THE EFFECT OF TASK COMPLEXITY ON TIME PERCEPTION IN THE VIRTUAL REALITY ENVIRONMENT: AN EEG STUDY

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Abstract

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Background: Virtual reality (VR) technology is increasingly being utilized for multiple purposes. Unlike traditional 2D devices, VR headsets allow individuals to enjoy an immersive experience that includes multisensory interaction and a sense of presence. However, VR is not a perfect copy of the real world, and individuals may perceive differently on time in the virtual reality environment (VRE) than they do in their daily lives. Time perception is the process by which individuals subjectively judge the length of time and time duration estimation is proved a robust way to measure the time perception. As time perception is known as critical in the performance of time-related tasks, it is worth studying how time perception is affected in the VR applications. While the importance of time perception has been investigated, little is known about various factors' influence on time estimation in the VRE. Given that both time perception and task complexity are associated with attentional resources, it merits investigating how time perception is influenced by task complexity in the VRE.

Objective: The goal of this thesis study was to investigate the effect of task complexity on time perception in the VRE using behavioral, subjective, and physiological measurements. Three research questions were investigated in this study: (1) Does task complexity in the VRE affect time perception? (2) Does task complexity in the VRE affect brain signals? and (3) Are there relationships among time perception, brain signals, and subjective workload in the VRE?

Methods: Twenty-nine participants performed a jigsaw puzzle task at different levels of task complexity (low and high) in the VRE. Each task was repeated three times. The independent variables were task complexity and the sequence of the block, and the dependent variables were time estimation error, electroencephalogram (EEG) as the physiological measurement, and the NASA-TLX score as the subjective workload measurement.

Results: I found significant effects of task complexity on time estimation error and the NASA-TLX score. This result indicates when individuals conducted a more complex task, they may overestimate the elapsed time than the task actually takes and perceive a higher workload. Simultaneously, the maximum EEG amplitudes and the maximum high beta-band power at Cz, Fz, and Pz increase with the task complexity. The result also shows the sequence of the block only impacts the NASA-TLX score but has no significant effect on time estimation error or EEG signals. Finally, I found positive correlations between NASA-TLX score and time estimation error. Also, I observed significant correlation between NASA-TLX score and some brain signals—i.e., the maximum EEG amplitudes at Cz and Pz and the maximum high beta-band power at Cz, Fz and Pz.

Implications: The results of the study demonstrate that higher task complexity negatively influences the accuracy of individuals' time estimations in the VRE. To improve the performance of time-related tasks in the VRE, a modest-complexity design is recommended. The findings support the idea that using time estimation as an indicator of workload assessment in the VRE.

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DEDICATION

This thesis is dedicated to my parents, Huaihong Li and Hong Yu, for their endless support and love.

Chapter 1. INTRODUCTION

Virtual reality (VR) is not a new term. Although the term has been used to describe any digital environment that is different from the real world, VR refers to computer-simulated worlds that rely on headsets or other devices to generate an immersive environment [1]. Most of the consumer VR systems available nowadays take the form of a head-mounted display (HMD), the genesis of which can be traced back to the 1960s. In 1965, Ivan Sutherland introduced the concept of "The Ultimate Display" [2]. VR technology was subsequently popularized in multiple fields, including military simulation and medical training. Jaron Lanier, a well-known modern VR pioneer and the founder of VPL Research, invented the first commercial VR system in 1984 [3]. Since then, more and more technology companies invested in VR development, causing the technology to grow rapidly in popularity.

According to a recent report from SuperData (Nelson), the number of VR systems shipped in 2019 reached 5.7 million, indicating the promising market of VR system [4]. As VR technology becomes increasingly portable and inexpensive, so do the consumer-level VR systems see wider applications in a variety of fields. Modern VR devices can create a world where individuals can interact with the virtual reality environment (VRE) in much the same way as they do in reality which could enhance the user experience [5]. Unlike traditional two-dimensional (2D) devices, VR devices enable individuals to enjoy an immersive experience that benefits from the multisensory interaction and the sense of presence facilitated by the VRE. In recent decades, numerous VR researchers and designers have expended much effort on improving the interaction technologies to make them more natural and efficient, allowing for VR applications in additional areas. In addition to influencing the entertainment and gaming industries, VR technology is playing an important role in education, training, and healthcare [1]. The limitations of the real-world environment including the reproduction of scenarios that may be dangerous or hard to generate have contributed to VR technology’s application in those areas. For example, in VR military training, soldiers can learn strategies under fatal conditions in virtual combat scenarios without facing danger.

Chapter 2. LITERATURE REVIEW

2.1 TIME PERCEPTION

Time perception is the process by which a human subjectively judges the time. It is affected by the attentional resources or external cues in the environment [6][7], that is, people are likely to have metabolic time perception when the environment varies. Time estimation is a generally accepted measure of time perception and is proved a robust way to measure individuals' time perception when they cannot refer to external time indicators [8][9]. For example, in Hornik's study, the difference between estimated waiting time and actual waiting time was employed as a measure of time perception [10]. In another study where VR was used as an intervention in chemotherapy, patients were required to estimate the time that had elapsed during treatment and the estimations were compared with the actual time durations [11]. In general terms , there are two categories of time estimation: prospective time estimation and retrospective time estimation[12]. Whether the time interval to be estimated is on-going or has already passed distinguishes the prospective and retrospective time estimation from one another [13]. Among the prospective models, the internal clock model, also known as the pace-maker model, has been widely utilized in revealing the mechanism of time perception. This model assumes the human body has an internal clock, and this clock has a pacemaker that produces a series of time intervals that are stored in an accumulator [14]. When a human makes a time estimation, the accumulated time intervals, which represent the experienced time duration, are compared to the time periods stored in the long-term memory [15].

Less accurate time perception is associated with slower reaction times with larger variance, as well as poorer-quality decision-making and lower user satisfaction. Researchers found that children with attention deficit hyperactivity disorder (ADHD) had larger variance in motor reaction times during a rope jumping task compared to children in a non-ADHD group [16]. The difference was ascribed to deficits in time perception of the children with ADHD. These deficits were thought to have contributed to larger errors in time estimation and thus have impacted reaction time. In a study conducted by Schubotz et al., participants were first presented with preset sequences of continuous visual/auditory stimuli. Then the participants were shown other sequences of stimuli that differed from the preset sequences in time duration, color, or tone [17]. The results showed that the participants tended to have longer reaction times in the trials when they perceived a time duration deviating from the preset than in the trials when they perceived color or tone deviants. In addition, the participants’ error rates in button-pressing in the trials with time interval deviance were higher than those in other trials. Such a correlation between time perception and reaction time may be explained by the fact that human time perception and response time execution involve similar brain regions [17][18].

Several studies have suggested time perception is connected to the quality of decision-making. Wittmann and Paulus demonstrated that impulsive decisions are made when individuals overestimate the time when they could receive a reward [15]. Individuals who overestimate the time prefer the instant reward even if the delayed reward has a higher expected value. Based on the attention allocation model, Zakay argued that when decision-makers perceive a time shortage, they allocate more attentional resources to time estimation, leaving fewer attentional resources available for decision-making [19]. This reduces decision-making quality. The findings of Francis-Smythe and Robertson indicated that individuals who more accurately estimate the duration of tasks consider themselves to be better at using time-management behaviors based on the results of Time Structure Questionnaire (TSQ), a self-report time management questionnaire [20].

In addition, researchers have found that customers’ overestimation of time is linked to their dissatisfaction with waiting in line [21]. Tom and Lucey concluded customers’ satisfaction with a server at a restaurant decreased as their perception of the amount of time they had waited increased [22]. The researchers also emphasized that customer satisfaction was determined by perceived waiting time, not actual waiting time. In Davis and Heineke's study on the experience of waiting time, similar results were found: Time perception was shown to be a valid indicator of customers' satisfaction [23].

