ELECTROENCEPHALOGRAM STRESS LEVEL CLASSIFICATION USING K-MEANS CLUSTERING AND SUPPORT VECTOR MACHINE

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DEDICATION

This thesis is dedicated to Almighty God, who has blessed my humble effort. Specially with gratitude to my beloved family, whose affection and encouragement truly make this all meaningful.

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ABSTRACT

Stress is the body’s natural reaction to life events and chronic stress disrupts the physiological equilibrium of the body which ultimately contributes to negative impact on physical and mental health. For this reason, an endeavour to develop stress level monitoring system is necessary and important to clinical intervention and diseases prevention. Various standardized questionnaires for assessing stress are available, yet they are based on individual perceptions and not subtle enough to capture mental state. Since an array of stress responses is initiated by the brain, thus, it is highly desirable to capture the stress non-invasively through neuroimaging technique, specifically electroencephalography (EEG) acquisition tool. The EEG acquisition tool was exploited in this study to capture the brainwave signals at prefrontal cortex from 50 participants and to investigate the brain states related to stress induced by virtual reality (VR) horror video and intelligence quotient (IQ) test in order to provide objective inspection of the brain functions. The collected EEG signals were pre-processed to remove artifacts and divided into four frequency bands including Delta (0.5 – 4 Hz), Theta (4 – 8 Hz), Alpha (8 – 13 Hz) and Beta (13 – 30 Hz) respectively. This was followed closely by extracting power spectral density (PSD) features from EEG frequency domain using Welch’s fast Fourier transform (FFT). In particular, absolute power of Theta, Alpha, Beta frequency bands, Alpha asymmetry and Theta/Beta power ratio were further analysed. Wilcoxon signed-rank test was carried out to find out the statistically significant features that react sensitively to stress-related changes. The results showed that Theta absolute power was significantly increased at Fp1 electrode ($p<0.001$) and Fp2 electrode ($p<0.015$) during post-IQ. Whereas Beta absolute power at Fp2 electrode was observed to significantly increase during both conditions, the post-VR ($p<0.024$) and post-IQ ($p<0.011$) respectively. However, Alpha asymmetry and Theta/Beta ratio did not significantly differ from the resting baseline. Evidently, these two parameters were indeed a good indicator of underlying bioregulatory responses especially the emotional regulation, behavioural motivation and attentional control. Following this, the significant features were selected for k-means clustering to assign the features into three groups of stress levels according to their inherent homogeneity whereby each group share similar patterns of stress response and finally, the labelled data based on clustering method were fed into support vector machine (SVM) to classify the stress level. The performance of SVM classifier was validated by 10-fold cross validation method and the result affirmed the highest performance of 98% accuracy by using only the feature of Beta-band absolute power (Fp2) on account of the significant changes of Beta activity during pre- and post-stimuli. In essence, stress pattern has been found in brain activity of Beta frequency band within right prefrontal cortex that has shown to be significantly more active under stimuli. The hybrid approach of classification using k-means clustering and SVM has been proven to be effective methods in lieu of pre-labelling the stress level to reduce individual differences in stress response, and in turn to improve the reliability and detection rate of mental stress. More future studies can be conducted to further validate and implement a stress level classification system. The system can be of assistance to support the current practice of stress diagnosis as well as be a beneficial future health indicator to improve stress management.

