in numerical form. Such numerical data can be analyzed statistically and classification by machine learning is thus possible. Raw EEG signals cannot be translated into any meaningful data without going through a working framework. These signals need to be interpreted as classified data based on a computational model. The neuro-affective model – a computational model to refer how the neuron of the brain being affected by affective valence and arousal – is the core of this research analysis. The novel framework is thus developed to classify gameplay data from two distinct Design Styles into emotional valence and arousal responses.

3.1 EMOTIONS AS BRAIN SIGNALS

To acquire the actual emotions from the subjects directly from their brain is a crucial stage that distinct this research among others. It contrasts to the statistical experiment that assumes subjects' Design Styles preference. The drawback of those studies is that the results are less accurate due to human error in reflecting their true emotions. The advent of Electroencephalogram allows this research objective possible.

However, raw signals are meaningless and are not possible to be interpreted into meaningful information or data. They need to be classified using machine learning process to translate brain signals into emotional valence and arousal data. The classification process take place in three stages (Yaacob, 2013):

1. Pre-processing and data preparation

Raw data acquired from signal capturing devices usually need to be prepared before processing. Some may contain a particular signal noises that need to be removed. Others may need trimming to a specified time capture length. There are even data that need to be cleaned up by filtering certain frequencies and amplitudes. Specifics about the preprocessing depend on the research needs.

2. Feature Extraction of Known Data

The aforementioned IAPS stimuli will serve as the catalyst to acquire EEG data of known emotions. A feature extraction process will use these data to generate a computational model. The computational model of valence and arousal can then be used to classify unknown data, which in the case of this research is the game play.

3. Classification of Unknown Data

Once the computational model of the emotional valence and arousal has been acquired, data of unknown emotions such as during a game play of a particular design style can be classified. It is then possible to learn the emotional responses and behavior during that game play session.

3.1.1 MODELLING EMOTIONS THROUGH FEATURE EXTRACTION.

Each subjects/participants who volunteered in this research will have their own computational model for their own emotional response. During the session where they are being exposed to the IAPS stimuli, their brain signals are captured via the EEG machine. This EEG data is a known variable data since the particular emotion for each particular data set is known. The data is then undergone a process known as the feature extraction (Yaacob, 2013). What it does is actually recognize the pattern or features form the signal waves that are distinct for each emotion and transform them into numerical features that can identify the particular emotions. The result from the feature extraction process yields the computational model required to classify unknown data.

There are many methods of feature extraction to generate a computational model. These include manual and automated feature extractions. Naturally, with such a complex nature of the brain wave, the automated method is desired. Automated feature extraction requires an algorithm to process the raw data into the needed model. The numerical/computational model is also known as a Perceptron.

When it comes to computational modeling of the EEG signals, the known data can be re-used to test and train the model to increase its accuracy. The final model can then be used to classify data from non-emotionally stimulated signals such as in this case, gameplaying data.

The most commonly used feature extraction is known as Power Spectral Density Analysis (PSD) (Wei, et al., 2019). It analyze signals power over frequency and shows the signal's magnitude as a function of frequency (Ibrahim, 2018). The accuracy of PSD is also reliably high, sustaining results of around 90 percent (Ibrahim, 2018). It is thus the preferred method for this research.

3.1.2 MACHINE LEARNING CLASSIFIER

There are three types of machine learning. An excerpt from *The Three Types of Machine Learning* (Abdi, 2016) explains the differences between them :

1. **Supervised machine learning**

   This algorithm consist of a target / outcome variable (or dependent variable) which is to be predicted from a given set of predictors (independent variables). Using these set of variables, we generate a function that map inputs to desired outputs. The training process continues until the model achieves a desired level of accuracy on the training data.

2. **Unsupervised machine learning**

   In this algorithm, we do not have any target or outcome variable to predict / estimate. It is used for clustering population in different groups, which is widely used for segmenting customers in different groups for specific intervention.

3. **Reinforced machine learning**

   Using this algorithm, the machine is trained to make specific decisions. It works this way: the machine is exposed to an environment where it trains itself continually using trial and error. This machine learns from past experience and tries to capture the best possible knowledge to make accurate business decisions.

In this research, there are variables to predict (emotions) the unknown (gameplay data). Thus, supervised machine learning is the type of machine learning algorithm to use. However, there are several algorithms for supervised machine learning to choose from. Some of the commonly used ones are as follows (Mohammed, Bashier, 2016):

1. Decision Trees
2. Rule-Based Classifiers
3. Naïve Bayesian Classification
4. The *k*-nearest Neighbours Classifiers
5. Neural Networks
6. Linear Discreminant Analysis
7. Support Vector Machine

The benchmark for selecting the algorithm is classification accuracy. To test each of them above would take quite some time to evaluate. Because of that, this research look up to the previous works that have been done to classify valence and arousal. The Multi-Layer Perceptron (MLP), a derivative of Neural Network classification, was demonstrated to achieve a consistent accuracy of around 90 percent and above (Yaacob 2013). It is concluded that this research will also apply the same algorithm. Table 3.1 is a selected references that shows the combination of stimuli instruments, feature extraction, and classifier algorithms along with their accuracy results.

Table 3.1: Combination of different stimuli, feature extractions, and classifier

Sources	Stimuli	Feature Extraction	Classifier	Accuracy
Yaacob, Omar, Handayani, Hassan, (2018)	IAPS	PSD	MLP	Above 90%
Tseng, Lin, Han, & Wang (2013)	Music	Normalized EEG power	SVM	80%
Shams, Wahab, & Fakhri (2013)	Facial Images	TDOA	RLS, MLP	Above 90%
Yoon & Chung (2011)	Movie Clips	PSD	SVM	Above 80%
Nie, Wang, Shi, & Lu (2011)	Images	FFT with a Hamming window	ANOVA	About 90%
Yoon & Chung (2011)	Music & Vocal Pieces	KDE, GMM	One-Rule	90%
Mu Li & Lu (2009)	Facial Images	Common Spatial Patterns (CSP)	SVM	About 93%

3.2 DEVELOPING A FRAMEWORK BASED ON AN EXISTING NEURO-AFFECTIVE COMPUTATIONAL MODEL.

The main goal of this research is to analyze quantitative measurements of the emotional activity with Design Styles. Design Styles have already been determined and categorized by the choices of games used for this research. Details about the game selections are discussed in the section 4.1 GAME SELECTION PROCESS in Chapter 4. The other data needed for analysis is the

EEG signals of the subjects playing the video games. However, game playing EEG data requires other sets of EEG data before it can be analyzed.

First of all, the data needs to be classified into emotional responses. Classifications using machine learning means a known model of the subject's emotional responses is required. The need of this model necessitates the use of a stimuli to induce specific emotional valence of the subject. By recording the EEG data of the stimulated state of the subject's brain, known emotional valence and arousal models can be acquired via feature extraction.

Second, the subjects other state of mind are needed for reference as well. For instance, the rest/initial state of the brain prior to playing video games can reveal how video games change the state of mind/emotions of the subject. Apart from initial/default state, the subject's other profiling constructs can be captured in EEG data for direct correlation of design and subjects' profile.

The conceptual framework is based on these procedures:

1. Volunteers who participate in this research are the subjects providing EEG data from their brain signals.
2. After attaching the EEG device on the subject's head, they are exposed to a stimuli to make them feel a particular emotion. The stimuli is a form of static pictures that when looked at, the viewer will respond with a specific emotional reaction.
3. Following the emotion stimulation, the subject simply plays two different video games representing two different design styles.
4. After the gameplay session is done, there will be two types of EEG data acquired:
    i. Data with known emotional responses (known data)
    ii. Data with unknown emotional responses (unknown data)
5. To analyze the gameplay data – which is the unknown data – they will be classified with the known data before they can be scrutinized. By analyzing the emotional responses within the gameplay (unknown) data, the relationship between them can be learned and understood.

The classification process is separated into two components: one is to measure emotional valence and the other is to measure the arousal. They are split for enabling the data to be plotted on horizontal and vertical axis. By doing this, statistical analysis and numerical vectoring is made possible. Figure 3.1 is the draft schematic to which a new framework is to be based on.

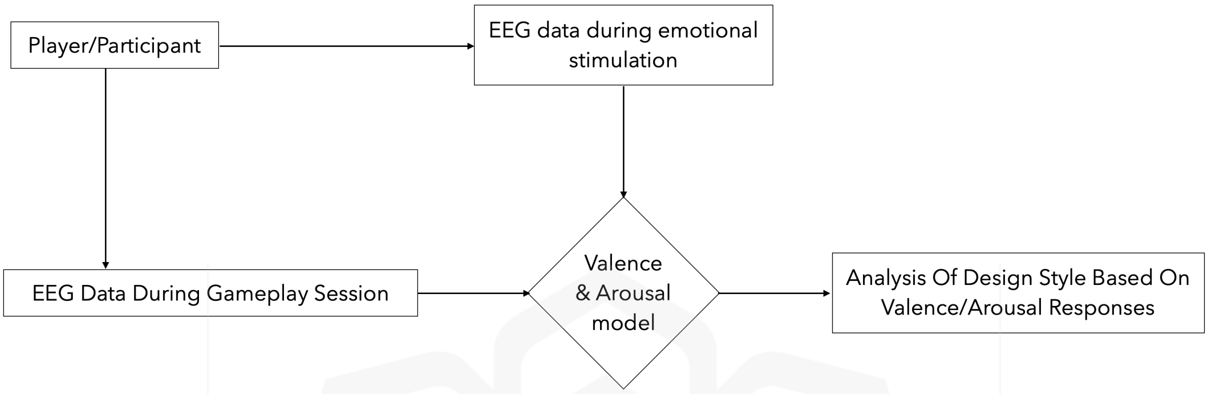

Figure 3.1: Schematic of a framework concept.

To turn this concept into a working framework, an existing method can be used to serve as the base reference. Yaacob (2013) has a similar classification objective, and his framework to generate a computational model looks like in the Figure 3.2.

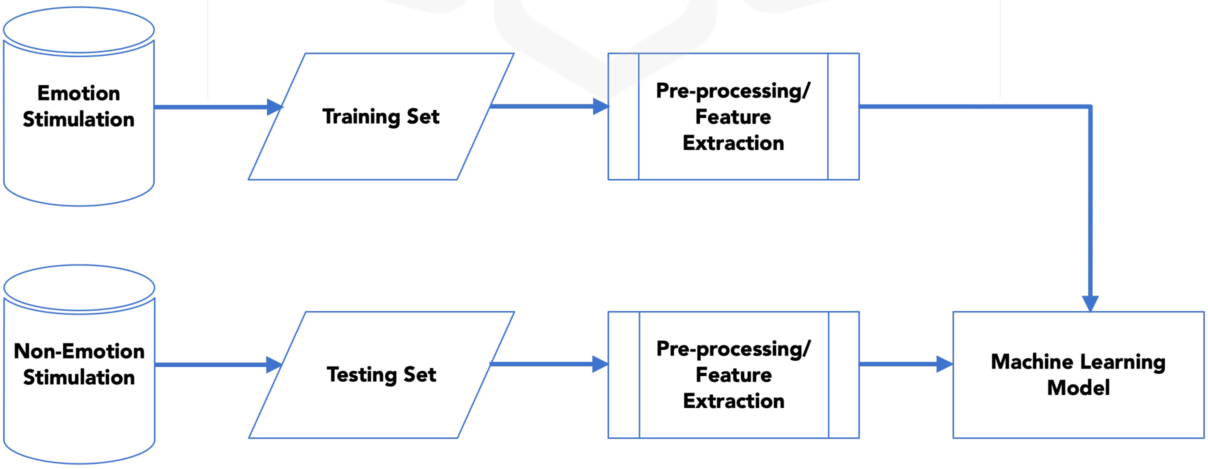

Figure 3.2: A working framework to establish a machine learning model. (Yaacob, 2013)

This existing framework was conceived to generate a machine learning model for the subject's affective responses. Affection is the term to define the emotional valence and arousal transmitted from the neurons of the brain. By quantifying affection into numerical measurements, the "neuro-affective" computational model can be generated for machine learning classification.

The non-emotional stimulation data set is actually the same emotional data set acquired from a stimulated subject. The purpose of doing the testing set process is to train the machine learning model to better predict unknown data. In this way, the accuracy can be increased. The classification of gameplay data can then be processed the same way as the computational model being trained to maximize its accuracy. The machine learning model yielded from the above can thus be used to classify gameplay data. The only difference is that this time the model is being used to predict a really unknown emotional data.

Refining the above framework is needed to adapt to this research's objectives. Adding several similar processes for inputs coming from gameplay data that represents the two different Design Styles is possible since the process is the same. The programming code to do it is thus easier to modify to achieve the research objectives. The end product for the framework should be spreadsheets of emotional responses happened during the subject plays the games.

Figure 3.3 is the new working framework, named **Design Styles Neuro-Affective Classification** (DSNAC) Framework, to classify Abstract and Realistic gameplay data set and prepares the resulting emotional responses in a valence and arousal spreadsheet. The emotional responses can then be further analysed statistically for better understand the effects of Design Styles.

The DSNAC framework can be adapted to accommodate other parameters besides gameplay data as well. For instance, the aforementioned resting state as well as brain performance activity that will be included in the data collection protocol can also be classified using the same framework. The process of classifying emotional responses from unstimulated activity remains the same. The conceived framework in Figure 3.3 is basically the core of this research, in which it is also the main contribution to the field of computer science and games design.

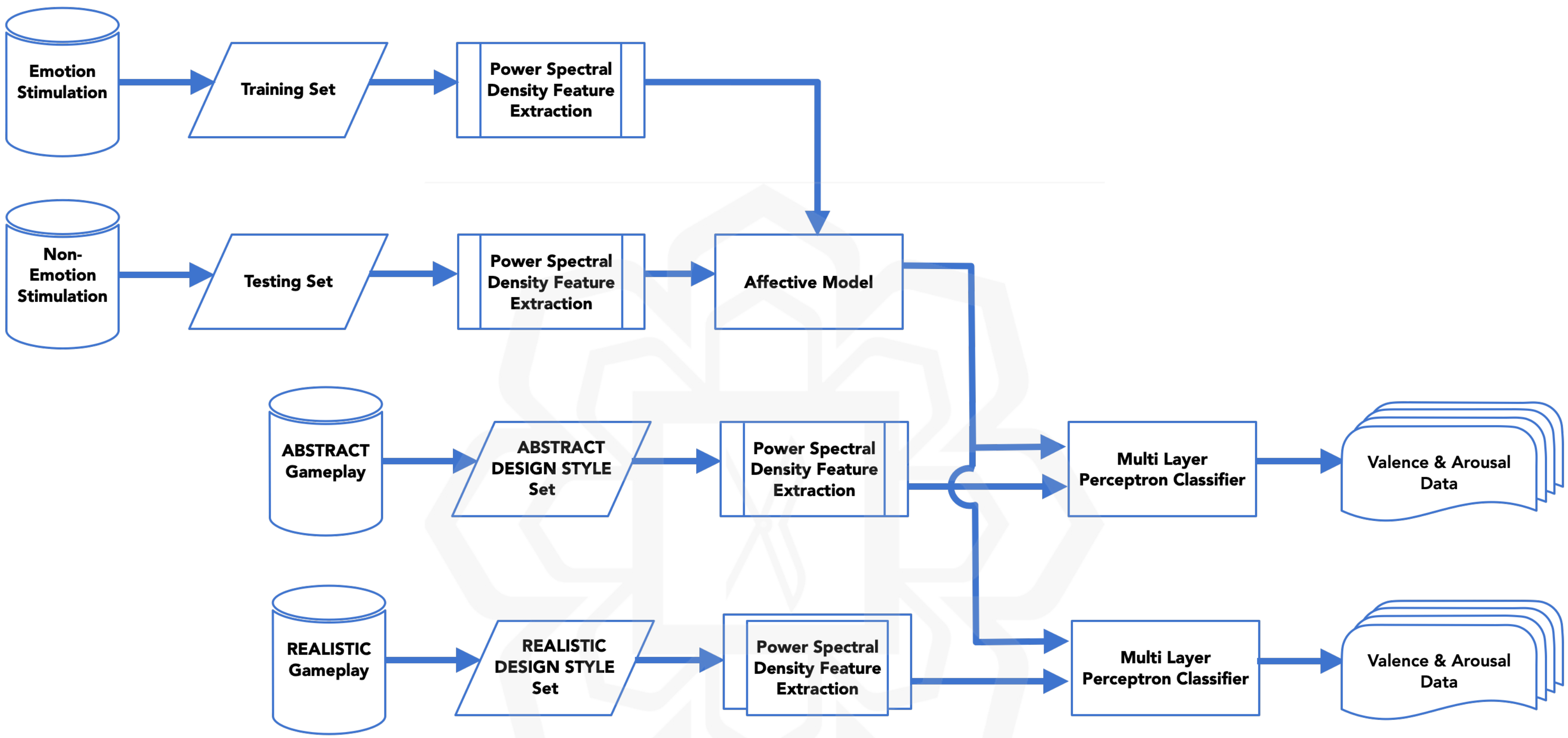

Figure 3.3: The Design Styles Neuro-Affective Classification (DSNAC) Framework, based on the neuro-affective computational model

3.3 DSNAC FEATURES AND SPECIFICATIONS.

DSNAC is designed around a proven and tested working framework. The components that build up DSNAC consist of a combination of feature extraction and classifying algorithm that yields high accuracy results. It is expected that the prediction of emotional responses by this novel framework is higher than 90 percent. For high data sampling rate (250 samples per second) that will generate thousands of data count, 90 percent is more than adequate to reliably classify unknown data.

DSNAC is also modular in design. Much like a prefabricated components of a building, the framework has the flexibility to be used for a lot of other analysis constructs. If required, a third or more gameplay data from different levels of realism in the Design Styles spectrum can be added to the framework. Modular design also made debugging errors much easier and a more organized way. Since each module operates independently, errors will not affect other modules easily.

The modular design of DSNAC is contributed largely from the way the source code is written. Built using Python programming language, each components in the DSNAC framework is executable separately and individually. Parallel processes for multiple subjects are also possible, speeding up the classification process for analysis.

The only drawback to these features is that the framework has no user interface designed in it. To operate, the source code has to be executed via an IDE (Integrated Development Environment). The IDE used in this research is the Microsoft's Visual Studio Code. The Python packages were installed via Anaconda software, for better management of Python modules. The Spyder IDE was also used initially but only for testing.

3.4 EEG DEVICE AND ITS SPECIFICATION TO CAPTURE EMOTIONS.

Design styles and the human psychology are usually qualitative subjects of research. In this research, classifying and correlating these two components together requires them to be measured and analyzed quantitatively. Being able to measure specific components allows the classification and correlation of data to be more accurate when compared to the human survey approach. Quantitative data can also be classified and correlated using machine learning for better statistical analysis.

This research utilizes existing and proven technology and method to classify known and unknown data. To acquire the EEG data from the subject's brain, the brain signals are captured using DABO, an EEG recording and capturing instrument. The device's specifications are as follows:

Sampling rate: 250 samples per seconds

EEG terminals: 19 channels (1 ground, 1 reference, 4 frontal, 3 cortex, 4 occipital, and 6 temporal.)

Data format: *.csv, *.edf

There are many other EEG devices that are available for this research purposes. However, DABO was the instrument of choice for several reasons:

1. Portability: DABO is a portable device, making it convenient for experiments in remote locations.
2. Noise cancelling feature: DABO has a built-in blink (and other sources) filters that omits unnecessary and unwanted 'noise' in the EEG signals due to the movements of the subject's limbs and eye lashes. Although these noise can be filtered out post-process, it is a valuable enhancement to the research analysis since it can be done automatically.
3. The specifications: As mentioned above, the specifications of this device is suitable for this research's purpose. Sampling rates of 250 per second is more than adequate since it is higher than the frequency of the brain waves to be analyzed – which is 80 Hz for Gamma bandwidth. The number of channels are also adequate, all 19 channels covering the major part of the skull/brain that can allow spatial analysis when needed.
4. File formatting and saving features: File format are suitable for spreadsheets and machine learning analysis via Python programming language. Saving features are also convenient, with the option to include profiling of the subjects in the database as well as customizing file name conventions straight from the recording.
5. Last but not least, DABO is really easy to use, with all menus and buttons clearly labelled. The setup of the electrodes on the subjects' head is also very easy, requiring only minimal adjustment with the electrode gel to ensure getting a clean signal.

Of course, DABO is not perfect. It must be noted, however, that due to the device's portability, its built-in safety procedure means it must be used with the battery instead of being plugged in. While this is by itself not an issue, it is the battery performance that hinders long-hour data collection. Recharging rate is inconvenient too, and this means data collection per person is quite slow.

3.5 NEURO-AFFECTIVE COMPUTATIONAL MODEL WITH INTERNATIONAL AFFECTIVE PICTURES SYSTEM (IAPS)

This research uses multilayer perceptron (MLP) to classify game-playing EEG data with the players' emotional responses. The reason for using MLP is that it is able to solve problems stochastically (statistical analysis possible, but can't predict precisely).

A multilayer perceptron is a class of feedforward artificial neural network for classifying and/or correlating of known and unknown data. In supervised machine learning, the ability to simulate a brain to recognize or discriminate requires a trained perceptron – a computational model generated and trained from data sets of known variables.

In this case, the known variables are the EEG data of emotional responses from the subjects. To acquire known emotional data, the subjects must be stimulated to the desired emotional valence and arousal state while their EEG signals are being recorded.

To setup the emotional model, a standard emotional stimuli - the International Affective Picture System (IAPS) - is used. The participant is exposed to these stimuli and their EEG signals that corresponds to each particular emotional valence and arousal are obtained. IAPS is a well-established source for providing picture references that provoke specified emotions and attention. It has been used by many researches particularly in Psychology. Thus, it is a suitable instrument to be used for this research.

The IAPS material contains four sets of pictures that are categorized with the four basic emotions: Happy (positive arousal and positive valence), Sad (negative arousal and negative valence), Calm (negative arousal and positive valence), and Fear (positive arousal and negative valence). Each category are exposed for one minute while the EEG device records the brain signals. These sets of EEG data contain signal features that correspond to the known emotions. Applying a feature extraction process on these data enable the computer model for valence and arousal to be constructed. The flowchart in Figure 3.4 shows how the IAPS can aid to model a perceptron for use in machine learning classification:

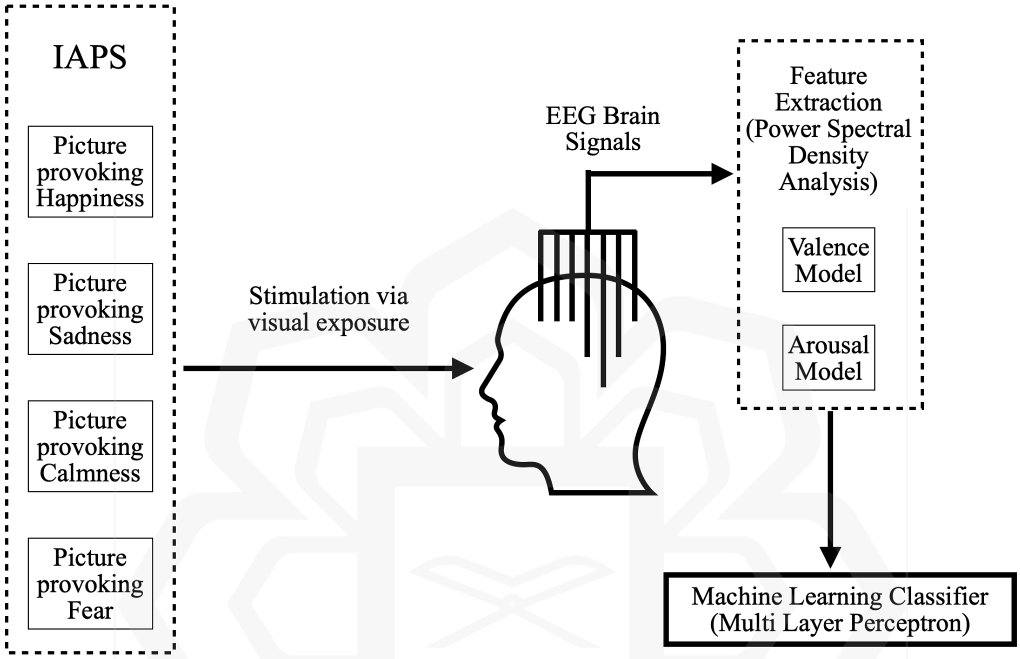

Figure 3.4 Schematics of how IAPS works.

The feature extraction method being use is known as the Power Spectral Density (PSD). By analyzing the PSD of the emotional EEG data, the power content versus frequency of the EEG signals can be characterized into distinguishable data sets. The result is the perceptron for classifying emotional valence and arousal. The computational model of the emotions is applied using a feedforward artificial neuro network to compare data of unknown emotional states. Consequently, EEG data collected during other activities – such as resting state, game playing sessions, and brain cognitive tests – can be analyzed to recognize their emotional valence and arousal. By curating emotional responses of varying activities, analysis for correlation, classifications, and other statistical analysis can be made.

The IAPS is one of the most important component in this research. It is the key to acquiring emotional model in computational form. Through the advent of EEG technology, this research is able to reach one of its objectives, which is to analyze design styles quantitatively by capturing subjects' emotional responses – valence and arousal – into numeric and measurable form. These numerical data are the building blocks for the computational models of emotional valence and arousal that will be used to classify game playing EEG data. Without the IAPS stimuli, it will be impossible to acquire a perceptron that can classify unknown data.

3.6 SUMMARY OF DSNAC FRAMEWORK

A novel research requires a novel framework. To ensure the success of achieving the research objectives, the DSNAC framework was conceived based on an existing working framework. Through the tried and proven record of the existing machine learning classification process, DSNAC is expected to perform with high accuracy.

The components that built-up DSNAC is modular and flexible. Although a user-friendly interface is non-existence, the individual components of DSNAC is easy to execute and debug. The simplicity and aesthetic design of Microsoft Visual Studio Code helps with operating the source code without an interface.

In the case of hardware, DABO EEG instrument is more than adequate to perform data collection. Its specification on paper is excellent. However, its slow battery recharge rate and inability to be used while on external power supply may hinder data collection speed.

Finally, DSNAC would not work without a reliable stimuli. IAPS in this research plays a major role in providing known data for generating neuro-affective computational model. This model is the key to unlock unclassified data to achieve research objectives.

CHAPTER 4

EXPERIMENTAL DESIGN

4.0 INTRODUCTION

In this chapter, the experimental design of the entire data collection process is discussed. The experiments are conceived, planned, and executed to acquire data for analysis. The requirement of this research experiment is that it provides gameplay data of two distinct Design Styles which will then be classified as emotional valence and arousal responses. Everything that are associated to the gameplay data are taken into considerations, including minimizing data noise, ensuring safe & non-intrusive experiment, smooth operation, and detailed data collection protocol.

4.1 GAME SELECTION PROCESS

For this research, only two Design Styles are used: Abstract and Stylized. Selection of theses styles are dictated by the available games used for research. While the ideal research situation would be to use abstract and realistic game styles, stylized game design is adequate to provide significant data variation compared to abstract. After all, stylized design sits in the middle of the visual spectrum – close enough to realistic style for familiarity but different enough from abstract for comparison

Ideally, one game that allow player to customize their game characters into different design styles is the best choice. The reason for this is that such a game can avoid data clutter that might influence the EEG reading. The only difference is the design styles of the character while the rest of the game remains the same. Alas, such a game that fit to this research's purposes does not exist. A compromise must be made and clutter must remain to a minimum. Criteria for games selection are therefore as follows:

i. Two games must be selected to represent each design styles
ii. Their game mechanics must be the same

iii. Their inputs and controls must be similar
iv. Minimum learning curve to play: low motor skills required to play, avoiding complex controls
v. Both games must be as similar as possible in terms of genre, them, and fun factor.

The fun factor is based on the feedback and ratings of the game. Games that are not well received are to be avoided, to prevent additional uncanny valley effects.

Four platforms are chosen to be in this research. They are iOS, Android, Sony Playstation, and Microsoft's Xbox. These platforms are not just popular, but they are dominant in the video games market. Huge selection can be chosen from each platform, and they all have online stores for easy access and downloads.

Method of survey in their online store is by category/genre and sorted by ratings. Each online store for a particular platform categorize their content by genres. This is particularly useful as each genres usually have the same or similar game mechanics. Previews of highly rated games are screened for characters that are designed with different design styles. In addition to the survey, articles and feedback from online forums also contributes to the selection of the games.

There are many options to choose from. Selections of games are narrowed down to have both games representing each design styles in a theme/gameplay as similar as possible. Design styles are also restricted to character designs. For instance, a flight simulator and aviation themed games may be able to represent each design styles, but their main visual elements are vehicles and man-made objects rather than characters. To relate the uncanny valley effect, the main visual elements must be characters.

At the end of it all, there are two games that have been decided to be used in this research. One game – *Chameleon Run* represents Abstract design, and *Vector HD* represents Realistic design. They all run in iOS and Android platform, though preferably this research use iOS for consistent performance. Tap and swipe play interactions minimize clutter and complexity of learning the games. All three are of the same genre, have similar layout and visual architecture, and they all have running characters. On top of that, the characters resembles a human being – a form that is suitable for investigating the uncanny valley phenomenon in case if it is present in this research. Table 4.1 compares the two selected games with their specifications that make them fit the purpose of this research.

Table 4.1: Specifications of the selected games for this research

	Game 1: Chameleon Run	**Game 2: Vector HD**
Platform	iOS and Android	
Genre	Running Action	
Design Style	Abstract	Realistic
Game Mechanics	Tap and Swipe	
In-Game Tutorial	Yes	
Learning Curve	Low	
Online Store Rating	5 Star	

It is clear that the two games above are very similar in most respects. The main difference is the design styles each games uses. For the *Chameleon Run,* the protagonist character is modelled with simple block shaped polygons. Although every limbs are just rectangular blocks that resemble nothing like a real human being, the impression that the player gets is that it is indeed a human-like character (or a humanoid character). Contrast this to the other game, *Vector HD*, which the protagonist character is basically a silhouette of a complete human being. Even the movements are realistic, with the timing of the jumps, leaps, and runs all mimic an actual human. No other pair of games better suited for this research than these two, except for fighting games genre.

Fighting games are very popular among gamers. In fact, even non-gamers most probably heard some of the titles associated with this genre. There are a lot of AAA games with big budget developments are actually fighting games. Finding similar game titles with different design styles are quite easy, but fighting game genre has major problems to be used for this research. These problems are:

1. Violent-related content.

   Inevitably, fighting games are associated with fighting and violence. The visuals of such intense action and interaction may stimulate specific response for violence that will interfere with the emotional response that this research is looking for.

2. High learning curve

   The controls for playing fighting games consist of combination of pressing/tapping buttons with specific timing and sequences. These are known as *combos.* Combos are usually very complex and learning to execute them will require practice and takes quite a bit of time.

3. Complex game play

   Combos in fighting games are very complex requiring effort to learn playing them. While putting the effort may not be a problem for someone who enjoys playing the video game, it contributes to the time duration that is not desirable for this research. Furthermore, the articulation of the hands performing thee combos may also interfere with the EEG signals that respond to the design styles that this research is attempting to observe.

4. High arousal character design

   These games are usually associated with high-end character design. Unfortunately, high-end appeal also means the presence of sex appeal. While these attributes may arguably be a bonus element to study emotional reactions on design styles, such graphical content may exude the element of addiction, which may interfere with the research objectives. It may be suitable for future works with different context, but games of this genre are not ideal for this research topic.

4.2 MEASURING BRAIN FUNCTIONS AND ITS INSTRUMENTS

An important aspect of EEG analysis is the understanding the brain's cognitive functions. Apart from the emotional stimuli used as the classifying model, the measurement of the brain's performance are also an area of interest. Just as in the emotional responses, specific brain functions are triggered while their EEG data are being recorded. Only this time, no stimuli is being applied. Instead, an interactive tool designed to measure specific brain functions are used.

Many instruments of measuring brain performance exist. Established and reliable tool is desired for this research. Written and manual test instruments are one of the established option for reliable results as it has a lot of publications to support it. Such test is the "*Complete Book Of Intelligence Test"* by Philip Carter (2005) which are quite reliable for psychological studies. Although highly credible, it has several drawbacks. The obvious one is since it is a printed material, the test cannot be repeated on the same person for the second time. The less obvious one is the time it takes to complete the test is too long and impractical for this research.

Another test instruments to measure brain performance is the interactive type, looking similar to a video game. One example is the Cambridge Brain Lab Brain Test, which measures the brain's performance on four specific functions. While at a glance it looks like a gamified version of the written test instruments, the test is well developed and has solid research behind it. As supported by many academic publications, the Cambridge Brain Test is a reliable tool for the purpose of this research. Several advantages of this tool includes:

1. Precisely timed test
2. Tests only takes several minutes instead of hours
3. Instant results and formatted reports
4. Saved history for later retrieval of daily tests if necessary
5. Different test content for each subjects per day
6. Inclusive of additional data input such as stress level, sleep deprivations, and lifestyle can be added to enhance profiling database.
7. Automated scoring based on the input score and time responsiveness.

The test instrument measure four specific brain functions. They are:

1. C-Score (Overall cognitive performance)
2. Memory
3. Verbal
4. Reasoning.

Other benefits for using this instrument are the login feature which can retrieve past sessions for later references, digitally portable, easily accessible, and it can work in the same device as for the game play session. The latter is most useful for an uninterrupted EEG data collection process.

4.3 TEST CONDITIONS AND DATA COLLECTION SETTINGS

Now that the foundation of the data collection is laid out, let's look at the practical side of the acquiring all the EEG data for analysis. Apart from reassuring and comfortable environment for the subjects to volunteer for this research, some specific test conditions must also be considered for the best data acquisition possible.

The most important thing for EEG signal analysis and processing is the elimination or reduction of unwanted signals. This is known as noise. While the DABO machine has the advantage of automatically omits certain signals such as eye blinking and limb movements, there are other noises still need to be kept under control.

The most obvious noise or unwanted responses form the players during the experiment is the influence of music and sound effects from the games. Just as much as visual elements can influence the emotional responses of the brain, music and other auditory elements can also affect the players (Bradley, 1999). Such interference will be difficult to isolate from the visual elements responses during post data collection. In fact, the EEG signals may even be intertwine that it may even be impossible. Therefore, number one rule for this research experiment is that the games are played with all the sound settings muted. This means the game will be played without music, sound effects, and/or narrative voice overs. By doing this, sound responses of the brain are not going to be active. The EEG signals will purely be of the visual elements only.

However, muted gameplay may not be enough. Environmental sounds surrounding the experiment location may also interfere with data collection. For this reason, the test has to be done in an isolated environment, enclosed, quiet, and away from public distractions.

4.4 PARTICIPANTS SELECTION AND POPULATION

The experiment for this research requires volunteers of age between 20 – 40, who are considered as normal healthy adults. The age range is selected based on the context of this research. Children and teenagers are unsuitable due to the needs for parent/guardian consent to allow legal EEG experiments.. Older participants than the selected age range may not be familiar enough with video games to provide the best data for analysis.

In terms of population, the numbers are not relevant since the analysis will be on the instances of the streaming EEG signals came out of the brain. The analysis will be on the EEG signals, rather than profiled participants. On this basis, one participant should have been enough. However, for purpose of variety in data sets – gender, game enthusiasm levels, and other factors – more than one subjects are desirable albeit the exact number of participants are not specified.

The target age group is applicable mostly to University students, although in the upper ranges of 30 – 40 years old may consist of working people. This age range is an excellent specimen since they are not too young to grow up during the times when video games are everywhere (phones, tablets, etc.) but also not too old to not knowing what a video game is.

In spite of the fact that the analysis of this research will be on the EEG data rather than population statistics, an attention to minimize bias within the data collection for more than one subject must be taken care of. One such bias is the gaming habits (gaming enthusiasm and game play frequency) of the subjects. Sleep deprivations, healthy lifestyles, and health issues such as prone to seizures from screen flickers may also contribute to the factors that can cause certain bias in the analysis. It may not become an unwanted 'noise' within the EEG data, but it may affect the comparison analysis between abstract and realistic design styles.