2.2 TIME PERCEPTION IN THE VRE

There are not many studies investigating time perception in the VRE and the reported results mainly fall into two categories, overestimation and underestimation of time. An individual would experience a shorter elapsed time compared to the actual time when they underestimate the time, and a longer elapsed time when they overestimate it. In Schneider's study, most patients underestimated the duration during chemotherapy [11]. Sanders & Cairns found the connection between time perception and the sense of immersion in video games. They found that an increase in immersion resulted in an underestimation of time duration by individuals [24].

However, other studies have shown contrary results. Schatzschneider et al. reported that participants were more likely to overestimate the amount of time they had spent in the VRE [25]. Another study found that participants tended to overestimate time duration while walking in the VRE, but significant differences between the VR and the real world were not observed [26].

One of the reasons for the inconsistent conclusions regarding time perception in the VRE could be the different task settings [27]. In chemotherapy studies, Schneider et al. utilized the VR device as an intervention to reduce patients' awareness of pain [11]. Sanders and Cairns found the same underestimation result when they applied entertaining elements (e.g., music) in the VRE [23].

2.3 THE EFFECT OF TASK COMPLEXITY ON TIME PERCEPTION

There are various definitions of task complexity and one viewpoint is to relate the task complexity to resource requirement [28][29][30]. Previous studies have shown a connection between task complexity and attentional resources. Task with higher complexity has more information cues to be processed [29] and more interactions to be performed [31], leading to a higher attention requirement.

According to the attentional resource allocation model of time perception [12][32], attentional resources are required during the process of time perception. As the capacity of attentional resources is limited by other information-processing activities [32][33], fewer resources are available for processing time perception, resulting in less accurate time estimation results. Since both time perception and task complexity involve attentional resources in human brain, it is worth investigating the influence of task complexity on time perception.

In Zakay's studies [33][34], the accuracy of time duration estimation was found to decrease with an increase in task complexity. More specifically, humans subjectively estimated a longer duration when there was higher task complexity. An individual's time estimation was similarly likely to increase as the task complexity of a pin-to-hole assembly task and a task that required moving an object to a target area increased, as reported by Chan and Hoffmann [35]. A study that used an attentional task with three levels of complexity revealed that subjects tended to make larger errors both in prospective and retrospective time estimation in the high complexity tasks, compared to the low and medium [36].

2.4 TASK COMPLEXITY AND EEG

Electroencephalogram (EEG) captures changes in voltage responses that originate in a population of neurons in the brain from the electrodes of interest and reference [37]. A multi-channel EEG collects electrical signals from different areas of the brain cortex, allowing researchers to explore neural activities related to human behaviors in diverse work settings. The International 10-20 system is a standardized universal method of EEG electrode placement on the human scalp [38]. The electrodes are distributed equally, and the brain is divided into six parts: pre-frontal (Fp), frontal (F), parietal (P), temporal (T), occipital (O), and central (C).

Figure 2.1. shows the map and electrode labels of the International 10-20 system [39]. The rest of the thesis uses the labels of the International 10-20 system to identify the location of each EEG electrodes.

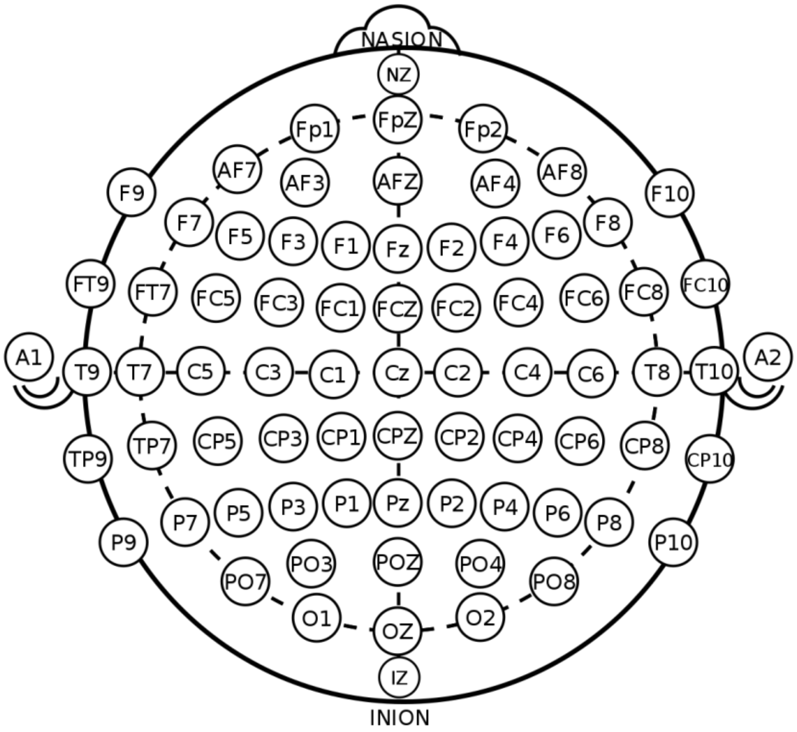

Figure 2.1. The International 10-20 System [40]

Numerous studies have revealed the impact of task complexity on EEG signals recorded in the frontal lobe and midline plane of the brain. It has been reported that EEG signals at electrodes Cz, Fz, and Pz, showed greater activities with the increased task complexity [41]. By analyzing the brain signals received from electrodes Fz, Pz, C3, and P3, Chaouachi developed a model for assessing an individual's mental workload, which manipulated by the complexity level of cognitive tasks [42].

Band activities of EEG represent the rhythm of the brain in the form of waves with continuous frequencies. Extensive progress has also been made in finding the connection between task complexity and mental workload using the power of certain frequency bands. EEG studies usually investigate four major frequency bands—theta, alpha, beta, and gamma—with frequencies ranging from 4–8 Hz, 8–12 Hz, 12–30 Hz, to 30–100 Hz, respectively. Among the four frequencies, the beta band was reported to be associated with attention-related mental activities [43]. Kamiński and colleagues observed increased band power of the beta band at 11 electrodes including Cz, Fz, and Pz, when there were enhanced attention stimuli [44]. In another study conducted between ADHD patients and non-ADHD individuals, beta-band activities at Cz were found to be correlated with attention level in the non-ADHD group [45]. Similar results were reported in research of Wilson et al. [46], and Rueda-Delgado et al. [47] that the beta-band activities were significantly enhanced as the level of task complexity increased. Since the relation between task complexity and the brain activity on the midline of the brain were revealed, according to the International 10-20 system, Cz, Fz, and Pz electrodes were utilized in this study.

In some EEG studies, the beta-band is divided into three components, Beta 1 (12–16 Hz), Beta 2 (16–20 Hz), and Beta 3 (20–30 Hz) [48]. Some researchers split the beta-band and consider only a single component. The 16–20 Hz band (Beta 2) was found to be significantly related to task complexity in research by Kakizaki [49] and Bizas et al. [50]. In this thesis, I used an EEG device that divided the beta-band into two beta-band components. I used one of the components called "high beta-band" (16–25 Hz), which covers Beta 2.

2.5 RESEARCH GOAL

The widespread application of VR technology indicates that an expansion of VR applications across society is likely. Time perception is believed critical in the VRE because accurate time perception is known to influence reaction time, decision-making, and user satisfaction. While the importance of time perception has been investigated, little is known about various factors' influence on time estimation in the VRE. Given that both time perception and task complexity are associated with attentional resources, it is imperative to investigate how time perception is influenced by task complexity in the VRE. EEG signals have been proven to be a reliable physiological method of measuring human perceptive and cognitive status in experimental conditions, and the relationship between EEG signals and task complexity has been investigated by multiple studies. However, there has not been a comprehensive EEG project exploring how task complexity impacts human time perception in the VRE.