ABSTRAK

Stres merupakan tindak balas semula jadi badan terhadap peristiwa kehidupan dan stres kronik mengganggu keseimbangan fisiologi badan yang akhirnya menyumbang kepada kesan negatif terhadap kesihatan fizikal dan mental. Atas sebab ini, usaha untuk membangunkan sistem pemantauan tahap stres perlu dan penting untuk intervensi klinikal dan pencegahan penyakit. Pelbagai soal selidik standard untuk menilai stres boleh didapatkan, namun kaedah tersebut berdasarkan persepsi individu dan tidak dapat menangkap keadaan mental yang rinci. Oleh kerana pelbagai tindak balas stres dimulakan daripada otak, khususnya alat pemerolehan elektroensefalografi (EEG) telah dieksploitasi dalam kajian ini untuk menangkap isyarat gelombang otak di korteks prefrontal daripada 50 peserta dan mengkaji keadaan otak yang berkaitan dengan stres yang disebabkan oleh realiti maya (VR) video seram dan ujian kecerdasan (IQ) untuk pemeriksaan objektif terhadap fungsi otak. Isyarat EEG yang dikumpul telah diproses sebelum menghilangkan artifak dan dibahagikan kepada empat kumpulan frekuensi termasuk Delta (0.5 – 4 Hz), Theta (4 – 8 Hz), Alpha (8 – 13 Hz) dan Beta (13 – 30 Hz). Diikuti dengan menggunakan transformasi Fourier cepat (FFT) Welch untuk mengekstrak ciri kuasa ketumpatan spektrum (PSD) daripada domain frekuensi EEG. Khususnya, kuasa mutlak Theta, Alpha, band frekuensi Beta, asimetri Alpha dan nisbah kuasa Theta kepada Beta telah dianalisis selanjutnya. Ujian pangkat bertanda Wilcoxon dijalankan untuk mengenal pasti ciri-ciri signifikan secara statistik terhadap perubahan yang berkaitan dengan stres. Hasil kajian menunjukkan bahawa kuasa mutlak Theta meningkat secara signifikan pada elektrod Fp1 ($p<0.001$) dan elektrod Fp2 ($p<0.015$) semasa pasca-IQ. Manakala kuasa mutlak Beta pada elektrod Fp2 diperhatikan meningkat secara signifikan semasa kedua-dua syarat, pasca-VR ($p<0.024$) dan pasca-IQ ($p<0.011$). Walau bagaimanapun, asimetri Alpha dan nisbah Theta/Beta tidak berbeza secara signifikan daripada garis dasar rehat. Malah, kedua-dua parameter ini merupakan petunjuk yang baik untuk mendasari tindak balas bioregulatori terutamanya peraturan emosi, motivasi tingkah laku dan kawalan perhatian. Berikutan itu, ciri-ciri penting dipilih dalam pengelompokan cara-k untuk memperuntukkan ciri-ciri ke dalam tiga kumpulan tahap stres mengikut kehomogenan yang wujud dalam setiap kumpulan yang berkongsi corak tindak balas stres yang sama dan akhirnya, memasukkan data yang dilabel berdasarkan kaedah kelompok ke dalam mesin vektor sokongan (SVM) untuk mengklasifikasikan tahap stres. Prestasi pengelas SVM telah disahkan oleh kaedah pengesahan silang 10 kali ganda dan hasilnya mengesahkan prestasi tertinggi dengan ketepatan 98% yang hanya menggunakan ciri kuasa mutlak Beta-band (Fp2) kerana perubahan signifikan aktiviti Beta semasa pra-dan selepas rangsangan. Pada dasarnya, corak stres didapati dalam aktiviti otak band frekuensi Beta dalam korteks prefrontal kanan yang menunjukkan secara signifikan lebih aktif di bawah rangsangan. Pendekatan hibrid klasifikasi menggunakan pengelompokan cara-k dan SVM telah terbukti sebagai kaedah yang berkesan bagi pengganti pra-label tahap stres untuk mengurangkan perbezaan individu dalam tindak balas stres, dan seterusnya untuk meningkatkan kebolehpercayaan dan kadar pengesanan stres mental. Lebih banyak kajian masa depan boleh dilakukan untuk mengesahkan dan melaksanakan sistem klasifikasi tahap stres. Sistem ini boleh menjadi pembantu untuk menyokong amalan semasa diagnosis stres serta dijadikan sebagai petunjuk untuk kesihatan masa depan dalam meningkatkan pengurusan stress.

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LIST OF ABBREVIATIONS

EEG	-	Electroencephalogram/Electroencephalography
FFT	-	Fast Fourier Transform
PSD	-	Power Spectral Density
SVM	-	Support Vector Machine
VR	-	Virtual Reality
IQ	-	Intelligence Quotient

LIST OF SYMBOLS

μV^2	-	Power spectral density
Hz	-	Hertz, unit of frequency
z	-	Standard score
p	-	Probability

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CHAPTER 1

INTRODUCTION

1.1 Research Background

Stress is a term easily used by everyone on daily basis as it occurs unavoidable from time to time. Modern life offers challenges and human beings are surrounded by stressful situations due to busy work schedule and deadline, relationship difficulties, family matters and financial problems. Stress is not a negative process at all times because it plays a factor in motivation to deal with challenges and lead to success. However, unrelenting stress in the long run can lead to a host of negative and detrimental consequences in terms of physiological functioning, physical health, emotional and behavioural changes [1, 2]. According to the National Institutes of Health (NIH), long-term stress can cause mental health problems and trigger the risk of developing various physical health problems such as heart disease, high blood pressure and diabetes [3].

In Malaysia, the National Health and Morbidity Survey (NHMS) conducted in year 2015 reported that 29.2% of the Malaysian adults aged 16 years and above were suffering from mental health problems like depression and anxiety disorder. The statistic was increased from 10.7% in 1996 to 29.2% in 2015 [4]. Furthermore, the NHMS in year 2017 revealed that adolescents aged 13 to 17 years old experienced stress, depression and anxiety with prevalence of 9.6%, 18.3% and 39.7% respectively [5]. A recent NHMS in year 2019 have demonstrated that 2.3% which was about half of a million Malaysian adults aged 18 years and above were reported to have depression, while 7.9%, approximately 424,000 of children aged 5 to 15 were found to have mental health problems [6].