To solve this issue, the subjects will undergo a screening process prior to the EEG recording sessions. The screening process is similar to the profiling of the subjects, as if this research is going to do sampling population statistics. However, it is important to keep in mind that the focus of this study is in the EEG data, not the profiling. Screening information only serve as additional references if the data analysis were to be found inconsistent between different subjects.

Details of this screening process is included in the section 4.8 LEGAL MATTERS AND OUTLINING PROCESSES, where a protocol for good research ethics has to be approved. However, the three main profile information required for this research are explained as follows:

1. Game Habits:
   a. Game playing frequency

      People have their own game playing frequency. The time they play, the duration, and how often they play are all unique to every person. Regardless of the degree of interest in video games, some game enthusiast may not play as often as casual gamers. This may be due to time constraints, funding limitations, or other factors. Indeed, casual gamers who are playing games just to kill time may actually play more often than the average gaming enthusiast.
   b. Game enthusiasm

      This is the degree of interest in the video game industry. Having a high interest in video games does not mean frequent game play or high level of expertise. For instance, one can be a fan of a specific game title for its content, design, story, or gameplay but he or she seldom play any other games other than the one liked.
   c. Game play expertise

      There is also a group of people that have the talent to always able to beat the game's challenges or mechanic. Video games have their own constructs that engages the player and challenge for high scores. Whether it is in the form of puzzles or kinesthetic challenges, a person who does not have any interest in video games can still have the ability to be good at playing them. The level of expertise sometimes does not relate proportionately with the level of enthusiasm and/or level of frequency.
2. Sleep deprivations

   Sleep deprivations may influence the subjects reaction during the experiment. In particular, the brain tests session may be affected with low performance if the subject is lacking enough sleep. In the brain test instrument, sleep pattern can influence the outcome of the test. Analysis of video games design styles do not require the precise score of the brain performance, but differences in brain health and state of alertness may distort some analysis.

3. Healthy lifestyles

   Just as in the sleep deprivation criteria, healthy bodies create healthy minds. And the habits of regular exercises and/or physical activities affects the way the mind respond to visual stimulations. Exhaustion may also influence emotional responses and brain performance. Although their effects may not alter the emotions completely, the amplitude of the EEG reading may be affected. These factors will not distort the analysis, but might surface as inconsistency in the comparison analysis.

Apart from the above information and some other basic particulars of the subjects, (such as age, gender, etc.) they will also be tagged with their brain performance scores from the aforementioned brain tests. Again, as in the profiling of the subjects, the brain test scores are not important for this research, since the focus of this study is on the EEG data analysis. However, some pattern of distinct characteristics that is associated with the cognitive functions of the brain might surface itself if there are variations, irregularities, or inconsistency in the data analysis between different subjects. Correlation of design styles and the brain's learning aptitude is a possibility. Discoveries of such connection between video game designs and the human psyche is what this research is aiming for.

4.5 EEG SECTIONS AND THEIR DURATION.

Now that pre-EEG session preparation is laid out, the EEG sessions themselves need to be seamless in execution. Obviously the session will be divided by separate objectives discussed above. In addition to that, there must be a couple of sections that must be added prior and after the main EEG sections are carried out. These are the resting state of the subjects, with their eyes close and open to determine their state of mind before and after the experiment. These EEG data are going to be the control variables and are the ground reference of each subjects. Thus, there are a total of 5 sections of the EEG recording session. The description of each sections, along with their time duration to record the EEG signals, are laid out in Table 4.2:

Table 4.2: EEG recording sessions and their time duration

Section	Activity	Duration
Part 1: Resting state	Eyes closed (1 minute): To initiate the baseline for EEG data, the subject will be required to sit still with eyes closed. This is to assess the default state of the brain.	1 minute
	Eyes open (1minute): Similar to eyes closed, but this time the subject will sit still with eyes open and staring at a blank white computer screen.	1 minute
Part 2: IAPS (Emotional Valence and Arousal Stimulation)	Emotion stimuli (4 minute, 1 minute for each different emotions): This procedure is to stimulate a particular emotion by exposing the subject with a specific video. The recorded emotional signals reacting to the stimuli will serve as a model for this research to analyse the effects of playing video games in the later sessions. There are 4 emotions to capture: Happy, Sad, Calm, and Fear. Each will take 1 minute to record the EEG data.	4 minutes
Part 3: Learning Aptitude Test	There are 4 interactive aptitude tests to be completed. At the end of this session, both EEG data during aptitude test and test result report will be obtained.	15 minutes
Part 4: Playing the Video Games	The subjects will be given two games to play. One will represent abstract design, the other will represent realistic design. For each game, the subject will play for 5 minutes.	10 minutes
Part 5: Closing Session	Finally, an eyes-closed and eyes-open session similar to part 1 earlier will be the closing stage of the EEG recording session.	2 minutes
	TOTAL DURATION	37 minutes

These sections must be performed in sequence and properly timed so that every data that came out of the EEG machine is identified and tagged with its appropriate sections. Fortunately, the DABO machine can be set up to accomplish this task automatically. The particular EEG machine being used is able to set up the duration of recording exactly to the length of time that is specified for each sections. The file formats, filenames, and other meta data such as date and time of recording can also be embedded in the files.

The timing of every section is crucial. It has to follow what is required of it. If the time of recording is less, analysis may be affected. If the time duration of the EEG recording is longer than necessary, the subjects – and therefore the quality of the EEG signals – are affected with fatigues and exhaustion. Longer recording durations are limited by the battery capacity of the EEG machine too, as it is not possible to be used while it is plugged in due to safety concerns.

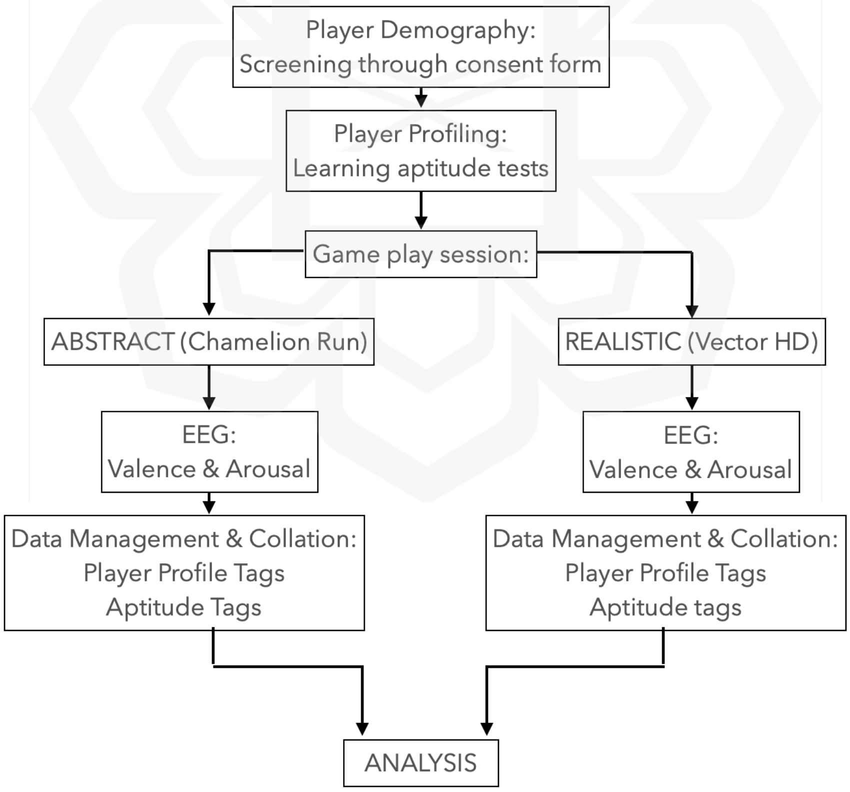

Figure 4.1: Overall work flow of data collection

The Figure 4.1 is the overall workflow for the data collection process. Note the EEG device is already in place and ready to record the brain signals prior to the brain test. Setup is being done while the subjects fill in the consent forms to save time.

4.6 DATA ANALYSIS METHODS

EEG signals data for every participants are tagged with their profiling constructs and learning aptitude allowing them to be sorted and projected onto a valence-arousal graph. The EEG signals during game play session cannot yet identify the participants' emotional valence and arousal when they are playing the game. These unknown data are to be analyzed with the emotional model established earlier during the EEG working protocol session. By using machine learning algorithm, the emotional valence and arousal of the participants during play time can be determined.

The classification process utilizes Python programming code. The code can be configured to analyze a specific frequency range of the EEG signals. This allow the possibility of analyzing the emotional valence and arousal at different bandwidth of the brain. However, it is not a software package where one can simply key in the parameters and wait for the results to come out. The codes are written in separate files by specific pre-processes. The classification processes flow as below:

1. Four EEG data of known emotions – happy, sad, calm, and fear – are processed with the feature extraction code. The code saves two preprocessed file.
2. The preprocessed files are then used to generate two models for valence and arousal each. The resulting process also generates a training data for each model. The training data is used to measure the ability of the model to predict the valence and arousal of the known value. The percentage of successfully predict the training data is the accuracy of the model.
3. The emotional model can now be used to classify other files of unknown emotional state. This particular code are the main workhorse to turn raw EEG data into spreadsheets of emotional valence and arousal responses.

4.7 DATA MANAGEMENT AND FILE NAMING CONVENTIONS.

The amount of data coming from the EEG machine is going to be insurmountable. Considering that for every participants/subjects will generate 19 EEG signal streams coming from the 19 channels of electrode attached on their heads, data streams of more than 30 minutes sampling EEG reading at the rate of 250 samples per second will inevitably going to give a tedious numerical analysis. Organizing the data and collating them for analysis in a proper format and workflow is important. Failed to do this and there will be mistakes in the analysis results. The consequences of false findings is intolerable. Since the EEG signals will produce long pages of spreadsheets, keeping them organized and easily trackable is a priority.

Here is how the files are managed and processed:

1. Data files are segregated into folders based on the subject. For each subject, EEG recording of the resting state (eyes-close and eyes open), emotional stimulation, aptitude tests, and game plays are in their own folder. All other files yielded by the machine learning processes will be saved in their own respective subject as well. Thus, there are two types of data files to keep in mind that will be saved in each of the subjects' folder:
    a. The raw EEG files that came from the EEG machine.
    b. The pre-processed and processed data that was yielded by the machine learning classifications process.
2. The naming convention for the files are consistent throughout the subjects, to avoid confusion. Therefore, each subjects have their own designated folder. They each contain the same file naming convention and organized in the same file structure.
3. The raw emotional stimulation files are named HAPPY, SAD, CALM, and FEAR. The resulting computational model from the feature extraction process generates the MLPR_model_Aro file for the Arousal model, and MLPR_model_val for valence.
4. The aptitude tests measure the subjects brain performance. However, these data files contain the emotional responses associated with each specific cognitive test. Since each subjects receive different version/activities for each specific cognitive test, the files are named as GAME1, GAME2, GAME3, and GAME4 for each specific cognitive activities. Classifying these data will reveal whether cognitive functions of the brain can be correlated or associated with emotional responses.

5. The ABSTRACT and REALISTIC games are the main focus of this research's analysis. They each contain 5-minute gameplay for different design styles. At a sample rate of 250 samples per second, one subject can reveal enough information on the emotional responses behavior and characteristics when playing two visually different games.

4.8 LEGAL MATTERS AND OUTLINING PROCESSES

Any research involving human subjects to execute certain experiments must not violate the human rights, privacy or harm the participants. In any case this research is committed to oblige any laws and ethics regarding the testing of human brains. In no way that this research has any illegal activities in its method and design. But to ensure a safe procedures and as a reassurance for the volunteers invited to participate, a certain protocol has to be followed.

The International Islamic University Malaysia (IIUM), the university of this research, has its own governing body for such regulations. Known as the IIUM Research Ethics Committee (IREC), a set of rules and requirements are prepared to regulate research experiments so that they comply to the correct ethics and etiquette during data collection.

In the effort for IREC approval, several documents are prepared to meet their demands. These documents are:

1. Approval application letter.
2. Consent Form for the participants to agree the terms and conditions of the experiment. This includes the rights to withdraw from the experiment.
3. An information sheet for the participants to enlighten them about the research, including the outline of safety and confidentiality.
4. Profiling form.
5. Privacy agreement form. The participant can choose whether to hide their identity or not as well as options to permit the level of sharing of information and research data.
6. Flowchart of data collection
7. Schedule and agenda of the data collection procedure.

After submitting an online application, this research is certified as IREC approved. The data collection procedure is safe, non-intrusive, low risk, and above all legal.

Once the consent form is signed and the participant agrees to proceed, the steps to obtain EEG data required by this research is outlined as follows:

1. Aid the participants to wear the EEG cap on their head. This is to mount and hold the EEG electrode firmly in the correct place around the subject's head. Note that the size has to be selected carefully so as no electrode are loose.
2. While the EEG device is off, electrodes are placed one by one on the participant's head and connected to the correct recording channel on the device.
3. A non-harmful electrolyte gel is applied inside the electrode mount to ensure physical contact with the scalp. This is to get a clear and uninterrupted signals from the brain.
4. The device is switched on and signal connections are checked. Once cleared for recording, the room lights are switched off and the environment are kept silence.
5. Recording proceeds as discussed in section 4.5 EEG SECTIONS AND THEIR DURATIONS.
6. At the end of the session, the device is switched off and the EEG cap is removed from the participant. While the electrodes are being removed from the cap and cleaned for the next session, EEG device is docked and recharged to prepare for the next volunteer.
7. Participants are given a towel and shampoo to clean up their head.
8. Repeat all of the above until the last participant.
9. End of data collection.

4.9 SUMMARY OF EXPERIMENTAL DESIGN.

The experimental design of this research has been laid out to achieve the research objectives and to answer the research questions. Three core elements in this research are emotion, brain signals, and machine learning classification. The ultimate aim is to classify game play activity into emotional responses so that the Design Styles of each game can be analyzed to learn their association with the human emotions.

In a nutshell, this research applies the following:

1. **Research Method**: Quantitative analysis of emotional valence and arousal responses towards abstract and realistic design styles in video games.
2. **Research Design**: Valence and arousal classifications of brain signals captured through electroencephalogram (EEG) while playing abstract and realistic video games using machine learning based on the computational model of stimulated emotions.
3. **Emotional Stimuli:** International Affective Pictures System (IAPS).
4. **Feature Extraction:** The algorithm to generate the emotional models will be the Power Spectral Density Analysis.
5. **Machine Learning Classification:** A Multi-Layer Perceptron algorithm for classifying data will be applied for this research.

Since the research involves human subjects, it is imperative that the research design is safe and non-intrusive to the volunteers. This research meets the laws and regulation of the IREC research committee and the research protocol has been approved. Not only that it is safe, the research framework can be adapted to study other topics and context such as game addiction and stimulation of audio design. More on that in Chapter 6.

CHAPTER 5

DATA COLLECTION

5.0 INTRODUCTION

The actual data collection process is discussed in this chapter. Unlike in Chapter 4, where the experimental design is laid out, this chapter discusses the practical side of acquiring the research data. The most important aspect in this regard is the handling of the human factor. Preparation is key to minimize mistakes and fatigue. Checklists also helped with consistency and smoothness of the data collection sessions.

5.1 PREPARATION OF DATA COLLECTION

Just like in a digital content creation process, there must always be a pre-execution phase where the real work is prepared before it begins. This is to ensure smooth and uninterrupted running of the data acquisition. The biggest benefit of preparation is to minimize problems, mistakes, and errors that could result in unusable data.

By the time the data collection stage is being prepared, fifteen candidates to volunteer to be the subjects for this research have already been found. These consist of ten male and five female students around the same age. One of the female subject is not a student and slightly older than the rest. There is also one significantly older male subject who is also not a student. All of the fifteen volunteers successfully completed the data collection process. Each subjects provided 14 emotional responses for different categories, based on the research protocol.

The EEG methods requires the attachments of electrode or nodes directly on the subject’s head. This is an issue for female subjects, since they have to take off their hijab. A solution would be to acquire help from female colleagues to conduct the EEG recording sessions. However, the added crew members need to be trained to perform all the necessary tasks. This is also an important aspect of preparation prior to the actual data collection process.

The flow of the EEG sessions had to be planned and prepares carefully as well. As each individual subjects requires about 33 minutes to complete the data collection, those waiting in line may experience boredom or fatigue while the others took their turn. A schedule is therefore given to the subjects so that they would only come to present themselves in the time slot assigned to them. There are also a recharge period for the EEG device as well as a cleanup session to prepare for the subsequent subjects.

5.1.1 PROTOCOL CHECKLISTS

To ensure consistency in executing data collection for every session, the protocol and tasks is prepared in a checklist. Checklists are very important so that nothing is forgotten and mistakes can be avoided. Table 5.1 is the checklist to ensure data collection is saved and organized with the correct naming conventions to make data analysis easier later on.

Table 5.1: Data Collection Protocol Checklist

Pre-recording preparation:

- ☐ Collect Signed Consent Forms
- ☐ Label Consent Form with folder/sequence number
- ☐ Naming convention: EEG Operator_#_name (e.g: Ayub_23_Nurul)
- ☐ Check EEG signal before recording session begins
- ☐ LIGHTS OFF

Section	**Activity**	**Remark**	**Duration**
Part 1: Baseline and Emotions Stimuli	- Eyes closed (1 minute): To initiate the baseline for EEG data, the subject will be required to sit still with eyes closed. This is to assess the default state of the brain.	☐ Total silence ☐ No movements ☐ Set time limit ☐ Set task as Eyes Close	1 minute
	- Eyes open (1minute): Similar to eyes closed, but this time the subject will sit still with eyes open and staring at a blank white computer screen.	☐ As above ☐ Blank screen with a center marking ☐ Set time limit ☐ Set task as Eyes Open	1 minute
	- Emotion stimuli (4 minute, 1 minute for each different emotions): This procedure is to stimulate a particular emotion by exposing the subject with a specific video. The recorded emotional signals reacting to the stimuli will serve as a model for this research to analyse the effects of playing video games in the later sessions. There are 4 emotions to capture, each will take 1 minute to record the EEG data.	☐ IAPS ☐ Do not mention the emotions ☐ Take note on the emotions sequences ☐ Set time limit ☐ Label suffix as emotion numbers ☐ Set task as Others	4 minutes
Part 2: Learning Aptitude Test	- There are 4 interactive aptitude tests to be completed. At the end of this session, both EEG data during aptitude test and test result report will be obtained.	☐ Label Suffix as game number ☐ Note game name if possible ☐ Set NO TIME LIMIT	15 minutes
Part 3: Playing the Video Games	- The subjects will be given two games to play. One will represent abstract design, the other will represent realistic design. For each game, the subject will play for 5 minutes.	☐ Mute speakers ☐ Label Suffix as Abstract (for Chameleon Run) and Realistic (for Vector) ☐ Set 5 minute time limit for each game	10 minutes
Part 5: Closing Session	- Finally, an eyes-closed and eyes-open session similar to part 1 earlier will be the closing stage of the EEG recording session.	☐ As on row 1 and 2 above	2 minutes
	TOTAL DURATION		33 minutes

Post recording tasks:

- ☐ Data transfer (after each participant) into external drive
- ☐ Clean up: Nodes and caps
- ☐ Switch off all switches and unplug all wires/cables
- ☐ Cleaned EEG cords to be laid properly
- ☐ Recharge EEG device for next session
- ☐ Transfer all data to cloud (shared folder)

5.1.2 FINDING A TEAM AND RECRUITING CREWS

Apparently, one person cannot execute the entire data collection process. Help is needed to perform multiple tasks at the same time. At least 3 persons are required. An additional 3 female crews are needed to perform data collection on female subjects. 6 post-graduate students volunteered for the assistance, and they were trained to operate the EEG devices prior to the data collection sessions. 3 of them lend their hands for the assistance for male subjects, while the other 3 female volunteers assist in the female subjects data collection.

The training to operate DABO EEG device is fairly straightforward, thanks to the device being easy to use. However, care and meticulousness is required when operating the device to ensure that the 19 cables connecting to the nodes channels on the subject heads are connected properly. Signals are checked for proper connection before the EEG data recording begins. The signals connection can be improved by applying non-damaging gel between the scalp and the electrode. The gel improves electrical conductivity without ruining the subject's hair. A shampoo is given to the subject for flushing out the gel after the data collection has been completed.

Gel residue may be present on the electrode and around the cap of the EEG device. These need to be cleaned as well before the next session can begin. Thus, in post data collection procedure one of the crew member helps with cleaning and preparing the cables, another with data saves and transfer, while the other brief and entertain the subjects for smooth EEG session.

5.1.3 PREPARING THE SPACE FOR EEG SESSION

The environment for EEG session is crucial for accurate data collection. The criteria for an ideal EEG data collection is as follows:

1. Dark room mode

   The room must be able to turn completely dark so that the subject will only focus his or her sights on the visual stimuli. However, a windowless room may make the environment feel awkward, unsafe (especially for female subjects), and claustrophobic. Hence a window blind as a solution.
2. Silence

The environment must be free from audio distractions. It must be away from any source of loud noises such as crowded activities.

3. Proper ventilation

   This is rather obvious. Nevertheless, traditional ventilation of air ducts may lead sound and noises from outside to intrude the room. An air-conditioned room is more preferable.

4. Adequate power source.

   This is also critical. Electrical socket is needed to power the EEG device, the workstation to save and transfer data, and to recharge the tablet computer to play the games.

It is to be noted that the data collection was conducted in December 2019, before Covid-19 pandemic started in March 2020 when the entire country was in lockdown. This fact is to explain how such enclosed environment and physical contact during these sessions are possible to be carried out freely. Were this procedure to be carried out during or post pandemic, the protocols has to be changed.

5.1.4 PRELIMINARY EEG RECORDING TESTS

A pilot data collection was conducted with the crew volunteers as part of their training. Since they are aware of the protocols and know the games that they will be playing, the data in this session will not be used in the final data analysis. Nevertheless, it is a good session to test the flow of the data collection procedure as well as refining the protocols and checklists.

One of the most important lesson learned in this preliminary session is the importance of grounding electrostatic during a rain storm. The crews accidentally caused a static discharge to the power cable of the DABO EEG device during recharging phase. The power cable was completely blown up and burnt but fortunately the rest of the device is intact. It turns out that the device is better to be powered down before being docked to its charger. This means that the data transfer had to be done after cleanup and this added a few minutes in the overall data collection session.

On a side note, the file save naming convention included these preliminary tests, and that is why the subject number in the data analysis starts with number 3 instead of 1. Subjects number 1 and 2 are one of the preliminary tests.

5.2 THE ACTUAL DATA COLLECTION SESSION

Thanks to the meticulous planning, the actual data collection went smoothly without any serious problems. Of course, small hiccups appear here and there, but they didn’t interfere the session altogether.

5.2.1 GETTING READY FOR ACTUAL DATA COLLECTION

To start the EEG recording session, the subjects were first briefed about the experiment. The consent form, along with the profiling survey were handed out and read to them. While the subjects digest all the information regarding what kind of data about them that was being collected, one crew member selected the right head gear size to mount the EEG nodes on the subject’s head. This is crucial for clear signal detection, as misconnected nodes can lead to noise within the signal.

The head gear, which basically looks like a swimming cap with many holes, serves as the rig to mount the EEG detection electrode at the right position on the subject’s head. Thus, it has to be worn with the right size. Too loose and the electrode will not detect the signal. Too tight will cause mis-location. Figure 5.1 is a photo of the one of the subjects being prepared with the EEG cap in place.

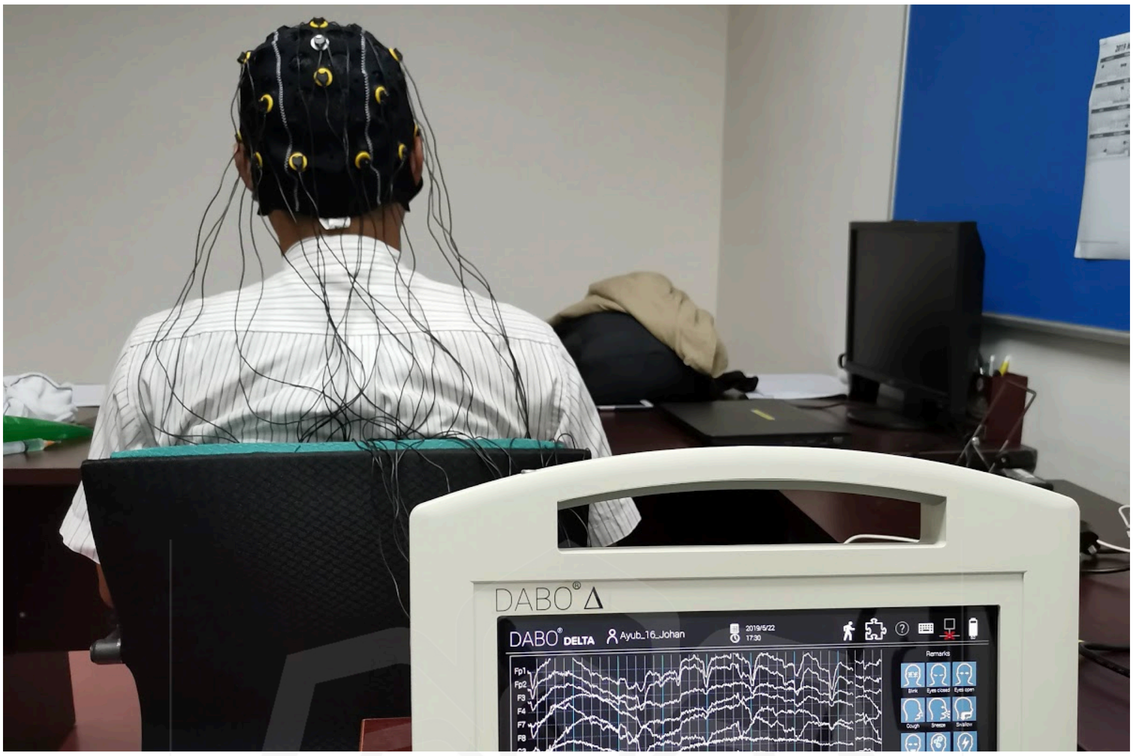

Figure 5.1: Subject is ready for EEG session

Note the wires attached to the subject's head. These wires must be connected to the right channel into the DABO EEG device. Otherwise the data analysis will be inconsistent and misinterpreted. The location of the electrodes on the subject's head corresponds with the brain anatomy for correct reading of the brain signals. If misplaced, the EEG recording may not be accurate.

5.2.2 SUBJECTS SCREENING AND PROFILING INFORMATION

While one of the crew assists setting up the EEG device on the subject, another briefed the subject and prepares the consent form. The form also includes certain questionnaire to collect a few profiling information of each subject. The profiling information will help the analysis of the EEG data in case if there are any discrepancies in the results.

The information that was collected is as follows:

1. **Basic Personal Information**

   This is the basic information regarding the subject's identity. However, such information remains unpublished and will not be exposed to comply with the privacy matters. The information collected in this category are:

   i. Name
   ii. Gender
   iii. Age range
   iv. Screen flicker sensitivity (if the subject has an issue with seizures when looking at a computer screen)

   Throughout the entire thesis the subjects will only be referred to their identification number: F01, F02,…..F10, etc.

2. **Gaming Familiarity and Exposure**

   This piece of profiling information is quite crucial, as there will certainly be a difference between a person who has played many games and familiar with the gaming industry compared to a person who seldom plays a video game and has no idea of whatever there is in the gaming industry. To gain the idea of each subject's game exposure and familiarity, the following information is collected:

   i. Enthusiasm

   Enthusiasm means that the person likes video games or specific kind of video games. For instance, an automotive enthusiast may like racing simulations, sports fan being sports game enthusiast, and those with cinematic eye may find themselves amazed with video games that has incredible storytelling in their visual design. Enthusiasm, however, does not mean that the person plays video games often. Nor that it means that the person even like any other types of video games. It is only an indicator whether the person is exposed to a certain game mechanics that can reveals him/her to be familiar with any specific game platforms/devices.

   ii. Frequency

   The frequency is obviously how often that the person plays video games. This survey ranges from multiple times a day to only a few times in a year. The frequency of gameplay may indicate a level of addiction for video games and can be correlated to the enthusiasm if the person likes only a specific type of video games.

   iii. Duration

Duration of game play means the length of time a person plays a video game in any particular time. The duration of the gameplay may indicate how immersed that person is into the game. Some games has narratives and storytelling aspect in its design. A very immersive game experience can motivate a player to play games for a very long time.

iv. Expertise

For some gamers, they are very competent in certain games that they have developed a muscle memory in their body. Such gamers may easily adapt from one game title to another, especially if the games are of the same genre. Even when trying different genre, they easily learn to beat the game challenges in a very short time. Expertise measure how well the subject can recognize, learn, and defeat the game. However, this is only in the opinion of each subjects, and the results may not be accurate enough for profiling data. It is a guide to recognize the subjects competency in video games. This profiling construct does not play a critical role in data analysis, however it may reveal extra insights when correlated with the analysis findings.

3. Fatigue and Sleep Deprivation

According to (Warner, 2007) sleep deprivation and fatigue affects emotional responses. Those with a lack of sleep will have a more irrational emotional behavior. Their emotional changes and reactions are 60 percent higher than those with enough sleep. Since this research is dealing with emotional responses, it is a good idea to know the subject's most recent sleep behavior and history.

4. Physical Fitness and Health

Apart from sleep deprivation, health and fitness may also affect emotional responses. However, this information is only a basic frequency and recent history of their physical exercises and activities. Statistics such as heartbeat, blood pressure, or body mass index (BMI) are not taken into account.

The summary of the consent forms are shown in the Table 5.2.

Table 5.2: Subjects profiling summary

Subject #	Gender	Age Range			Gaming Profile				Sleep Deprivasion		Lifestyle Profile		Screen Flicker
		17-24	25-30	31-40	Enthusiasm	Frequency	Duration	Expertise	Duration	Recent	Frequency	Recent	
F03	m				med	med	med	veteran	normal	normal	med	no	no
F04	m	✓			mp**	very high	med	veteran	low	low	very high	no	no
F05	m	✓			rpg*	very high	med	veteran	normal	low	very high	none	no
F06	f	✓			action	med	high	veteran	low	low	med	recent	no
F07	f	✓			rpg*	med	med	veteran	low	low	high	recent	no
F08	f			✓	low	low	low	novice	normal	normal	low	no	no
F09	f	✓			med	med	med	novice	normal	low	low	no	no
F10	f	✓			low	low	low	novice	normal	low	med	no	no
F11	m	✓			low	med	med	novice	low	normal	low	recent	no
F12	m	✓			football	med	med	novice	low	low	high	no	no
F13	m	✓			med	very high	med	novice	low	low	high	no	no
F14	m	✓			med	med	long	veteran	normal	normal	very high	very	no
F15	m	✓			action	med	low	novice	normal	low	med	no	no
F16	m	✓			med	med	med	expert	low	low	med	very	idk
F17	m			✓	rpg*	low	med	novice	normal	normal	high	recent	no

*rpg: Role Playing Games

**mp: Multiplayer

5.2.3 BRAIN PERFORMANCE TEST RESULTS

Apart from the profile of the subjects as individuals, the brain also has characteristics that can potentially be correlated to the emotional responses when playing video games. There are many aspects of the brain that can be of interests, but the most potent aspect is the cognitive function of the brain.

In this research, the brain is measured in its performance of the cognitive function. The instrument to perform this task is an established web-based interactive application that can track and record brain performance in 4 different categories:

1. Cognitive Performance (C-Score)
2. Memory
3. Verbal
4. Reasoning

During the data collection, brain performance test is carried out after the emotional stimuli has been completed. Table 5.3 is the summary of the brain performance test.

Table 5.3: Brain performance results

Subject #	C-Score	Memory	Verbal	Reasoning
F03	6.11/6.64%	11.06/30.41%	8.55/12.54	6.37/1.54%
F04	N/A	N/A	N/A	N/A
F05	N/A	N/A	N/A	N/A
F06	8.44/14.55%	11.41/38.41%	7.56/7.62%	10.95/20.66%
F07	10.43/27.05%	13.1/59.38%	7.62/7.62%	12.9/42.09%
F08	10.28/27.05%	16.13/87.55%	7.23/5.86%	10.41/16.37%
F09	12.29/42.9%	16.76/90.59%	9.6/18.79%	10.64/20.66%
F10	5.5/5.37%	10.86/30.41%	7.24/5.86%	6.8/2.13%
F11	N/A	N/A	N/A	N/A
F12	N/A	N/A	N/A	N/A
F13	N/A	N/A	N/A	N/A
F14	8.34/14.55%	6.72/4.26%	12.36/22.24%	10.88/20.66%
F15	9.2/20.28%	13.32/63.29%	10.13/22.71%	7.91/4.11%
F16	11.58/38.74	13.58/67.09%	10.75/27.09%	10.93/20.66%
F17	N/A	N/A	N/A	N/A

The table shows 2 values: the score of the brain test and the percentage of how many subjects they scored higher in the test database. A result of 90 percent, for instance, means that the subject scored higher than 90 percent of other people in the brain test database.

The N/A denotes that the test scores are unavailable. This is to take note for future researches because although the test instrument saved all the test history and kept them in the statistics, the log-in procedure using a social media platform had caused a problem retrieving the data. Logging with email address was more reliable, but unfortunately those subjects that used social media account could not retrieve their information. This problem is due to the test instrument's technical side. The issue had been brought to their attention, but alas, it has not been solved.

Fortunately, the scores are not part of the research objectives. It is the EEG data during the test session that matters. And these data are the ones that was collected for analysis and hopefully be able to correlate with the EEG data of the games and emotion sessions.

5.3 SUMMARY OF DATA COLLECTION

The data collection went reasonably smooth. All the required data needed for analysis are acquired as planned. For every subjects attended for the session, 14 EEG data sets have been saved. As far as critical data goes, the data collection was a success. There were a few hiccups, of course but these were unplanned and non-critical aspect of the data collection.

For future research adapting this research framework, some of the data collection procedure can be improved. There are 3 things that could have made this EEG session a lot smoother and quicker.

1. Digital Screening & Consent Forms: It was thought initially that these documents were to be handed out earlier to the subjects as they wait for their turn. The idea was to attempt the completion of this part of the data collection for several subjects simultaneously. It was also thought that it would take more time if the subjects read and signed their consent using the same device for the data collection (i.e the tablet

computer or laptop). Alas, experience had taught that it is better in the long term to do this digitally for easier and faster documentation.

2. Email Log-in Instead Of Social Media: Although the brain performance test is not a critical information for the EEG analysis, it would have given more opportunities to correlate the analysis results if it were complete. Unfortunately, despite the reliable database that is retrievable from the brain test instruments, signing up using a social media platform proved to be troublesome. An email account could have avoided such technical problem. As a consequence, the database is now unlockable.
3. Parallel Sessions: This requires a bit more funding to acquire a second EEG device. However, if such resources can be obtained, it is a good idea to have multiple sessions simultaneously. Especially when splitting into gender groups male and female. Both groups can have their sessions concurrently and independently. Parallel sessions would have a tremendous amount of time.

Despite small shortcomings, the data collection is finally complete. It is important to plan ahead of time to ensure everything runs smoothly. The preplanning must also be meticulous and in detail, leaving no room for error. Checklists are thus invaluable to carry out the plan as perfectly as possible without making any mistakes. As with other things, preparation is key. To ensure the data collection session runs smooth, several rehearsal sessions help to refine the process. Finally, even though some information is unretrievable due to log-in problems, the most important data – the EEG signals – are successfully collected, collated, and ready to be analyzed in a properly organized filing system.

CHAPTER 6

DATA ANALYSIS RESULTS

6.0 INTRODUCTION

In this chapter, data analysis and results are discussed. The objectives of the analysis is to scrutinize the characteristics, differences, and attributes of the brain activity via EEG signals from each design styles. This chapter is divided into five major sections:

1. Accuracy Analysis

   Raw EEG data are meaningless without any application of machine learning from a known computer model. As discussed in Chapter 3, this research applies the emotional stimuli to generate a perceptron for classifying game play (or other unknown) data. Accuracy analysis looks into the results of data modeling and thus explain how IAPs stimuli translates raw EEG data into emotional responses. Accuracy of the model to separate and cluster emotional responses in a scatter plot determines whether the data training is successful and justified for use in this research's analysis.