The goal of this thesis was to investigate the effect of task complexity on time perception in the VRE using behavioral, physiological, and subjective measurements. Three research questions were investigated in this study: (1) Does task complexity in the VRE affect time perception? (2) Does task complexity in the VRE affect brain signals? and (3) Are there relationships among time perception, brain signals, and subjective workload evaluation in the VRE? To uncover the impact of task complexity on dependent variables in the VRE, I designed two levels of task complexity. Time estimation errors, subjective workload evaluations, EEG amplitudes and high beta-band power received from Cz, Fz, and Pz were collected and analyzed in relation to task complexity.

Chapter 3. METHODOLOGY

3.1 PARTICIPANTS

Thirty-two subjects (15 males and 17 females) aged 21–29 years (Mean = 23.84, SD = 2.17) at the University of Washington participated in the study. Participants had either normal or corrected vision without visual and auditory impairments. Each participant signed a consent form prior to the experiment and received $20 in compensation for the participation. Two participants' data were excluded from the data analysis due to low EEG contact quality. To verify the outliers in the acquired data, I defined those data points bigger or smaller than the values three standard deviations away from the mean value as the outliers. One participant's data points were therefore excluded from the dataset. The results of my power analysis show that the sample size of 29 participants yielded a 0.6 statistical power. The study was reviewed and approved by the University of Washington's Institutional Review Boards (IRBs) before recruiting participants.

3.2 APPARATUS

The experiment was performed on a Lenovo X1 laptop (Lenovo) equipped with an Intel i5-10210U processor and Intel UHD 620 Graphics. The VR device used in the study was HTC VIVE (HTC), a mainstream consumer VR system. A single-player commercial VR software program, Jigsaw360 (Head Start Design), delivered the main task in the study. To minimize the impact of visual stimuli on EEG signals, a grey picture was used instead of the default pictures. Figure 3.1 and Figure 3.2 show the game interface of the two tasks with different complexity that the participants were mainly interacting with. The low task complexity condition used 8 pieces of the jigsaw and the high task complexity condition used 18 pieces of the jigsaw. The number of pieces was determined after the pilot study as described in section 4.1. Auditory and visual effects in the background of the game were also eliminated to minimize any nuisance effect on EEG signals. Participants' brain signals were collected using a 32-channel Ag/AgCl wireless EEG (Epoc Flex by Emotiv) with a sampling rate of 128 Hz. All raw data were recorded using EmotivPro software (Emotiv). During the recording, EmotivPro is able to stream the real-time contact quality and EEG voltage data. Also, the software shows the real-time power of theta, alpha, low/high beta, and gamma bands, which are automatically decomposed from voltage signals into frequency components by fast Fourier Transform (FFT). The study's statistical analysis was conducted in R version 3.6.1 [51].

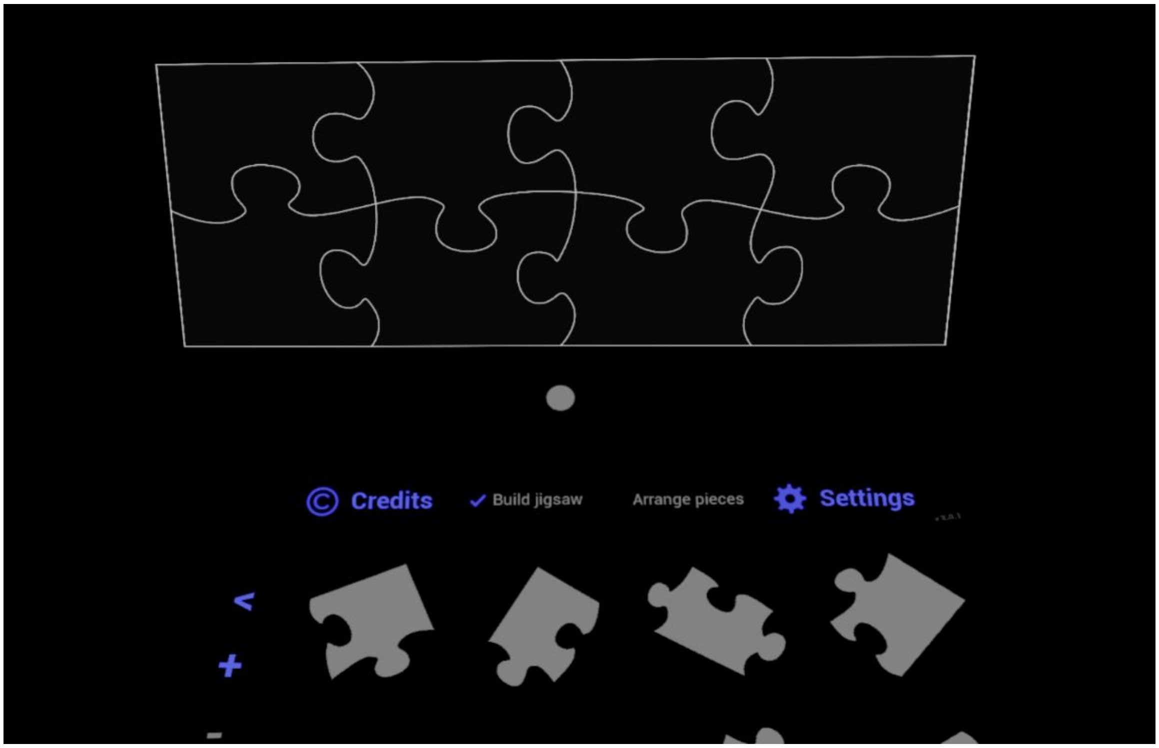

Figure 3.1. The interface of the low complexity task with 8 pieces in the experiment.

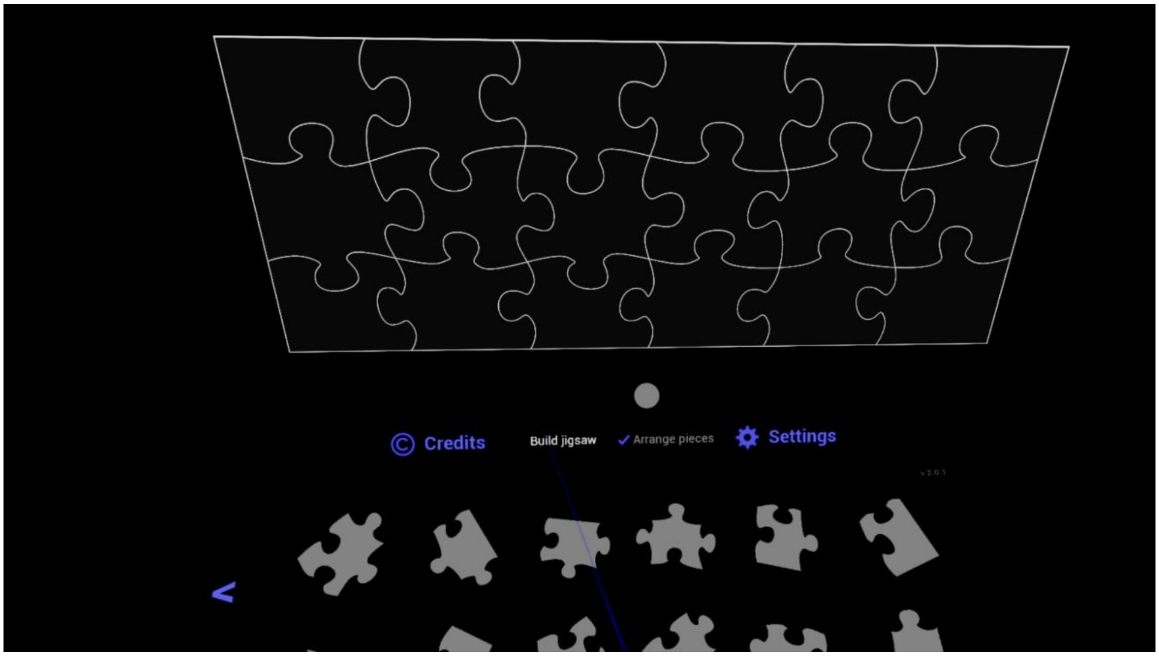

Figure 3.2. The interface of the high complexity task with 18 pieces in the experiment.