NHMS 2019 indicated 18.3% which was about 3.9 million of Malaysian adults and above had diabetes and 30% which was about 6.4 million of Malaysian adults had raised blood pressure. On top of that, the survey reported that 35.1% of Malaysian adults possessed low health literacy including health-related information, promotion and disease prevention. Hence, it is important to educate the general public on the impacts of prolonged exposure to stress on both physical and mental health. Furthermore, it is crucial to monitor stress levels for early diagnosis in order to prevent possible future illnesses since all are equally at risk of experiencing stress. Consequences of neglecting stress may trigger the risk of developing various health issues, thus research efforts are continuously being made on detecting and classifying stress levels [7-18].

Stress response originates from the brain but involving various biochemical and physiological effects [19]. Researchers have extracted the presence of specific hormones and features from different kinds of physiological sensors such as blood pressure, heart rate variability (HRV) and galvanic skin response (GSR) to assess stress [20, 21]. Besides that, brainwave activity has been revealed as potential biomarker and proved to represent important information of the brain function in responding to stress [22]. The use of electroencephalogram (EEG) device is becoming increasingly popular as its capabilities to see rapid changes of cortical activity across time to detect the brain activities [23] and specific diagnosis [24, 25]. Recent studies of using single modality EEG have empowered researchers to distinguish stress and relax state [26, 27] among human and further classify the stress into different levels [28-32].

Based on the study done by Fares Al-shargie et al. [33], Alpha power was identified to be significantly decreased at all the three levels of stress when each of the level compared to baseline. Classification was done on support vector machine (SVM) and the average accuracy obtained for recognition of three stress states was 94.79%. The study also proved that right prefrontal cortex was highly involved during mental stress in all the three levels. In the work of Jun and Smitha [34], they induced three stress levels by using Stroop colour-word test and mental arithmetic test. The result had recognized and confirmed the three levels of stress using SVM classifier commenting 75% accuracy. The study reported that Alpha power was higher than Theta and Beta power during baseline resting state. Conversely, Beta power was noticed to be relatively higher. Arsalan et al. [35] found that only Theta power was found significantly different from pre- and post-stimulus. Their study achieved classification accuracy at 46.42% for three levels of stress using SVM.

In order to model EEG based three-level stress classification system, the class label information of stress levels is given within the dataset for training the classifier. The previous studies mentioned above have classified the EEG signals through the pre-labelled stress levels. Nevertheless, individuals have different stress signals or perceptions in different situations or stress exposure because every individual cope with stress uniquely. The constraint can be overcome by quantifying the similar and identical EEG characteristics using clustering method [36] prior to building a stress level classification model. The purpose of this study is to reduce subjective bias shaped from human stress reactivity by working in conjunction with clustering method to improve the overall performance of stress level classification.

1.2 Problem Statement

Various psychological tests have been devised in research and clinical practice for the purpose to obtain statistically useful information and measure stress levels such as Stress Response Inventory [37], Holmes-Rahe Stress Inventory [38], Hamilton Rating Scale for Depression [39] and Perceived Stress Scale [40]. The assessments involve self-report or clinician-rated by using subjective perceptions and estimations to extract specific information on cognitive, emotional or behavioral stress responses. However, these methods are subjective and not sensitive enough to capture subtle patterns of mental state. Subjective self-reported stress has been reported to be insufficiently reflected by respective physiological parameters of the stress measurement [41, 42].

As compared to self-assessment questionnaires, physiological variables such as cortisol level [43], skin conductivity [44], heart rate [45], blood pressure [46] and EEG signal [47-50] served as an additional fairly objective and straightforward ways to measure stress. The high temporal resolution of electroencephalography (EEG) constitutes a possibly practicable and feasible neuroimaging technique. Despite the fact that there are a number of EEG related studies have been done to classify stress into different levels, yet the EEG features were classified according to the pre-marked stress levels, that is, the difficulties of stressors and/or self-perceived questionnaire.

In particular, Fares Al-shargie et al. [33] utilized mental arithmetic task with three levels of difficulty to induce variations in the brain cortical activities and collected by EEG signals. The stress features induced by the three levels of difficulty were labelled accordingly. By comparing the three levels of stress elicited by mental arithmetic tasks, the study showed that the Alpha power has greatly decreased from the first level to the second level of stress. But the power increased again from the second level to the third level. This result has also been verified that cortical activation failed at task level-three. The questionnaire survey on task load showed that with the increase of task difficulty, especially in the third level, the engagement of participants decreased significantly [51]. On the other hand, Arsalan et al. [35] arranged the participants to prepare and present on an unknown topic and classified the perceived stress into three different levels using the score obtained from perceived stress scale (PSS) questionnaire.