2. Scatter plot analysis of gameplay data

   Once the subjects' emotional model has been established with clear clusters of data in the scatter plot, similar scatter plot analysis is applied for game play data. In this analysis, the goal is to discover unique scatter characteristics or patterns that are associated specifically to each of the design styles of the video games being played. Correlation with the subjects' profile is also possible in this analysis, although that is not the main objectives of this research. With 5 minutes of game play for each game, scatter patterns that clump in a specific region of the valence versus arousal axis can definitely classify games design style consistently with emotional responses.

3. Multiple Bandwidth Statistical Analysis

   The brain emits pulses of signals in many different frequencies. Specific frequency ranges corresponds to certain brain state (Abo-Zahhad 2015). Lower frequencies usually associated with sub-consciousness activity of the mind while higher frequencies are associated with active motion of the body and the mind's concentration. Specific frequency ranges that are grouped by the same state of mind are known as the bandwidth. By analyzing the data in separate bandwidths, a more in-depth insights of how the brain responds to different game design styles can be observed. The analysis approach in this case is numerical statistics. Unlike the scatter plot observations, statistics objectively define data distribution patterns that are associated with the emotional responses while playing video games. Quantitative evidences of distinct reaction towards different design styles in video games are more concrete than visual inspections. Findings of multiple bandwidth analysis can give a more detailed insights to help designers create specific game content using the right design styles. The goal of this analysis is to further distinguish the emotional responses of the subjects to different video games design styles at every group of brain wave frequency bands.

4. Cognitive Correlation Analysis: Traces Of Brain Functions In Gameplay Activity

   Recall the brain performance test that was conducted prior to the gameplay EEG recording. This section of the data collection session was also recording the subjects' EEG signals. The objective of the brain test was initially for profiling. However, since the EEG data during the brain tests is available for analysis, it is an opportunity to find any connection between the brain's specific cognitive functions, emotional responses, and design styles. Surprisingly, as will be discussed in this section later in this chapter, a clear and distinct relationship between the brain functions and playing video games exist.

5. Spatial Analysis

   Spatial analysis is the observation of which area of the brain is active – or not active – during game play. It is hoped that different design styles will show different topographical maps on the brain. The device being used in data collection has 19 channels connected to subjects' scalp. This is more than adequate to study spatial activity of different game design styles.

6. Summary of Data Analysis Results

   Final section of this chapter will be the summary of the analysis results. The data collection experiences, pitfalls, hiccups, and other issues related to the analysis procedures will also be discussed here.

There were 15 participants took part in the research's data collection. Following the steps and protocols of acquiring quantitative data for analysis discussed in Chapter 3, each participants contributed a set of 14 EEG data. A total of 210 raw EEG data were acquired for analysis from all participants. These data are in numerical spreadsheet format (*.csv), and yielded 28 arousal and valence responses data after they have been processed with machine learning classification. Final output of machine learning classifications using Python programming yielded 420 numerical emotions data. The following list are some statistics and information of the data acquired:

- EEG file formats: *.csv and *.edf
- Number of participants: 15
- Total EEG files acquired: 210
- Total emotional response data obtained: 420
- Machine Learning platform: Python programming language, version 3.4 (later upgraded to 3.7)
- IDE used: Microsoft Visual Studio Code
- Spreadsheet statistical analysis platform: Microsoft Excel

The EEG recording session went well and smooth with a minor hiccup:

1. The recharge duration of the EEG device is longer than expected, causing subsequent participants in line to wait longer.
2. Data collection for several participants in one day is possible, but the timing had to be arranged so as to not induce the feeling of boredom that can affect EEG reading.
3. On paper planning will always be different than when practiced, especially timing. Several factors that was overlooked includes the time it takes to clean the device and prepare it for the next participant. Eating time for the research crews that had

helped with the data collection was also unnoticed during planning, and compromises were needed to accommodate basic needs.

4. Technical limitations of the EEG device were also underestimated causing power cable to sparked and melted. It was not dangerous in anyway, but there were concerns over the condition of the device. Fortunately, there were no injuries and no damage to the device. It seemed that the cable were electrostatically sensitive during rainstorm which was the weather at that particular moment. The remedy over this issue was to switch off the device before docking it to the charger for charging.

At the end of data collection, two file formats of EEG data sets were obtained. The formats are *.csv for spreadsheet statistical analysis and *.edf for machine learning applications. The *.csv format can also be used for machine learning apply using python programming language – and this is actually the method used in this research. Nevertheless, *.edf format data sets are always there for backups and other instances.

6.1 ACCURACY ANALYSIS

The first step to analyzing the EEG data is to take data sets from the stimulated emotions session to generate a computational model for valence and arousal responses. Since every person emits different brain wave pattern for the same emotions (much like a finger print), each subjects will have individual computational model to classify their own game play data sets.

A series of Python codes are applied to analyze Power Spectral Density (PSD) of the EEG data that were captured during emotional stimulation. The process is to recognize PSD features and convert numerical data from the EEG files into valence and arousal model. This is known as feature extraction process. By doing so, all 19 channels of brain signals streaming from the subjects' scalp are converted into a series of arousal and valence values.

Once the emotional model has been established, the same emotional EEG data can be used to train the model and observe its accuracy. The accuracy of the emotional model can be measured by its success percentage of predicting a known emotional data. Ideally, a success rate of 100% is desirable, but in practical there is always an error or imperfections. This is due to factors such as disturbances during EEG data collection, scalp-to-electrode signal detection efficiency, or the feature extraction process of generating the emotional model itself may have minor inconsistency. For this reason, it is important to look at the accuracy of the model before machine learning classification can be applied to game playing data.

From the data that were collected, all 15 subjects/participants give accuracy results of higher than 86 percent. The highest accuracy reading is 98 percent. This means that out of 10 known emotional data that were put into classification, 9 of them were successfully predicted by the model. 9 out of 10 may sound good enough, but the EEG data streamed 250 samples per second. With an emotional stimuli exposure of one minute per emotion (4 minutes total from 4 emotions), that is 60, 000 samples of data. With an error of 14 percent (for instance, 86 percent accuracy), there are around 8400 data that might be misinterpreted. They are data that might be useful for analysis.

The question is, what is the benchmark percentage that is considered as 'usable'? How to justify whether the model is good enough to be applied in the machine learning classification process? In the case of benchmarking the exact value of accuracy percentage, numbers alone cannot justify the usage of the model. It needs a clearer criteria to look at to warrant a model to be good enough. In science, numerical values need to be evaluated with context and in relation to a point of reference. Therefore, to validate the emotional model – other than statistically predicting the known data – is to observe whether the model can distinguish each emotions from each other. While numerical value may be an objectively valid justification of the usability of the emotions model, a scatter plot of valence vs arousal provides a clearer picture of its accuracy.

Figure 6.1 is a sample from one of the subjects' data. The vertical axis is the emotional valence value and the horizontal axis is the arousal value. As a recap of their definition in chapter 2, valence is the positive or negative affectivity, while arousal is how calming or exciting the subject matter is (Yaacob, 2015). Combination of the two values give the four basic emotions as shown in Table 6.1.

Table 6.1: Emotions interpreted as valence and arousal.

	Arousal	**Valence**
Happy	Positive	Positive
Sad	Negative	Negative
Calm	Negative	Positive
Fear	Positive	Negative

From the Figure 6.1, it can be seen that the emotional model is able to segregate the emotional data into four separate clusters. Since these data are of known variable, the plots can be made multi-colored to distinguish each emotions from each other. To justify whether the model is good enough to be used in machine learning, the cluster formation in that scatter plot must not overlap each other too much. A clear separation of each emotions must be observed. In the example shown in the figure, it is clear that only a few plots of the same color stray away from its own cluster and present in other cluster. Not only that, the cluster formation is correctly plotted on their appropriate valence and arousal axis. Despite accuracy reading of less than 100 percent, the scatter plot shows clear a separation of each emotions into their own individual clusters. All 15 subjects exhibits the same quality for their accuracy scatter plot, indicating that each of them provided usable emotional model to be applied in the machine learning analysis.

Thus, the scatter plot of valence versus arousal of the emotionally stimulated EEG data is important to:

- Justify the effectiveness of the PSD feature extraction in modeling emotions into a perceptron.
- Validate the perceptron for its usability for use in machine learning classification.
- Demonstrate the model’s ability in determining and distinguishing emotions from unknown data.
- Show that the analysis method and design works.

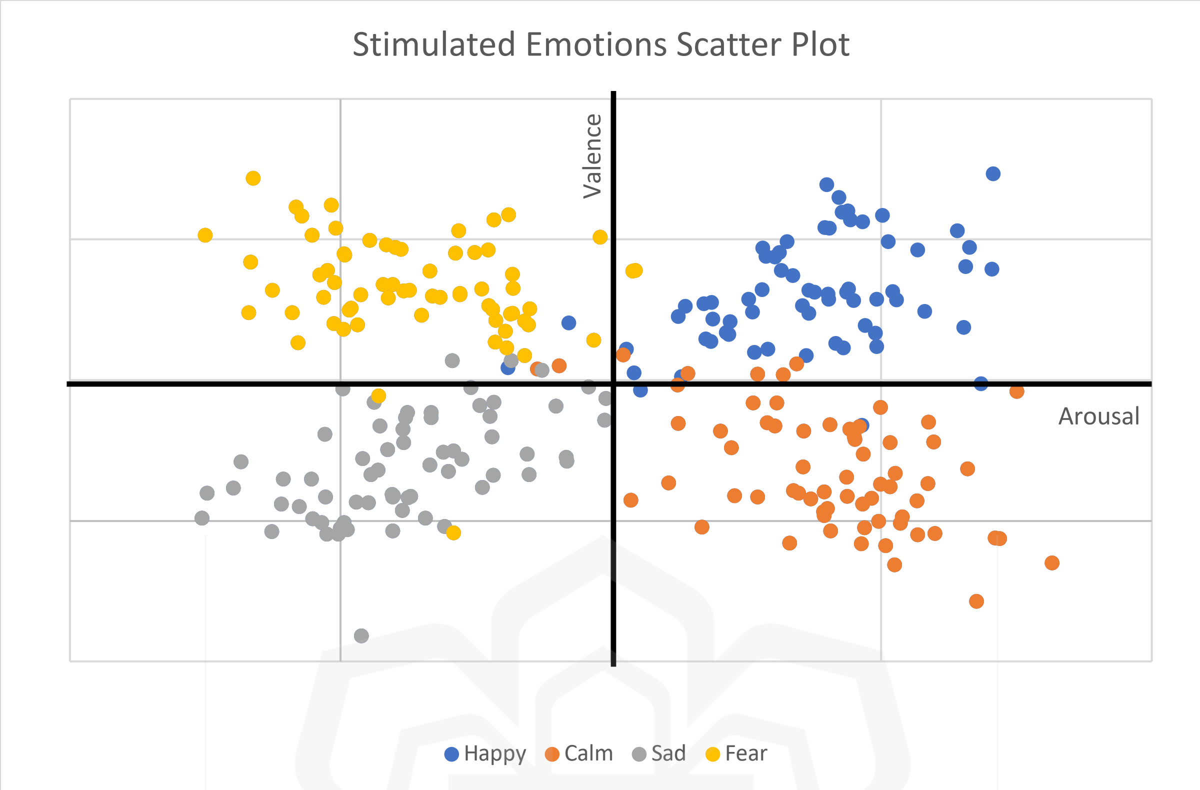

Figure 6.1: Scatter plot of emotional clusters from stimulated data.

Other than the above mentioned factors, the scatter plot also testify the contribution of the IAPS instrument that was used to stimulate the subjects' emotions. The emotional responses could not have been measurable if it were not because of the stimuli used. The success of this research's methodology in generating the perceptron for machine learning is a testimony of the effectiveness of the IAPS instrument.

Another important thing to mention in regards of the importance of the scatter plot is the ability of EEG signal processing to detect emotions regardless of the subjects' condition. During the data collection, subjects were different in various conditions. There are participants who lacked sleep, had a very bad toothache (that was feared to interrupt EEG signal, but it did not), was hungry and have not eaten, etc. Not one of them had their emotional stimulation ruined during the IAPS session. The result of this stage of the experiment to detect, measure, and model emotional valence and arousal is a success. The next stage of data analysis can therefore proceed.

6.2 SCATTER PLOT ANALYSIS OF GAMEPLAY DATA

Previously, the perceptron to classify data into emotional valence and arousal responses were tested and trained using a known emotions data. In this part of the experiment, it is put to its intended use – classifying data of other activities of unknown emotional state. By classifying data of other activities, it can be learned how the subject actually feels when reacting to activity he or she is engaging. This can provide a good insight to video games designers since the success of distinguishing design styles from the reaction of emotional responses means a general rule of design can be formulated. That is, of course, if the results show significant differences in emotional state of the subjects when playing the video games.

This is where the scatter plot matters. During the game playing session, subjects played two very similar games of different design styles. Their data are then classified using the emotional model before a plot of valence versus arousal are generated. It is expected to see cluster formations of specific emotions that are unique to each design styles.

The objectives of the scatter plot analysis is:

- To find distinct emotional state characteristics that are unique to each design styles.
- To observe any patterns and trends of the changes in emotional state associating to each design styles.
- To correlate, if possible, the relationship between design styles and the subjects' profile.
- To investigate where each game design style falls on the 'uncanny valley' curve.

To achieve the objectives above, the scatter plots from all 15 subject is observed visually. In this analysis, the numerical data is analyzed qualitatively. It is the first step to dive deeper in understanding how the human emotions respond to different design styles. The key points to look for are:

- Cluster formation and position on the valence and arousal axis.
- Differences in cluster formation between abstract and realistic game.
- The data distribution and its size of each design styles.
- The trending of the scatter plots.

- The dominant region where each design style's data distribution clumps together in the valence and arousal plot – in other words, the dominant emotion that may have stimulated by the specific design style.

The scatter plots must be the first to execute prior to other analysis because it reveals the obvious. If a particular design style influence the data points to cluster on a particular area in the valence-arousal plot, then it can be first identified before a detailed quantitative measurements can confirm. The less obvious details of the data samples will be studied in more detail with statistics and more complex methods which will be discussed later.

6.2.1 SCATTER PLOT RESULTS

As it turned out, each participants has their own unique plot characteristics for game designs. First impression is that there may not be any distinct patterns or significance in the data clusters to derive anything at all. The resulting scatter plots are too varied from subject to subject. But a closer look reveals some insights that are consistent for all subjects.

1. Cluster formation and position on the valence and arousal axis.

It was initially expected that the cluster formation for game play data may look similar to the accuracy scatter plot discussed earlier. The expectation was the valence and arousal plots would clump together in an area of specific emotion – either happy, calm, sad, or fear. However, the result is really different than the expectation.

Instead of clustering in a specific region of the valence versus arousal axis, all subjects consistently exhibits a characteristics whereby the emotional responses are centered in the neutral (or zero emotion) area. From there, there are spikes of emotional activities that peaks in the direction of different emotions. The spikes vary for each subjects, but all subjects display similar characteristics for both design styles. Figure 6.2 shows the characteristics from one of the subjects. Arrows indicates central mass. Every subjects responds similarly but with a notable difference by the formation of what looks like a spike (green arrow). Blue arrows show other subjects' spike direction. For both design styles on the same subject, these formation characteristics are the same.

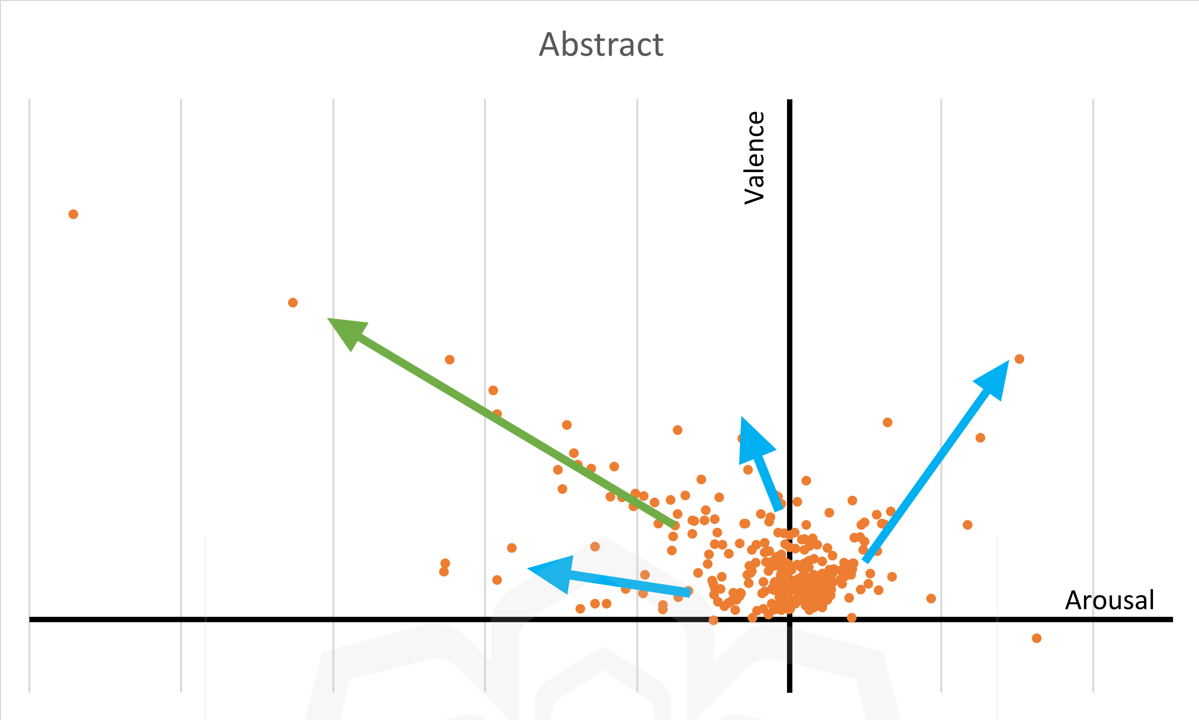

Figure 6.2 Typical characteristics of every subject's scatter plot

The fact that the spread pattern of the gameplay data varies by subject suggests a possible correlation of game playing activities with subjects' profiling. Alas, profiling and correlation is not the main objectives of this research. Even though there are hard evidences, the correlation with subject profiles will be a much bigger topic to include in this research. It is also inadequate to do with only 15 subjects – bigger number of subject population is needed for such statistical analysis. The main focus of this research is the study on the data instances. Here, the statistical analysis opportunities are plenty.

2. Differences in cluster formation between abstract and realistic game.

Between the design styles, there is little to no significant differences of the cluster formation in their scatter plots. Both games display similar cluster formation for every subjects. However, every subjects are varied. The spread pattern of both games data are centric, with emotional activities spikes outwards. There seems to be always one spike that dominates all others, and this behavior is similar to both design styles.

In the figure 6.3a and Figure 6.3b are examples from one of the subjects that has slight differences in the cluster formation between playing an abstract game and playing realistic game. At a glance, the overall formation of data seems as if they are a copy of each other. Considering there are some outliers within the data, that may have been true.

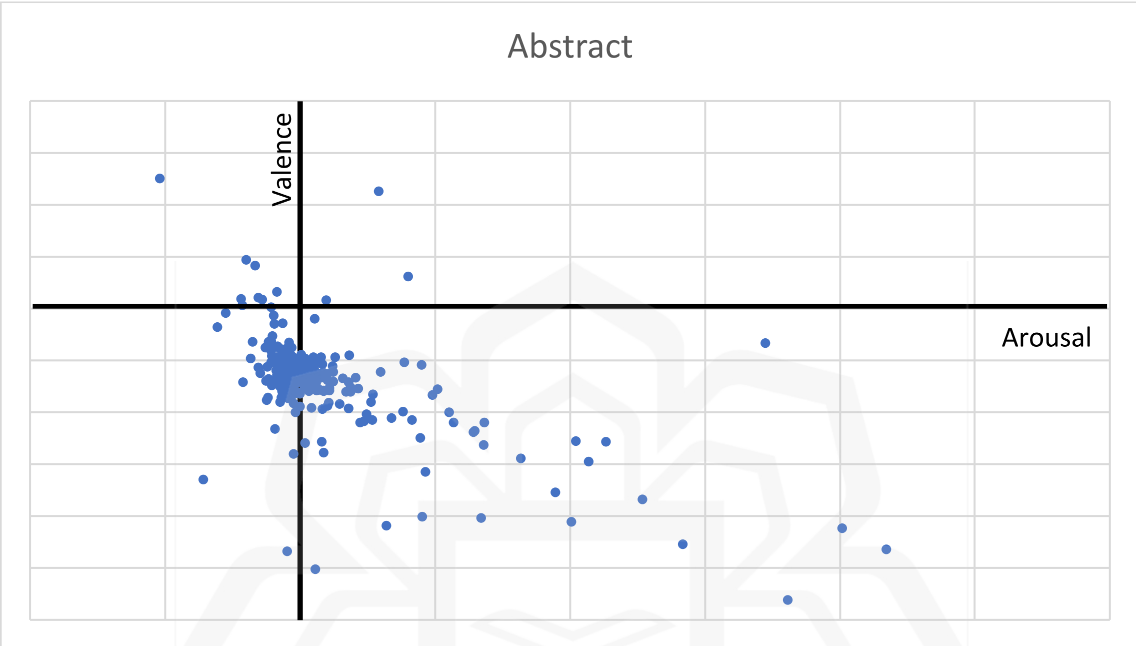

Figure 6.3a: Scatter plot of Abstract gameplay

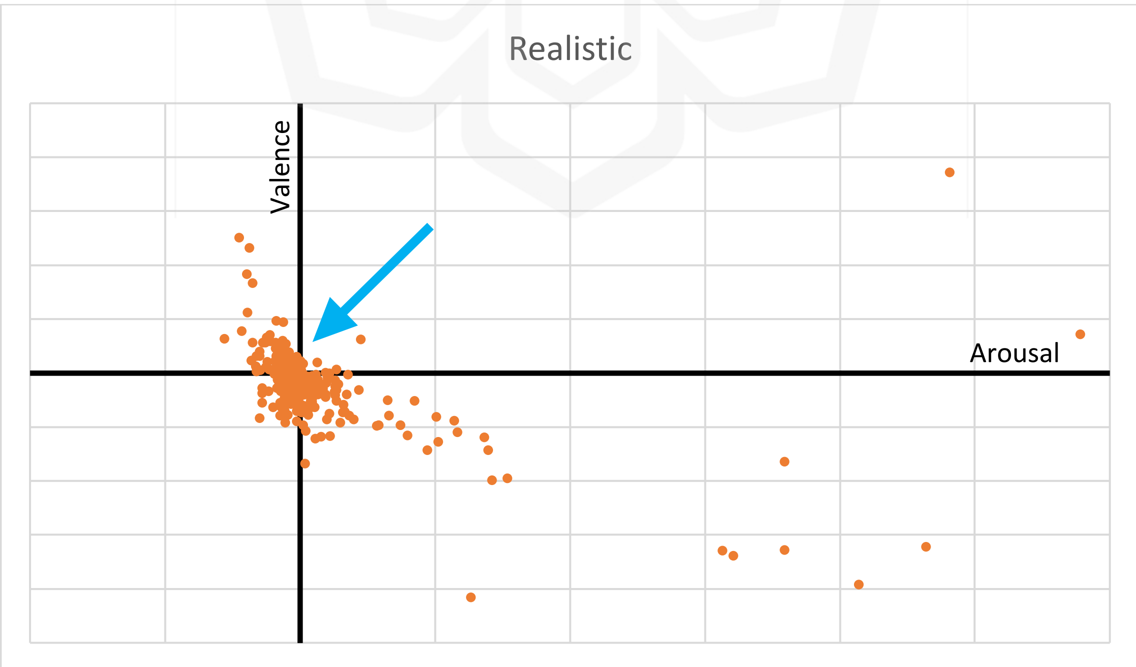

Figure 6.3b: Scatter plot of Realistic gameplay.

However, look closer at the smaller spikes reveals a different story (shown in the figure by the blue arrow). Some subjects also show their smaller spikes to behave differently between the two design styles. A more detailed observation on this trait is discussed later under the section "TRACES OF BRAIN FUNCTIONS PRESENT IN VIDEO GAMES."

3. The data distribution and its size of each design styles.

Data distribution is an important aspect of data analysis. It is also closely related to the cluster formation discussed earlier. The difference between data distribution and cluster formation is that the shape and anatomy of the scatter plot may have the same form, but the amount of data that are present in a particular area in the formation may be different. Figure 6.4 demonstrates this.

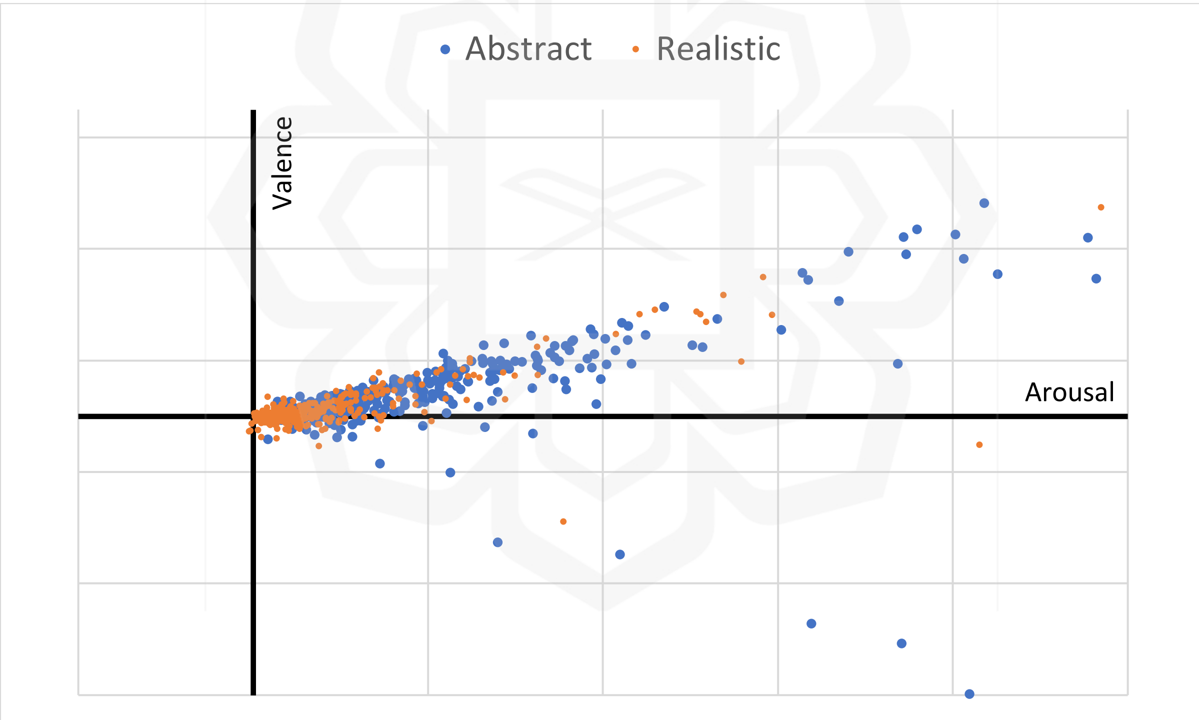

Figure 6.4 Two scatter plots of two different design styles from the same subject. Data density for both design styles are different.

Notice the density of the dots that represent emotions sampling instances. To determine the density visually, an observation to the area size of the data plots is made. It is obvious that one is bigger than the other. Larger plots from the same amount of sampling means less density.

The density of these plots reflects how the emotions are agitated or stimulated. In both design styles they are in the same cluster formation and emotional state. However, the realistic game has higher density plots. Higher density means the instances where the state of emotion changes is less than that in lower density. In the figure shown, abstract game seems to be more stimulating than realistic game.

The way the data spread within the scatter plots may be a signature that is unique to the data source (i.e. design style). Although the cluster formation and state of emotions for both game designs are the same, the plot distribution shows the instances of how the subjects were emotionally stimulated when playing the games.

Later in this chapter, statistical analysis of the data distribution will be discussed, but by observing at the scatter plot alone some differences can be found. After analyzing all subjects' scatter plot, abstract game is dominantly more stimulating than realistic game design styles. However, these differences require statistical analysis for validation.

4. The trending of the scatter plots.

The scatter plot of both game designs has a characteristics of having a centralized mass with spikes that indicates stimulation of emotions. Some subjects have several spikes, some do not. For those that do, usually have one spike being the dominant one. The dominant spike, however, points or converges into a point. This makes it possible to statistically derive a trend line to which emotion that the subject is stimulated by each game.

The trend lines observed in the scatter plots are generated using a tool in the spreadsheet software, Microsoft's Excel. The algorithm chosen to generate these trend lines is linear forecast.

In Figure 6.5, trend lines are drawn on the cluster formation of both game design styles scatter plot. The differences between them are only very slight slope deviation. The observation of these trend lines reveals no associations or whatsoever with the two design styles. Just like the cluster formation, the trend lines varies from subject to subject, indicating yet again for a possible profile correlation.

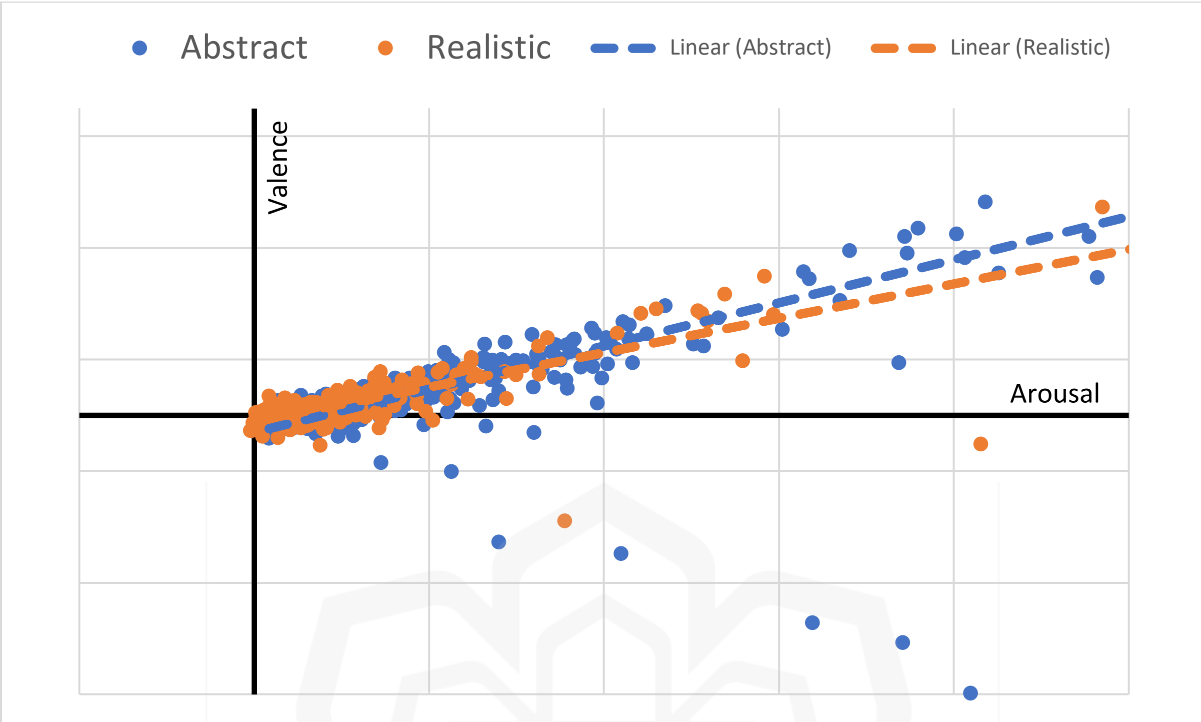

Figure 6.5 Abstract vs Realistic scatter plot with linear forecast trendlines.

The slope difference between the two trend lines of each design styles indicates the amount of emotional stimulation that the subject experienced when playing the games. But unlike the data distribution and size of the cluster formation, trend line slope difference signifies which axis in particular is being stimulated. It is either the valence or arousal that is being affected by the design styles.

By knowing which particular axis is more affected, it is possible to determine whether it's the valence or arousal that the game design is influencing. This would be a great insight for game designers who can fine tune their design to individually increase or decrease valence or arousal stimulation.

There is a downside to this trendline observation, however. While the slope can be observed to deviate between the two design styles, it is not known whether it increases stimulation or decreases the stimulation of emotions. A more detailed statistical analysis is needed to understand this aspect of the observation.

5. The dominant region of valence vs arousal plot being stimulated.

The dominant region where each design style's data distribution clumps together in the valence and arousal plot is the dominant emotion that may have been stimulated by the specific design style. On previous sections, the scatter plot characteristics discussed are the plot shapes and formations. Here, the attention is to observe where the plots lie in relation to the axis. To demonstrate the point, below are figures of two samples (Figure 6.6a & 6.6b) with similar scatter plot formation but located differently on the valence vs arousal axis.

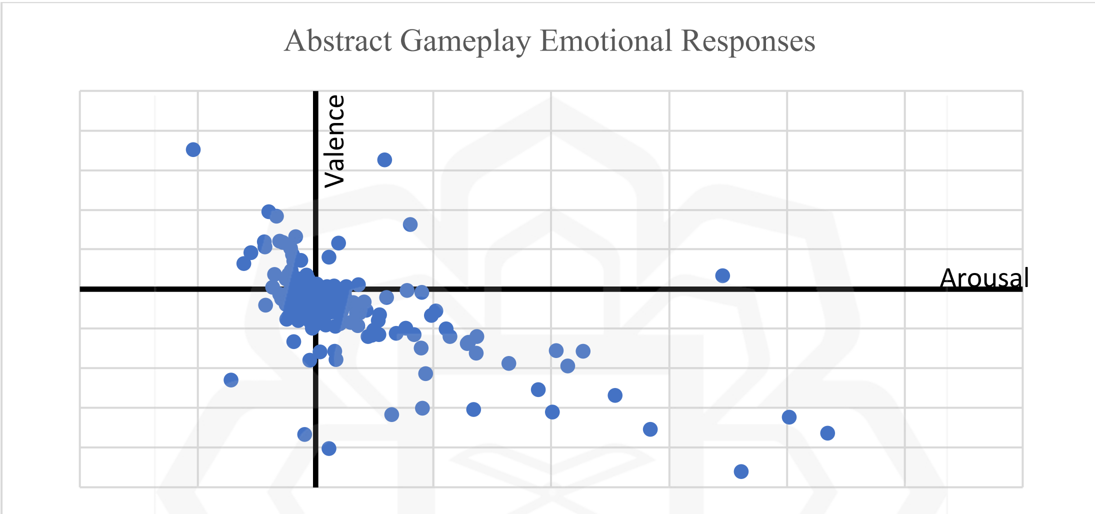

Figure 6.6a Majority of the data points sit below the horizontal line.

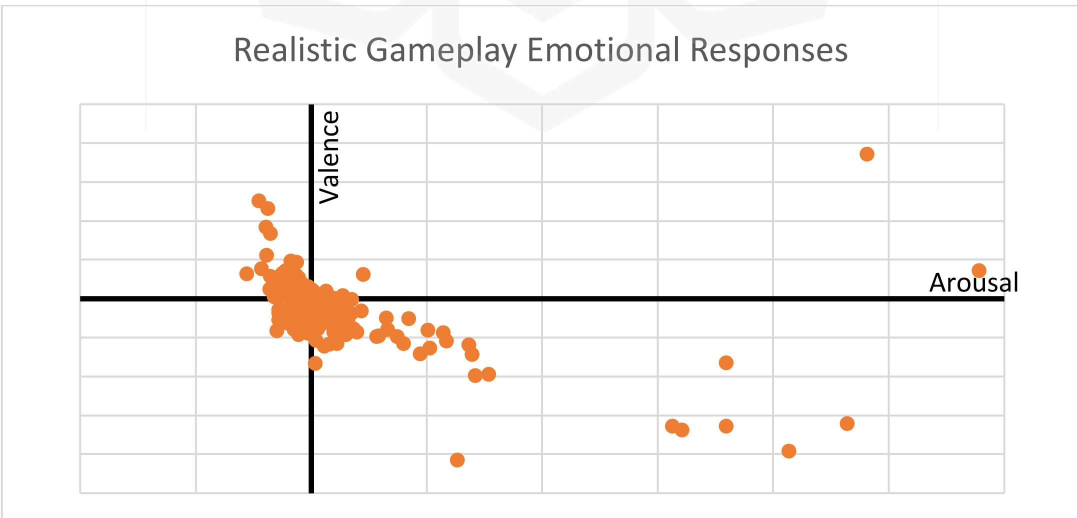

Figure 6.6b Slight difference of the location of the central mass of the data cluster.