3.3 EXPERIMENTAL DESIGN

I employed a 2 x 3 within-subjects design, as shown in Table 3.1. The jigsaw task had two levels of complexity: 8 pieces (low task complexity) and 18 pieces (high task complexity). Each block contained both levels of high complexity and low complexity, and there were three blocks in total. Each participant needed to complete all three blocks (i.e., six trials). The order of the trials within a block was randomized to avoid any order effect.

The dependent variables were time estimation error, subjective mental workload, and brain signals. The NASA-Task Load Index (NASA-TLX) was used as the subjective workload evaluation method in this study. In the aspect of brain signals, I used the maximum values of EEG amplitude and beta-band power at the Cz, Fz, and Pz electrodes.

All dependent and independent variables are shown in Table 3.1.

Table 3.1. Experimental design

Factors	**Levels**

Task complexity	Low, high
Block sequence	First, second, third
Dependent variables	Time estimation error, NASA-TLX score, maximum EEG amplitudes, maximum high beta-band power

3.4 PROCEDURE

Before beginning the experiment, each participant was asked to sign a consent form and read a brief set of instructions for the experiment. Each participant then performed a practice trial with the VR headset. During the practice trial, the participant learned how to make selections in the game and react with jigsaw pieces; the participant also became familiar with the VRE. Participants were also informed in the practice trial that, in the main study, they would be asked a time estimation question verbally each time they finished a jigsaw puzzle. After the practice trial, the participant put on the Epoc Flex EEG device with the help of the researcher. The Cz, Fz, and Pz electrodes were attached to the participant's head with electric gel. Before the main experiment began, the EEG device was calibrated and the baseline signal was recorded.

Each trial required the participant to first play the jigsaw game with a given number of pieces. The goal of the game was to put every jigsaw piece in the right place on a blank tray with a white border, as shown in Figure 3.1 and Figure 3.2. Keystroke markers, which had been set up in advance, were used to record the start and the end of the game on the EEG signal timeline in EmotivPro. After completing the game, the participant was required to answer a question: "How long do you think you spent on the previous jigsaw game?" Participants were instructed that they should estimate the time in seconds. Participants' subjective workloads were assessed using the NASA-TLX before the participants moved on to the next trial. Given the difficulty of manipulating the mouse pointer in the VRE and the negative effect on the connectivity of the EEG device that would be incurred by a participant taking off the VR headset, the researcher asked all questions verbally. Each participant gave their answers verbally while they were still wearing the VR headset. There was a one-minute break between trials. During the experiment, participants' brain signals, time estimations, the actual completion time for each trial, and NASA-TLX answers were recorded by the researcher. The participants were instructed to play the game at a comfortable pace and avoid excessive movement to maintain the good connectivity of the EEG. The average total length of the experiment was about one and a half hours.

3.5 DATA ANALYSIS

3.5.1 *Time Estimation Error*

In this study, I utilized time estimation error, which is derived from the comparison between time estimation and actual time duration, to measure time perception. The absolute value of the time estimation error reflects the accuracy of subjective time judgment. At the same time, the positive or negative sign of the estimation error indicates whether overestimation or underestimation has occurred. The participants in the study were required to estimate the time in seconds; for example, a participant might describe their estimation result as either 3 minutes and 6 seconds or 186 seconds. The time estimation error (ER) was specified as the difference between the estimated time (ET) and the real elapsed time (RT). The equation used for calculating the time estimation error is [52]:

$$ER = ET - RT \tag{3.1}$$

3.5.2 *Subjective Workload Evaluation*

NASA-TLX is a subjective workload evaluation questionnaire that is designed to gauge subjective workload from operators while or after performing tasks. Numerous studies have proven it to be a reliable and sensitive approach to evaluating workload under different experimental conditions [53]. It records individuals' mental, physical, temporal demand, frustration, effort, and performance. In practical usage, many researchers have modified the NASA-TLX to suit different purposes and situations. The most common modification is the elimination of the weighting process in the NASA-TLX [53]. The same modification was made in this study. As the VR jigsaw puzzle game involved visual, physical, and cognitive activities that are associated with multiple subscales of the NASA-TLX, I considered the overall score rather than using the scores of one or only some subscales. To make it easier for participants to answer the questions verbally, I simplified the scale to 21 gradations. The original items of the NASA-TLX were still used.

3.5.3 *Brain Signals*

EEG raw data and band power were used as physiological measurements of brain signals in this study. As mentioned in the introduction, the signals at Cz, Fz, and Pz were collected during the experiment. In addition to gathering the raw EEG voltage data, I used the band power spectral density transformed by FFT to observe the change of distinct waves with different frequency bands while participants were performing tasks with different levels of complexity. Unlike the traditional segmentation of beta-band, the beta-band is split to low-beta (12–16 Hz) and high-beta (16–25 Hz) by EmotivPro as mentioned in section 2.4. Both the EEG data and band power were monitored throughout the experiment. To filter the data, I used the beginning and the ending of each trial, as indicated by keystroke markers in EmotivPro.

Chapter 4. RESULTS

4.1 PILOT STUDY

To verify the experimental design, I conducted a pilot study before beginning the main study. Three participants (two males and one female) were recruited for the pilot study. In the beginning, I used three levels of task complexity, with the numbers of pieces set to 18, 32, and 50 for two of the participants, and 32, 50, and 72 for the remaining one. The pilot study included two blocks, each of which contained three levels of complexity. Each participant needed to engage with each level of complexity two times. In the pilot study, I picked six of the default pictures and randomly assigned one of them to each of the six trials. During the experiment, the EEG data and band power at electrodes Cz, Fz, and Pz, as recorded by Epoc Flex; the time elapsed during each experiment trial; and the participants' time estimation results were collected. After each iteration of the jigsaw game, each participant was required to complete a verbal NASA-TLX questionnaire.

In the pilot study, unlike the main study, I asked each participant about their experience and for their opinion on the experimental design. All participants indicated that the number of jigsaw puzzle pieces was somewhat high and they were likely to experience fatigue and frustration during or after the second block. The participant who played 72 pieces mentioned that he felt the stuffiness due to the VR headset while playing the 72-piece trial. Secondly, two of the participants pointed out the pictures of the jigsaw puzzles affected the task complexity; that is, some pictures might increase the complexity, but other pictures might make the game much easier.

The experimental design was optimized on the basis of the problems revealed during the pilot study. In the main study, the picture of the jigsaw puzzle was better controlled by applying a grey picture to all trials, so the impact of different pictures on the results was eliminated. Only two levels of task complexity were maintained instead of the original three, and the number of the pieces was reduced to 8 and 18 to control participants' fatigue and limit the overall time duration of the experiment. In order to obtain sufficient data and investigate the effects of the blocks as another independent variable, each task complexity level was repeated three times in the main study.

4.2 DESCRIPTIVE STATISTICS

Table 4.1 summarize the descriptive statistics of the behavioral response (i.e. time estimation error), subjective response (i.e., NASA-TLX score), and physiological responses (i.e., the maximum EEG amplitudes and the maximum high beta-band power at Cz, Fz, and Pz) under the low and high task complexity conditions. Participants had a trend of overestimating the time when they conducted both the low and high complexity tasks, but the high task complexity condition showed greater time estimation errors than the low task complexity condition. Also, the NASA-TLX scores, the maximum EEG amplitudes, and the maximum high beta-band power at Cz, Fz, and Pz were greater in the high task complexity condition.