Likewise, Nagar and Sethia [28] used the stress scores calculated from the PSS questionnaire to specify three target stress levels. In fact, veridical stress state is potentially inaccurate and limited by the factors like unwilling to appear fragile and also lacking of conscious perception [52]. Consequently, the result based on the self-reported stress labelling and the labelling using the levels of task difficulty might be less convincing due to incapable of dealing with the difference between subjects. Inter-subject variability is apparent and indisputable because of the time-variant and subject-specific brain processes rely on the experimental setting, psychological and neurophysiological factors. In accordance with that, clustering method has been suggested to have effective quantification of subjects who share similar and identical EEG signal characteristics [36].

Clustering method was introduced in a study to cluster the inherent homogeneity of all subjects' stress response into subgroups through trained and tested various physiological features such as EEG, electrocardiography (ECG), electromyography (EMG), galvanic skin response (GSR) and saturation of peripheraloxygen (SpO2). The study found that a small number of clusters showed a good balance between within-cluster homogeneity and between-cluster heterogeneity [53]. To the best of our knowledge, cluster related method and results solely based on the EEG signals and stress remain limited in the literature [54, 55]. The EEG data in these studies was processed using discrete wavelet transformation (DWT) and k-means clustering, followed by calculating stress indices value of cognitive data and physical data for clustering and establishing low and high stress level.

The present study has utilized EEG signal processing technique with clustering method to develop a three-level stress classification model. Stress response was triggered through stimuli in laboratory settings and the features were extracted for investigation to determine the significant and related stress features. Subsequently, clustering was applied in order to overcome the inter-subject differences to divide and assign the features into three groups of stress levels. Cluster assignment is vital to modify the problem to find a fair solution before proceeding to classification. The clustered data with known class labels was then split into training and testing sets to build a classification model.

1.3 Research Objectives

The objectives of the research are as follow:

(a) To determine the significant features in distinguishing stress response.

(b) To cluster the inherent homogeneity of stress features into three groups.

(c) To verify the accuracy performance in classifying three levels of stress.

1.4 Research Scopes

The scope of the research is divided into four categories as follows:

(a) Participants: 50 healthy students from Universiti Teknologi Malaysia, Kuala Lumpur were chosen. They were undergraduate and postgraduate students aged ranging from 19 to 38 years old.

(b) Stimuli: Virtual reality (VR) horror video and non-verbal intelligence quotient (IQ) test.

(c) Parameter: 5 electrodes (Ag/AgCl material) with conductive gel were used to attach on the surface of forehead and connect with bio-signal acquisition software (g.MOBIlab+) to transmit EEG signals to PC via Bluetooth.

(d) Data Analysis: Brainstorm application under Matlab software was used for EEG signal processing and feature extraction. Statistical test was performed using IBM SPSS to recognize significant feature. Weka tool was selected for feature clustering and classification.

1.5 Research Significance

The stress level classification model can be employed for the implementation of stress monitoring system or health indicator which potentially provides better health care. The reliability and accuracy on the application can be used to facilitate traditional tools such as the self-report or clinician-rated questionnaires. Moreover, the system can be adopted clinically or perhaps by individuals to monitor stress levels. Physicians, clinicians, psychologists or counsellors can perform stress prediction in real-time and save time for mental stress assessment. The enhancement of the diagnosis accuracy enables clinicians to support their decision during treatment of patients about the severity of stress. The decision can prevent patients from getting more intense disorders like anxiety and depression by identifying it at an early stage. Indeed, such study is important for future development of stress diagnosis system to help people and assist clinicians by providing reliable information and giving maximum treatment benefits before significant physical and mental disorders occur.

1.6 Thesis Outline

The research proposal is organized in five chapters as follows:

(a) Chapter 1 presents the background information related to this research project. It also introduces the problem statement, objectives, scopes and expected contributions of the project.

(b) Chapter 2 elaborates the current literatures related to the study which were mainly about the stress, EEG and brain signal processing techniques. The previous works related to classifying stress levels based on EEG signals are presented as well.

(c) Chapter 3 illustrates the methodologies which were used to complete this research such as experimental procedure during data collection, EEG measurement and steps of data processing including features extraction and selection as well as data clustering, classification and model validation.

(d) Chapter 4 reports the findings from the experiments that were conducted with the purpose of extracting and identifying significant stress features jointly with the performance of stress level classification model.

(e) Chapter 5 summarizes the study that has been conducted with the purpose of achieving the objectives of the research and recommends some directions for further research works on possible expansion that could be done in future.