The reason to observe this aspect of the scatter plots is to find out if design styles can cause phase shift in the plot formation. The phase shift would mean that there is a change in overall emotion of the subjects when playing different games of different design styles. The phase shifts must be consistent for all subjects if it is to conclude that the design styles are causing it.

The challenges in observing phase shifts are the amount of outliers and the scale in which the outliers deviate from the main plot mass. These are causing difficulties in identifying where most of the data lie within the valence vs arousal axis. To determine which region of the plot that the data dominates, a simple true/false algorithm is applied to the data spreadsheet. The idea here is to count how many hits do these data hit on a particular area relative to the valence-arousal axis. By summing up the number of hits for each design styles, they can be compared for differences.

This hit counter approach is only a guide to see any changes in emotions between the two design styles. The drawback is that it lacks information such as the emotional intensity, the distribution behavior, the magnitude of changes, and central tendency. To obtain those information and analyze them, a statistical analysis is carried out and discussed in section 6.3.

The hit count inspection is done in the spreadsheet Excel. True and false algorithm filters the data and separate them according to which emotion each plot is located. For every row of the valence and arousal spreadsheet, a new column calculates = if [COLUMN][ROW]>=0.5, 1, 0. Summing up the results yields how many data points located on which side of the positive and negative values of the valence and arousal axis. It is now possible to compare the difference in which emotion is dominant for different design styles. The result is presented as bar charts in Figure 6.7 to visualize the comparison between Abstract and Realistic designs.

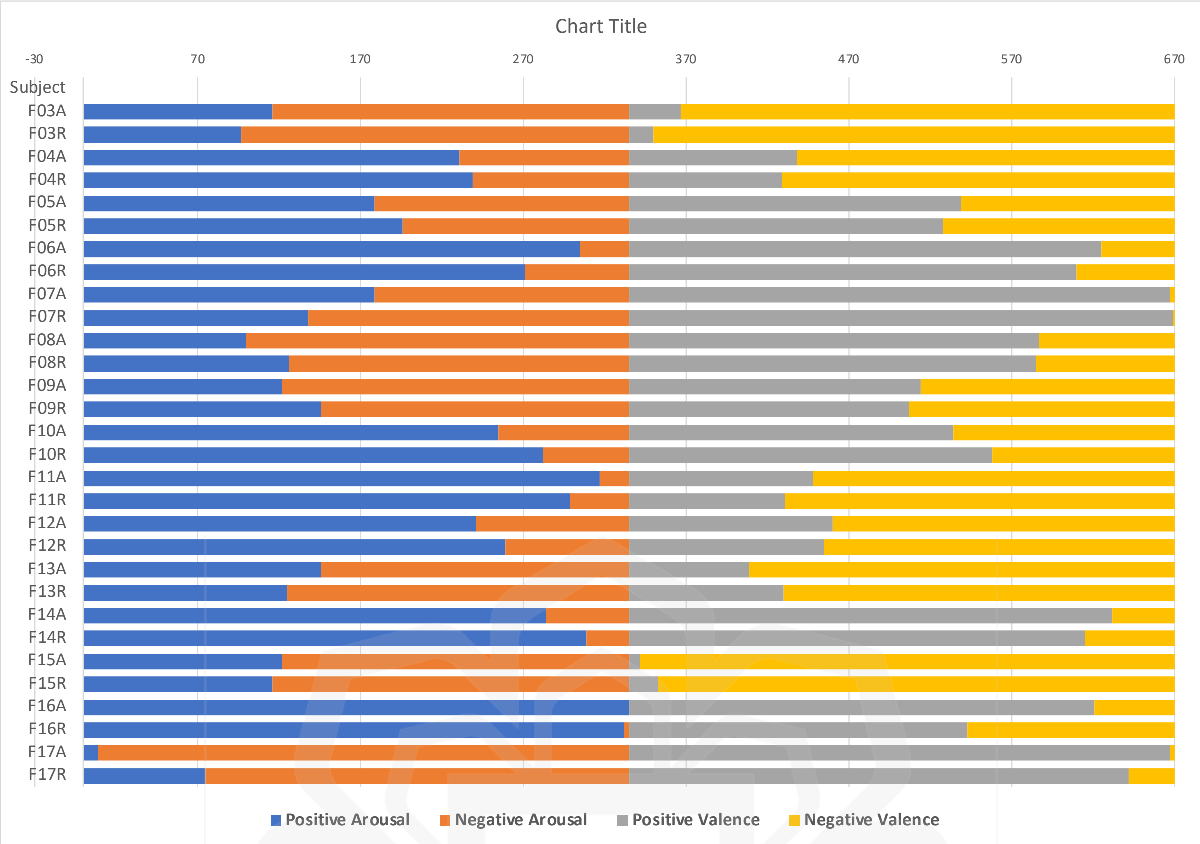

Figure 6.7: Bar charts of arousal and valence dominance.

From the results of analyzing emotional dominance on the valence/arousal axis, there seem to be no correlation between the two design styles. Although there are differences between abstract and realistic games that suggest a phase shift, the differences vary from subject to subject. Apart from the majority of the subjects – 11 out of 15 participants – experienced the reduction of emotional valence in Realistic game, there are no other distinctive phase-shift characteristics of the scatter plots between the two games. Nevertheless, differences do occur, and perhaps the variations between subjects are influenced by the subjects' profile. Since this research does not focus on subject-population based statistics, such profiling matter of interest is outside the research scope. This research do not attempt such objective, thus the correlation with subject profiles will not be investigated. Instead, the focus will be on scrutinizing the data instances and their distribution behavior.

6. Scatter plot characteristics call for central tendency statistical analysis.

The consistent characteristics in all scatter plot of the game play data exhibit similar emotional responses for both design styles. At a glance, the scatter plot of Abstract game play is not much different than the Realistic game play. These similarities are the result of visual observations of the emotional response distribution while playing the two games.

However, upon a closer look, there is a consistent distinction between the two design styles – the overall emotional responses distribution. In most cases, the distribution of emotional response data in Abstract game play has a bigger area (or a bigger footprint) than the ones in Realistic game play. It hints at a reduced emotional responses as the design style leans towards realism. This might explain why realistic graphics were discovered to have the tendency to cause the 'uncanny valley' effect. As familiarity to realistic human form and animation are increased, emotional valence and arousal decline.

The difference in area size of the scatter plot calls for a statistical central tendency analysis. Statistical analysis provides objective and unbiased quantitative measurements of the emotional responses of both design styles. Any distinct data distribution that characterizes each design styles can therefore be identified and hopefully be synthesized to aid designers exploit the neuro-affective nature of each design styles.

In the following section, statistical analysis of all EEG data are discussed. To delve deeper into the way the design styles affect the brain, the analysis is split into multiple bandwidth analysis to cover from sub-conscious level to the most alert form of emotional responses in the brain.

6.3 MULTIPLE BANDWIDTH ANALYSIS

An EEG signal contains more than just recorded brain activity per time. Since signals work in a cycle of time called frequency, statistical analysis on frequency related matter is abundance. Time is thus another dimension to analyze the effects of design styles on the human mind. The EEG data acquired in from the data collection can be filtered and analyzed by different frequency ranges. According to many studies (Balducci, 2017), (Benlamine, 2017), each range – or known as bandwidth – is associated with different aspect of the mind's consciousness. It is possible that the emotional responses may be different for each bandwidth with the possibilities of correlating with Design Styles.

In the previous section of the data analysis, all of the scatter plot were analyzed on Theta – Alpha frequency ranges. The reason for this initial selection of bandwidth is from literature reviews (Malik, 2012), (Yaacob, 2013), and previous works (Benlamine, 2017). However, the other bandwidths may have their own reactions towards different design styles. Statistical analysis on all these bandwidths may uncover more information on how design affects the user.

The EEG signals that contain these multi-frequency bands were analyzed separately based on their bandwidth by repeating the machine learning classification processes on different frequency range. The process includes the feature extraction on the stimulated emotional data to model the arousal and valence responses for each bandwidth's classification.

The objectives of analyzing emotional responses in separate bandwidths are:

1. To find out whether design styles affects the emotional responses at different bandwidths:
    a. To learn if design styles stimulate emotional valence and arousal at sub-conscious level.
    b. To observe whether the focused mind diverting its attention to playing video games would affect its emotional valence and arousal responses.
    c. To observe if emotional responses at different bandwidths behave differently.
    d. To find out and measure if a particular design style stimulate either valence or arousal **individually differently** at every bandwidth.
2. To correlate emotional responses of each design styles with different bandwidths.
3. To measure quantitatively the difference in emotional valence and arousal response between abstract and realistic design styles.

Apart from analysis of the EEG signals in separate bandwidths, the emotional valence and arousal are also to be looked at individually. By doing this, a more detailed view of the design style's influence over the emotions can be observed.

To achieve the objectives of the multiple bandwidths analysis, all EEG data undergone statistical analysis. Since the result in section 4.2 has shown that the scatter plot of the valence and arousal responses are characterized with central mass distribution, statistical analysis will look at the central tendency of each design styles.

Naturally, when looking at the central tendency, the data will also look into the spread pattern. As opposed to visual observation in the scatter plot analysis previously discussed, the statistical analysis will determine the differences – if there is any – between design styles numerically.

6.3.1 STATISTICAL ANALYSIS ON SPECIFIC BANDWIDTH.

Statistical analysis for every bandwidth are separated into 2 parts:

1. Descriptive Analysis
2. Box and Whiskers Data Distribution Analysis

Descriptive analysis will mainly look at the central tendency of the data sets. The figures resulted from this analysis may provide some kind of numerical distinction between playing abstract and realistic video games.

Box and whiskers plots provide analysis results of data distribution – i.e. the manner in which the data spread. In the context of the emotional responses of the subjects, the data spread behavior means the activity levels of the valence and arousal when playing video games of different design styles. Compared to the descriptive statistics, box and whiskers can filter outlier and segregate data distribution into quartets. A more detailed observation can be observed through first, second, and third quartile of the data distribution.

6.3.1.1 DESCRIPTIVE ANALYSIS

Once the EEG data for every subject are filtered by their respective bandwidth, descriptive statistics are applied. Tabulated results of the descriptive analysis for each category is presented and described individually. The tables are grouped by design styles and their respective bandwidth. Each columns represent each subjects/participants, however, between them there is no sorting order. From left to right is simply the first to the final subjects participated in the data collection.

Mean

Table 6.2 is the tabulated mean values from both Abstract and Realistic gameplay data. It is divided into Abstract and Realistic games. Each Bandwidths are sorted from Delta to Gamma and they are also split to show Arousal and Valence individually.

Abstract Game

DELTA	**Arousal**	-3.71E+07	1.91E+07	1.05E+08	4.14E+08	1.61E+07	6.06E+08	1.66E+08	3.65E+08	1.72E+08	-8.12E+08	3.14E+08	-3.41E+09	-2.39E+07	3.92E+07	1.82E+10
	Valence	1.93E+08	-1.08E+07	-2.15E+07	-4.88E+08	1.84E+07	-3.66E+08	1.37E+08	9.77E+07	2.10E+08	2.57E+08	9.96E+07	6.29E+09	4.22E+07	5.59E+07	-2.30E+10
THETA	**Arousal**	3.03E+05	1.14E+05	7.14E+04	4.76E+06	-4.02E+04	6.99E+05	1.88E+05	-2.97E+07	9.68E+06	-1.51E+06	-4.72E+06	-3.15E+06	-7.71E+05	1.39E+06	2.01E+08
	Valence	-1.67E+05	1.04E+05	5.32E+04	5.27E+05	2.37E+05	1.13E+07	-3.13E+05	-5.74E+06	-5.35E+06	1.33E+06	7.04E+06	3.17E+06	7.57E+05	5.18E+06	6.95E+08
ALPHA	**Arousal**	4.08E+05	2.66E+04	-9.72E+03	2.65E+05	3.68E+04	5.87E+03	8.19E+03	1.82E+05	1.87E+05	-4.11E+04	9.51E+03	-1.10E+05	3.26E+03	1.64E+04	5.57E+07
	Valence	-9.55E+04	2.01E+04	2.14E+04	-2.06E+05	-9.61E+02	-1.45E+05	-4.38E+04	-1.53E+05	2.42E+05	1.08E+04	1.58E+05	3.67E+05	-5.49E+04	2.13E+04	4.52E+07
BETA	**Arousal**	1.02E+06	-7.55E+05	9.55E+04	1.88E+05	3.15E+05	8.07E+03	-6.11E+03	1.31E+05	1.12E+04	2.38E+04	2.43E+05	-4.14E+03	-2.15E+03	9.74E+04	6.28E+06
	Valence	-8.50E+05	-5.44E+05	-8.47E+04	1.16E+04	-1.96E+05	5.37E+01	2.02E+04	-2.75E+05	-4.43E+04	4.52E+03	9.94E+04	-4.88E+04	-7.33E+03	-3.42E+04	2.18E+05
GAMMA	**Arousal**	6.73E+06	1.86E+05	-1.94E+04	4.67E+04	-8.22E+04	-2.85E+02	4.17E+04	7.70E+03	-6.74E+03	-2.00E+03	-5.15E+04	-3.87E+03	2.03E+02	-2.60E+04	-1.32E+05
	Valence	2.06E+06	-4.80E+05	2.16E+04	-2.94E+04	-1.41E+05	1.75E+03	4.13E+04	3.96E+03	8.78E+03	7.61E+03	-3.00E+04	-5.41E+02	2.65E+04	5.32E+04	-2.93E+04

Realistic Game

DELTA	**Arousal**	8.21E+07	1.47E+07	3.48E+08	5.57E+08	-5.34E+06	3.88E+08	2.18E+08	9.21E+07	1.75E+08	-2.90E+08	1.36E+08	-4.61E+09	-2.97E+07	4.29E+06	3.75E+09
	Valence	7.31E+07	2.81E+06	-1.40E+08	-5.84E+08	5.26E+06	-2.52E+08	1.84E+08	4.69E+06	4.84E+07	1.25E+08	2.13E+07	1.13E+10	5.69E+07	1.81E+07	-4.57E+09
THETA	**Arousal**	-1.02E+05	1.12E+05	1.58E+05	8.70E+06	-1.29E+05	7.16E+05	-1.11E+05	4.17E+06	1.30E+07	-7.73E+05	-3.28E+06	-3.03E+06	-1.08E+06	1.77E+05	5.49E+07
	Valence	-1.64E+05	1.35E+05	9.90E+04	1.45E+06	3.45E+05	6.71E+06	1.47E+05	-5.74E+06	-5.41E+06	7.32E+05	5.03E+06	6.52E+06	1.14E+06	6.77E+05	1.90E+08
ALPHA	**Arousal**	1.13E+05	2.49E+03	-1.02E+04	3.04E+05	1.45E+04	-1.18E+03	-3.08E+03	-1.86E+05	4.96E+05	-2.06E+04	-3.69E+04	-2.12E+05	1.41E+04	5.01E+03	3.36E+07
	Valence	-8.27E+04	6.51E+03	-5.31E+03	-1.75E+05	5.63E+02	-5.05E+04	-1.69E+04	-1.86E+05	6.44E+05	9.32E+03	3.66E+05	1.28E+05	-4.36E+04	5.06E+03	2.73E+07
BETA	**Arousal**	3.29E+05	-4.02E+05	1.57E+04	5.12E+04	4.96E+05	2.94E+03	4.38E+03	3.54E+04	1.15E+04	9.17E+03	1.27E+05	-1.41E+04	7.22E+02	3.34E+04	4.73E+06
	Valence	-4.00E+05	-2.40E+05	-9.52E+03	1.40E+04	-3.12E+05	-2.73E+03	3.46E+03	9.82E+04	-6.41E+04	1.74E+03	8.53E+04	1.03E+04	-1.58E+04	-1.13E+04	1.87E+05
GAMMA	**Arousal**	3.16E+06	1.34E+05	1.20E+03	6.04E+03	-2.20E+05	-5.16E+02	1.09E+04	5.52E+04	-8.21E+03	-2.37E+03	-4.19E+04	-2.29E+04	2.80E+02	-5.49E+03	-1.25E+05
	Valence	-1.01E+06	-3.22E+05	2.82E+03	-6.00E+03	-3.43E+05	3.17E+03	1.12E+04	-6.65E+03	8.06E+03	6.16E+03	-5.43E+03	-9.87E+03	7.77E+02	1.20E+04	-1.98E+04

Table 6.2: Mean values

The means value is simply the average value of the emotional responses values along the entire length of game play period. In itself, considering how far the outliers can stray away from the main data clusters, may not give any meaningful insights. Nevertheless, it can be a rough indicator to which direction of the arousal or valence vector do each player's/subject's emotional reaction is pointing.

In the scatter plot analysis discussed earlier, emotions changes mainly in a cluster but spikes to a direction unique for each individual. These spikes are the outliers that influences the average values of the whole data set. Since the mean values are calculated separately for valence and arousal, it is possible to determine the general vector of the emotional changes during game play.

The mean values range between 10E5 to 10E10. These numbers lie on the valence and arousal axis and they are the emotional values of classified game play data. The values from the these tables are directly related to the strength of the EEG signal captured from the participant. Thus, the magnitude of the classified value is unique form person to person. It is not possible to connect or correlate the value between different subjects. It is possible, however, to relate differences in values between bandwidths and the two design styles from the same player.

Between different bandwidths, the means of the classified data values seems to have a trend. From low frequency bandwidth Delta to the middle range bandwidth Alpha, the exponential power values of the means are trending downward. Regardless whether the value is positive or negative, the general magnitude is decreasing. While positive and negative values indicate the vector of the emotion, the magnitude signifies the strength. This is consistent for all the subjects.

Beta and Gamma bands, however, the results are a bit inconsistent. All except for a few subjects exhibit the downward trend as exhibited in the Delta – Alpha bands. Other subjects show either an upward trend, or do not seem to vary between the two bands (Beta and Gamma). Nevertheless, Delta bandwidth has the highest value, regardless of the discrepancies in other bandwidths.

The trend of the mean magnitude value of the emotional responses are similar for both design styles. There are no apparent differences numerically between the two different games that can be identified to distinguish each design style. As far as mean values of the emotional responses go, it has no relationship with the different design styles.

Apart from the analyzing the numerical attribute of the mean values, a qualitative aspect can also be observed. Since the mean is the average of the total emotional activity during game play, it points the general direction to which emotion is mostly active. The negative and positive value can therefore determine the overall emotion of the subjects. Although there are still no significant pattern to correlate with different design styles, it is important to note that the emotions of the same person vary between different bandwidths.

Having two different emotions at different bandwidth and at the same time raises more questions. Is it possible for a person to experience more than one emotions at the same time? Which bandwidth influences the person's emotions more? Which bandwidths matter most for game designer to exploit, if the game were to be designed to stimulate specific emotions?

Recall in the methodology chapter that each bandwidth has its own computational model to classify the game play data. For every bands, the accuracy of the perceptron are more than 90 percent. This figure is good enough to classify unknown data since to achieve percentage higher than this is difficult and rare (Yaacob, 2015). Furthermore, scatter plots also show good separation between different emotions. Considering that the stimulated emotions are the same for all bandwidths, it is intriguing that during a game play one player can experience different emotions at the same time but at different level of attention/consciousness.

Median

Table 6.3 is the tabulated median values from both Abstract and Realistic gameplay data. Just as in the mean table, the results are organized and sorted in similar fashion. EEG data distribution scatters along the valence and arousal axis. In the middle of the frequency of the data distribution is the median. Thus it is a good indicator of where the center of the data distribution along an axis is. The median, in the context of this research, is akin to the center of mass. While the mean indicates the vector of the emotional activity in the mind, the median indicates the main emotion that the activity is centered on.

Abstract																
		F03	F04	F05	F06	F07	F08	F09	F10	F11	F12	F13	F14	F15	F16	F17
DELTA	Arousal	9.74E+04	2.08E+06	2.55E+06	4.53E+07	5.61E+06	2.02E+08	8.76E+06	4.05E+07	7.38E+06	-1.47E+08	-1.29E+06	-1.66E+08	-2.50E+06	2.88E+05	3.00E+09
	Valence	8.04E+06	-6.56E+05	-1.58E+06	-2.67E+07	1.33E+07	-2.32E+07	3.98E+06	-2.38E+06	1.47E+07	4.31E+07	-1.85E+04	2.34E+08	7.51E+06	6.24E+06	-3.77E+09
THETA	Arousal	9.16E+04	5.41E+04	9.63E+03	2.62E+05	2.56E+04	-1.43E+04	4.87E+04	3.99E+04	8.64E+04	-1.17E+05	9.05E+04	-1.92E+04	-1.87E+04	2.39E+04	9.19E+07
	Valence	8.93E+04	4.22E+04	-8.51E+02	2.10E+05	1.19E+05	2.43E+05	6.20E+04	-1.98E+05	-1.03E+05	5.34E+04	1.02E+04	1.23E+05	2.99E+04	6.52E+03	3.17E+08
ALPHA	Arousal	1.74E+03	2.26E+03	-4.85E+03	1.85E+04	1.94E+04	-1.92E+03	-1.55E+03	-2.60E+04	2.30E+04	-1.36E+04	1.25E+04	-7.86E+02	-2.41E+02	3.78E+03	3.19E+07
	Valence	-4.79E+04	2.91E+03	5.91E+03	1.21E+04	8.30E+02	-1.57E+04	-1.33E+04	3.78E+02	7.42E+03	6.43E+03	8.73E+02	8.30E+03	-1.54E+04	3.45E+03	2.58E+07
BETA	Arousal	2.24E+05	-3.05E+05	3.87E+04	1.13E+05	1.90E+05	5.21E+03	-1.03E+03	-5.13E+03	9.17E+03	1.08E+04	2.26E+04	5.38E+02	1.26E+03	4.93E+04	3.59E+06
	Valence	-5.05E+03	-2.35E+05	-2.76E+04	2.92E+04	-1.49E+05	-2.50E+02	6.00E+03	-5.20E+03	-1.11E+03	1.33E+03	1.06E+04	-2.27E+03	-1.03E+04	-1.87E+04	1.13E+05
GAMMA	Arousal	1.69E+05	1.91E+03	7.91E+03	5.52E+03	1.67E+04	-1.97E+02	1.59E+03	1.64E+03	-1.33E+03	9.11E+01	-1.81E+03	-8.58E+02	1.17E+02	-5.92E+03	-5.27E+04
	Valence	8.94E+04	-1.02E+05	9.01E+03	-9.58E+03	-1.63E+04	8.84E+02	2.52E+03	-6.06E+02	2.15E+03	8.21E+02	2.21E+03	-2.26E+02	3.35E+03	8.55E+03	-1.07E+04
Realistic																
		F03	F04	F05	F06	F07	F08	F09	F10	F11	F12	F13	F14	F15	F16	F17
DELTA	Arousal	2.83E+06	1.09E+06	3.85E+06	4.06E+07	3.11E+06	8.60E+07	7.28E+06	1.81E+07	9.02E+06	-3.51E+07	-3.40E+06	-1.87E+08	-1.47E+06	-1.09E+05	8.35E+07
	Valence	2.69E+06	-1.52E+04	-1.63E+06	-5.88E+07	3.83E+06	-3.10E+07	4.33E+06	-2.74E+06	4.90E+06	1.37E+07	6.40E+04	3.84E+08	5.41E+06	2.45E+06	1.01E+06
THETA	Arousal	9.16E+04	4.23E+04	9.54E+03	2.02E+05	1.36E+04	4.45E+03	4.92E+04	4.00E+04	5.45E+04	-3.93E+04	1.05E+05	-1.39E+04	-1.01E+04	1.75E+04	-3.38E+03
	Valence	7.55E+04	4.13E+04	1.85E+03	1.57E+05	4.22E+04	3.18E+04	5.84E+04	-1.40E+05	-3.21E+04	2.50E+04	9.05E+04	7.57E+04	2.10E+04	4.63E+03	1.50E+04
ALPHA	Arousal	3.19E+03	1.37E+03	-5.62E+03	8.45E+03	9.36E+03	-4.67E+02	-3.03E+03	-6.88E+03	1.93E+04	-8.19E+03	1.19E+04	3.37E+03	-7.83E+02	2.37E+03	2.22E+03
	Valence	-3.97E+04	2.69E+02	-5.02E+03	3.79E+03	2.10E+02	-8.67E+03	-1.02E+04	1.10E+03	4.05E+03	3.10E+03	4.42E+03	1.20E+03	-1.07E+04	1.57E+03	1.84E+04
BETA	Arousal	9.81E+04	-8.77E+04	1.00E+04	1.22E+04	2.92E+05	1.08E+03	-3.30E+02	-5.97E+03	1.00E+04	5.12E+03	8.62E+03	-1.52E+03	4.19E+02	1.06E+04	2.71E+04
	Valence	-8.69E+03	-7.06E+04	-8.66E+03	3.74E+03	-2.20E+05	-1.09E+03	3.40E+03	-6.90E+03	-2.31E+02	3.61E+02	1.05E+03	-2.99E+04	-1.27E+04	-4.23E+03	8.26E+03
GAMMA	Arousal	5.31E+04	3.43E+03	6.15E+02	8.55E+02	-3.44E+04	-4.22E+02	1.49E+03	5.56E+02	-7.11E+02	1.22E+02	-2.54E+03	-1.75E+02	1.81E+02	-7.65E+02	-1.70E+04
	Valence	3.56E+04	-2.56E+04	1.75E+03	-9.45E+02	-6.58E+04	1.29E+03	2.78E+03	-3.55E+02	9.66E+02	4.45E+02	1.89E+03	3.78E+03	2.60E+02	1.98E+03	2.92E+03

Table 6.3: Median

The reason why it is a good reference point to determine the center of emotional response is because of the cluster formation of the scatter plot as discussed earlier in this chapter. It is perceivable that the emotional changes during game play seem to clump into a main mass of data. As if while playing the game, the emotional valence and arousal increase and decrease based on a central point. Statistically this is the median.

Based on the threshold of 0.5, the median values can be used to determine the central emotion for every bandwidth and for each design style. A value of larger than 0.5 along the arousal axis is considered positive arousal, while less than 0.5 is a negative arousal. The same threshold is also applied for the valence axis, more or less than 0.5 equals to positive and negative valence respectively. The combination of the arousal and valence polarity defines the emotion. Refer section 5.1 ACCURACY ANALYSIS for emotional definitions.

But why is the threshold value is 0.5? This is because the value is the same as in the training of the perceptron when the modelling the emotions. In the accuracy analysis discussed earlier, the separation of all four different emotions are divided by the vertical and horizontal lines at (0.5,0.5) point. Therefore, to determine the central emotion of the subjects, the median value is referenced at this threshold value. The table 6.4 is the summary of the central emotion of every subject playing two games of different design styles at every bandwidth.

	Abstract Central Emotions														
	F03	F04	F05	F06	F07	F08	F09	F10	F11	F12	F13	F14	F15	F16	F17
DELTA	Happy	Fear	Fear	Fear	Happy	Fear	Happy	Fear	Happy	Calm	Sad	Calm	Calm	Happy	Fear
THETA	Happy	Happy	Fear	Happy	Happy	Calm	Happy	Fear	Fear	Calm	Happy	Calm	Calm	Happy	Happy
ALPHA	Fear	Happy	Calm	Happy	Happy	Sad	Sad	Calm	Happy	Calm	Happy	Calm	Sad	Happy	Happy
BETA	Fear	Sad	Fear	Happy	Fear	Fear	Calm	Sad	Fear	Happy	Happy	Fear	Fear	Fear	Happy
GAMMA	Happy	Fear	Happy	Fear	Fear	Calm	Happy	Fear	Calm	Happy	Calm	Sad	Happy	Calm	Sad
	Realistic Central Emotions														
	F03	F04	F05	F06	F07	F08	F09	F10	F11	F12	F13	F14	F15	F16	F17
DELTA	Happy	Fear	Fear	Fear	Happy	Fear	Happy	Fear	Happy	Calm	Calm	Calm	Calm	Calm	Happy
THETA	Happy	Happy	Happy	Happy	Happy	Happy	Happy	Fear	Fear	Calm	Happy	Calm	Calm	Happy	Calm
ALPHA	Fear	Happy	Sad	Happy	Happy	Sad	Sad	Calm	Happy	Calm	Happy	Happy	Sad	Happy	Happy
BETA	Fear	Sad	Fear	Happy	Fear	Fear	Calm	Sad	Fear	Happy	Happy	Sad	Fear	Fear	Happy
GAMMA	Happy	Fear	Happy	Fear	Sad	Calm	Happy	Fear	Calm	Happy	Calm	Calm	Happy	Calm	Calm

Table 6.4: Central Emotion within data clusters

In terms of value, the magnitude of the central emotion varies from person to person. Just as in other aspect of the statistics, the numerical reading of the classified data is unique to every subject. To relate these numbers to different design styles, though, must be through the data distribution behavior. Nevertheless, the table 6.4 can contribute to understand the behavior of the data distribution. Emotional state can be compared between different bandwidths and more importantly different design styles.

Similar to the mean values, the median for all of the data sets strangely exhibit different emotions for different bandwidths. While there are no distinct characteristics between the two different design styles, not all subjects experience any emotional changes at any bandwidth. Eight out of fifteen participants do not show their central emotions to change between the two games at all. Those that do have changes only happens with three bandwidths the most. None of the subjects has any differences on all bandwidths.

Mode

The EEG data sets are continuous streams of emotional changes during a game play session. Such data sets cannot provide a meaningful mode value as the type of data is a continuous numerical data. Thus, mode calculation is unavailable.

Standard Deviation, Standard Error & Sample Variance.

Standard deviation is important to get an idea how data is spread. Standard deviation values show how far away the data spread from the average (mean). The larger the deviation, the larger the spread. However, this is only an estimate, and not exactly accurate because the data are non-linear. Still, the standard deviation gives a clue to how much the emotional reaction fluctuates upon playing video games of different design styles.

In the table of 6.5, Standard Deviation values are consistently high. They range from 10E5 to 10E9. This shows that emotions are actively and rapidly changing as the subject continues to play the two differently styled video games.

Results of the Standard Deviation between the two design styles are very similar. For some subjects, abstract games have higher deviation, while the others show vice versa. It should be noted, however, such large deviation may contain outliers that obscure the actual data cluster spread of each design styles. For a more detailed look at that, a box and whiskers investigations are discussed later in this chapter.

On the other hand, standard error is not applicable in the data set in this research. The standard error values are also presented in the Table 6.5. The EEG data that are being analyzed are streaming data from a single game play session. Extending the play time does not necessarily mean a lower error result. Even at a count of 334 samples, the standard error being calculated is seemingly huge. Interestingly, however, the calculated values in by the Microsoft Excel software are always twenty times smaller than the standard deviation values.

Sample Variance is the square root of the Standard Deviation. Just like the Standard Error, the role in this research is not significant to identify characteristics that are unique to each design styles.