Table 4.1. Descriptive statistics of the measurements

Response	**Low task complexity**		**High task complexity**	
	Mean (SD)	**95% CI**	**Mean (SD)**	**95% CI**
Behavioral				
Time estimation error	9.05 (25.29)	[3.66, 14.44]	27.38 (68.72)	[12.73, 42.03]
Subjective				
NASA-TLX score	3.35 (2.06)	[2.91, 3.79]	5.56 (2.46)	[5.04, 6.08]
Physiological				
Maximum EEG amplitude at Cz	81.59 (64.91)	[65.52, 97.67]	116.15 (93.75)	[93.63, 138.67]
Maximum EEG amplitude at Fz	109.29 (86.77)	[90.68, 127.89]	162.34 (200.30)	[118.88, 205.81]
Maximum EEG amplitude at Pz	137.39 (119.14)	[109.79, 164.99]	188.19 (137.52)	[156.10, 220.27]
Maximum high beta-band power at Cz	0.53 (0.44)	[0.42, 0.63]	0.76 (0.64)	[0.61, 0.92]

Maximum high beta-band power at Fz	0.71 (0.66)	[0.57, 0.85]	0.95 (0.81)	[0.77, 1.12]
Maximum high beta-band power at Pz	1.19 (0.58)	[1.06, 1.32]	1.53 (0.72)	[1.36, 1.70]

4.3 THE EFFECTS OF TASK COMPLEXITY ON DEPENDENT VARIABLES

A repeated-measures analysis of variance (ANOVA) that considered the influence of the two dependent variables, task complexity, and block sequence, on each measurement of participants' responses was conducted in the study.

4.3.1 *Time Estimation Error*

The significant effect of task complexity on time estimation error is shown in Table 4.2. It suggests that though participants overestimated the time in both conditions, the higher the level of task complexity was, the larger the time estimation errors made by the participants. Figure 4.1 is the interaction plot of the two independent variables with the time estimation error as the dependent variable, the slope of the straight lines is the visualization of the interaction effect, and the error bars denote the standard errors. The plot also presents a positive relationship between time estimation error and task complexity. However, there was no evidence that the sequence of blocks significantly affected the participants' time estimation errors. This may suggest that the familiarity of the task did not affect the participants' time estimation results. According to both the ANOVA table and the interaction plot, there was no significant main effect for the interactions between task complexity and block sequence on the time estimation error results.

Table 4.2. The repeated-measures ANOVA with time estimation error

Source	**Df**	**SS**	**MS**	**F**	**p**
Task complexity	1	14621	14621	5.74	0.02*
Block sequence	1	9217	9217	3.62	0.06
Task complexity × Block sequence	1	916	916	0.36	0.55

$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

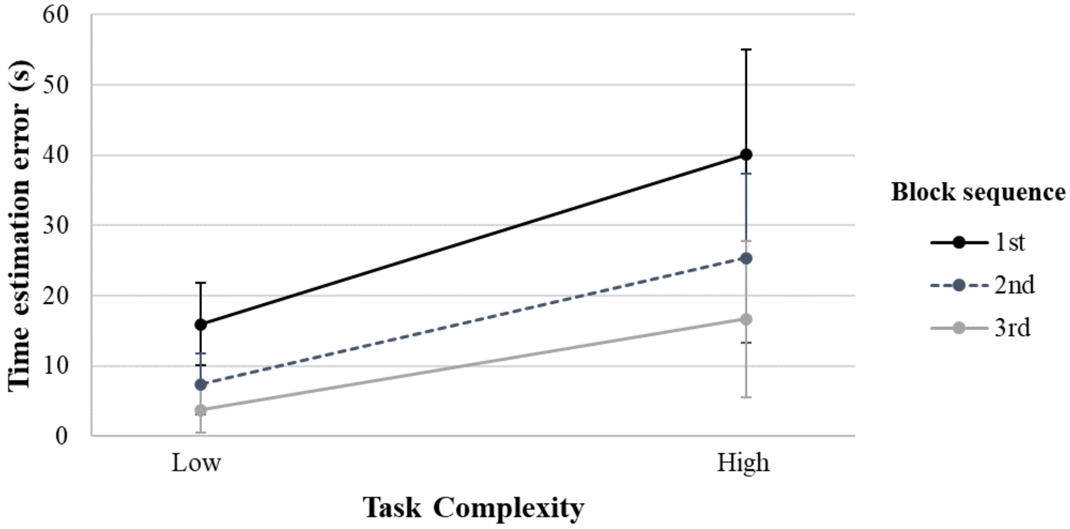

Figure 4.1. The interaction plot with time estimation error as dependent variable (Error bars denote standard errors)

4.3.2 *Subjective Mental Workload*

Table 4.3 shows that there was a significant effect of task complexity on the NASA-TLX score. As the level of task complexity increased, a higher NASA-TLX score, that is, a higher workload was perceived by the participants, as shown in Figure 4.2. The sequence of blocks also significantly impacted the NASA-TLX results. Figure 4.2 presents a negative trend of NASA-TLX score from the first block to the third block. It demonstrates that, for each level of complexity, as the participants performed the task more times, the subjective workload evaluation score dropped. It indicates the participants became familiar with the task, as well as the VRE, over time. In order to identify between which pair of the blocks the difference occurred, I conducted a post-hoc analysis of the three levels of block sequences using Fisher's Least Significant Difference (LSD). The post-hoc analysis results show significant differences existed between all three pair comparisons—i.e., the first and second block, the first and third block, and the second and the third block.

Table 4.3. The repeated-measures ANOVA with NASA-TLX score

Source	**Df**	**SS**	**MS**	**F**	**p**
Task complexity	1	212.41	212.41	50.55	<0.001***
Block sequence	1	126.84	126.84	30.18	<0.001***
Task complexity × Block sequence	1	17.85	17.85	4.25	0.04*

**p < 0.05, **p < 0.01, ***p < 0.001*

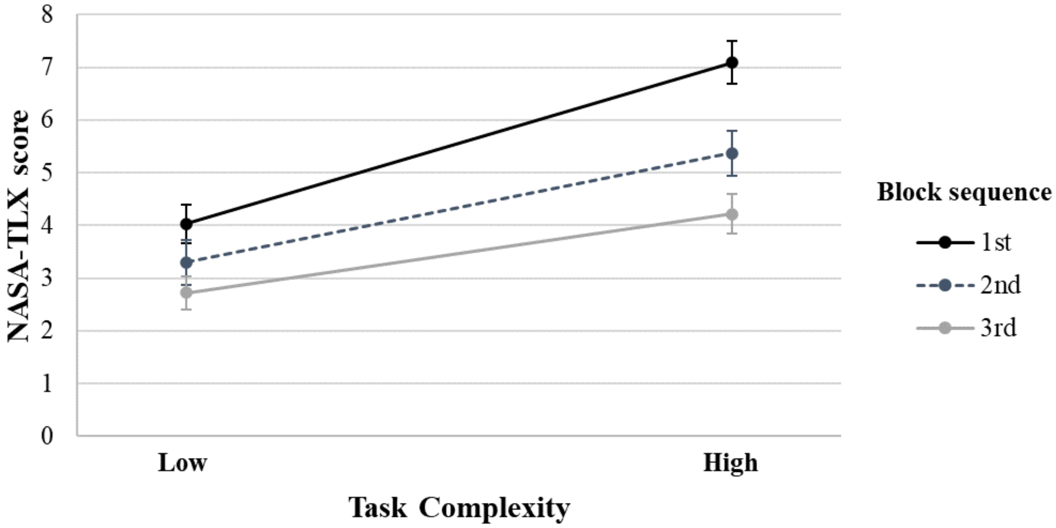

Figure 4.2. The interaction plot with NASA-TLX score as dependent variable
(Error bars denote standard errors)

4.3.3 *Maximum EEG Amplitudes*

I observed a significant effect of task complexity on the maximum EEG amplitudes at Cz, Fz, and Pz. That is, EEG activities at the three electrodes had larger maximum amplitudes in the high task complexity condition rather than in the low task complexity condition. The results of the ANOVA are reported in Table 4.4, Table 4.5, and Table 4.6. The block sequence had no significant effect on the results. In other words, the participants' familiarity with the task had no statistical impact on the maximum EEG amplitudes. Similarly, no interaction effect between block sequence and task complexity was found. The interaction plots with the maximum EEG amplitudes at Cz, Fz, and Pz as dependent variables are shown in Figure 4.3, Figure 4.4, and Figure 4.5.