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Appendix A Consent Form

Informed Consent Release

Part A: Explain by the Investigator

"My name is **Tee Yi Wen**, and I am a **postgraduate student** at **Razak Faculty of Technology and Informatics**. I am inviting you to participate in a research study. Involvement in the study is voluntary, so you may choose to participate or not. I am now going to explain the study to you. Please feel free to ask any questions that you may have about the research; I will be happy to explain anything in greater detail.

"I am now working under **Dr Siti Armiza Mohd Aris** from **Razak Faculty of Technology and Informatics**. We are interested in learning more about **<u>THE BRAIN RESPONSE BEFORE AND AFTER USING THE VIRTUAL REALITY (VR) TOOLS</u>**. You will be asked to wear Electroencephalogram (EEG) wires to have an initial baseline recording. After the recording, you will be asked to use a VR device and we will record your EEG brain signals one more time after the VR session completed. This will take approximately **ONE** (1) hour of your time. All information will be kept **<u>confidential</u>**. If anonymous, this means that your name will not appear anywhere and no one except me will know about your specific answers. If confidential, I will assign a number to your responses, and only I will have the key to indicate which number belongs to which participant. In any articles I write or any presentations that I make, I will use a made-up name for you, and I will not reveal details or I will change details about where you work, where you live, any personal information about you, and so forth.

"The benefit of this research is that you will be helping us to understand more about **EARLY DETECTION OF DEMENTIA IN EEG SIGNALS USING ADVANCED SIGNAL PROCESSING TECHNIQUES**. This information should help us to benefit of the research and better understanding. The risks to you for participating in this study affect your brain for those who have their brain surgery before. These risks will be minimized. If you do not wish to continue, you have the right to withdraw from the study, without penalty, at any time."

Part B: Fill up by the Participant

"All of my questions and concerns about this study have been addressed. I choose, voluntarily, to participate in this research project. I certify that I am at least 18 years of age.

____

Name of participant

______________________________ ______________

Signature of participant Date

Name of investigator

Signature of investigator | Date

Appendix B Depression Anxiety Stress Scale (DASS-21)

DASS-21 Name: Date:

Please read each statement and circle a number 0, 1, 2 or 3 which indicates how much the statement applied to you *over the past week.* There are no right or wrong answers. Do not spend too much time on any statement.

The rating scale is as follows:

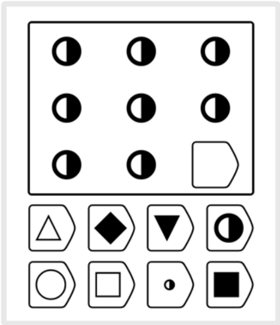
0 Did not apply to me at all
1 Applied to me to some degree, or some of the time
2 Applied to me to a considerable degree, or a good part of time
3 Applied to me very much, or most of the time

1	I found it hard to wind down	0	1	2	3
2	I was aware of dryness of my mouth	0	1	2	3
3	I couldn't seem to experience any positive feeling at all	0	1	2	3
4	I experienced breathing difficulty (e.g. excessively rapid breathing, breathlessness in the absence of physical exertion)	0	1	2	3
5	I found it difficult to work up the initiative to do things	0	1	2	3
6	I tended to over-react to situations	0	1	2	3
7	I experienced trembling (e.g. in the hands)	0	1	2	3
8	I felt that I was using a lot of nervous energy	0	1	2	3
9	I was worried about situations in which I might panic and make a fool of myself	0	1	2	3
10	I felt that I had nothing to look forward to	0	1	2	3
11	I found myself getting agitated	0	1	2	3
12	I found it difficult to relax	0	1	2	3
13	I felt down-hearted and blue	0	1	2	3
14	I was intolerant of anything that kept me from getting on with what I was doing	0	1	2	3
15	I felt I was close to panic	0	1	2	3
16	I was unable to become enthusiastic about anything	0	1	2	3
17	I felt I wasn't worth much as a person	0	1	2	3
18	I felt that I was rather touchy	0	1	2	3

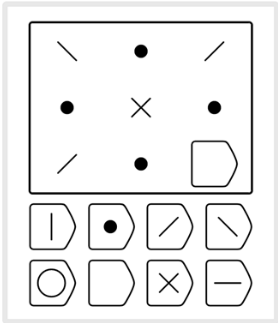
19	I was aware of the action of my heart in the absence of physical exertion (e.g. sense of heart rate increase, heart missing a beat)	0	1	2	3
20	I felt scared without any good reason	0	1	2	3
21	I felt that life was meaningless	0	1	2	3

Appendix C IQ Test (40 Questions)