		Abstract														
DELTA Arousal	Standard Error	2.93E+07	4.52E+06	3.44E+07	7.08E+07	4.79E+06	7.25E+07	4.97E+07	7.60E+07	5.87E+07	1.37E+08	1.06E+08	8.34E+08	5.99E+06	1.11E+07	2.74E+09
	Standard Deviation	5.36E+08	8.26E+07	6.28E+08	1.29E+09	8.75E+07	1.32E+09	9.08E+08	1.39E+09	1.07E+09	2.50E+09	1.95E+09	1.52E+10	1.09E+08	2.03E+08	4.99E+10
	Sample Variance	2.87E+17	6.82E+15	3.95E+17	1.68E+18	7.66E+15	1.75E+18	8.25E+17	1.93E+18	1.15E+18	6.23E+18	3.78E+18	2.32E+20	1.20E+16	4.13E+16	2.49E+21
DELTA Valence	Standard Error	4.44E+07	5.85E+06	1.89E+07	8.20E+07	1.22E+07	7.62E+07	4.85E+07	4.68E+07	7.91E+07	4.48E+07	3.49E+07	1.10E+09	7.21E+06	1.25E+07	3.47E+09
	Standard Deviation	8.12E+08	1.07E+08	3.46E+08	1.50E+09	2.24E+08	1.39E+09	8.87E+08	8.55E+08	1.45E+09	8.18E+08	6.38E+08	2.01E+10	1.32E+08	2.29E+08	6.33E+10
	Sample Variance	6.59E+17	1.14E+16	1.20E+17	2.25E+18	5.00E+16	1.94E+18	7.86E+17	7.32E+17	2.09E+18	6.70E+17	4.07E+17	4.03E+20	1.74E+16	5.23E+16	4.01E+21
THETA Arousal	Standard Error	5.45E+05	1.43E+04	4.66E+04	1.09E+06	2.95E+04	1.71E+05	5.46E+05	1.74E+07	2.27E+06	3.14E+05	2.25E+06	1.88E+06	1.70E+05	6.62E+05	1.95E+07
	Standard Deviation	9.97E+06	2.61E+05	8.50E+05	1.99E+07	5.39E+05	3.13E+06	9.97E+06	3.18E+08	4.15E+07	5.73E+06	4.11E+07	3.44E+07	3.11E+06	1.21E+07	3.55E+08
	Sample Variance	9.93E+13	6.80E+10	7.23E+11	3.97E+14	2.90E+11	9.81E+12	9.94E+13	1.01E+17	1.72E+15	3.28E+13	1.69E+15	1.19E+15	9.70E+12	1.46E+14	1.26E+17
THETA Valence	Standard Error	5.26E+05	1.94E+04	3.16E+04	3.94E+05	2.69E+04	1.42E+06	7.01E+05	2.33E+06	1.24E+06	2.73E+05	2.97E+06	5.80E+06	1.58E+05	2.51E+06	6.72E+07
	Standard Deviation	9.61E+06	3.54E+05	5.77E+05	7.20E+06	4.91E+05	2.60E+07	1.28E+07	4.25E+07	2.26E+07	4.99E+06	5.43E+07	1.06E+08	2.90E+06	4.59E+07	1.23E+09
	Sample Variance	9.24E+13	1.26E+11	3.33E+11	5.18E+13	2.41E+11	6.74E+14	1.64E+14	1.81E+15	5.12E+14	2.49E+13	2.95E+15	1.12E+16	8.39E+12	2.11E+15	1.51E+18
ALPHA Arousal	Standard Error	1.94E+05	2.01E+04	2.48E+03	9.03E+04	4.77E+03	1.84E+04	1.08E+04	1.22E+06	6.86E+04	6.57E+03	1.50E+04	2.79E+05	6.85E+03	6.32E+03	4.98E+06
	Standard Deviation	3.54E+06	3.67E+05	4.53E+04	1.65E+06	8.72E+04	3.36E+05	1.98E+05	2.22E+07	1.25E+06	1.20E+05	2.73E+05	5.09E+06	1.25E+05	1.16E+05	9.08E+07
	Sample Variance	1.25E+13	1.35E+11	2.05E+09	2.72E+12	7.60E+09	1.13E+11	3.93E+10	4.94E+14	1.57E+12	1.44E+10	7.47E+10	2.59E+13	1.57E+10	1.34E+10	8.25E+15
ALPHA Valence	Standard Error	1.31E+05	5.12E+03	5.99E+03	1.10E+05	1.47E+03	4.98E+04	1.90E+04	3.91E+05	1.06E+05	5.63E+03	6.75E+04	3.56E+05	8.79E+03	4.69E+03	4.03E+06
	Standard Deviation	2.39E+06	9.35E+04	1.09E+05	2.00E+06	2.68E+04	9.11E+05	3.47E+05	7.14E+06	1.93E+06	1.03E+05	1.23E+06	6.50E+06	1.61E+05	8.58E+04	7.36E+07
	Sample Variance	5.70E+12	8.75E+09	1.19E+10	4.01E+12	7.19E+08	8.30E+11	1.20E+11	5.10E+13	3.73E+12	1.05E+10	1.52E+12	4.23E+13	2.58E+10	7.36E+09	5.42E+15
ALPHA Arousal	Standard Error	1.99E+05	8.02E+04	2.60E+04	2.83E+04	2.33E+04	6.11E+02	6.16E+03	1.41E+05	6.14E+03	5.01E+03	8.09E+04	5.96E+03	1.32E+03	1.11E+04	7.01E+05
	Standard Deviation	3.63E+06	1.47E+06	4.75E+05	5.18E+05	4.26E+05	1.12E+04	1.13E+05	2.58E+06	1.12E+05	9.14E+04	1.48E+06	1.09E+05	2.42E+04	2.02E+05	1.28E+07
	Sample Variance	1.32E+13	2.15E+12	2.25E+11	2.68E+11	1.81E+11	1.25E+08	1.27E+10	6.66E+12	1.26E+10	8.36E+09	2.19E+12	1.19E+10	5.84E+08	4.08E+10	1.64E+14
ALPHA Valence	Standard Error	4.23E+05	4.58E+04	4.38E+04	3.41E+04	1.03E+04	5.09E+02	6.88E+03	1.98E+05	3.41E+04	1.17E+03	3.69E+04	2.13E+04	2.16E+03	3.88E+03	2.88E+04
	Standard Deviation	7.73E+06	8.38E+05	7.99E+05	6.24E+05	1.88E+05	9.31E+03	1.26E+05	3.62E+06	6.24E+05	2.14E+04	6.74E+05	3.89E+05	3.94E+04	7.10E+04	5.26E+05
	Sample Variance	5.98E+13	7.02E+11	6.38E+11	3.89E+11	3.53E+10	8.67E+07	1.58E+10	1.31E+13	3.89E+11	4.58E+08	4.54E+11	1.51E+11	1.55E+09	5.04E+09	2.76E+11
ALPHA Arousal	Standard Error	4.11E+06	6.94E+04	3.05E+04	7.77E+03	2.49E+04	4.31E+01	1.41E+04	7.08E+04	2.36E+03	1.58E+03	2.15E+04	1.06E+04	1.69E+02	3.45E+03	1.55E+04
	Standard Deviation	7.51E+07	1.27E+06	5.56E+05	1.42E+05	4.54E+05	7.88E+02	2.57E+05	1.29E+06	4.31E+04	2.88E+04	3.93E+05	1.95E+05	3.09E+03	6.30E+04	2.82E+05
	Sample Variance	5.64E+15	1.61E+12	3.09E+11	2.02E+10	2.06E+11	6.21E+05	6.62E+10	1.67E+12	1.86E+09	8.27E+08	1.54E+11	3.78E+10	9.55E+06	3.97E+09	7.95E+10
ALPHA Valence	Standard Error	1.53E+06	7.74E+04	8.69E+03	1.02E+04	2.70E+04	1.27E+02	1.23E+04	2.98E+04	1.46E+03	3.88E+03	2.81E+04	5.31E+03	8.42E+03	8.54E+03	3.56E+03
	Standard Deviation	2.79E+07	1.42E+06	1.59E+05	1.87E+05	4.93E+05	2.32E+03	2.24E+05	5.45E+05	2.67E+04	7.09E+04	5.13E+05	9.70E+04	1.54E+05	1.56E+05	6.50E+04
	Sample Variance	7.79E+14	2.00E+12	2.51E+10	3.48E+10	2.43E+11	5.40E+06	5.01E+10	2.97E+11	7.13E+08	5.02E+09	2.64E+11	9.41E+09	2.37E+10	2.43E+10	4.23E+09
		Realistic														
DELTA Arousal	Standard Error	2.69E+07	3.31E+06	1.13E+08	1.13E+08	3.66E+06	5.37E+07	7.25E+07	3.34E+07	7.49E+07	9.25E+07	7.36E+07	1.15E+09	8.63E+06	1.89E+06	7.17E+08
	Standard Deviation	4.91E+08	6.03E+07	2.06E+09	2.06E+09	6.69E+07	9.80E+08	1.32E+09	6.11E+08	1.37E+09	1.69E+09	1.34E+09	2.10E+10	1.58E+08	3.45E+07	1.31E+10
	Sample Variance	2.41E+17	3.64E+15	4.26E+18	4.23E+18	4.48E+15	9.61E+17	1.75E+18	3.73E+17	1.87E+18	2.85E+18	1.80E+18	4.41E+20	2.49E+16	1.19E+15	1.71E+20
DELTA Valence	Standard Error	2.31E+07	5.73E+06	4.46E+07	1.02E+08	3.26E+06	3.87E+07	6.93E+07	3.26E+07	1.09E+08	4.41E+07	2.74E+07	2.50E+09	1.40E+07	4.10E+06	9.05E+08
	Standard Deviation	4.22E+08	1.05E+08	8.14E+08	1.87E+09	5.95E+07	7.06E+08	1.27E+09	5.95E+08	2.00E+09	8.05E+08	5.00E+08	4.56E+10	2.55E+08	7.49E+07	1.65E+10
	Sample Variance	1.78E+17	1.09E+16	6.63E+17	3.48E+18	3.54E+15	4.98E+17	1.61E+18	3.54E+17	3.99E+18	6.48E+17	2.50E+17	2.08E+21	6.50E+16	5.61E+15	2.73E+20
THETA Arousal	Standard Error	1.08E+05	2.71E+04	5.84E+04	3.83E+06	1.18E+05	9.70E+04	7.12E+04	4.83E+06	5.21E+06	1.78E+05	1.87E+06	8.96E+05	2.85E+05	7.12E+04	1.44E+07
	Standard Deviation	1.97E+06	4.95E+05	1.07E+06	6.99E+07	2.15E+06	1.77E+06	1.30E+06	8.83E+07	9.53E+07	3.25E+06	3.41E+07	1.63E+07	5.21E+06	1.30E+06	2.62E+08
	Sample Variance	3.89E+12	2.45E+11	1.13E+12	4.89E+15	4.64E+12	3.13E+12	1.69E+12	7.80E+15	9.08E+15	1.06E+13	1.16E+15	2.67E+14	2.71E+13	1.69E+12	6.88E+16
THETA Valence	Standard Error	1.00E+05	3.43E+04	4.24E+04	1.26E+06	2.63E+05	8.35E+05	1.25E+04	3.42E+06	1.59E+06	1.77E+05	2.36E+06	1.53E+06	2.90E+05	2.99E+05	4.96E+07
	Standard Deviation	1.83E+06	6.25E+05	7.74E+05	2.30E+07	4.80E+06	1.52E+07	2.28E+05	6.25E+07	2.90E+07	3.22E+06	4.31E+07	2.79E+07	5.30E+06	5.46E+06	9.05E+08
	Sample Variance	3.34E+12	3.91E+11	6.00E+11	5.28E+14	2.31E+13	2.32E+14	5.22E+10	3.90E+15	8.41E+14	1.04E+13	1.86E+15	7.77E+14	2.81E+13	2.98E+13	8.20E+17
ALPHA Arousal	Standard Error	3.75E+04	2.96E+03	9.82E+02	1.33E+05	1.10E+03	5.29E+03	2.52E+03	1.04E+05	2.22E+05	2.76E+03	6.98E+04	9.86E+04	6.92E+03	1.30E+03	1.74E+07
	Standard Deviation	6.86E+05	5.40E+04	1.79E+04	2.43E+06	2.02E+04	9.65E+04	4.61E+04	1.90E+06	4.06E+06	5.04E+04	1.27E+06	1.80E+06	1.27E+05	2.38E+04	3.18E+08
	Sample Variance	4.71E+11	2.92E+09	3.21E+08	5.90E+12	4.07E+08	9.31E+09	2.13E+09	3.61E+12	1.65E+13	2.54E+09	1.62E+12	3.24E+12	1.60E+10	5.65E+08	1.01E+17
ALPHA Valence	Standard Error	1.67E+04	3.54E+03	1.47E+03	5.99E+04	6.02E+02	1.42E+04	4.02E+03	2.08E+05	3.32E+05	2.69E+03	3.46E+05	7.11E+04	6.29E+03	1.18E+03	1.41E+07
	Standard Deviation	3.05E+05	6.46E+04	2.67E+04	1.09E+06	1.10E+04	2.58E+05	7.35E+04	3.81E+06	6.07E+06	4.91E+04	6.31E+06	1.30E+06	1.15E+05	2.15E+04	2.58E+08
	Sample Variance	9.31E+10	4.18E+09	7.15E+08	1.20E+12	1.21E+08	6.67E+10	5.40E+09	1.45E+13	3.68E+13	2.41E+09	3.99E+13	1.68E+12	1.32E+10	4.64E+08	6.63E+16
ALPHA Arousal	Standard Error	1.76E+05	6.42E+04	1.17E+03	8.60E+03	3.84E+04	4.69E+02	2.85E+03	2.31E+04	4.91E+03	9.61E+02	4.03E+04	1.66E+04	4.69E+02	3.84E+03	1.62E+06
	Standard Deviation	3.22E+06	1.17E+06	2.13E+04	1.57E+05	7.02E+05	8.56E+03	5.22E+04	4.22E+05	8.98E+04	1.75E+04	7.35E+05	3.02E+05	8.57E+03	7.01E+04	2.96E+07
	Sample Variance	1.03E+13	1.37E+12	4.53E+08	2.47E+10	4.93E+11	7.33E+07	2.72E+09	1.78E+11	8.06E+09	3.08E+08	5.40E+11	9.15E+10	7.35E+07	4.92E+09	8.74E+14
ALPHA Valence	Standard Error	1.43E+05	4.89E+04	6.97E+02	2.70E+03	1.70E+04	5.64E+02	1.02E+03	7.59E+04	3.47E+04	9.61E+02	4.22E+04	3.69E+04	7.23E+02	1.34E+03	6.67E+04
	Standard Deviation	2.62E+06	8.92E+05	1.27E+04	4.93E+04	3.11E+05	1.03E+04	1.87E+04	1.39E+06	6.34E+05	1.75E+04	7.70E+05	6.73E+05	1.32E+04	2.44E+04	1.22E+06
	Sample Variance	6.86E+12	7.96E+11	1.62E+08	2.43E+09	9.64E+10	1.06E+08	3.49E+08	1.93E+12	4.02E+11	3.07E+08	5.93E+11	4.53E+11	1.75E+08	5.96E+08	1.48E+12
ALPHA Arousal	Standard Error	1.45E+06	5.82E+04	1.99E+02	1.71E+03	5.68E+04	9.44E+01	2.29E+03	3.05E+04	3.71E+03	2.23E+03	1.70E+04	2.18E+04	3.27E+01	1.12E+03	2.59E+04
	Standard Deviation	2.65E+07	1.06E+06	3.62E+03	3.13E+04	1.04E+06	1.72E+03	4.19E+04	5.58E+05	6.78E+04	4.07E+04	3.10E+05	3.98E+05	5.97E+02	2.05E+04	4.72E+05
	Sample Variance	7.03E+14	1.13E+12	1.31E+07	9.78E+08	1.08E+12	2.96E+06	1.76E+09	3.11E+11	4.60E+09	1.66E+09	9.60E+10	1.58E+11	3.56E+05	4.21E+08	2.23E+11
ALPHA Valence	Standard Error	1.72E+06	7.33E+04	2.24E+02	1.38E+03	5.93E+04	3.76E+02	1.84E+03	5.45E+03	2.39E+03	4.48E+03	9.53E+03	1.67E+04	1.01E+02	2.72E+03	6.00E+03
	Standard Deviation	3.15E+07	1.34E+06	4.09E+03	2.51E+04	1.08E+06	6.86E+03	3.36E+04	9.96E+04	4.38E+04	8.17E+04	1.74E+05	3.06E+05	1.85E+03	4.97E+04	1.10E+05
	Sample Variance	9.93E+14	1.79E+12	1.67E+07	6.32E+08	1.17E+12	4.71E+07	1.13E+09	9.92E+09	1.91E+09	6.68E+09	3.02E+10	9.34E+10	3.41E+06	2.47E+09	1.20E+10

Table 6.5: Standard Deviations

Skewness & Kurtosis

One of the objective of this analysis is to understand how the data spreads. Single quantity value does not reflect the nature of the sampled data behavior within a time span. The information needed to comprehend the behavior of the data distribution is the description of how much of data that is straying away from the median value. The Skewness and Kurtosis can describe this data spread behavior.

Since they can describe the way the data are distributed, Skewness and Kurtosis allow the identification of possible correlation, characteristics, and attributes of the data with design styles. Apart from distinguishing the data to relate with design styles, different bandwidths can also be investigated to see if there is any difference of emotional responses between them. The benefit, of course is the ability to see clearly the changes of emotional valence and arousal in every layer of consciousness while playing video games of two different design styles.

In the Table 6.6, skewness coefficients for every bandwidths are presented. Unfortunately, nothing can be said to relate the skewness (positive or negative) to a specific design style. The result exhibit variation of skewness for every subject at every bandwidths.

		Abstract														
		F03	F04	F05	F06	F07	F08	F09	F10	F11	F12	F13	F14	F15	F16	F17
DELTA	Arousal	-1.86E-01	5.60E+00	1.07E+01	6.72E+00	-2.37E+00	1.69E+00	1.06E+01	6.65E+00	6.38E+00	-5.68E+00	8.31E+00	-8.91E+00	-1.18E+01	7.90E+00	6.30E+00
	Valence	6.15E+00	7.71E-01	7.99E-01	-5.56E+00	-3.98E+00	-4.82E+00	9.70E+00	8.24E+00	6.44E+00	6.03E+00	7.93E+00	5.62E+00	1.01E+01	7.10E+00	-6.30E+00
THETA	Arousal	1.78E+00	4.06E+00	9.65E+00	7.19E+00	-8.57E+00	9.16E+00	9.51E+00	-1.34E+01	7.89E+00	-6.67E+00	-1.03E+01	-2.86E+00	-5.96E+00	1.11E+01	4.73E+00
	Valence	1.73E+00	3.53E+00	9.79E+00	2.68E+00	7.14E+00	5.09E+00	-1.47E+01	-1.19E+01	-1.00E+01	6.29E+00	9.98E+00	-1.57E+01	6.03E+00	1.08E+01	4.73E+00
ALPHA	Arousal	1.13E+01	1.68E+01	-1.11E+01	1.29E+01	9.19E+00	1.29E+01	1.64E+01	4.79E-01	1.66E+01	-4.34E+00	-9.68E+00	8.19E+00	-7.69E-01	1.44E+01	6.48E+00
	Valence	8.03E+00	7.75E+00	1.28E+01	-1.23E+01	-7.91E+00	4.33E-01	-1.72E+01	-5.04E+00	1.66E+01	-6.66E+00	1.04E+01	1.44E+01	-7.23E+00	8.15E+00	6.48E+00
BETA	Arousal	6.77E+00	-3.94E+00	1.70E+01	-4.03E+00	2.60E+00	2.89E+00	-1.24E+01	1.38E+01	1.23E+00	1.68E+01	1.31E+01	-1.15E+01	-2.66E+00	9.11E+00	7.68E+00
	Valence	-1.57E+01	-3.55E+00	-1.81E+01	-1.71E+01	-2.83E+00	5.32E+00	1.23E+01	-1.62E+01	-1.76E+01	1.07E+01	9.80E+00	-1.14E+01	2.25E+00	-9.27E+00	7.72E+00
GAMMA	Arousal	1.75E+01	6.96E+00	-1.82E+01	2.49E+00	-5.28E+00	-2.82E+00	1.21E+01	-6.97E+00	-1.69E+00	-1.56E+01	-9.44E+00	-1.34E+01	-1.46E-01	-5.11E+00	-6.90E+00
	Valence	1.54E+01	-7.13E+00	1.80E+01	1.20E+01	-3.88E+00	2.50E+00	9.87E+00	7.82E+00	7.32E+00	1.26E+01	-1.45E+01	-7.92E+00	1.33E+01	5.59E+00	-6.78E+00
		Realistic														
		F03	F04	F05	F06	F07	F08	F09	F10	F11	F12	F13	F14	F15	F16	F17
DELTA	Arousal	7.35E+00	7.13E+00	8.45E+00	7.24E+00	-4.94E+00	4.61E+00	1.09E+01	-2.33E+00	1.12E+00	-1.10E+01	9.63E+00	-1.03E+01	-1.00E+01	3.13E+00	5.83E+00
	Valence	9.46E+00	8.93E+00	-9.51E+00	-6.70E+00	-2.77E+00	-4.87E+00	1.09E+01	9.78E+00	2.26E+00	1.45E+01	6.63E+00	7.55E+00	1.07E+01	7.14E+00	-5.84E+00
THETA	Arousal	-1.08E+01	8.53E+00	1.03E+01	1.65E+01	-1.79E+01	4.63E+00	-8.81E+00	1.81E+01	1.45E+01	-1.02E+01	-1.62E+01	-8.62E+00	-8.76E+00	9.76E+00	8.20E+00
	Valence	-6.91E+00	1.05E+01	1.06E+01	1.46E+01	1.82E+01	4.00E+00	2.93E+00	-1.77E+01	-9.53E+00	1.04E+01	1.66E+01	7.33E+00	6.99E+00	9.36E+00	8.20E+00
ALPHA	Arousal	8.30E+00	-8.61E+00	-1.90E+00	1.56E+01	5.75E+00	-4.37E+00	1.17E+01	-1.70E+01	1.34E+01	-4.93E+00	-1.75E+01	-1.05E+01	9.71E+00	1.04E+01	1.72E+01
	Valence	-1.08E+01	1.29E+01	-6.50E-01	-9.92E+00	6.48E+00	-5.97E+00	6.87E+00	-1.83E+01	1.43E+01	-1.16E+00	1.82E+01	8.45E+00	-4.75E+00	4.23E+00	1.72E+01
BETA	Arousal	-9.74E+00	-6.18E+00	2.61E+00	3.52E+00	3.10E+00	1.66E+00	1.18E+01	1.10E+01	-3.47E+00	5.88E+00	9.10E+00	-1.04E+01	-1.31E-01	4.99E+00	1.07E+01
	Valence	-1.12E+01	4.21E+00	-8.72E-01	7.91E+00	-2.96E+00	-9.58E+00	-3.44E+00	1.69E+01	-1.39E+01	1.69E+01	1.16E+01	1.19E+01	-1.80E+00	-2.91E+00	1.07E+01
GAMMA	Arousal	1.55E+01	1.05E+01	4.58E+00	9.00E+00	-4.72E+00	2.30E+00	8.13E+00	1.53E+01	-6.11E+00	-1.74E+01	-1.07E+01	-1.73E+01	3.21E+00	-7.40E+00	-6.68E+00
	Valence	-1.66E+01	-6.18E+00	5.69E+00	-8.72E+00	-6.98E+00	5.70E+00	6.96E+00	-9.67E+00	9.00E+00	1.72E+01	-4.75E+00	-1.76E+01	5.17E+00	8.65E+00	-6.56E+00

Table 6.6: Skewness

The Kurtosis is another coefficient that describes data distribution. It measures whether the data is heavy-tailed (indicating abundance of outliers) or light-tailed (showing lack of outliers). As in skewness, Kurtosis is observed through its positive and negative signs. A positive value means it is a Leptokurtic curve, which means it has thick and heavy tails. A negative value means it is a Platykurtic curve that elucidate light tails on the data distribution curve.

For the EEG data acquired in this research, all resulting Kurtosis values are positive for both design styles at every bandwidths and on both valence and arousal axis. This value makes sense since on the scatter plot alone the amount of outliers are quite plentiful. This signifies the need to analyze the data distribution using box and whiskers plots that can separate outliers from the main mass of distribution. The Table 6.7 is a summary of the Kurtosis coefficients.

Abstract																
		F03	F04	F05	F06	F07	F08	F09	F10	F11	F12	F13	F14	F15	F16	F17
DELTA	Arousal	4.91E+01	4.13E+01	1.26E+02	5.76E+01	2.24E+01	1.41E+01	1.33E+02	4.86E+01	7.28E+01	3.62E+01	7.91E+01	9.98E+01	1.79E+02	7.33E+01	5.17E+01
	Valence	5.49E+01	3.79E+01	6.90E+01	3.78E+01	2.61E+01	3.24E+01	1.21E+02	8.48E+01	5.92E+01	4.11E+01	7.35E+01	3.78E+01	1.38E+02	5.83E+01	5.17E+01
THETA	Arousal	7.20E+01	2.88E+01	1.29E+02	6.19E+01	9.02E+01	1.12E+02	2.03E+02	1.93E+02	7.32E+01	5.19E+01	1.14E+02	1.12E+02	4.07E+01	1.30E+02	2.97E+01
	Valence	6.70E+01	3.07E+01	1.20E+02	4.44E+01	7.16E+01	3.67E+01	2.69E+02	1.69E+02	1.35E+02	4.71E+01	1.04E+02	2.76E+02	4.40E+01	1.23E+02	2.96E+01
ALPHA	Arousal	1.33E+02	2.96E+02	1.55E+02	1.94E+02	9.85E+01	2.15E+02	2.89E+02	1.60E+02	2.92E+02	4.06E+01	1.27E+02	1.70E+02	7.85E+01	2.29E+02	6.42E+01
	Valence	1.61E+02	8.04E+01	1.86E+02	1.68E+02	1.13E+02	6.03E+01	3.07E+02	1.54E+02	2.90E+02	8.89E+01	1.17E+02	2.53E+02	7.07E+01	8.32E+01	6.42E+01
BETA	Arousal	5.11E+01	2.05E+01	3.02E+02	8.93E+01	8.32E+00	1.56E+01	1.58E+02	2.45E+02	6.10E+01	2.97E+02	2.00E+02	1.87E+02	1.50E+01	1.09E+02	7.18E+01
	Valence	2.67E+02	1.58E+01	3.29E+02	3.06E+02	1.05E+01	6.10E+01	1.55E+02	2.75E+02	3.16E+02	1.27E+02	1.29E+02	1.42E+02	1.67E+01	1.13E+02	7.24E+01
GAMMA	Arousal	3.14E+02	5.87E+01	3.33E+02	1.89E+01	3.74E+01	2.43E+01	1.73E+02	1.85E+02	3.21E+01	2.58E+02	1.34E+02	2.24E+02	6.94E+01	3.10E+01	6.58E+01
	Valence	2.60E+02	6.66E+01	3.26E+02	1.97E+02	2.14E+01	8.84E+00	1.14E+02	1.91E+02	6.85E+01	1.65E+02	2.50E+02	9.87E+01	2.02E+02	3.60E+01	6.46E+01
Realistic																
		F03	F04	F05	F06	F07	F08	F09	F10	F11	F12	F13	F14	F15	F16	F17
DELTA	Arousal	6.36E+01	6.96E+01	7.93E+01	6.14E+01	2.74E+01	2.30E+01	1.32E+02	6.87E+01	2.59E+01	1.36E+02	1.29E+02	1.34E+02	1.27E+02	2.84E+01	4.14E+01
	Valence	1.06E+02	1.76E+02	1.02E+02	5.47E+01	2.62E+01	3.34E+01	1.32E+02	1.44E+02	3.03E+01	2.34E+02	9.99E+01	6.56E+01	1.40E+02	5.52E+01	4.18E+01
THETA	Arousal	1.51E+02	9.95E+01	1.22E+02	2.88E+02	3.26E+02	3.12E+01	1.02E+02	3.30E+02	2.34E+02	1.34E+02	2.80E+02	8.43E+01	9.75E+01	1.07E+02	7.50E+01
	Valence	5.49E+01	1.34E+02	1.28E+02	2.47E+02	3.33E+02	2.17E+01	1.33E+01	3.20E+02	1.01E+02	1.42E+02	2.92E+02	6.89E+01	5.57E+01	9.81E+01	7.50E+01
ALPHA	Arousal	7.79E+01	1.30E+02	6.34E+00	2.65E+02	5.27E+01	4.39E+01	1.86E+02	3.02E+02	2.04E+02	4.41E+01	3.16E+02	1.36E+02	1.30E+02	1.51E+02	3.06E+02
	Valence	1.40E+02	2.06E+02	9.94E+00	1.10E+02	7.91E+01	6.78E+01	9.83E+01	3.33E+02	2.26E+02	4.12E+01	3.32E+02	1.26E+02	2.82E+01	4.09E+01	3.06E+02
BETA	Arousal	1.71E+02	4.56E+01	1.02E+01	4.94E+01	1.30E+01	9.71E+00	1.62E+02	1.31E+02	6.69E+01	9.62E+01	9.23E+01	1.94E+02	4.28E+00	3.14E+01	1.23E+02
	Valence	1.48E+02	8.88E+01	6.80E+00	7.11E+01	1.20E+01	1.36E+02	3.86E+01	2.98E+02	2.13E+02	3.01E+02	1.82E+02	1.68E+02	4.91E+00	3.04E+01	1.24E+02
GAMMA	Arousal	2.62E+02	1.40E+02	3.69E+01	9.36E+01	3.80E+01	3.87E+01	7.57E+01	2.54E+02	8.59E+01	3.09E+02	1.33E+02	3.12E+02	2.06E+01	6.23E+01	4.89E+01
	Valence	2.96E+02	4.14E+01	4.68E+01	8.88E+01	6.81E+01	4.11E+01	5.64E+01	1.46E+02	8.89E+01	3.03E+02	1.04E+02	3.18E+02	3.79E+01	8.25E+01	4.76E+01

Table 6.7: Kurtosis

Minimum, Maximum and Range

Of course, all data set must have the lowest and highest value. And the spread of data between them is known as its range. Minimum and maximum values denote the extreme ends of the emotional intensity's reach along its valence and arousal axis. But since the outliers are too far away from the central clump of the data, their numerical values do not have any meaningful relationship with the two different design styles.

Count

All classified game play data sets contain 334 data points. These are the results from machine learning processes of classifying 19 channels each with 74908 data points of EEG recording for 5 minutes at a sampling rate of 250 samples per second. The data is translated into emotional valence and arousal.

Summary of Descriptive Statistic

Through EEG and machine learning methods the emotions of playing video games can successfully be translated into numerical data. Statistical analysis allow these data to be interpreted and studied to learn the connections between emotional responses and design styles. Quantitatively, the numbers are varied from person to person. The relationship between emotions and design seems to be the data distribution behavior rather than discrete quantity.

The mean values between subjects varied significantly. The deviation between them is too enormous that it is difficult to plot bar charts of them all together. The mean value is also too inaccurate to consider as the center of the data set due to the presents of extreme outliers. A more accurate estimation of the center of data is the median.

The median sits at the middle of the data distribution. A kin to a center of mass, the value of the median is the fulcrum for changing valence and arousal along the time line. It can be used to identify the emotional state of the subject while playing the game. The valence and arousal state were also scrutinized at different bandwidths

It is important to note that discrete emotions can be different for the same person on separate bandwidths. While it may not make sense to think a person could have experienced more than one emotions, the evidences from these computational model showed that it is indeed the case.

The mode is simply non-existent since the EEG data are continuous stream of signals. There are no values repeated more than once. Analyzing data distribution on this research's data set is not about peak frequency of a particular value. Instead, it is about data density which happens at a specific time instances and period.

Skewness and Kurtosis describes the nature of the data distribution. Due to the extreme deviations of the data – along with outliers which values are too excessive – distribution curve is difficult to analyze. Nevertheless, Skewness and Kurtosis are able to illustrate the characteristics of the data distribution.

Skewness coefficients exhibits inconsistent traits for both design styles. Their important telltale sign of data distribution behavior is their positive and negative signs. Results in the data collection and machine learning classification simply shows no concurrences with design styles. On top of that, the inconsistency also happens at every bandwidths. If there is one thing that is consistent with the skewness of these data is that none of them show a normal distribution. It is either extremely skewed to one side or the other.

Kurtosis coefficients show consistency. All data have positive Kurtosis, therefore their distribution curves are heavy-tailed. This result confirms the visible outliers from the scatter plot. Unfortunately, there is no distinguishing characteristics that signifies each particular design styles.

Other statistical figures such as mode, sum, count, etc. do not show significant characteristics to distinguish the two design styles as well. However, these figures are there for future work in case they can be of use in other context.

6.3.1.2. BOX AND WHISKERS PLOT (ABSTRACT VS REALISTIC)

The objective of this analysis is to analyze the spread density of emotional reactions towards different design styles. Emotions per se has been observed to be unrelated to different design styles. However, scatter plots of these data hints at different footprint sizes of data dispersions for each design style. Visual observation, of course, is not enough to validate this finding. Numerical statistics are needed to find out whether design styles influence the behavior of the emotional changes during game play.

To analyze the spread density, box and whiskers plots can provide both quantitative and visual assessments. A single plot from the data shows the interquartile range, outliers, and spread density of the emotional responses. Comparing two plots for different design styles reveals details of differences that are not possible to notice by numerical values alone. Another benefit for plotting box and whiskers is the separation of outliers. Although outliers is not necessarily a meaningless data, excessively huge value gaps between them and the main scatter body can distract from the important part of the data distribution. Box and whisker plots allow focused observation of the main scatter formation of the valence and arousal responses while simultaneously takes out outliers out of attention.

Interquartile Ranges Between Abstract and Realistic Design Styles

Emotional valence and arousal data resulted from the machine learning classification are all visualized as box and whisker plots. The tremendous difference in magnitude of emotions between subjects prevents all of the plots being presented together on the same chart. Axis scaling and axis normalization are difficult to execute for a side by side comparison. Despite that, analysis is still possible even by looking at the plots one by one.

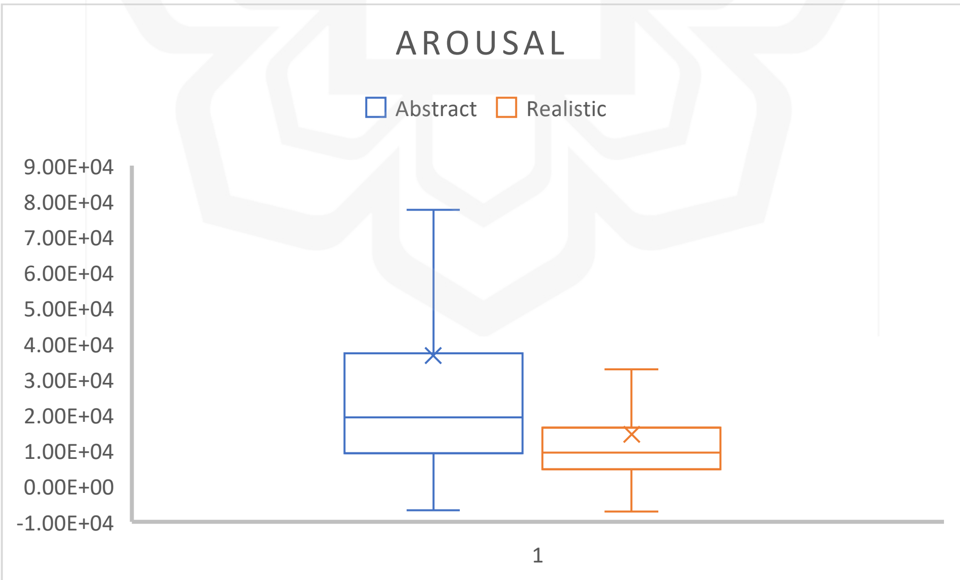

Figure 6.8: Arousal box and whiskers plot of two different Design Styles.

In the Figure 6.8, information that can be gained from an annotated sample of the box and whiskers plot is explained below:

1. **The interquartile ranges:** The length of the entire "box" in the box and whisker plot is the range of value that is contained within 50 percent of the data samples at the bulk of the distribution. This is the most important visualization of the data distribution as the attention is focused on the part of the data where the position of the data points are the most. The interquartile range (IQR) value can also be calculated by subtracting the third quartile (Q3) with the first quartile (Q1).

   $$\mathbf{IQR = Q3 - Q1}$$

   This value can be used to compare magnitude of emotional changes between Abstract and Realistic video games.
2. **The median's relative position:** In the descriptive statistical analysis, the numerical value of the median does not provide the picture of the data spread around it. Here, it is clear how the responses of the emotional valence and arousal behave above and below the median, between upper and lower limits of the interquartile ranges.
3. **The mean's relative position:** As with the median, the mean or the average can also be seen in context with the data spread. It's location within the distribution pictures the magnitude of the data deviations. The larger the deviations, the further away it is from the median. As it turned out, some of the subjects exhibit the mean location outside the interquartile ranges – suggesting extreme fluctuations in emotional activity in one direction than the other.
4. **Extreme ranges sans outliers:** Anything that is 1.5 times interquartile ranges (1.5*IQR) below the first quartile (Q1) or above the third quartile (Q3) is considered an outlier. The maximum and minimum values of the data distribution without outliers are within these ranges. They are indicated by the "whiskers" in the box and whiskers plot – hence the name. Unlike the maximum and minimum values acquired from the data set, box and whiskers plot determines the extremities of the main cluster of data distribution. The range between the two whiskers can be considered as the larger footprint size of the emotional fluctuations.

The objective of these box and whiskers plot is to understand the data dispersion differences between Abstract and Realistic video games. The interquartile ranges of both design styles seems to consistently confirm their correlation with emotional activity. After analyzing all subjects at every bandwidths, Abstract games primarily reveals a larger magnitude of valence and arousal activities. The Table 6.8a and 6.8b is the complete overview of the IQR analysis results.