Table 4.4. The repeated-measures ANOVA with maximum EEG amplitude at Cz

Source	**Df**	**SS**	**MS**	**F**	**p**
Task complexity	1	42282	42282	6.29	0.01*
Block sequence	1	2839	2839	0.42	0.52
Task complexity × Block sequence	1	37	37	0.01	0.94

**p < 0.05, **p < 0.01, ***p < 0.001*

Table 4.5. The repeated-measures ANOVA with maximum EEG amplitude at Fz

Source	**Df**	**SS**	**MS**	**F**	**p**
Task complexity	1	119750	119750	5.03	0.03*
Block sequence	1	31684	31684	1.33	0.25
Task complexity × Block sequence	1	12813	12813	0.54	0.46

**p < 0.05, **p < 0.01, ***p < 0.001*

Table 4.6. The repeated-measures ANOVA with maximum EEG amplitude at Pz

Source	**Df**	**SS**	**MS**	**F**	**p**
Task complexity	1	97625	97625	6.12	0.01*
Block sequence	1	1053	1053	0.07	0.80
Task complexity × Block sequence	1	5958	5958	0.37	0.54

**p < 0.05, **p < 0.01, ***p < 0.001*

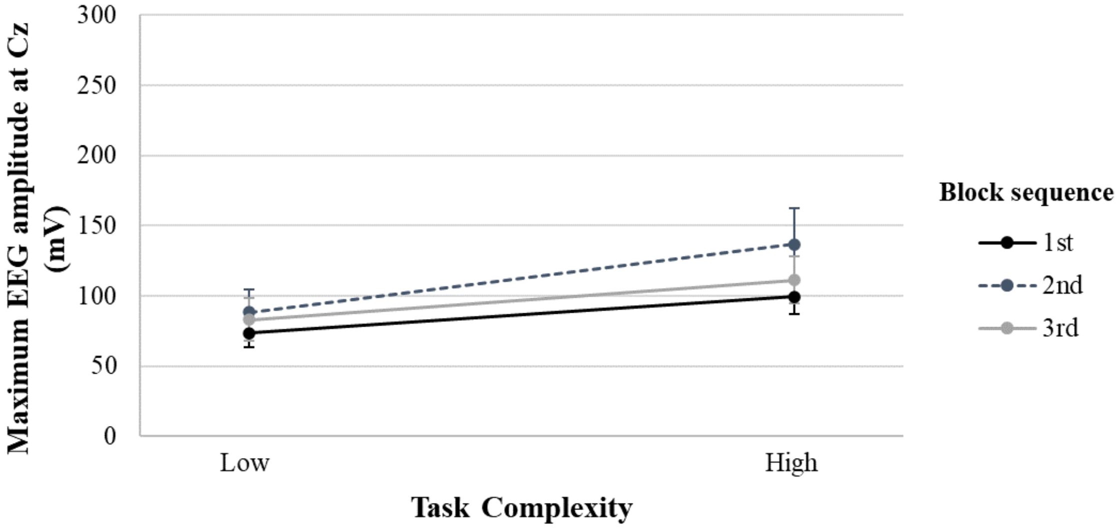

Figure 4.3. The interaction plot with maximum EEG amplitude at Cz as dependent variable (Error bars denote standard errors)

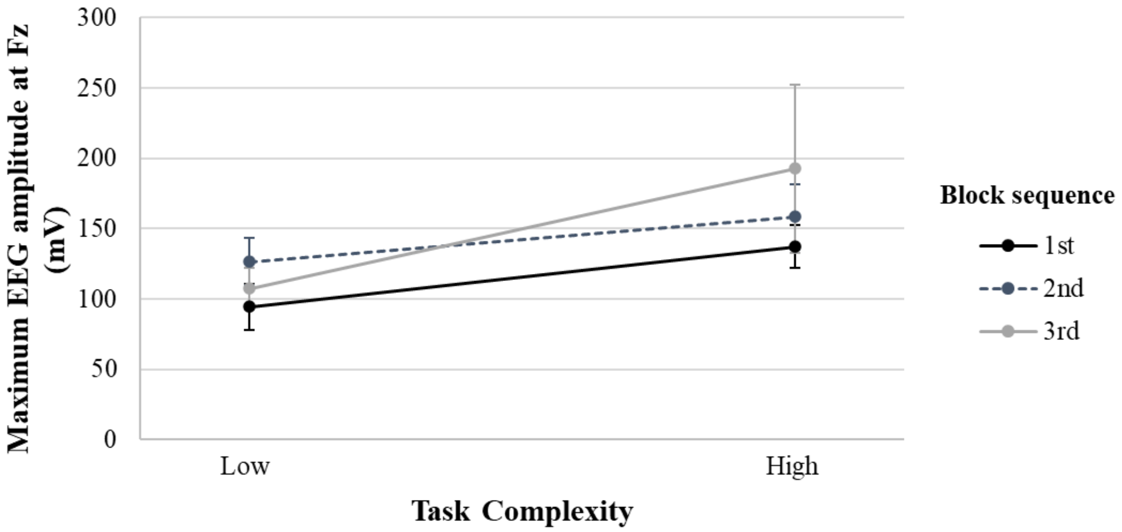

Figure 4.4. The interaction plot with maximum EEG amplitude at Fz as dependent variable (Error bars denote standard errors)

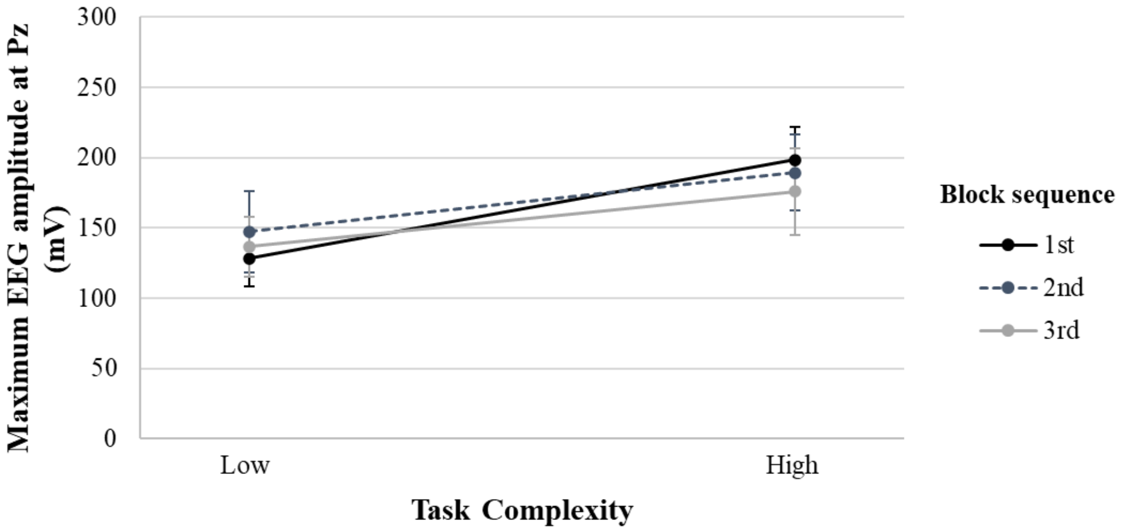

Figure 4.5. The interaction plot with maximum EEG amplitude at Pz as dependent variable (Error bars denote standard errors)

4.3.4 *Maximum Band Power*

In addition to EEG amplitude data, the maximum high beta-band power of the Cz, Fz, and Pz electrodes were considered in the study. A significant effect of task complexity on the maximum power of high beta-band was observed at the three electrodes. The maximum high beta-band power of Cz, Fz and Pz increased with an increase in task complexity. Finally, the block sequence presented no significant results, indicating that task familiarity did not affect the maximum high beta-band power. The results are shown in Table 4.7, Table 4.8, and Table 4.9. The interaction plots with maximum high beta-band power at Cz, Fz and Pz are shown in Figure 4.6, Figure 4.7, and Figure 4.8.