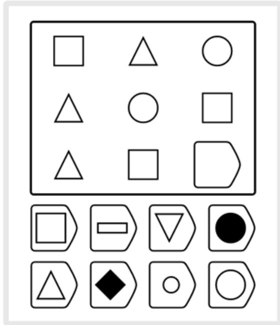
IQ TEST: QUESTION 1 / 40



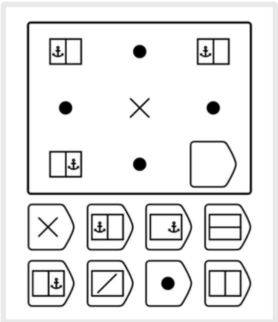
IQ TEST: QUESTION 2 / 40



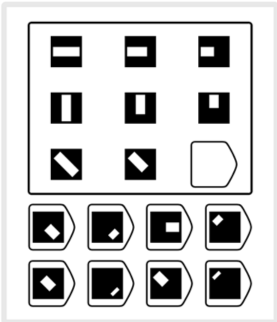
IQ TEST: QUESTION 3 / 40



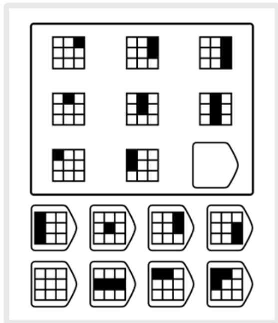
IQ TEST: QUESTION 4 / 40



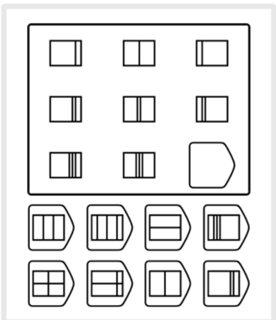
IQ TEST: QUESTION 5 / 40



IQ TEST: QUESTION 6 / 40



IQ TEST: QUESTION 7 / 40



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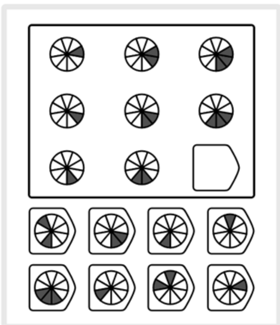
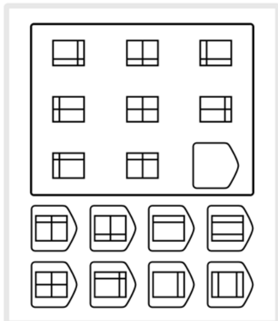
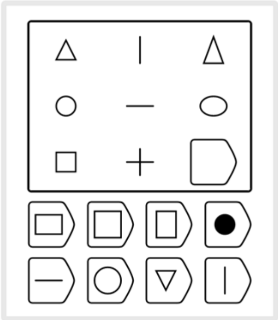