AROUSAL	F03	F04	F05	F06	F07	F08	F09	F10	F11	F12	F13	F14	F15	F16	F17
DELTA A	4.19E+07	1.36E+07	1.65E+07	2.46E+08	3.13E+07	6.75E+08	5.24E+07	1.88E+08	1.30E+08	4.29E+08	2.31E+07	9.66E+08	1.73E+07	9.18E+06	1.17E+10
DELTA R	1.84E+07	8.92E+06	1.77E+07	3.01E+08	1.12E+07	2.76E+08	3.90E+07	8.78E+07	1.08E+08	1.05E+08	6.57E+07	1.32E+09	1.05E+07	3.16E+06	1.05E+09
RATIO	2.28	1.53	0.93	0.82	2.80	2.45	1.34	2.14	1.19	4.09	0.35	0.73	1.65	2.90	11.11
THETA A	1.74E+05	1.07E+05	2.55E+04	7.37E+05	6.53E+04	5.22E+05	1.34E+05	6.06E+05	4.87E+05	5.14E+05	2.95E+05	3.14E+05	1.32E+05	5.99E+04	1.95E+08
THETA R	1.37E+05	8.42E+04	1.81E+04	6.32E+05	3.43E+04	8.57E+05	1.26E+05	3.34E+05	3.06E+05	1.84E+05	4.59E+05	1.97E+05	1.91E+05	3.78E+04	8.01E+06
RATIO	1.27	1.27	1.41	1.17	1.90	0.61	1.06	1.82	1.59	2.78	0.64	1.59	0.69	1.58	24.30
ALPHA A	7.74E+04	2.73E+04	1.44E+04	3.23E+04	2.80E+04	3.62E+04	1.84E+04	9.97E+04	6.55E+04	4.60E+04	4.96E+04	8.41E+04	2.65E+04	9.15E+03	5.07E+07
ALPHA R	3.53E+04	1.91E+04	1.35E+04	2.26E+04	1.16E+04	2.40E+04	1.38E+04	5.89E+04	5.12E+04	2.31E+04	5.52E+04	7.06E+04	2.57E+04	9.73E+03	4.82E+06
RATIO	2.19	1.43	1.07	1.43	2.41	1.51	1.33	1.69	1.28	1.99	0.90	1.19	1.03	0.94	10.53
BETA A	4.87E+05	7.79E+05	8.07E+04	2.34E+05	3.57E+05	9.12E+03	9.48E+03	1.33E+04	1.56E+04	2.08E+04	7.17E+04	6.72E+03	1.23E+04	8.44E+04	4.81E+06
BETA R	1.91E+05	2.37E+05	1.86E+04	4.90E+04	5.53E+05	5.89E+03	9.17E+03	8.90E+03	1.28E+04	1.07E+04	4.08E+04	6.71E+03	7.51E+03	3.44E+04	1.05E+06
RATIO	2.55	3.29	4.34	4.77	0.65	1.55	1.03	1.49	1.22	1.95	1.76	1.00	1.63	2.45	4.57
GAMMA A	9.84E+05	1.09E+05	1.15E+04	3.09E+04	1.38E+05	5.93E+02	7.65E+03	4.78E+03	2.30E+03	4.87E+02	9.34E+03	1.30E+03	5.85E+02	1.76E+04	1.07E+05
GAMMA R	2.25E+05	3.46E+04	1.90E+03	3.49E+03	1.90E+05	8.12E+02	7.07E+03	3.30E+03	1.35E+03	3.41E+02	8.61E+03	7.21E+03	4.57E+02	3.22E+03	3.03E+04
RATIO	4.37	3.15	6.05	8.86	0.72	0.73	1.08	1.45	1.70	1.43	1.09	0.18	1.28	5.47	3.52
4BANDS A	6.55E+06	2.68E+06	1.97E+06	2.15E+07	9.32E+06	4.17E+08	3.73E+06	2.68E+06	2.66E+07	1.67E+07	1.29E+06	1.20E+08	5.57E+06	1.67E+06	4.45E+09
4BANDS R	5.05E+06	1.51E+06	1.28E+06	1.36E+07	3.75E+06	2.29E+08	2.63E+06	1.66E+06	1.84E+07	6.26E+06	3.61E+06	1.01E+08	4.66E+06	5.93E+05	5.14E+08
RATIO	1.30	1.77	1.54	1.58	2.48	1.82	1.42	1.61	1.44	2.67	0.36	1.19	1.20	2.81	8.65

Table 6.8a IQR and Difference Ratio of Arousal Responses

VALENCE	F03	F04	F05	F06	F07	F08	F09	F10	F11	F12	F13	F14	F15	F16	F17
DELTA A	5.24E+07	9.06E+06	1.48E+07	3.12E+08	7.43E+07	2.52E+08	3.06E+07	4.93E+07	1.07E+08	1.41E+08	1.27E+07	3.11E+09	3.07E+07	2.01E+07	1.49E+10
DELTA R	1.96E+07	5.46E+06	1.33E+07	3.88E+08	1.63E+07	2.37E+08	2.08E+07	3.78E+07	4.67E+07	4.51E+07	3.50E+07	4.32E+09	2.04E+07	6.25E+06	1.09E+09
RATIO	2.68	1.66	1.11	0.80	4.57	1.06	1.47	1.30	2.30	3.13	0.36	0.72	1.50	3.22	13.63
THETA A	2.44E+05	1.19E+05	3.98E+04	4.96E+05	1.97E+05	1.44E+07	1.18E+05	1.43E+06	3.86E+05	3.71E+05	1.81E+05	4.93E+05	9.72E+04	5.57E+04	6.71E+08
THETA R	1.66E+05	9.78E+04	2.33E+04	5.12E+05	8.22E+04	7.72E+06	1.56E+05	4.91E+05	1.80E+05	1.29E+05	5.01E+05	2.83E+05	9.90E+04	3.31E+04	2.83E+07
RATIO	1.47	1.22	1.70	0.97	2.40	1.86	0.76	2.91	2.14	2.88	0.36	1.75	0.98	1.68	23.70
ALPHA A	1.25E+05	2.72E+04	2.48E+04	2.62E+04	7.32E+03	6.61E+04	3.16E+04	2.54E+04	4.36E+04	2.85E+04	3.26E+04	9.47E+04	2.94E+04	1.57E+04	4.11E+07
ALPHA R	6.06E+04	2.06E+04	1.71E+04	1.33E+04	4.73E+03	2.84E+04	2.64E+04	2.16E+04	2.70E+04	1.29E+04	3.32E+04	9.82E+04	2.92E+04	1.17E+04	3.81E+06
RATIO	2.06	1.32	1.45	1.97	1.55	2.33	1.20	1.17	1.61	2.22	0.98	0.96	1.01	1.34	10.79
BETA A	4.03E+05	5.26E+05	5.54E+04	5.35E+04	1.39E+05	5.46E+03	1.11E+04	2.56E+04	8.61E+03	5.58E+03	5.93E+04	1.70E+04	2.14E+04	3.01E+04	2.04E+05
BETA R	1.93E+05	2.07E+05	1.34E+04	1.05E+04	2.76E+05	5.32E+03	6.12E+03	1.64E+04	7.06E+03	2.37E+03	4.04E+04	2.93E+04	1.37E+04	1.26E+04	2.29E+04
RATIO	2.09	2.55	4.15	5.07	0.50	1.03	1.81	1.56	1.22	2.36	1.47	0.58	1.56	2.38	8.91
GAMMA A	5.58E+05	2.46E+05	9.92E+03	2.96E+04	1.99E+05	1.79E+03	8.97E+03	2.01E+03	5.09E+03	1.38E+03	7.49E+03	1.21E+03	1.01E+04	2.69E+04	2.58E+04
GAMMA R	2.12E+05	8.40E+04	2.23E+03	3.17E+03	2.30E+05	2.37E+03	5.82E+03	1.63E+03	1.60E+03	1.08E+03	6.60E+03	7.40E+03	7.34E+02	4.70E+03	1.08E+04
RATIO	2.62	2.92	4.45	9.35	0.86	0.75	1.54	1.23	3.17	1.28	1.13	0.16	13.71	5.71	2.39
4BANDS A	1.03E+07	1.25E+06	8.66E+05	8.72E+06	1.09E+07	1.63E+07	2.12E+06	4.08E+06	1.44E+07	4.62E+06	2.26E+06	4.74E+07	1.69E+06	1.11E+06	3.98E+08
4BANDS R	2.15E+06	8.68E+05	6.77E+05	4.98E+06	3.66E+06	1.98E+07	2.23E+06	1.78E+06	8.72E+06	2.11E+06	9.24E+06	7.72E+07	2.41E+06	3.58E+05	5.31E+07
RATIO	4.78	1.45	1.28	1.75	2.97	0.82	0.95	2.29	1.66	2.18	0.24	0.61	0.70	3.11	7.49

Table 6.8b IQR and Difference Ratio of Valence Responses

The table is laid out with the subjects at different columns. The rows organize the results in separate bandwidth. Bandwidths are arranged starting from the lowest frequency ranges (DELTA) at the top towards the highest frequency ranges GAMMA at the bottom. The last row of the bandwidth segment is labelled as 4BANDS indicating classification of data that range from DELTA to BETA. 4BANDS does not include GAMMA because based on literature review, DELTA to BETA is the most common bandwidths to study emotions (Balducci, 2017).

There are three rows for every band, beginning from the top is the interquartile range for the Abstract game, the interquartile range for the Realistic game in the middle, and the difference ratio between Abstract and Realistic. The ratio is calculated top to bottom, thus if Abstract is larger, the result is > 1 and colored green. Otherwise the result is in orange. They are color coded to make analysis easier. Ratio if Realistic game has larger emotional response is < 1 and can be obtained simply by inverting the value.

Table 6.8a is a compilation of all arousal data while Table 6.8b is a compilation of valence data. Out of fifteen subjects, six of them have Abstract game Interquartile ranges larger than Realistic game at every bandwidth. When observing arousal or valence separately, seven of the subjects have larger Interquartile range for Abstract game at every bandwidth while the same can be said for eight subjects in the valence data set. The other subjects mainly have the Interquartile ranges larger for Abstract games for most of the bandwidth except one or two bandwidths. The exception being subject F13 and F14, where Realistic game seems to be dominant instead.

Identifying which games has the larger fluctuation amplitude in both valence and arousal responses, it is apparent that Abstract games dominate the result. There are of course a few inconsistencies, especially for subject labelled F13 and F14 where most the results show higher responses in realistic games. At this point, it cannot be confirmed that Abstract video games engage emotions more than Realistic games yet, but the result is converging towards that conclusion. Furthermore, those that exhibit larger emotional responses for the Realistic game do not measure a difference ratio as big as with those that are more influenced by the Abstract game.

Apart from analyzing data distributions of valence and arousal individually, it is also possible to investigate the distribution of emotional intensity. Valence and arousal are the separate horizontal and vertical axis that make up the emotional state of the subject. Referring to the ACCURACY ANALYSIS earlier, emotions scatter on the valence and arousal plane. By calculating the distance from the threshold point, the intensity of the emotion can be measured. The threshold point, as stated earlier is at (0.5,0.5) on the valence vs arousal plot.

Regardless of what the emotional state is at any time instances, the interest here is to look at how strong the emotions fluctuates over time. Emotional intensity is measured as follows:

Emotional Intensity = $\sqrt{[(\text{Arousal} - 0.5)^2 + (\text{Valence} - 0.5)^2]}$

Analogous to the separate arousal and valence analysis, emotional intensity's data distribution for all subjects at every bandwidths are also examined. The interquartile ranges for emotional intensity can be seen in the Table 6.9.

INTENSITY	F03	F04	F05	F06	F07	F08	F09	F10	F11	F12	F13	F14	F15	F16	F17
DELTA A	1.13E+08	3.31E+07	3.01E+07	3.98E+08	1.29E+08	9.68E+08	7.46E+07	2.24E+08	3.93E+08	4.67E+08	8.84E+07	4.04E+09	3.85E+07	2.45E+07	1.89E+10
DELTA R	4.18E+07	1.55E+07	2.60E+07	5.29E+08	3.49E+07	4.60E+08	5.45E+07	1.11E+08	2.26E+08	1.23E+08	1.76E+08	5.33E+09	2.90E+07	7.78E+06	1.67E+09
RATIO	2.71	2.14	1.16	0.75	3.70	2.11	1.37	2.02	1.74	3.79	0.50	0.76	1.33	3.15	11.30
THETA A	4.48E+05	1.82E+05	6.27E+04	9.89E+05	2.26E+05	1.45E+07	2.32E+05	1.90E+06	6.60E+05	7.16E+05	5.37E+05	6.04E+05	2.14E+05	9.39E+04	6.99E+08
THETA R	2.90E+05	1.53E+05	2.88E+04	9.21E+05	9.02E+04	8.92E+06	2.49E+05	1.58E+06	5.30E+05	2.51E+05	1.20E+06	4.71E+05	3.02E+05	5.45E+04	2.91E+07
RATIO	1.54	1.19	2.17	1.07	2.50	1.62	0.93	1.20	1.25	2.85	0.45	1.28	0.71	1.72	24.00
ALPHA A	1.65E+05	3.59E+04	2.55E+04	4.17E+04	2.71E+04	1.43E+05	3.30E+04	1.24E+05	7.86E+04	5.62E+04	5.55E+04	1.77E+05	4.12E+04	2.01E+04	6.53E+07
ALPHA R	7.07E+04	2.40E+04	1.83E+04	2.62E+04	1.22E+04	7.51E+04	3.08E+04	8.95E+04	6.29E+04	2.92E+04	5.36E+04	1.71E+05	5.10E+04	1.52E+04	6.02E+06
RATIO	2.33	1.50	1.39	1.59	2.23	1.91	1.07	1.39	1.25	1.92	1.04	1.04	0.81	1.32	10.85
BETA A	5.29E+05	9.33E+05	9.80E+04	2.45E+05	3.39E+05	1.00E+04	1.39E+04	2.64E+04	1.84E+04	2.19E+04	9.28E+04	1.93E+04	2.43E+04	8.65E+04	4.82E+06
BETA R	1.88E+05	3.38E+05	2.04E+04	5.12E+04	6.06E+05	6.86E+03	9.51E+03	1.91E+04	1.54E+04	1.09E+04	4.58E+04	3.21E+04	1.49E+04	3.58E+04	1.05E+06
RATIO	2.81	2.76	4.80	4.78	0.56	1.46	1.46	1.38	1.20	2.02	2.03	0.60	1.63	2.42	4.61
GAMMA A	1.32E+06	2.85E+05	1.49E+04	4.75E+04	2.20E+05	1.75E+03	1.22E+04	4.81E+03	6.12E+03	1.36E+03	1.57E+04	2.70E+03	9.81E+03	3.52E+04	1.09E+05
GAMMA R	3.92E+05	9.79E+04	2.81E+03	4.79E+03	2.89E+05	2.40E+03	9.15E+03	3.01E+03	2.11E+03	1.12E+03	1.24E+04	9.55E+03	8.18E+02	5.54E+03	2.99E+04
RATIO	3.37	2.91	5.29	9.91	0.76	0.73	1.33	1.60	2.90	1.22	1.27	0.28	11.99	6.36	3.64
4BANDS A	5.09E+14	1.12E+13	1.44E+13	4.96E+14	2.54E+14	1.88E+17	2.89E+13	3.40E+13	2.07E+15	4.04E+14	1.22E+13	1.75E+16	4.18E+13	7.92E+12	2.67E+19
4BANDS R	7.41E+13	3.50E+12	7.25E+12	3.16E+14	4.10E+13	5.19E+16	1.74E+13	1.51E+13	5.22E+14	4.74E+13	7.59E+13	2.82E+16	2.70E+13	9.18E+11	2.61E+17
RATIO	6.87	3.21	1.99	1.57	6.19	3.62	1.66	2.24	3.96	8.51	0.16	0.62	1.55	8.64	102.35

Table 6.9: IQR And Difference Ratio For Emotional Intensity

With emotional intensity, Abstract game is still dominantly more active than Realistic game. Particularly in Alpha band where only one subject exhibit more agitation towards Realistic game than Abstract. Alpha band is the primary bandwidth usually associated with emotions (Benlamine, 2017). Another interesting point to take note is on the subject number F17. That particular subject's emotional intensity ratio between Abstract and Realistic on 4BANDS is higher than 100:1. No other subject shows such a stark difference between the two design styles at any bandwidths.

Alpha vs Beta

According to other studies related to emotions and brain waves, emotional valence and arousal responds primarily in alpha and beta bands (Benlamine, 2017, Malik, 2012). For this reason, the next stage in statistical analysis – the box and whiskers plots for an in-depth look at data spread patterns – will be focused on these two bands.

1. Eyes Closed and Eyes Open Emotional Responses

   At the start of the EEG recording session, the participants had to undergo a session of relaxed state. The Figure 6.9 shows data spread of gameplay data and resting state. This is the ground reference of the subject's emotional responses. The data during this stage were also classified to analyze their arousal and valence as well.

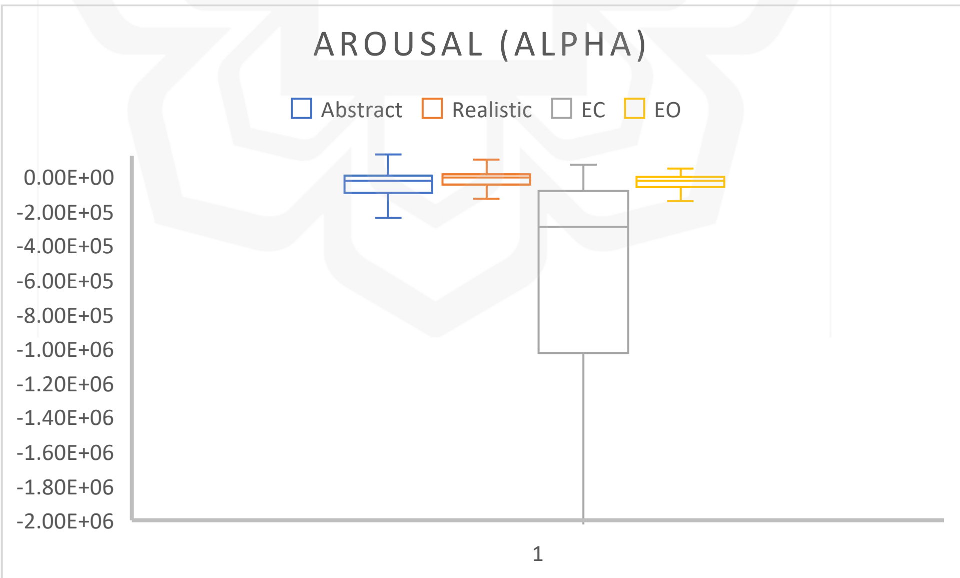

Figure 6.9a: Alpha gameplay data spread alongside resting state

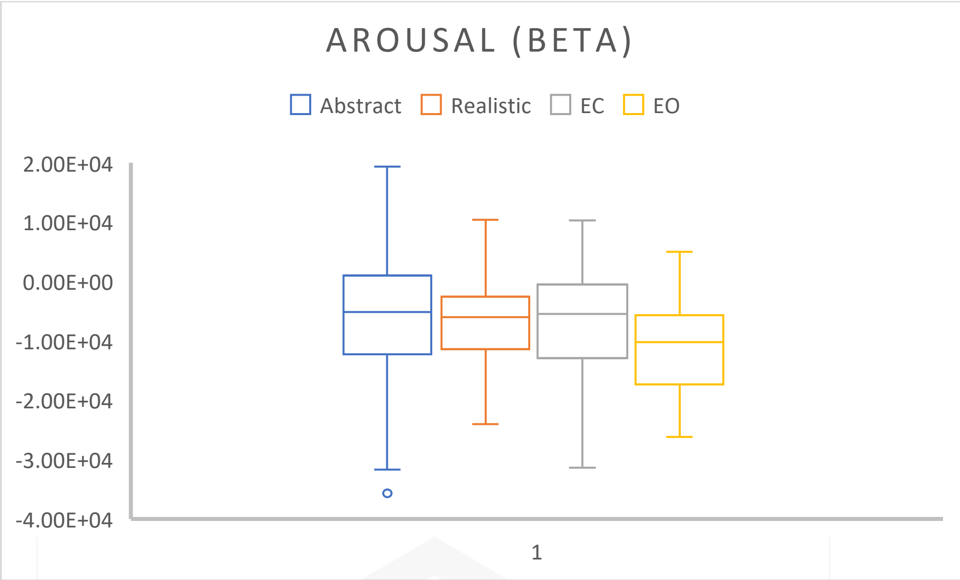

Figure 6.9b: Beta gameplay data spread alongside resting state

a. Eyes close and eyes open emotional fluctuations for Alpha band have significant differences compared to Beta Band. In particular, the eyes close valence and arousal readings are in general many times more than the eyes open measurements.
b. For Beta band, the differences are slight and usually it is the eyes open data that are more active in emotional changes.
c. Differences between eyes closed and eyes open emotional state reflects the study of emotions and brain waves relationship. Here it testify the Alpha band emotional changes are related to a relaxed state while Beta band are associated with awake state.
d. Notice the spread size of the Eyes Open in Alpha band is closer to the game playing size. In most cases, Abstract game is more identical to Eyes Open.
e. Spread size of Eyes Closed in Alpha band is simply too enormous to correlate with the two design styles.
f. For Beta bandwidth, Eyes Closed and Eyes Open is much closer in their data spread differences compared to the Alpha Band. This is also a proof to testify the relationship between Beta band with awake state.

2. Arousal – Valence spread in 1-minute interval

In the previous section of box-and-whiskers analysis, the data distribution was a 5-minute exposure of the entire time length of the game play. To understand data distribution better, the data is split into a 1-minute intervals. Here, the changes for each minute of gameplay can be seen. In the Figure 6.10, a typical response behavior in the Alpha band is demonstrated. Labelled as A1 to A5, each of them are data distribution of a one minute play. Realistic sessions are labelled as R1 to R5.

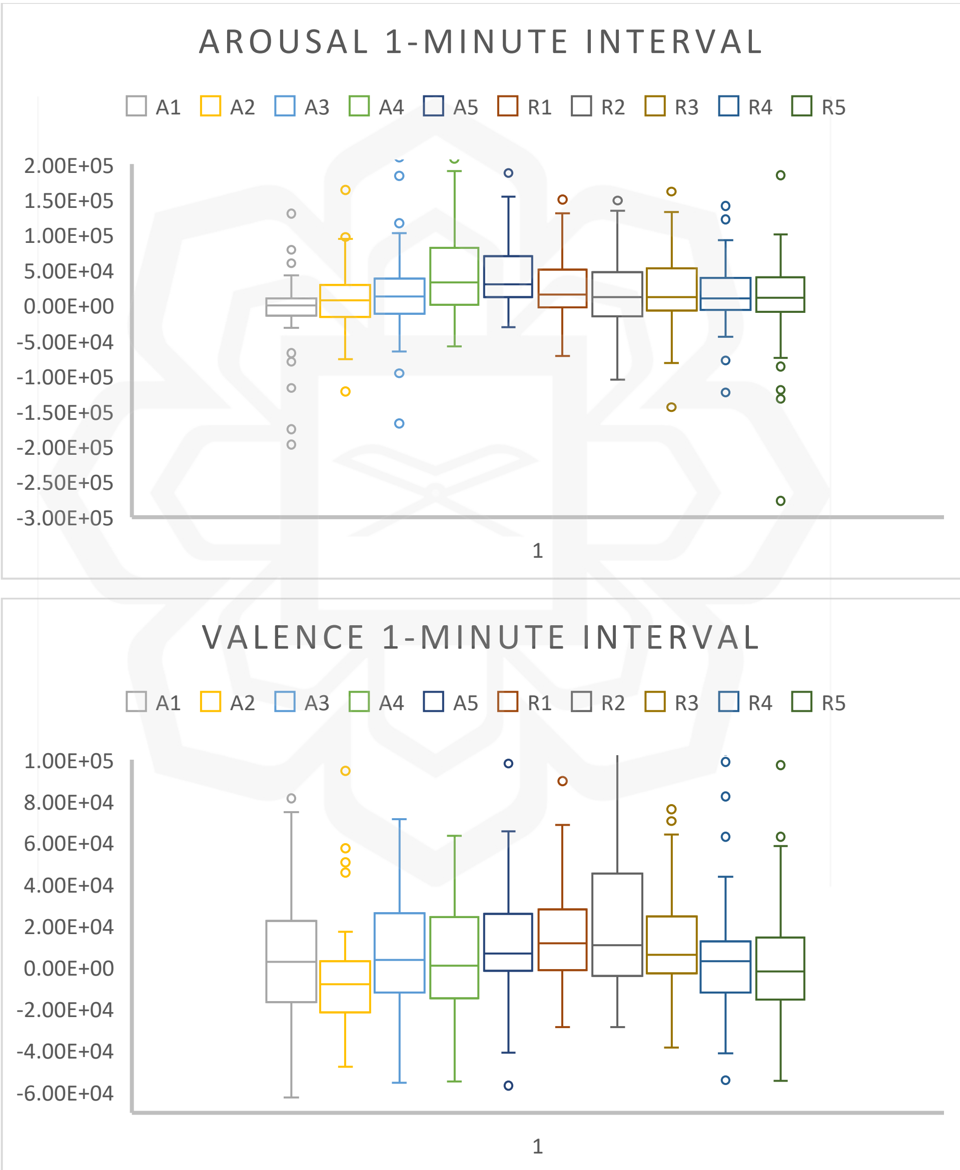

Figure 6.10: 1-minute interval spread for arousal and valence in the Alpha band.

a. Abstract game is more erratic in valence and arousal while for the Realistic games the changes are not as dramatic nor as aggressive. Realistic game either shows minimal changes in its interval medians or the changes are much smoother.
b. Even with a smaller distribution spread, Abstract game tends to have aggressive emotional changes within 1-minute duration. The changes in median values for each interval can be higher and lower relative to the adjacent intervals too. Realistic game tends to have a steady one-directional changes.
c. Spread size for each interval in Abstract game is also more erratic than Realistic game. The latter has a more uniform and gradual changes of its interval interquartile ranges.

For the Beta bandwidth, the typical data distribution of valence and arousal is shown in Figure 6.11:

a. In the Beta bandwidth, characteristics of the data distribution is almost similar to the Alpha band, except that for Realistic game each interval spread has a more prominent differences.
b. In the example shown in Figure 6.11, the Realistic design seems to have a larger interquartile ranges for every interval. However, the behavior of each interval is similar to those that has Abstract game having a larger spread – Abstract is more unstable in characteristics than Realistic.
c. Fluctuations in Abstract design is more aggressive, the median for each interval is higher or lower than the adjacent intervals. And just as in Alpha band, the median changes in Realistic design is smoother and more progressive.
d. Other traits exist, however they are less consistent from one subject to another. It is perhaps an opportunity to correlate these emotional changes behavior with the profile of the participants, but since that is not the focus of this research, it will not be investigated.

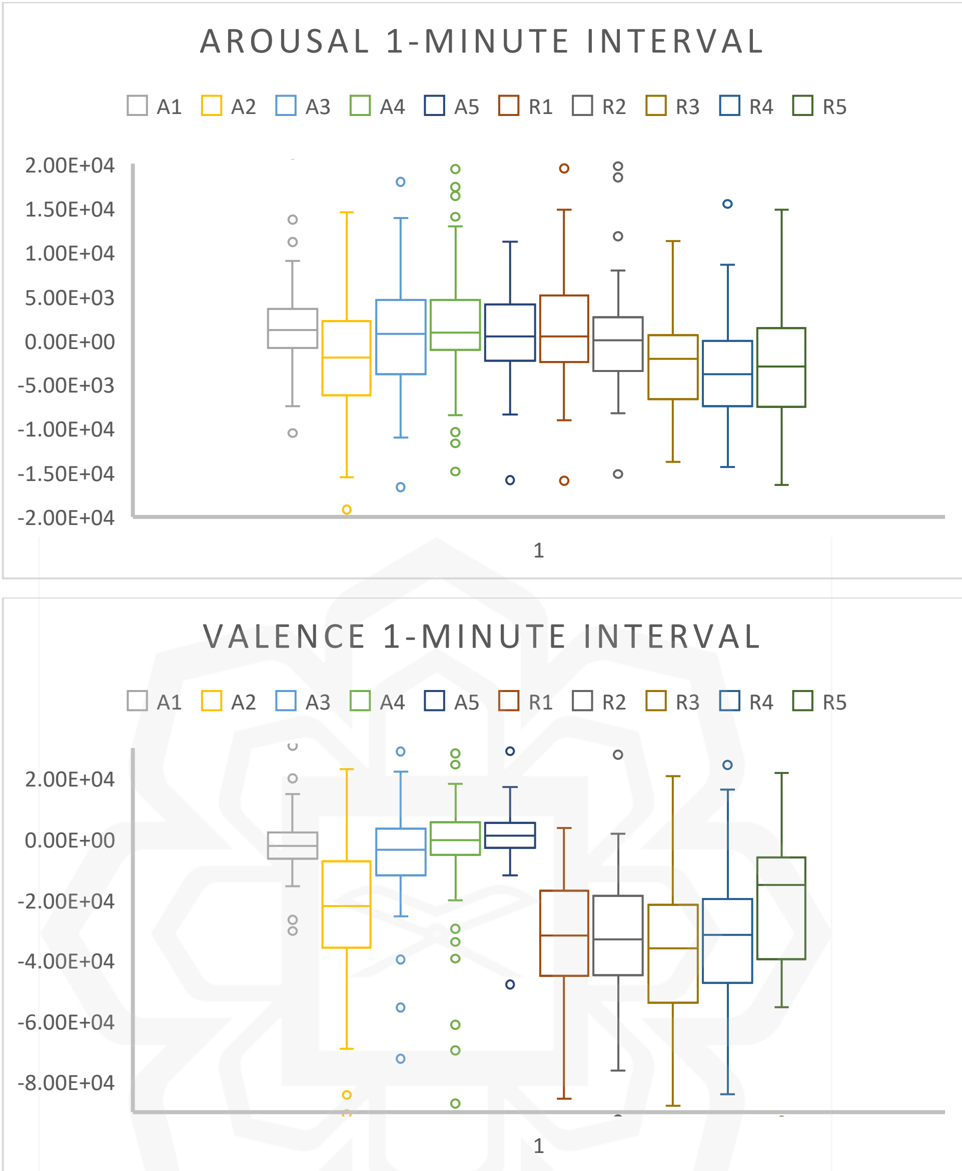

Figure 6.11: 1-minute interval spread for arousal and valence in the Beta band.

3. Arousal – Valence Accumulated 1-minute Interval Spread
   In this section of the analysis, the data distribution behavior is split into 1-minute progressive intervals. Instead of simply dividing the data stream in 1-minute intervals, the data distribution changes is observed after every one minute. Contrast to the previous 1-minute interval analysis, the accumulated progress of emotional responses after every minute can be observed. The main difference is that this time the final minute of game play show the resulting emotional distribution rather than showing each emotional changes within a one minute instances.

A typical result of the box-and-whiskers plot of an accumulated 1-minute interval data distribution of the subject's emotional activity is shown in the Figure 6.12.

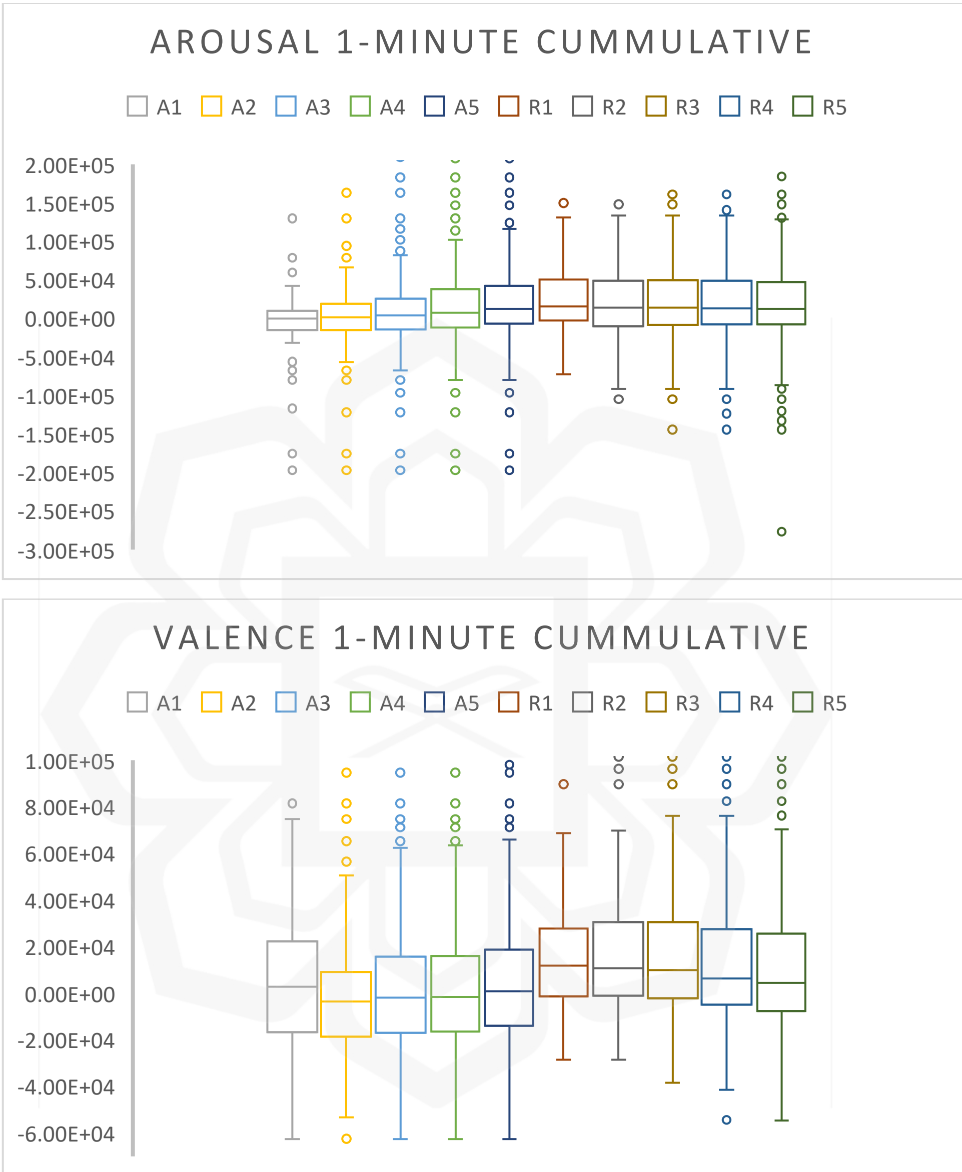

Figure 6.12: Accumulated arousal and valence data spread after every minute in the Alpha band.

a. At a glance, the main feature of the Alpha band when playing Abstract and Realistic games back to back is that there seems to be a seamless continuity for both games. It is as if the emotions in the Alpha band (perhaps subconsciously) attempts to adapt to different games as smoothly as possible.

b. Since this is an accumulation of emotional reactions after every minute of gameplay, the changes appear smooth for both game designs.

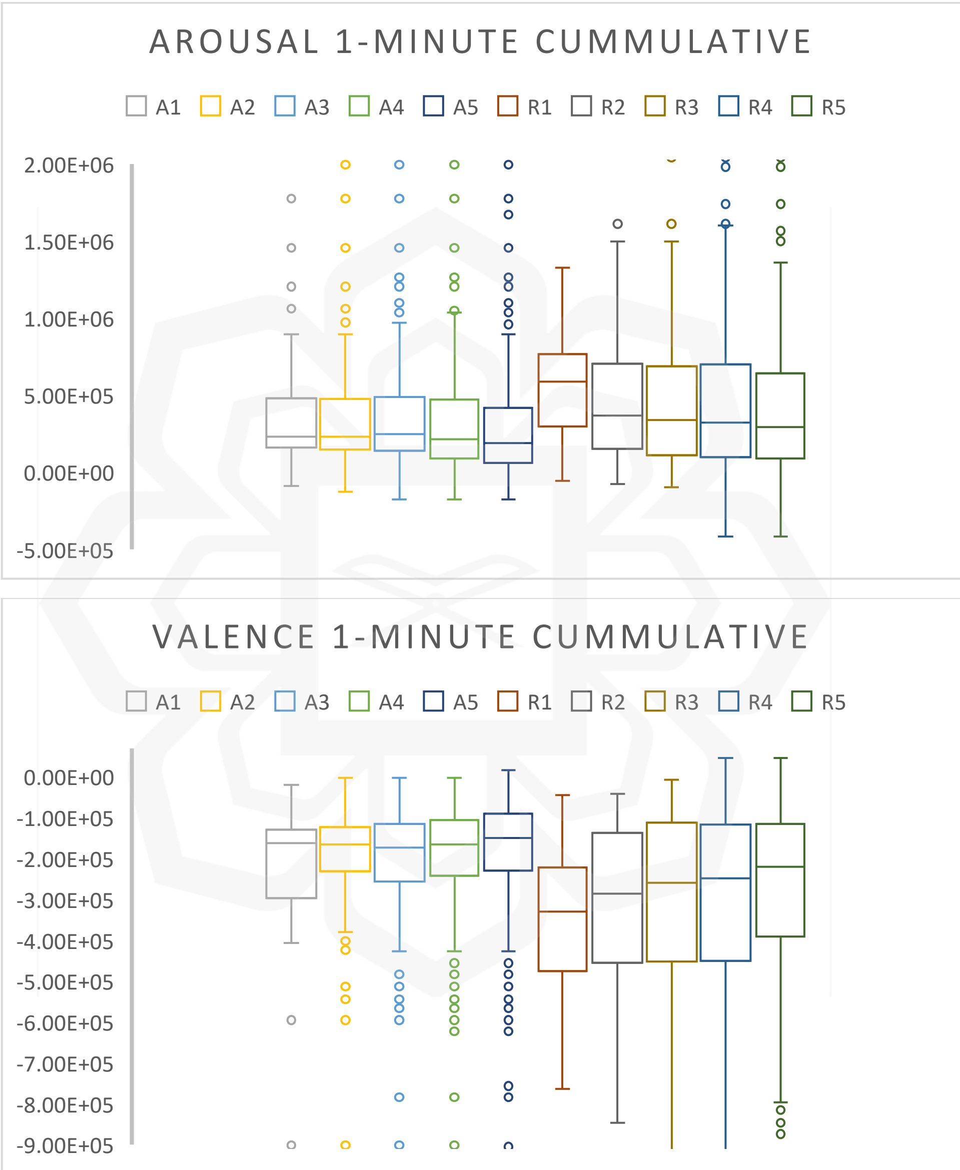

Figure 6.13: Accumulated arousal and valence data spread after every minute in the Beta band.

a. For Beta bandwidth, the most distinguishing feature of the plot is the discontinuity of between playing Abstract and Realistic games.
b. For each game design there is a smooth continuity, but as soon as the first minute of the next game started, the emotional state instantaneously changes. Figure 6.13 shows this behavior.
c. This sudden change may be related to the fact that Beta band is related to the awake state, which involves a conscious awareness of change in design style.