Table 4.7. The repeated-measures ANOVA with the maximum high beta-band power at Cz

Source	**Df**	**SS**	**MS**	**F**	**p**
Task complexity	1	1.98	1.98	6.72	0.01*
Block sequence	1	0.03	0.03	0.10	0.75
Task complexity × Block sequence	1	0.00	0.00	0.00	0.96

**p < 0.05, **p < 0.01, ***p < 0.001*

Table 4.8. The repeated-measures ANOVA with the maximum high beta-band power at Fz

Source	**Df**	**SS**	**MS**	**F**	**p**
Task complexity	1	2.43	2.43	4.56	0.03*
Block sequence	1	0.03	0.03	0.05	0.83
Task complexity × Block sequence	1	0.10	0.10	0.18	0.67

**p < 0.05, **p < 0.01, ***p < 0.001*

Table 4.9. The repeated-measures ANOVA with the maximum high beta-band power at Pz

Source	**Df**	**SS**	**MS**	**F**	**p**
Task complexity	1	4.36	4.36	10.19	<0.01**
Block sequence	1	0.01	0.01	0.02	0.90
Task complexity × Block sequence	1	0.01	0.01	0.01	0.90

**p < 0.05, **p < 0.01, ***p < 0.001*

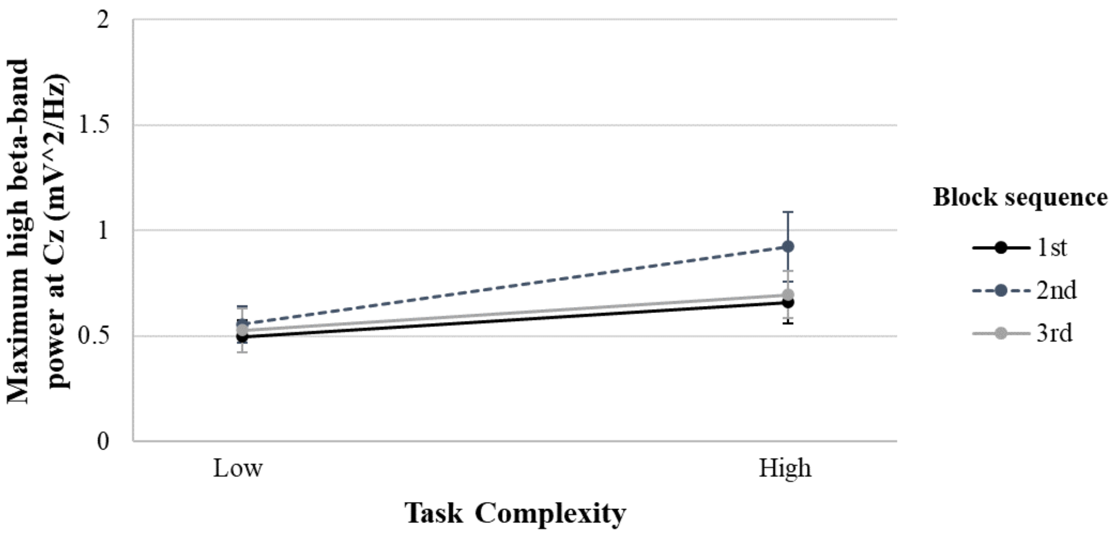

Figure 4.6. The interaction plot with maximum high beta-band power at Cz as dependent variable (Error bars denote standard errors)

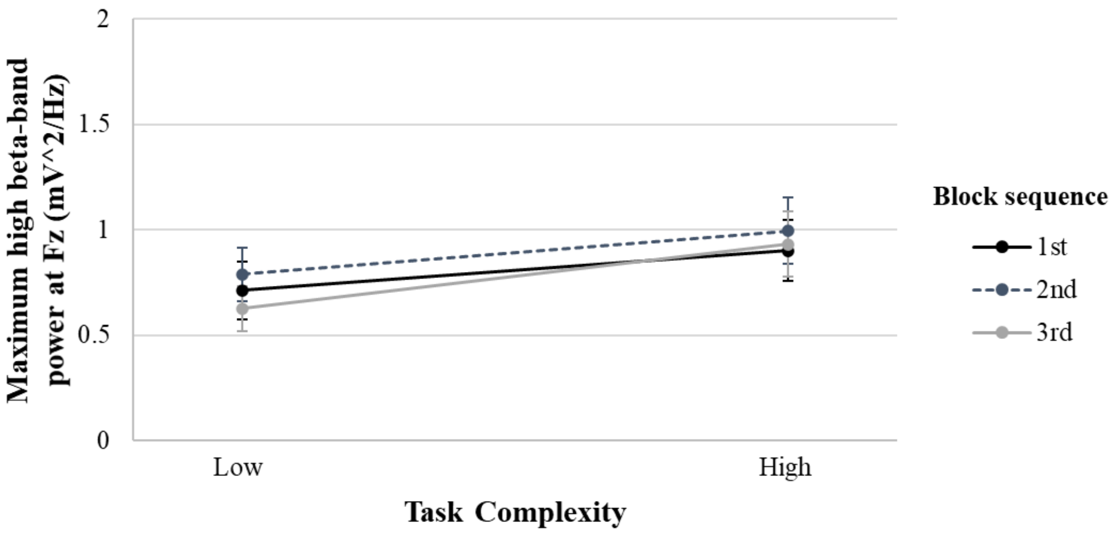

Figure 4.7. The interaction plot with maximum high beta-band power at Fz as dependent variable (Error bars denote standard errors)

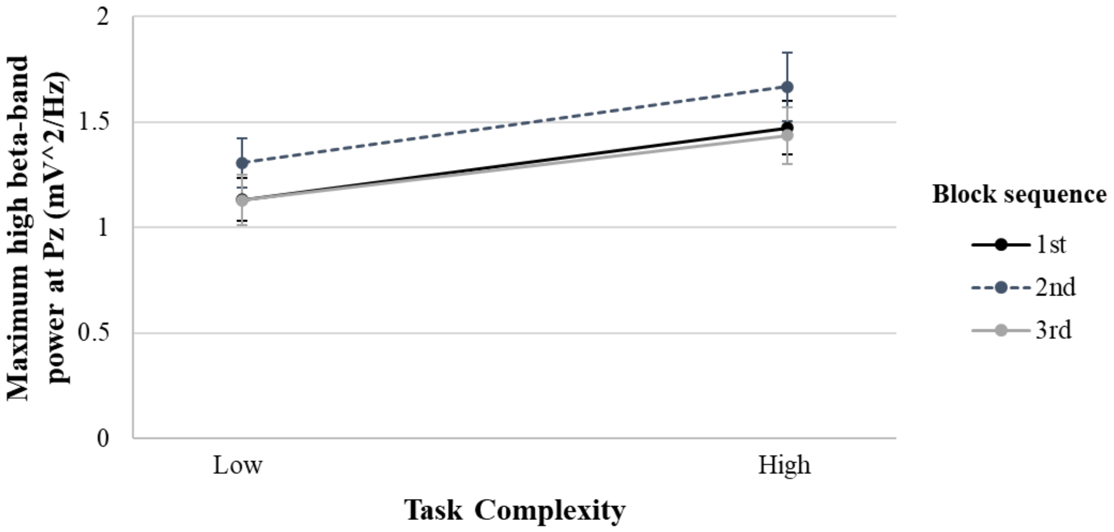

Figure 4.8. The interaction plot with maximum high beta-band power at Pz as dependent variable (Error bars denote standard errors)