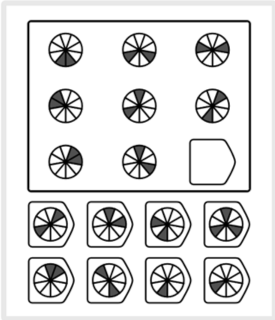
IQ TEST: QUESTION 9 / 40



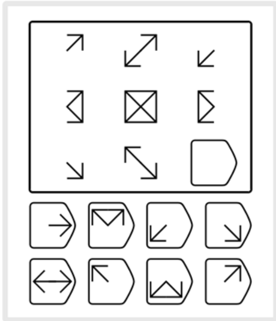
IQ TEST: QUESTION 10 / 40



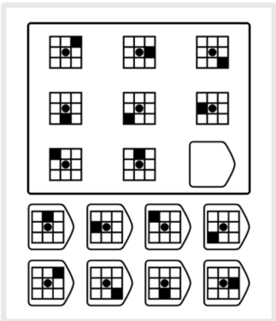
IQ TEST: QUESTION 11 / 40



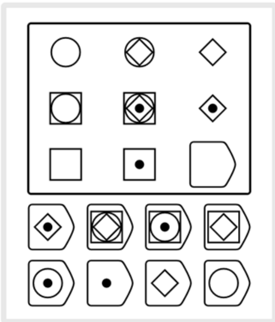
IQ TEST: QUESTION 12 / 40



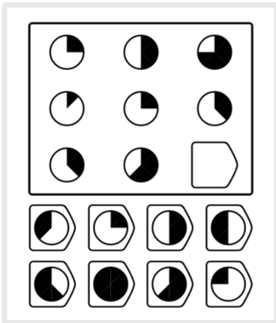
IQ TEST: QUESTION 13 / 40



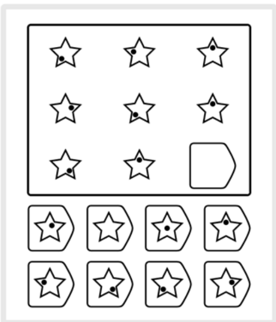
IQ TEST: QUESTION 14 / 40



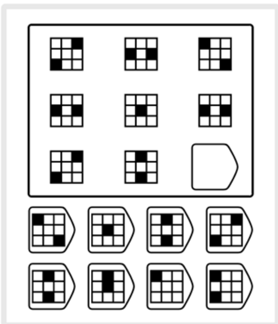
IQ TEST: QUESTION 15 / 40



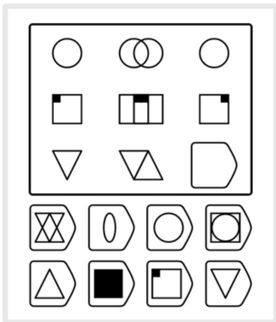
IQ TEST: QUESTION 16 / 40



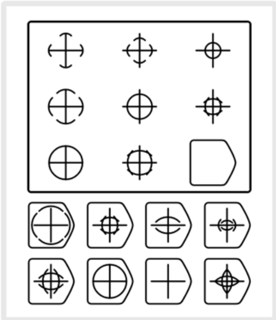
IQ TEST: QUESTION 17 / 40



IQ TEST: QUESTION 18 / 40



IQ TEST: QUESTION 19 / 40



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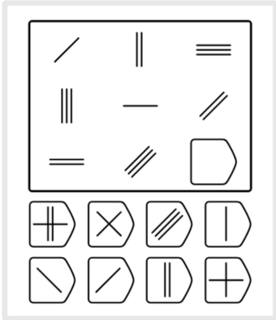

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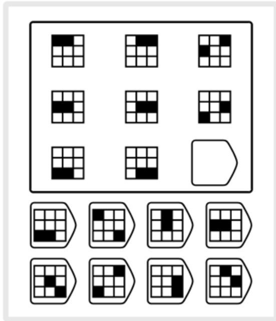
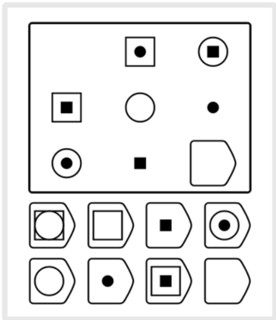


IQ TEST: QUESTION 22 / 40



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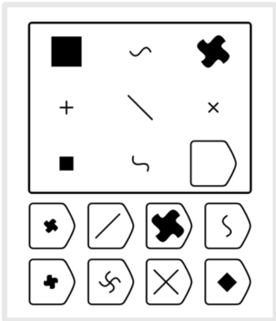

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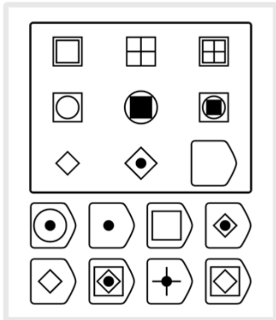

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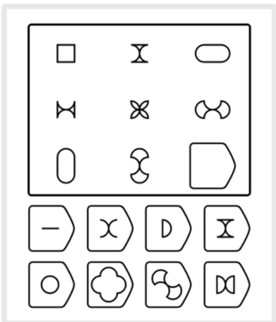

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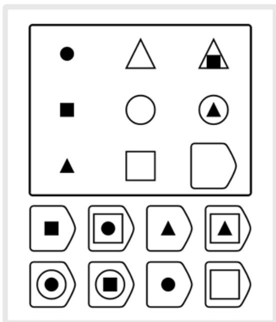

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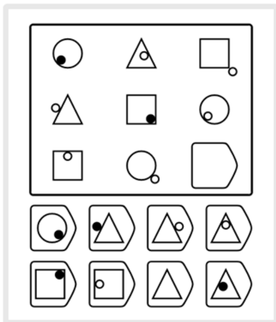

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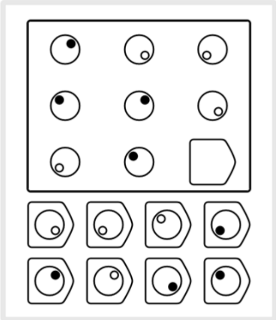

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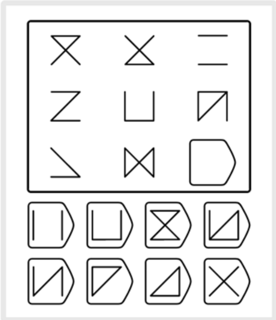

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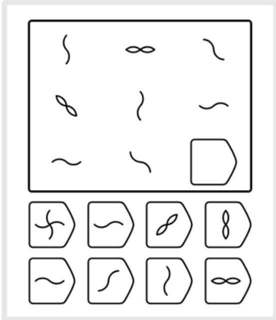