6.4 TRACES OF BRAIN FUNCTIONS IN GAMEPLAY ACTIVITY

Prior to the video games playing session during EEG data collection, a brief brain cognitive performance test was conducted. To simplify the procedure of the data collection and making sure the session was running smoothly, the EEG signals during the brain performance test was also recorded.

This section of the data collection was originally meant to be part of the profiling of the subjects. Profiling requires quite a large number of population to get the data analysis accurate. Considering the amount of data that will be acquired after the data collection, analysis of such a number of population would be unsurmountable. Limited time, budget, and constrained situation during the pandemic forced the decision to execute in-depth analysis of the EEG data stream. Instead of having the subjects as the population sample, this research takes each data instances as the sample.

Nevertheless, the extra data acquired was too valuable to be wasted away, therefore they too were classified using the emotional valence and arousal model. A simple scatter plot was briefly observed to quickly catch any significant attributes that connect the brain's cognitive function with design styles.

There are four brain's performance test, each engages the four different types of learning aptitudes: Cognitive function, Creativity, Memory, and Verbal competency. After the machine learning process, each individual brain test data may not have any significance. But when combined together in a single plot, an unexpected result was discovered. The findings of these aspects of the research were published in the International Conference on Information Technology and Digital Applications (ICITDA) conference in June 2020.

6.4.1 VIDEO GAMES AND EDUCATION

Educational value in video games is nothing new. Many production studios already made educational video games that are designed to educate the end users – who are the players – with a specific topic. Most educational video games are designed to combine educational philosophy and game design principles. Such games range from spelling activities to mathematical challenges. Games like these are known as educational games. Most of the time, they are categorized as edutainment games.

Video games outside the edutainment category, however, are perceived to have no educational values (Ashinof, 2014). They are designed purely for entertainment and fun. Such games can be a good time-killer for some situations such as during long hours of commute in a public transportation. Due to the big impressions that these games serve nothing but pure enjoyment, some people think that they are time waster. Such negative perception gave these kind of video games a bad reputation of being destructive to the society (Palaus, et.al., 2017).

Despite the mixed views of their place in the society, video games are something that no one can ignore. While non-educational games were never intended to be educational, there are published articles that use these kind of games to stimulate children learning (Ashinof, 2014; Blacker, 2014; Boot, 2015). Such research findings provoke questions whether video games have any psychological effect to the human mind/brain. Are there any correlation between non-educational video games and learning activities? Can something that was designed purely for enjoyment can be valuable to the growth and potential of the brain?

6.4.2 STIMULATING THE MIND WITH VIDEO GAMES

Diving into details of the games used for experiments in the psychology of the human mind, it is startling that quite a lot of these researches use non-educational games. One of the most significant one is done by Franceschini (2017) who applied action video game as a training medium to improve dyslexic children's literacy ability. The game being used is called *Space Invader* which is a 2D platform shooter with no literacy elements whatsoever. Training those children by playing *Space Invader* results in improved literacy performance. In fact, it is also claimed that action video games can actually cure dyslexia. The author did not specify why that particular game was chosen. The only criteria was that the game was chosen because it falls under the genre category.

Video games related researches are many and each has a different approach. Nevertheless, most that studied their relationship to the human psychology always found that video games have an effect on the player's mind regardless whether they are educational by design or not (Ashinof, 2014). Their influence over the human psyche are too consistent to be assumed as coincidental. Although these video games were never meant to be educational, those researches that found it to be a 'wonder tonic' that cures psychological symptoms and boost learning potential (Chandra, 2016; Gori, 2016) are too significant to be ignored.

Those findings by other researches support the claims that video game is a medium that stimulates the mind. And it opens a huge question as to whether they have any correlation at all with specific brain's cognitive functions and their performance. A question that this paper is not to answer yet, but to reveal traces and evidences of specific learning aptitude might be present during a game play session.

6.4.3 DATA COLLECTION ON COGNITIVE FUNCTIONS (LEARNING APTITUDE)

The learning aptitude test was originally meant to be as a component for profiling the subjects that undertake this experiment. The test instrument measures four different brain functions and ideally the test result should be obtained just before the game play session. This is the reason why EEG data of the aptitude test was recorded. The EEG device was already in place when the aptitude test was taking place, thus their signals were recorded anyway.

The test instrument for measuring learning aptitude was provided by the Cambridge University's Brain Lab. It is available online at https://brainlabs.me. The instrument measures four brain functions:

1. Cognitive
2. Verbal
3. Creativity
4. Memory

Each brain functions was measured with a score. These scores can be accumulated over time to monitor changes of the brain performance after every 24 hours. This instrument was a valid and credible instrument and is backed by numerous articles and publications.

For data analysis, raw data out of the EEG device was input and ran into Python codes that applies supervised machine learning to classify the unknown variable. Data from the learning aptitude was also ran with the code even though their result may not be useful for the research's objective. However, when the resulting analysis laid out in a scatter plot graph, a constant pattern of similarities is noticed for all subjects of the experiment.

In Figure 6.14, there are two things that can be observed from these scatter plots. First, for each aptitude tests that measures a specific brain function, their scatter plot is almost unique to each other. The plots shows the emotional valence versus arousal (VA) of the player during each tests. The plots reveals that when a specific brain function is at work, their valence vs arousal is in a specific state. The scatter plots below demonstrate one subject's valence versus arousal analysis.

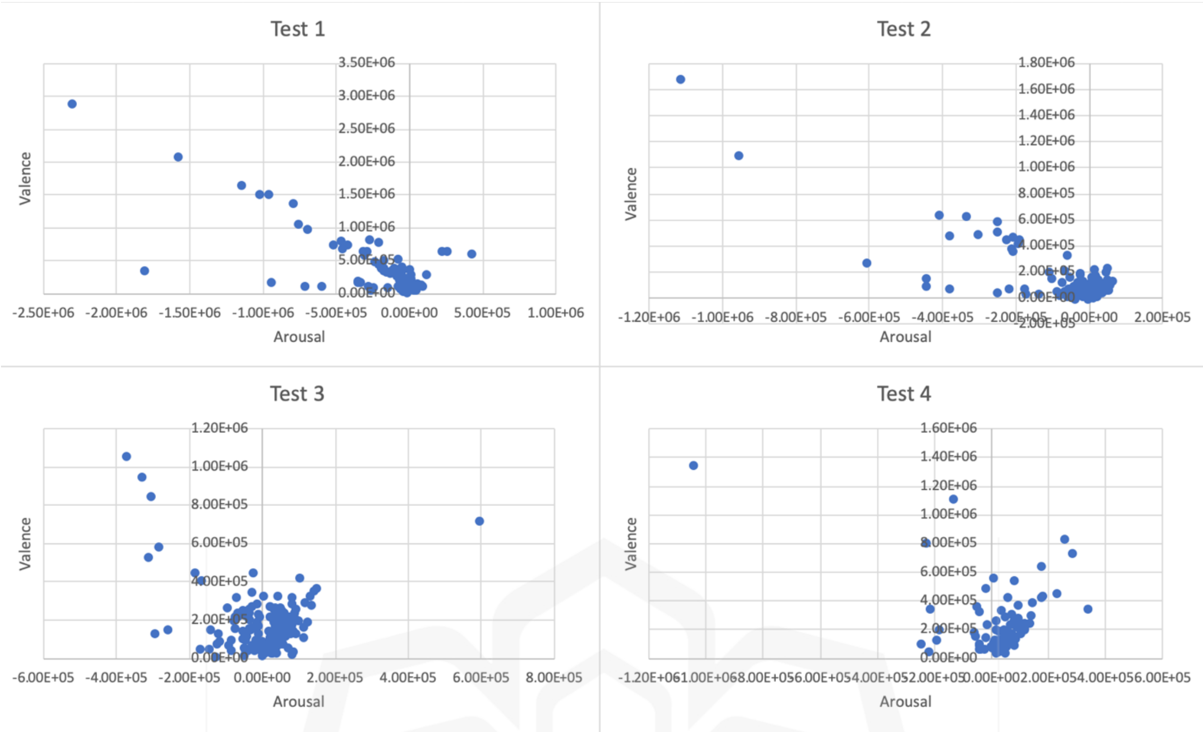

Figure 6.14: Four scatter plots exhibit unique patterns for each brain functions (cognitive, creativity, memory, and verbal).

Second, when these scatter plots are superimposed or combined into a single plot, it resembles the pattern of the game play emotional state. The plots above are used again for demonstration and the result can be seen in Figure 6.15:

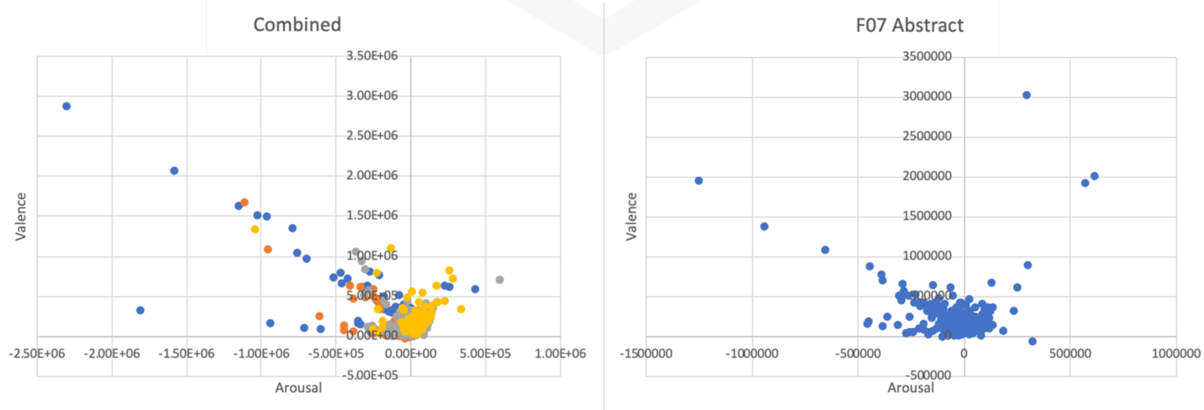

Figure 6.15: Combined aptitude test VA plots (left) versus gameplay VA plots (right).

The similarities are obvious when they are seen in visual observation. At this point, it is tempting to converge into a conclusion that four different components of the brain functions are present in a game that were not designed to stimulate any of those functions at all.

One might say that this finding is obvious since the brain have to work using all of its function all the time. But that is not the case. Aptitude test results measure varying result of the brain performance. And in this experiment, the same subject may only shows not all of the brain's function when playing a different video game. This can be observed in Figure 6.16:

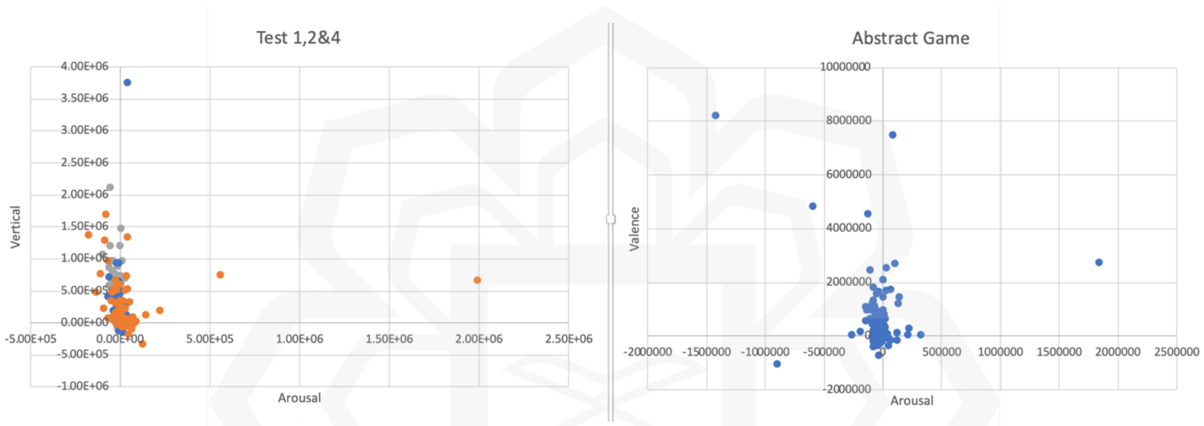

Figure 6.16: Aptitude tests 1, 2, and 4 (left) resembles scatter plot of gameplay of an abstract design scatter plot (right) when combined.

As in Figure 6.15, Figure 6.16 shows another subject's similarities of valence versus arousal scatterplot between aptitude tests and playing a video game. Only this time, only three brain functions are apparent. However, when the subject played another similar game but with a different design style, the scatter plot only reminiscent to only one of the brain functions, as can be seen in Figure 6.19.

These scatter plots are based on the emotional valence versus arousal data. Thus, it is not a concrete correlation between design styles in video games and learning aptitudes. However, Figure 6.16 and Figure 6.17 both reveals as if it can be assumed that different games lit up different aspect of brain functions. The same experiment but using the aptitude tests as the machine learning model may provide a more solid evidence of this assumption.

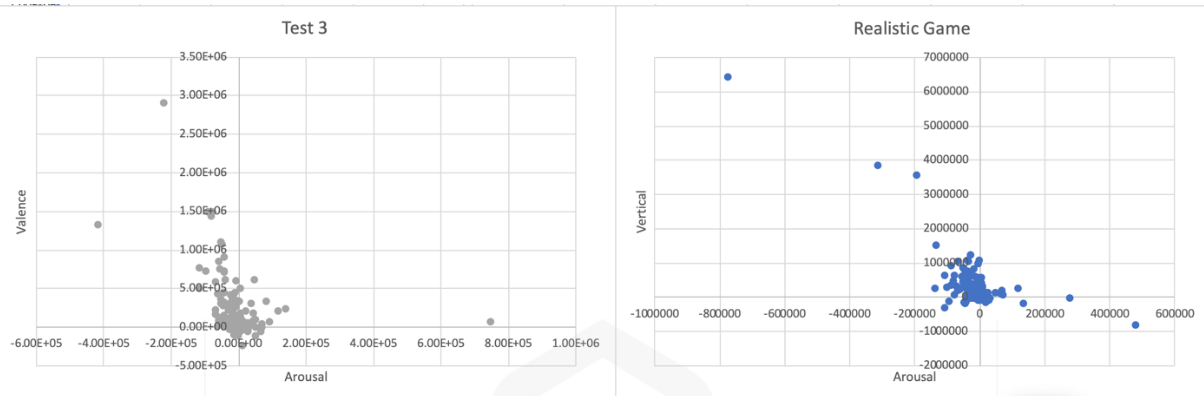

Figure 6.17: Only one of the aptitude test resembles the gameplay of a realistic game. The other patterns from other tests seem absent.

6.4.4 A HYPOTHESIS FOR THE PRESENCE OF COGNITIVE FUNCTION

The distribution of the valence and arousal signals from the EEG signals provided by the emotional scatter plots exhibit clear visual correlation between brain functions and video games designs. It is amazing to see that multiple brain functions indeed respond to video games that are not even designed to stimulate them. Unfortunately, the lack of quantitative analysis and statistical correlation means that it is not a concrete proof. This is due to the following:

a. The research was not designed to reach this conclusion and it is actually outside the research scope. It is merely a bonus discovery during data analysis.
b. The scatter plots similarities are only visual. No statistical correlation has been done to confirm this claim yet.
c. A more accurate research design is needed to verify this finding. Instead of emotional valence and arousal model, a specific computational model of the brain functions can be applied in the machine learning process.

Despite the above, the findings can be synthesized into a hypothesis for future research:

Specific cognitive and learning aptitude functions of the brain are present and respond in varying degrees in a video game that are not even designed to stimulate them. Each brain functions emits unique EEG signals and they are possible to be correlated with video game designs. The brain's cognitive, creative, memory, and verbal functions may each be individually stimulated by the visual elements of the game. This includes design styles, colors, textures, shapes, and other design elements.

The idea of having fun and entertaining activities that simultaneously improve learning potential may not be a far-fetched concept after all. While this paper cannot give a concrete proof and concludes the presence of brain functions within a video game that was not designed to stimulate them, the trace of evidence can at least be observed visually in the research this paper discusses. And that trace is hard to ignore.

6.5 SPATIAL AND TOPOGRAPHICAL ANALYSIS

Another area of analysis for the EEG data is the observation of the brain's topographical activity. Apart from trying to make sense of the numbers within the data, the physical region of the brain that are active during each of the two game plays may also provide an insight of how design styles affect the players. A simple measurement from the values recorded by each of the 19 channels are translated into a visual presentation of the brain's active regions. Note on this section, however, is that the spatial values mapped on the brain topography are raw unclassified data. They merely visualize which area of the brain is active during game play.

For the spatial analysis, the data are filtered into separate bandwidth just as in the data distribution analysis. The results are shown in Figure 6.18 with every subject arranged in a row. The column on the left are results for Abstract design while the column on the right are the results for Realistic design. Each column contains five visualization of the spatial activity of the brain for each bandwidth. From left to right are Delta, Theta, Alpha, Beta, and Gamma bandwidths activities.

One drawback of this analysis is that it is a one-exposure observation rather than a study on a particular time instance. Despite the setback, if there are activities associated with each design style, they can be spotted from these images. Unfortunately, the differences in spatial activities for every subject are unique. As a result, it is not possible to identify specific spatial characteristics traits to be associated to a particular design style.

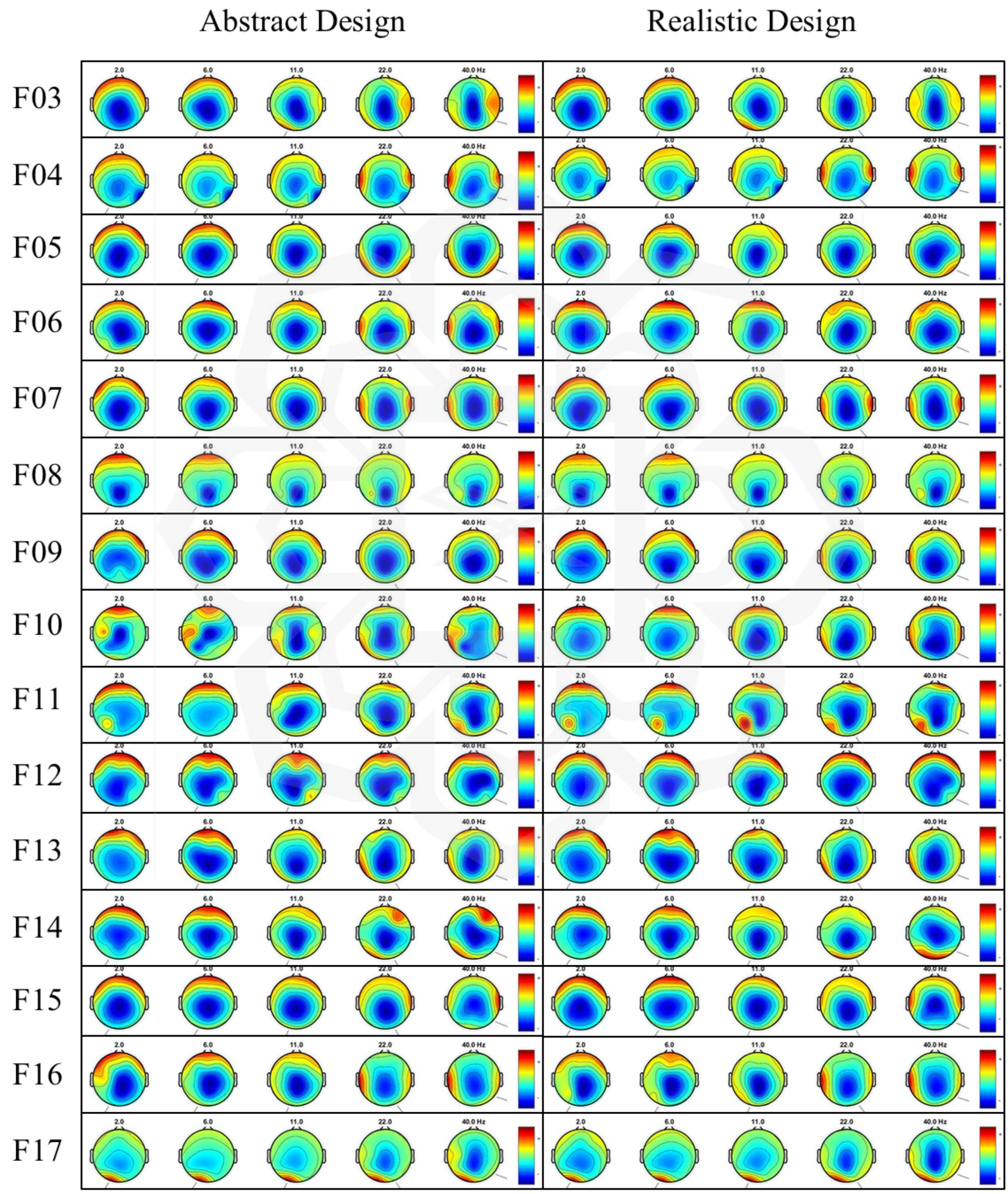

Figure 6.18: Spatial activity of every subject on every bandwidth for both Design Styles.

Notable differences in spatial activity are frontal lobe which is more active in Abstract than in Realistic, particularly in Delta and Theta bands. Temporal lobes are also similar in characteristics in Beta and Gamma bands, but to some subjects the Realistic game is more active than Abstract.

The patterns of distinction is inconsistent for all subjects. It turns out that spatial analysis may require more specific analysis that it can be a separate topic all of its own. One recommendation learned from this research is that spatial analysis may benefit from machine learning classification on separate lobes. This means classifications of each EEG channel or specific groups of channels. Considering that there are five primary brain lobes, at least five times the workload of this research is needed to analyze spatial activities quantitatively. For this research, spatial analysis will not go further due to time and resources constrains.

6.6 SUMMARY OF DATA ANALYSIS RESULTS

The objective of this data analysis is to classify EEG data collected from subjects into emotional valence and arousal responses. It is also to understand, once the classification process is successful, the effects on valence and arousal when playing two video games of distinct design styles. The final analysis results are hoped to be able to provide the understanding of what it takes to fully maximize the design potential of video games by choosing the right design styles.

Accuracy analysis was the gateway for the rest of the quantitative analysis in this research. Without validating that the computational model works, other aspects of this research analysis would have been questionable. But the results are more than satisfying. While figures of more than 90 percent on prediction success of the emotional model may sound like a high accuracy, pure numbers are meaningless if it is not put into context. The scatter plots clearly verify the accuracy of the model to classify EEG data into emotions, showing unambiguous distinction of stimulated emotions on the valence versus arousal plane.

Scatter plots analysis went beyond accuracy analysis and the first obvious investigations on design styles were made. Unique data cluster formations are apparent for every subjects but they all share the same characteristics. They are not too different between design styles, however, eliminating the predicted expectations of results. Common traits to distinguish between the two games seems to be the data points density. Since density is difficult to calculate and analyze, data spread and distribution is investigated instead.

Descriptive statistics analysis on classified data provided some meaningful numbers, however it only hints at the correlation with design styles. Some results appear random, while some suggests connections with the two games. Particularly the hit counts on valence, which suggest lower valency towards realistic game. Other than that, numbers per se is simply not enough to connect the data with design styles.

Data distribution, on the other hand, is the most reliable way of linking emotional responses with design styles in video games. It quantitatively confirms the earlier suspicions on data density during scatter plot analysis. Data spread was analyzed in detail on every major brain signal bandwidths and on every minute of exposure. While the results have some discrepancies, they were all converging into one direction: Abstract design style in video games have larger data spread than Realistic games. This is consistent in Arousal, Valence, and Emotional Intensity responses.

Along the way came an unexpected discovery. With extra EEG data during brain performance test, classification of emotions within cognitive activities were obtained. Startlingly, the emotional scatterplot of combined four separate brain functions resembles the gameplay cluster formations. This would have not been the case if each of the brain functions data were plot separately. Interestingly, some subjects even showed associated responses to separate cognitive functions for different design styles.

Spatial analysis is somewhat only introductory. The result is inadequate to provide any meaningful information to achieve the analysis objectives. But to go in-depth with spatial analysis would be beyond the resources and scope of this research. One important thing that can be learned from this research for spatial analysis, however, is the adaptability of the framework to analyze spatial activities on different channels. It is in no-doubt that this separate channel analysis can indeed be the recommendation for future works.

So did all the objectives achieved for this data analysis? The answer is absolutely yes. All EEG data were classified into emotional arousal and valence responses, allowing quantitative analysis to correlate with design styles. The effects of design styles are within the emotional agitation of the subjects – the data distribution, the cluster patterns, and the rate of change of emotions. Understanding that the Abstract video games made players more prone to emotional changes than Realistic games may help determine game designers to choose which is best for a particular content. More on that as these findings are discussed in the next chapter.

CHAPTER 7

FINDINGS AND DISCUSSIONS

7.0 INTRODUCTION

After all measurements have been taken, statistics being analyzed, and graphs plotted, they all comes down to what it means to game designers – and to the gaming industry as a whole. The findings and analyses done in the above mentioned sections are brought together and discussed. Numeric data are to be interpreted into meaningful facts and information. In this section, research questions has to be answered. Research objectives must be achieved. A new body of knowledge will be added to the pool of video game design wisdom. Future recommendations will also be discussed, especially for similar EEG experiments with different context.

In this chapter, results from data analysis are put into context and are synthesized to make sense for game designers to exploit this body of knowledge. The final conclusion of this chapter may not be a step-by-step guide to achieve design success, but to make design decisions a more objective task rather than simply a 'designer's taste'.

At the end of this chapter, the influence of Design Styles in video games on the players is to be understood. The context over this entire research analysis is emotions. The findings, therefore, is only a small part of the bigger picture of how Design Styles can affect the audience. The contribution of this research – and this thesis – is that it is hoped to pave the way for more studies to scrutinize every elements of video game productions to refine and adds value to the products. In the industry as a whole, the frame work of utilizing EEG and machine learning to maximize design potential can bring the design process to new heights.

7.1 AN ATTEMPT TO UNDERSTAND THE EFFECTS OF DESIGN STYLES THROUGH EMOTION

The most obvious and important aspect prior to synthesize data analysis results into a new body of knowledge is to prove the hypothesis. Before the effects of Design Styles over the human mind and emotions can be understood, it must be proved that the two different design styles indeed exhibit changes in the EEG signals that can be picked up consistently after being classified via machine learning.

As it turned out, Design Styles proved to have influences over the emotional activity of the subjects. First impressions from visual observations of the scatter plot reveals that Abstract design has a larger response area in the arousal-valence plane than Realistic design. Scatter plots were first to be analyzed since any patterns of the emotional reaction by the subjects will obviously be visible by visual observation alone. Following the casual observations, detailed analysis were conducted to dig deeper into the arcane art of video games design.

7.1.1 THE CONTRIBUTION OF ACCURACY ANALYSIS

The accuracy analysis is a very important initial stage to the research. It validates the relationship of the captured EEG data with emotional valence and arousal. Without the connection of the brain signals with the context of emotions, this research would have not been possible at all. Apart from measuring the success rate of classifying emotions, it also provides other information that is less obvious:

1. The Computational Model Works

Besides validating the model to be effective for classification process, the accuracy analysis demonstrated that the perceptron works. Once the computational model of every individual subjects is obtained through Power Spectral Density feature extraction, it was tested with the stimulated EEG data. Resulting classifications revealed by the Valence vs Arousal scatter plots justifies the ability of the model to be used in the research. Individually assigned colors for each known emotional data resides on the appropriate region of the valence-arousal plane.

Less obvious about the accuracy scatter plot is that the data distribution has consistently similar spread for all four emotions. This indicates that the strength of the emotions being modelled is equal on all four emotions and the computational model is not biased towards any particular emotions. This is very important when classifying unknown data.

2. The Method Works

The accuracy analysis also proves that the method of using Power Spectral Density (PSD) feature extraction works. Although there are still minor discrepancies that can be improved for better analysis results, the method chosen for this research can be a template for other context. As long as there is a reliable stimulant to serve as the reference for generating a model for analysis, it is possible to execute researches beyond the context of emotions with the same approach.

3. Classification works

The machine learning process to classify unknown data also works. A peak to the box-and-whiskers plot of the resting state in the Alpha band shows clear evidences of emotional behavior between eyes closed and eyes open. The so-called Alpha block – the sudden change of emotional activity from high to low agitation upon eyes open – is clearly evident, supporting the works by Ashtaputre-Sisode, (2016) and Hartoyo, (2020) that found Alpha band is particularly active in the resting state.

4. Allow research to seek answers

By knowing that the computational model works, the method is justified, and the classification process is successful, the accuracy analysis is the first step to unlock the rest of the research's analysis. It may sound obvious, but it is utmost important that if the framework of this research is to be applied for a different context in the future, a similar accuracy test is needed for validation. Validation is not simply the results of classifying known data, but to take considerations of other aspects (such as unbiased results) as well.

5. Contribution of IAPS

The final insights of the accuracy analysis provided that are less obvious is the importance of a reliable stimulant for generating a computational model. In this respect, it is of the highest gratitude to the researchers who had worked on to provide a visual instrument for stimulating the right emotions successfully and consistently. The IAPS used in this research is the key to study the effects of Design Styles over the human emotions. Without it, stimulating and validating the stimuli will be near impossible.

7.1.2 SCATTER PLOT REVELATIONS OF DESIGN STYLES

The next step to prove that Design Styles affect the human emotions is to look at the clustering of data in the valence-arousal scatterplot. A definitive indication that design and emotions are related is the formation of data is unique to a particular Design Style. Unfortunately, the relationship between them is not how it was anticipated. Rather than each Design Style clusters in a particular area of the valence-arousal plane, they both have their data spread in the same region. The difference is in the data distribution, rather than cluster location.

Despite the unexpected results coming from the scatter plot analysis, there are many findings to be learned from it:

1. Design Styles do not generally change the state of the player' emotion.

Although in the statistical analysis revealed few instances where the emotions of the player changed at a certain point, these changes are the results of statistical calculations. The cluster shapes and patterns when playing games of two different Design Styles are very similar to each other. This an evident of the emotional responses were phase-shifting instead of morphing when reacting to different Design Styles.

2. Design styles may not alter an emotion completely, but agitate the valence and/or arousal in one dominant direction.

Regardless of how the subject feels when playing the video games, the fluctuations of the emotional responses spikes in a single dominant direction of that particular emotion. None of the subjects showed sperate clustering of data in a single session.

3. Abstract design style is dominantly more stimulating than realistic game.

Plotting both Abstract and Realistic data together reveals differences in the spread density. Realistic game has higher density in its data distribution, visible in the scatter plot – its plot area is always overshadowed by the Abstract data. There are exceptions, but further details regarding this will be discussed in the later sections.

The difference in data spread density means that there is a difference in the magnitude of change in emotions per time. The bigger the spread, the higher the active level of the emotional responses. On the other hand, the smaller the spread (higher density), the more stable the emotion is. This is important. It points out that one agitates emotions much easier than the other.

4. Design Styles trigger emotional intensity rather than encourage emotional changes.

Each participants may react emotionally differently towards the games they play, but their stimulation rate and agitation may have a connection. During game play, subjects emotions scatter in many direction but centers around the neutral area. The emotions fluctuates in intensity when reacting to the game activity. This can be observed from the centric spread of the data clusters and stimulated spikes section of the scatter plots. In both Design Styles, emotional data spread behaves similarly except their intensity. All subjects exhibit this behavior.

5. Positive valence decreases upon playing Realistic game.

A simple hit count confirmed this, but there are a few exceptions. Only 4 out of 15 subjects resulted in increased valence, and out of those 4 only one of them experienced both arousal and valence increments for playing Realistic video game. The trending here is that Realistic video game causes negative effect to emotional valence – although not to the extent that it changes the overall emotion of the subject. This is not a coincidence, since from the literature review the "Uncanny Valley" phenomenon is a natural reaction towards realism in the artificial human design. Perhaps this findings confirms that natural behavior through the 'phase shifting' of the emotional responses found on chapter 5.

Figure 7.1 shows the difference of valence chart when transiting from Abstract design to Realistic. The bar in blue indicates the difference in valence count is inclined towards the Abstract game. Therefore the positive valence decreases as the subject transit to playing Realistic game. The bar in orange indicates the opposite, positive valence increases when those particular subjects transit to playing Realistic game. It appears that the result shows Abstract mostly has higher valence count than Realistic game.

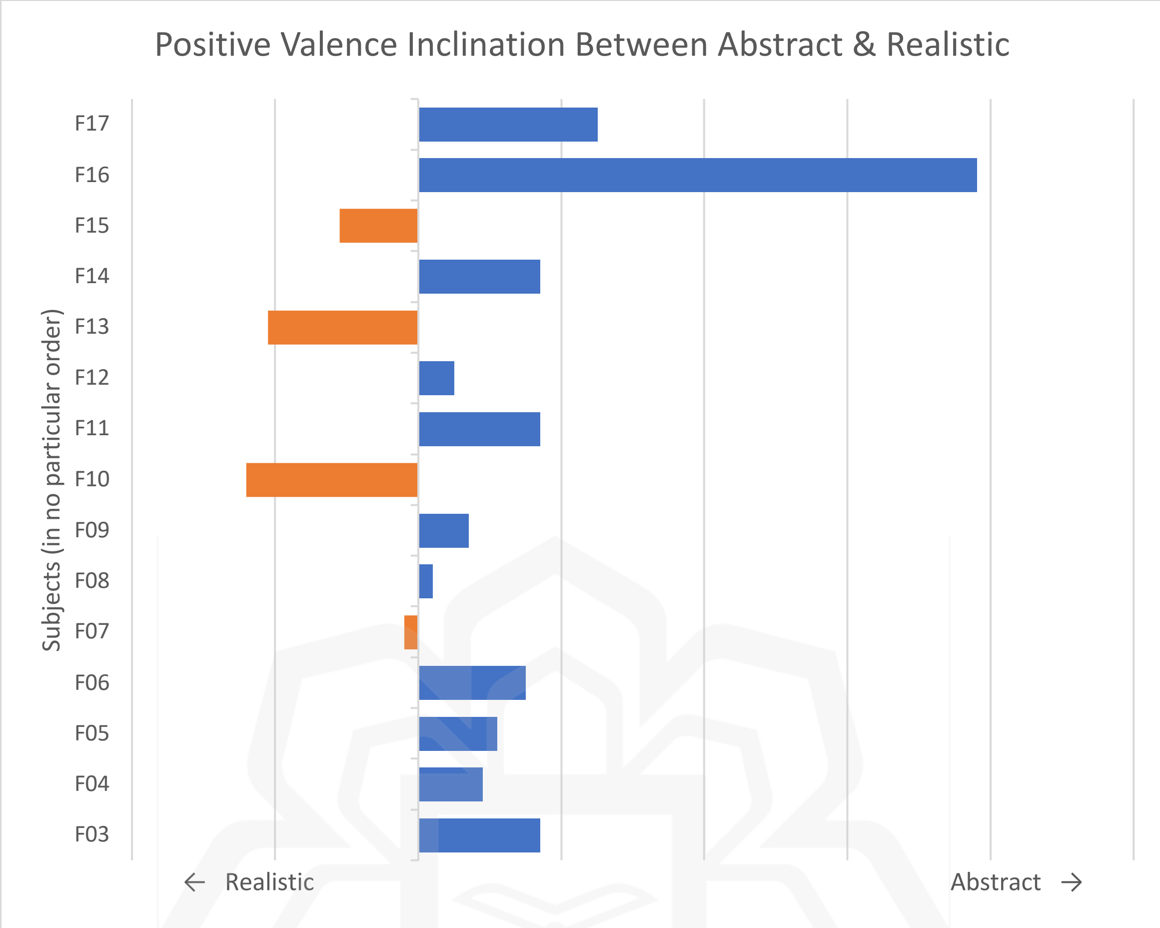

Figure 7.1: Valence declination when transiting from Abstract to Realistic Design Styles

The subjects that are not displaying valence reduction have to be influenced by their profiling factors. The consent forms filled in prior to data collection confirm this, as these subjects are usually the ones that are not exhibiting similar emotional responses as the others. It seems that being familiar with video games – along with frequent play time, longer play duration, and has played many games before – slightly affects the Design Style influence over emotions. As in the statistical and data distribution analysis, the effects is only slight. The overall analysis results show similar behavior consistently.