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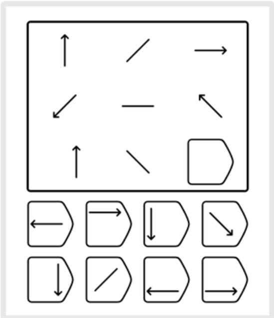

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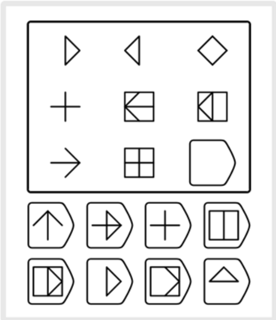

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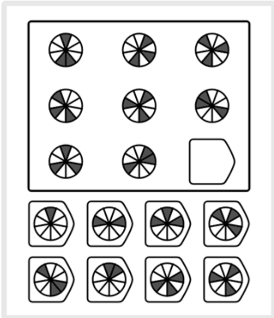

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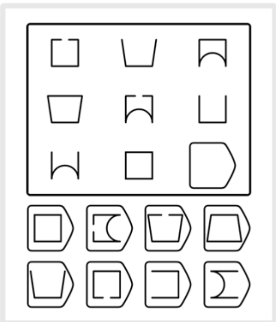

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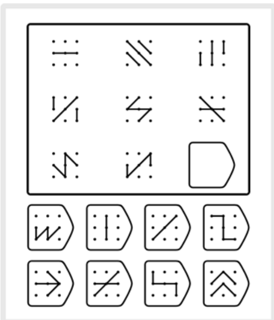

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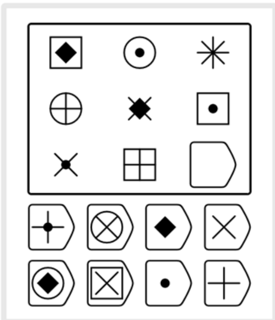

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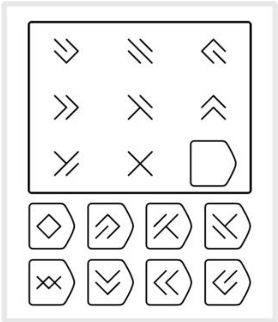

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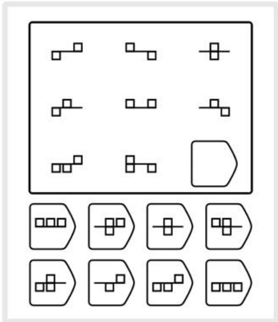

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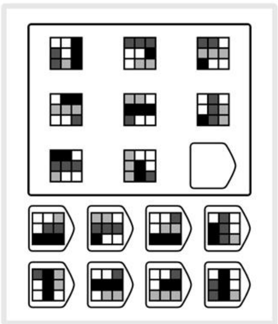

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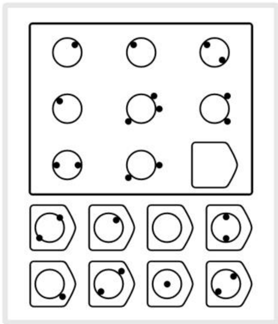

Appendix D   Self-Report Assessment (Post-VR Questionnaire)

Please rate your experience during or after the Virtual Reality (VR) experience.

* *Mark only one oval per row.*

	Not at all	A little bit	Somewhat	Very much	Extremely
Headache	◯	◯	◯	◯	◯
Dizzy	◯	◯	◯	◯	◯
Stressed	◯	◯	◯	◯	◯
Frightened	◯	◯	◯	◯	◯
Excited	◯	◯	◯	◯	◯
Enjoyed	◯	◯	◯	◯	◯

Appendix E NASA-Task Load Index (Post-IQ Questionnaire)

NASA Task Load Index

Hart and Staveland’s NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.

Mental Demand — How mentally demanding was the task?

Very Low — Very High

Physical Demand — How physically demanding was the task?

Very Low — Very High

Temporal Demand — How hurried or rushed was the pace of the task?

Very Low — Very High

Performance — How successful were you in accomplishing what you were asked to do?

Very Low — Very High

Effort — How physically demanding was the task?

Very Low — Very High

Frustration — How physically demanding was the task?

Very Low — Very High

LIST OF PUBLICATIONS

T. Y. Wen, and S. A. M. Aris, "Electroencephalogram (EEG) stress analysis on Alpha/Beta ratio and Theta/Beta ratio," *Indonesian Journal of Electrical Engineering and Computer Science*, vol.17, pp. 175-182, 2020

T. Y. Wen, N. A. Bani, F. Muhammad-Sukki, and S. A. M. Aris, "Electroencephalogram (EEG) human stress level classification based on Theta/Beta ratio," *3rd International Conference on BioSignal Analysis, Processing and Systems*, vol. 12 (6), pp. 174-180, 2020