It must be noted, however, despite the decrease of valence as realism increases, the arousal can increase. Maybe that is why all these times designers are confused whether increase in realism excites the audience or not. The confusion is between the change in arousal versus the increase in valence. Having an increased interest in realistic renderings does not mean the experience is pleasant. According to the chart in Figure 7.2 excerpted from Gu, et al. (2019), one of the emotions that lies in the positive arousal and negative valence region is disgust, the bottom point of the "uncanny valley" (Mori, 2012). The hit count confirms the relationship between Design Styles and the "uncanny valley" phenomenon.

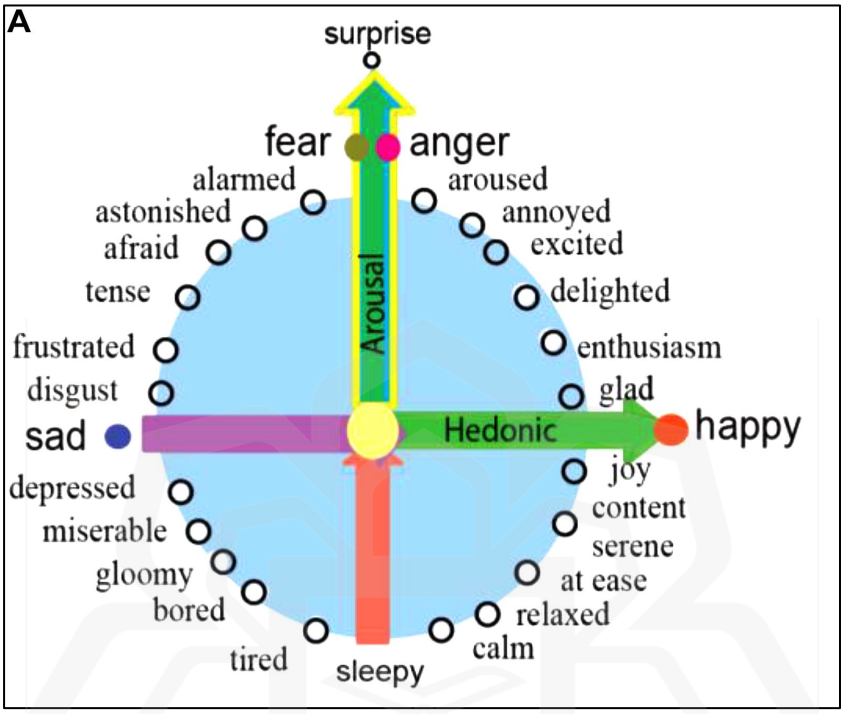

Figure 7.2: Emotions in the valence-arousal plane (Gu, et al, 2019)

6. Proof that the game selected works for this research.

This is the most important information obtained from the scatter plot analysis. It is also less obvious, because the attention to analyze the scatter plots is naturally paid to the emotional data. In order to understand the effects of Design Styles, the two games selected for the experiment must be similar so as to minimize or eliminate any bias or distortion to the data. The scatter plots displayed identical cluster formation for both games of different design styles. It is evident that the cause-and-effect of the two Design Styles relates to the emotional intensity and its fluctuations. The emotions per se for both Design Style are analogous to each other which means they are influenced by other factors. If one game is too different than the other, the cluster formation would have been different as well. Thus, it is proof that the games selected for this research works well to give unbiased results and allow distinct recognition of the effects of two different Design Styles.

7.2. MULTIPLE FINDINGS FROM MULTIPLE BANDWIDTHS

The frequency range of the human brain is divided into five bandwidths that correspond with various state of mind and consciousness. Since the machine learning process can include all of these bandwidths as well as filtering them separately, it is a good opportunity to see how Design Styles affect the human emotions in each bands.

7.2.1 STATISTICAL FINDINGS

In the scatter plot observations, findings of Abstract design is more active and intense than Realistic design is purely visual. Statistics measure these findings and turn them from subjective discovery into objective facts. As it turns out, Abstract design does indeed causing the emotional responses to be more agitated and more intense, but not always to all the subjects at every bandwidths. The numbers measured some inconsistencies in the findings. However, it is to note that the difference of emotional state in different band is on one of the VA axis only. Not both.

The discrepancy also has a pattern to them. Apart from the spread size variations, all of the subjects emotional responses spikes or in the vector of the central tendency. In other words, if the median is negative in value, the spread is wider towards the negative direction of the scale. None of the subjects showed otherwise. This can be observed by the skewness of the data as well as the range between the median and third interquartile of the box and whiskers plot.

The discrepancies in the results between subjects may be caused by each individual's own unique position on the Uncanny Valley Curve. While it is true that everyone will react towards realistic renderings the same way as the uncanny valley curve describes, each individual may respond on a different scale or magnitude. Thus, by playing the same game – as in this research – each participants shows that they each have different emotional reactions.

This discrepancy does not mean that the emotional responses are inconsistent for each subjects. The spread patterns are consistent throughout the entire game playing session. As has the segmented box and whiskers analysis shown, emotional activity spread between the two design styles are consistent. With the exposure time of five minutes for each design style, this is a consistent pattern.

7.2.2 SIGNIFICANCE OF DIFFERENCES IN DATA DISTRIBUTIONS

The most important and distinct characteristics associated with each Design Styles is the behavior of the data distribution. Consider the Figure 7.3:

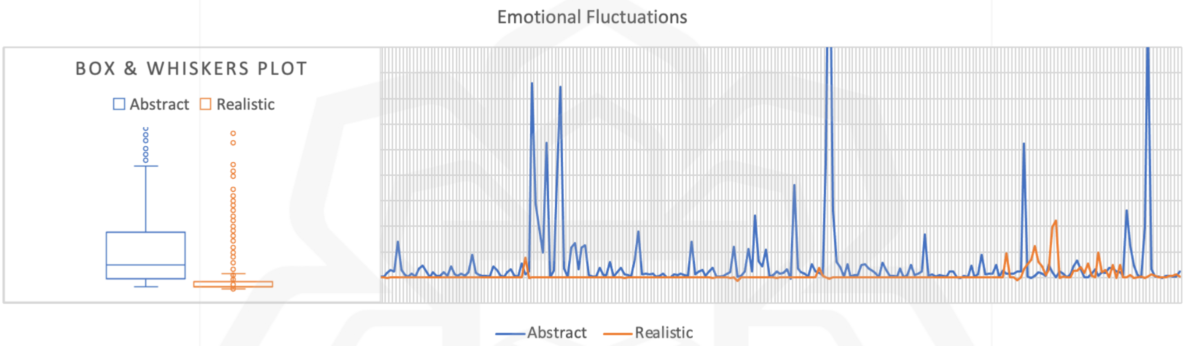

Figure 7.3 high versus low level emotional fluctuations

The figure is a sample from a fraction of the entire emotional response. The high level activity show a bigger spread in its box-and-whiskers plot compared to the low level activity. It is more prone to change and the changes are erratic. A low level fluctuation is more stable in sustaining a particular emotion. A stable emotional state creates a stable mood.

These differences are significant in that one can encourage change of emotions while the other attempts to sustain a stable and consistent mood. They do not change the emotions nor mood, but if a game is designed to have its content stimulating a specific emotion at a specific moment (changing emotions the same way the IAPS does), the rate for change is faster and more effective if the visual design is less realistic.

On the other hand, if the game content is intended to immerse the player in a sustained mood, highly detailed realistic renderings may help to achieve that objective. Perhaps this could explain why most animated movies can generate emotional experience to the audience in a much shorter time frame. Animation films tend to be shorter than live action.

But what about the small instances from one or two subjects that exhibit higher valence and arousal for realistic games? While the quantitative value for valence and arousal do indeed have inconsistency in the findings, those that seem to be emotionally heightened by the Realistic game still displayed the same response behavior: emotions when playing Abstract are still erratic and fluctuates more aggressively in every minute of play while the mood when playing Realistic game is more stable and less susceptible to change.

The reason why some subjects showed higher intensity emotions in Realistic games may be down to individual background. This research could not find any correlation with the subject's profile because:

1. It intentionally not to be part of the analysis
2. Number of subjects required for such objective will be many times higher
3. The profiling constructs is insufficient for correlation

The relationship between emotional fluctuations and Design Styles are consistent throughout the frequency ranges of the brain. From Delta band to Gamma band, the emotional valence and arousal are prone to fluctuations and higher intensity. Discrepancy is very few, and the numbers from all analysis seems to converge on the same conclusion.

And since Abstract and Realistic are polar opposite on the same scale, it can be considered that their influence over the emotional valence and arousal is continuous in the Design Style spectrum. This research was unable to pick the most realistic example for Realistic style, but distinctive enough to compare with the Abstract example. It is thus expected if the realistic game represented in this research were even more detailed and one of the best in the industry, the emotional responses between two Design Styles would have been even more distinguishable – Abstract design is more emotionally erratic while realistic design is more stable in sustaining a mood.

The slight inconsistencies may be down to several factors:

1. Small differences may be caused by insufficient distinction of design styles.

At the time of this research was conducted, limited choices of games were available to be a good sample of Abstract and Realistic design styles. While the game Chameleon Run is an excellent example of Abstract Design – its simple geometric shapes and disconnected limbs of the humanoid character are exemplary testimony of the Abstract definition, the Realistic example is less than satisfactory. However, Vector HD is still distinctive enough to represent design that is straying away from Abstract and closer to Realistic in the Design Styles spectrum. Perhaps if a more realistic game which are similar in game play may provide better resolution of the emotional response differences between them.

2. Familiarity Influences

The human mind can be influenced by familiarity Schneider (2007). After all, the basis in which the uncanny valley occur is the familiarity with the visual reference of the real human being. The memory of being used to the complexity of the facial muscle movements made artificial human animations look awkward and – in some degrees – repulsive. Thus, it is perhaps the reason for variations in this research findings when compared between different subjects.

Some subjects are already familiar to a various degree of realism in video games while some may found it something entirely new. When these varied familiarity of the subjects participate in this research, their position on the “uncanny valley” curve are different from each other. As a consequences, the scale of differences in emotional response between Abstract and Realistic Design Styles are unique to each individual. This assumption is confirmed when the consent form of each subjects were reviewed to find that indeed their enthusiasm, frequency, and duration of playing video games are different from each other.

Unfortunately, the profiling acquired prior to data collection is insufficient to correlate video game habits with the analysis results. The number of subjects are insufficient as well. But because the scope of this research does not include profiling correlation, this particular aspect of the finding is left for future works.

Slight variations in the findings prompted the investigation and review of the research methodology. To validate that all conclusions converging from all analysis, the research methods was re-evaluated post analysis to see if there is something that might have contributed to these inconsistencies. The only caveat to be found in the research design was the sequence of which games is to be played first. During the data collection, all subjects played the Abstract game before the Realistic. A question arose whether the findings are due to fatigue rather than Design Styles.

Evidently, fatigue is not an issue. If it was, then the result should have been the opposite than to what had been analyzed. This is because according to Warner (2007), fatigue actually causes a more erratic emotional responses. There were also subjects that was sleep deprived during data collection (based on their profiling information), which would have already impacted the analysis results. Tiredness may have an influence over the emotional responses, but it was not significant enough to disrupt the dominance of Abstract game to be more emotionally responsive than Realistic game.

In the Alpha versus Beta analysis, their results are important in that these are the primary bandwidths that associate with emotions and physical activity – two undeniable components of video game activity. When comparing the two bandwidths data at segmented time intervals (1-minute intervals and 1-minute accumulated intervals), they seem to differ mostly in continuity of the mood.

Alpha data has smooth and almost seamless transition between Abstract and Realistic game play that is consistent to other researches (Ashtaputre-Sisode, 2016) findings which state that Alpha brain waves tend to experience good moods. Meanwhile, Beta data has abrupt and almost instantaneous change from Abstract to Realistic game play. Beta band analysis also confirms the bandwidth's association with alertness and physical activities.

At the end of the tedious and exhaustive data analysis, there is one thing that was missing and yet unavailable to obtain at the time of this research. And that is measuring the Design Style itself on its own scale. The downside of this is not able to mathematically correlate Design with emotional responses. Or in other words to came up with a formula for designers to measure how much realism/abstractness to achieve a particular level of emotional responses.

At the very least, this research already contributed significantly to understand design influence over emotions.

7.2.3 SUMMARY OF MULTIPLE BANDWIDTH ANALYSIS

In a nutshell, the multiple bandwidth statistical analysis found out the following:

1. All bandwidths share similar behaviour when analysed statistically.
2. All bandwidths exhibit one of two condition: either Abstract spreads more than Realistic, or it deviates (changes) more aggressively in the same time intervals.
3. In Abstract design, emotions jump from one state to another much faster, easier and more dramatic than in realistic design. Realistic is more stable. This is an observation of the changes in median: the central emotion in which the emotional activity is centred on.
4. The erratic behaviour of the Abstract emotional responses in the 1-minute interval occurs even if the spread is smaller than Realistic – this indicates that the median (i.e. emotional state) changes aggressively almost beyond its interquartile ranges of the adjacent time interval.
5. Alpha band transitions between different Design Styles are smooth. Beta band shows discontinuity.
6. Emotional intensity is mostly higher for abstract. For subjects that showed otherwise, their responses for Abstract in separate time intervals are still more active than Realistic, not vice versa.

7.3 COGNITIVE FUNCTIONS AS ADDED VALUES IN VIDEO GAMES DESIGN

The separate brain functions that when combined made up a scatter plot formation reminiscent to the game play data is very interesting indeed. What is more interesting is that some subjects shows coincidences of specific cognitive functions with specific Design Styles. This research cannot prove or validate that there is a direct correlation between the two. However, in the context of emotional response, the traces of such evidences are consistent throughout the subjects.

The link between cognition and playing video games are not uncommon. Research such as that by Franceschini (2017) even made it as some kind of rehab activity to cure dyslexic children. Many others such as (Gori, 2016) and (Kuk, 2012) also relates the learning ability and processes of the brain with video games. However, none of them connects to Design Styles: a visual elements that may help designers to actually exploit to design games specifically to boost mental health and performance. A practical future design would be a brain tonic video games, where players play not just to learn but to get better in learning as well.

The concept of 'magic potion' game to boost cleverness and learning aptitudes may seem far-fetched, but the idea sounds better than swallowing a pill. Curing dyslexia, autism, hyperactivity in children are a few of the things that can take the video game industry to new heights. Such design exploitations can indeed add values in video games that are beyond entertainment and immersion. It is an added value that can actually improve the quality of life.

7.4 DESIGN STYLES: A DECISION NOT TO BE TAKEN LIGHTLY

Design Style may have been a designer's taste/choice/preference. For many years it is an artistic decision for artistic matter. But the visual renderings that stretch the spectrum from Abstract to Stylized to Realistic have more than meets the eye. They actually have influences over the behavior emotional activities. Design Styles have a significance that when taken advantage of, can perhaps add life-changing values to what seem like a purely entertainment-only activity. Not only that, entertainment itself can be more effective if the right Design Style is put to use. The following are a few of the benefits in designing the right style for the visual element of a video game.

1. Control over storytelling effectiveness

Most video games have a story. Stories help the player to immerse themselves in the game play and add more fun. However, effective story telling is essential to engage the players. The most important thing to make the engagement interesting is to tackle the player's emotion. This is where the right design style can help to make the story a whole lot better. By strategizing the visual styles to be more abstract or realistic, designer can decide whether the story needs fast emotional changes or sustained mood. For instance, action based genre may benefit design more inclined to abstract for quick suspense and surprises while dramatic war scenario or horror themed story can sustain the right mood with realism. Although this research is not able to measure the amount of Abstract/Realism to mathematically correlate Design Style with emotional responses, designers can at least have an educated guess to the concept that they are working for.

2. Make learning faster

Edutainment genre is not an alien concept in the video game industry. Many developers develop games inclined for learning activities. Educational sector itself attempt at gamifying learning processes. Apart from the findings that there is a possibility of correlation between Design Styles and learning abilities, games that are intended for learning is better if they are inclined towards abstract design. Learning activities involve quick and instantaneous switch of different emotions as well as the need to prevent learning content from being boring. This is the reason why educational based games can benefit more with abstract inclined design.

3. Maximizing the game's shelf life and playability

One of the values of great video games is the long-term playability and longevity. Being repetitious is the utmost pitfall to avoid. Developers want their games to be addictive enough for people to keep playing but not to excite too much so as to make the game boring after a few months. The interplay between change of emotions and long-term stability of consistent mood is essential to keep the game interesting in the long run. The challenge, though is to figure out which emotional responses are suitable for what kind of games. Fighting games, arcade shooting games, and the likes would benefit fast emotional changes as it has short level-based progress. Games that rely on storytelling requires consistent mood suitable for each chapter of the story – hence it may be more effective with added realism in its design.

7.5 NOVELTY AND CONTRIBUTIONS

The advent and development of EEG and machine learning technologies paved the way to a new point of view at how the human emotions can be understood. This research took advantage of that opportunity to look at the effects of Design Styles on video game players. The Design-

Emotion relationship has never been explored in this way before. The numerical analysis even brought insights to the cognitive function of the brain being associated with a particular Design Style. Quantitative analysis Design Styles on emotions allow game designers exploit their work with hard facts backed by solid proofs and substantial measurements.

The framework of this research, on the other hand, is the core contribution that will hopefully inspire new researches in different contexts. Not only did it work to achieve the research objectives, new ideas and new research potential were discovered along the way. The combination of the selected stimulation instrument, feature extraction process, and classification algorithm works really well without any troubles. It is a modular framework, therefore readily adaptable to any other research needs.

The following are the novelty and contribution of this research:

1. A new insights on how Design Styles affect the emotions of the player.

Analysis results show that Design Styles can be exploited in a way that has never been done before. Game developers and designers can now learn to understand the relationship between design and emotions, consequently able to objectively select the right amount of realism or stylized with the right amount of disproportion to suit a particular need.

2. A working framework

Some of the findings in this research supports other researches' findings. For instance, the emotional responses of the resting state in Alpha and Beta bands behave just as described by Ashtaputre-Sisode (2016). Although that research referred to raw EEG signals, the classified data in this research exhibit similar results. Another example is the slight reduction of emotional valence in the hit count results. Despite the main difference between the two Design Styles is in the data distribution, the decline in valence on realistic design is in line with the "uncanny valley" phenomenon described by Mori (2012). Valence is associated with the feeling of pleasantness and unpleasantness when reacting to emotional stimulus (Kauschke, 2019). The emotional stimulus in this case is the design styles. The findings that support previous works and the clear distinction of emotions in the accuracy of its classification process mean that the framework of this research works. The research methodology works, the research design works, the machine learning classification process works, and the analysis structure works. While analysis result on design styles contribute to the video games industry, the research methods designed to achieve it pays a bigger contribution in the field of computer science. Future research can refer to this framework and even adapt it to other context for its own topics.

3. The Framework Adaptability

The framework of this research can even be applied as is for different stimuli to do research based on other computational model. The components to classify particular EEG data using a computational model in this research is quite modular. It is flexible to adapt to any research context which attempt to classify unknown variables from brain signals with a subject of stimulus. Examples of how it can be reworked into other topics are:

- Adding value to productions
- Detect, measure, and remedy any elements of addiction
- Hypnotizing effects
- Learning potential booster
- Cognitive training and therapy
- Brain health therapy
- Method of evaluation for newly released titles
- Automated censorship using machine learning

The key is to work with the right and validated/established stimuli that are needed to construct the computational model for analysis. This is demonstrated by this research by applying the IAPS as the stimuli for emotions.

7.6 ANSWERING THE RESEARCH QUESTIONS AND ACHIEVING ITS OBJECTIVES

The analysis results and findings have enabled the research questions to be answered and the research objectives achieved. Brain wave data collected via EEG device were classified into emotional valence and arousal responses using machine learning classification. Emotional fluctuations, now quantified and measurable, have different behavior when reacting to similar video games but with different Design Styles.

The emotions themselves are not affected by the two video games. Both games show how similar the players actually feel. So if the Design Styles cannot change the emotional state, how can it be useful to designers? Firstly, The difference between the Design Styles lie at how prone the emotions are to change. Abstract design is associated with high agitation and erratic fluctuations of emotional activity, while Realistic design is in tune with stable and sustained mood. Secondly, the emotional valence indicated a particular relationship with Design Styles too. It seems that the feeling of pleasantness is inversely proportionate with the increase in realism (even if arousal is increasing). Finally, the valence – design style relationship is the proof of the "uncanny valley" phenomenon. With these findings, the research questions have been answered.

This research has concluded that emotional fluctuations over a short period of time is inversely proportional to the level of realism in the visual renderings of the video games. Or, to put it simply:

$$\text{Emotional Fluctuation per time} \propto (1/\text{Level of Realism in visual design})$$

Or

$$\Delta \text{ emotions} \propto (1/\text{Realism})$$

It is also noted that the quantity of positive emotional valence is also inversely proportional to the level of realism.

$$\text{Sum of Positive Valence in a gameplay} \propto (1/\text{Level of Realism in visual design})$$

Or

$$\Sigma \text{ Valence} \propto (1/\text{Realism})$$

Research Questions Answered:

1. What is the quantitative and measurable connection between Design Styles and affective (emotional) responses of the brain?
   Emotional valence and arousal respond to different Design Styles by fluctuating at different rates and magnitudes. Abstract design stimulate erratic emotional changes while Realistic sustains a stable mood. In addition, emotional valence decreases as design gets more realistic – despite the heightened arousal in some cases. This is in line with the Uncanny Valley phenomenon.

2. What are the effects of Design Styles on the brain's cognitive functions?
   While it is not mathematically confirmed, the trace of correlation is present within the emotional responses of the cognitive function. Scatter plots analysis exhibit different levels of realism may affect any particular cognitive functions.

3. Why do emotional responses in video games matter when playing video games?
   Emotions help video games to be immersive and enjoyable. It helps prolong playability and shelf-life of the game. Elevated arousal helps prevent repetitious game mechanic to be boring. It is also known to affect the learning potential of the brain and thus an important fact to design educational game.

4. How can the understanding of Design Styles – emotions relationship help designers to maximize their design potential?
   This research concludes the relationship between emotional responses and Design Style. Consequently, designers can take advantage of this connection to design better games more efficiently. The understanding of which Design Styles to use can improve video game design. However, the success to make game design appeal to its target audience still depends on other aspect of the game content. In that respect, the right Design Style is not the only factor for successful design.

Research Objectives Achieved:

1. To develop a framework for classifying game playing EEG data with neuro-affective model.

This entire research was conducted from the conceived framework discussed in chapter 3. It was based on an existing framework made to classify emotional responses from visual based stimulation. Stimulation instrument used was also the same, utilizing the well-established IAPS stimuli. In this research, however, it is tuned to compare visuals of two different game designs. All other aspect of the game was ensured to be as similar as possible, leaving only the Design Style is its only difference.

2. To verify that the conceived framework works.

   Classification accuracy of the stimulated data are consistently high at rate of 90 percent and higher. Furthermore, the clustering of the emotional plots on the valence/arousal plane has clear separation for each known emotions. The findings, apart from contributing to adding new-found relationship between Design Styles and Emotions, are also in line with other researches. The uncanny valley phenomenon (Mori, 2012), for instance, is now apparent in the valence/arousal plane. The traces of brain's cognitive function that exhibit a particular behaviour for each Design Style can be related to the studies by Franceschini (2017), Gori (2016), and Kuk (2012) who used video games as a learning potential tool. All of these concurrences that support other researches findings point out that the framework of this research works. The data collection procedure, the feature extraction algorithm, the classification methods, and the statistical analysis all proved to be a success.

3. To analyse emotional responses from two different Design Styles.

   EEG data were classified via Multi-Layer Perceptron algorithm for high accuracy capability. The computational model acquired for data classification were obtained through Power Spectral Density feature extraction. The resulting classified data are then put into statistical analysis for Design – emotion related investigation.

4. To understand the effects of Design Styles over arousal and valence.

   Classified data in the form of numerical values in spreadsheets allow the observation of their clustering in the valence-arousal plane. The numbers themselves were analyzed statistically to investigate the data distribution of the emotional responses for each Design Styles. The analysis was repeated for multiple bandwidths to investigate emotional fluctuations at every level of consciousness.

Abstract design is associated with erratic and quick emotional changes while Realistic design is more suitable for sustained mood. Positive valence also decreases as the design gets more realistic. Figure 7.4 summarize the relationship between Design Styles and Affective responses in a diagram. Table 7.1 shows the overview of differences between Abstract and Realistic design.

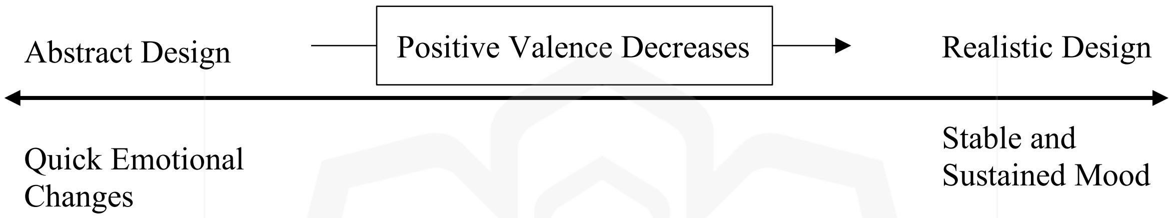

Figure 7.4: The summary of research findings in an Abstract-Realistic scale.

Table 7.1 : Overview of differences between Abstract and Realistic Design Style

	Abstract	**Realistic**
Emotional state	Mostly emotional state does not change. But to the few bandwidths that does change, it only changes on one of the AV axis and not both. No correlation with specific emotions. Each subjects varies emotionally.	
Arousal and Valence	Higher positive valence count.	Lower positive valence count.
Emotional Spread	Mostly larger distribution	Mostly higher concentration
Segmented spread	Erratic changes	Stable and progressive changes
Accumulated spread	Smooth transition of mood between the two Design Styles in alpha band In Beta band, the transition between two Design Styles is abrupt and has no continuity.	

7.7 PRACTICAL BARRIERS

It is important to point out a couple of practical barriers experienced while conducting this research. This is so that future works recommended by this research can anticipate such issues and prepare to overcome them. Any other research topics can also take note on these matter as it might also be relevant.

The first barrier that occurred during data collection is the privacy of Muslim women who volunteered to be the subjects. It must always be a priority for them to cover their *aurah* (such as their head) and free from physical contacts with men. Since EEG experiments require physical contacts and reveal the subjects' head, it is impossible to collect data from female subjects without the help of female colleagues who can aid in the experiment. In this research, three female colleagues aided as operators to collect data. They had to be trained so that the data obtained are consistent and no problems occur during the EEG sessions.

The second barrier occurred due to the reliance on third party instruments to collect a particular type of data. In this case, this research relied on Cambridge Brain Lab's online brain test instrument that required participants to log-in using either email or a social media account. Unfortunately, sometimes after data collection has completed, Cambridge Brain Lab changed its policy. The online brain test instrument cannot be logged-in with a social media account and thus preventing this research to retrieve additional data and information that might have missed earlier. Although there have been many attempts to contact Cambridge Brain Lab for assistance, the performed brain test data could not be retrieved.

7.8 RESEARCH LIMITATIONS

This research has potential limitations. The results analysis was made using existing commercially available software. Every data analysis discussed were based on static 2-dimansional observation of the data. It is possible, however, that there is more to learn and uncover should an animated 3D visualization of data is available. Alas, such a software is not available. The only option available was a python plug-in by MNE-Python (https://doi.org/10.5281/zenodo.592483) which requires a steep learning curve to utilize fully.

An animated 3-dimensional visualization of EEG data can potentially reveals a new perspective of the connection between emotions and Design Styles. By having the data in a 3D animated medium, the rate of change, the dynamics of topological activities, and partial classification can all be made visible. For now, these aspects of data analysis can be reserved for future works.

7.9 FUTURE RECOMMENDATION

During the entire time this research was in progress, new questions and gaps were found along the way. Although they are beyond the scope of this research, they present a new challenge and opportunity for future works.

7.9.1 A STUDY ON COGNITIVE FUNCTIONS

It was not a coincidence that the emotional responses from four separate brain tests appear to be similar to the gameplay. Scatter plots revealed cluster formation of individual brain test measuring different cognitive functions to be distinctive from each other. It is interesting to found that the combination of all or some of them actually resembles the game playing cluster.

In this research, the correlation between cognitive functions and design styles cannot be done. This is due to the stimuli and context of research being emotions. If the stimuli and research framework are tuned to study cognitive functions instead, it is possible to find the influence of Design Styles to the brain's performance.

7.9.2 A UNIQUE LOOK AT JAPANESE ANIME

The two video games selected in this research were polar opposites in the spectrum of Design Styles. Although the Realistic game represented was not as realistic as the most recent high-end games, it is enough to differentiate from Abstract design. Between Abstract and Realistic is combination of both, known as stylized. And one of the most popular stylized design style is the Japanese anime.

Japanese anime is a unique combination of realism and abstract. The shape of the characters are so memorable and interesting, that the design style has a massive fans and followers from all over the world. In fact, Japanese anime is considered one of Japanese National Treasures.

It would be very interesting to include anime in this research. Alas, during the game selection, there are no suitable example to obtain for data collection. Nevertheless, a brief browse over the Japanese anime examples revealed that this design styles have many iterations of it. Itself can be a topic all on its own. It is possible to repeat this research with multiple versions of anime-themed video games – that is, if the suitable games selections are available.

7.9.3 ADAPTING FRAMEWORK FOR AUDIO DESIGN

Besides visual stimulation, sound can also have a deep impact to the game experience. Simply by substituting Design Styles with any Audio Design topics and there is an opportunity to take advantage of exploiting yet another aspect of video game production.

Audio design has many branches of knowledge. It is outside the scope of this document to list them all, but some examples would be musical genre, musical beat frequencies, audio reproduction frequency range, and stereo vs surround to name a few. It is quite an easy adaptation of this research frame work to analyze sound in the context of emotional responses.

In addition to the audio design analysis against visual emotional stimuli, there is also an audio emotions stimuli available for sound specific topic. This non-visual stimuli is known as International Affective Digitized Sounds (IADS). The benefits of being able to exploit both sound and visual aspect of video games production would surely be sensational.

7.10 CONCLUSION

In conclusion, the research to understand Design Styles affecting the human emotions is a success. It is apparent that Abstract design is associated with high agitation of emotion and high positive valence responses. Realistic design is better suited for stable and sustained moods. Additionally, the lower valence response of realistic design may cause unpleasantness if it is not taken care of – such is the effect of the vaunted "Uncanny Valley" phenomenon.

Analysis of video games Design Styles based on neuro-affective computational model has been successful. The purpose of this research is to understand the effects of Design Styles on the human mind. The context of the psychological aspect of the research is emotional responses. To capture the emotional reactions of a player while playing video games, an electroencephalogram (EEG) method was proposed. Quantitative analysis was then executed with the aid of machine learning to classify brain signals into emotions data.

The study on Design Styles is to unfold the hidden design potential that can be exploited to make video games better in terms of achieving the right visual communication for its content. This is contrast to the usual exploitation of the Design Styles which focuses on the target audience. This is why this research scrutinized the data streams themselves and not attempting to profile the preferences of Design Styles to the subject population. The benefit is a more effective and immersive game play that in turns indirectly draws the right target audience.

To delve in deeper in the understanding of the effects on emotional responses, the brain signals were analysed on separate bandwidth. Psychological studies determined that each frequency range of a bandwidth corresponds with a specific level of consciousness. From relaxed and sleep associated state of the Delta band to the high alert activity in the Gamma band, this research had scrutinized the emotions data and dug as many information as possible to answer the research questions.

The emotional data were analysed statistically to investigate emotional changes, characteristics, magnitudes, fluctuations, and distribution for each Design Styles. It was hypothesized that a particular Design Style influences emotions in a particular manner, connecting visual elements of video games with emotions. This research found that connection.

The results from the analysis also found traces of evidences that may lead to the stimulating ability of Design Styles over the cognitive functions of the brain.

As it turns out, there are no changes in emotional state between the two designs. Meaning, if the subject is feeling happy, then he or she remains happy while playing the two games. The differences, however, is in the magnitude of fluctuations, emotional stability, and statistical sum of the emotional valence. This is a good indication that the games selected in this research is close to ideal. If it were otherwise, then the results of the analysis may bias to a particular game and/or distorted due to the dissimilarity in game play, game mechanics, and game content.

In terms of emotional characteristics, they cluster on the valence-arousal plane in patterns that are unique to each participants rather than the Design Styles. There are no correlation that can be derived but they are further proof that the content of the game is similar enough to justify the difference in emotional activity belongs to the design styles of the game. There are clues of correlation, however, with the brain's cognitive function. Although this findings could not be validated objectively or numerically, the evidences of the scatter plots between playing video games and undergoing cognitive tests were undeniable. Further tests are recommended for future works in this respect.

Valence count, fluctuation magnitude, and emotional stability all have distinct changes when playing Abstract and Realistic games back to back. The differences signifies the connection on how Design Styles influence the emotions when playing video games. Although there were a few discrepancies, the results are mostly consistent throughout the analysis.

Emotional valence, it seems, decreased when realistic game was played. In a way, it confirms the "Uncanny Valley" phenomenon discovered by Masahiro Mori in 1970s (Mori, 2012). As the visual representation of the game gets more and more realistic, a certain feeling of unpleasantness starts to draw in. Although at the same time Arousal can get higher, the positive arousal and negative valence combination still points at the feeling of disgust. Unfortunately, hit count summation cannot measure the magnitude of the combination to confirm disgust.

The emotional data distribution showed a larger spread for Abstract games and therefore the emotional fluctuations are bigger. Bigger fluctuations mean that the emotions are susceptible to changes. If the game has multiple content sections that can each stimulate different emotions – such as those games that have a storyline – then it is easier to switch between emotions with a visual that is less realistic. On the other hand, small data spread means higher density on that particular emotion. Higher concentration of a particular emotion resists change and thus able to sustain a particular mood.

Mood stability associated with Realistic design is further emphasized by the less erratic emotional activity in the separate time interval analysis. Emotional distribution in Abstract design is a lot more abrupt and changes more actively than in Realistic design. Realism in video games graphics can indeed sustain a mood and thus is suitable for games that requires such condition.

Apart from the findings resulted from data analysis, this research framework is also a contribution to the field of computer science. The EEG methodology works. The computational model of emotions works. The machine learning classification works. The results of the analysis showed clear relationship between Design Styles and emotional responses. Not only that, the findings also compliment findings from other researches.

The key to the cause-and-effect analysis between Design Styles and the human psyche is emotions. A 2-dimensional emotions model defines emotion in a valence-arousal plane. It allows the emotions to be measured in a vector of 2-D space. Standard EEG protocol of capturing emotions from brain signals is conducted using the IAPS instrument as the emotions stimuli. These stimulated data were translated into computational model via Power Spectral Density for feature extraction. The model was successful in that it is able to distinguish the correct emotions in the right region of the emotional valence and arousal plane.

The emotional data from the game playing sessions were then successfully classified by employing the Multi-Layer Perceptron (MLP) classifier. This particular classifier algorithm is quite widespread by researches and the results are relatively accurate, at a constant 90% and higher. MLP is used because it is able to solve problems stochastically – allows possible statistical analysis, but may not be able to predict precisely. MLP is ideal for analysing data streams and instances. Each Design Style yielded their own emotional valence and arousal responses that can be compared for analysis.

Ultimately, all of the research objectives achieved and the research questions answered. And while this thesis can help designers to exploit Design Styles to maximize their design potential, the findings are not substitutes to designer's skills to make good video games. Designer's honed artistic skills and experiences gained over many years are still the most important factor in making great designs.

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