4.4 CORRELATIONS AMONG TIME ESTIMATION ERRORS, BRAIN SIGNALS, AND SUBJECTIVE WORKLOAD EVALUATION

In order to investigate the relationships among dependent variables, the correlations among time estimation error, brain signals, and the NASA-TLX score were calculated using Pearson's correlation, as summarized in Table 4.10. In this study, I found strong correlations between NASA-TLX score and brain signals, including the maximum EEG amplitude at Cz and Pz, and the maximum high beta-band power at Cz, Fz, and Pz. The significant correlations between the brain signals and NASA-TLX score were positive, shown in Figure 4.11, Figure 4.12, Figure 4.11, Figure 4.12, and Figure 4.13. The red points present the individual data and the blue line in each figure represents the fitted line, and its slope suggests one dependent variable is positively associated with the other. Besides, I observed a significant correlation between the NASA-TLX score and time estimation error. These findings demonstrate the nature of the positive relationship among the variables.

Table 4.10. Correlation among dependent variables

Dependent Variable	**p**
Maximum EEG amplitude at Cz and time estimation error	0.30
Maximum EEG amplitude at Fz and time estimation error	0.50
Maximum EEG amplitude at Pz and time estimation error	0.22
Maximum high beta-band power at Cz and time estimation error	0.24
Maximum high beta-band power at Fz and time estimation error	0.21
Maximum high beta-band power at Pz and time estimation error	0.11
Maximum EEG amplitude at Cz and NASA-TLX score	0.02*
Maximum EEG amplitude at Fz and NASA-TLX score	0.57
Maximum EEG amplitude at Pz and NASA-TLX score	<0.001***
Maximum high beta-band power at Cz and NASA-TLX score	<0.001***
Maximum high beta-band power at Fz and NASA-TLX score	<0.001***
Maximum high beta-band power at Pz and NASA-TLX score	<0.001***
NASA TLX score and time estimation error	0.02*

$p < 0.05$, $**p < 0.01$, $***p < 0.001$

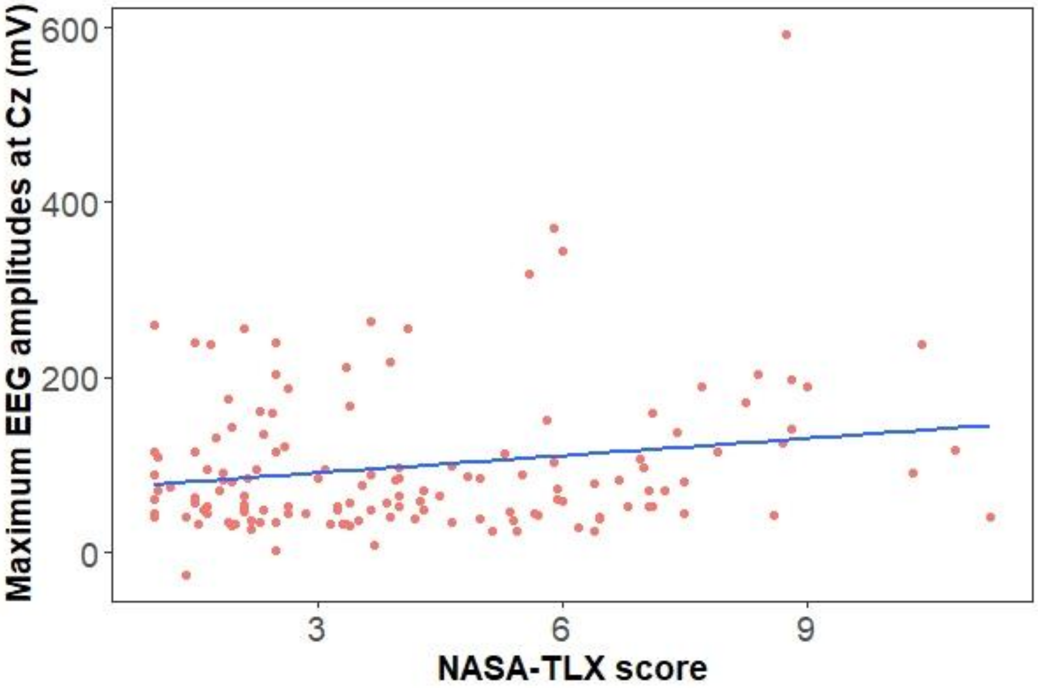

Figure 4.9. Correlation between maximum EEG amplitude at Cz and NASA-TLX score

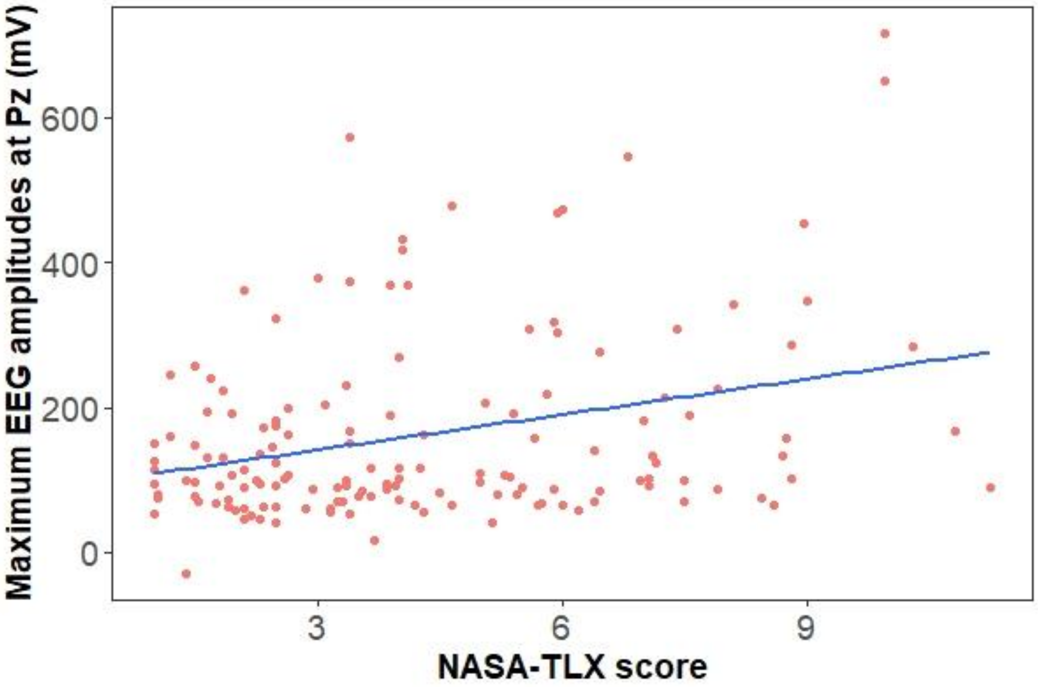

Figure 4.10. Correlation between maximum EEG amplitude at Pz and NASA-TLX score

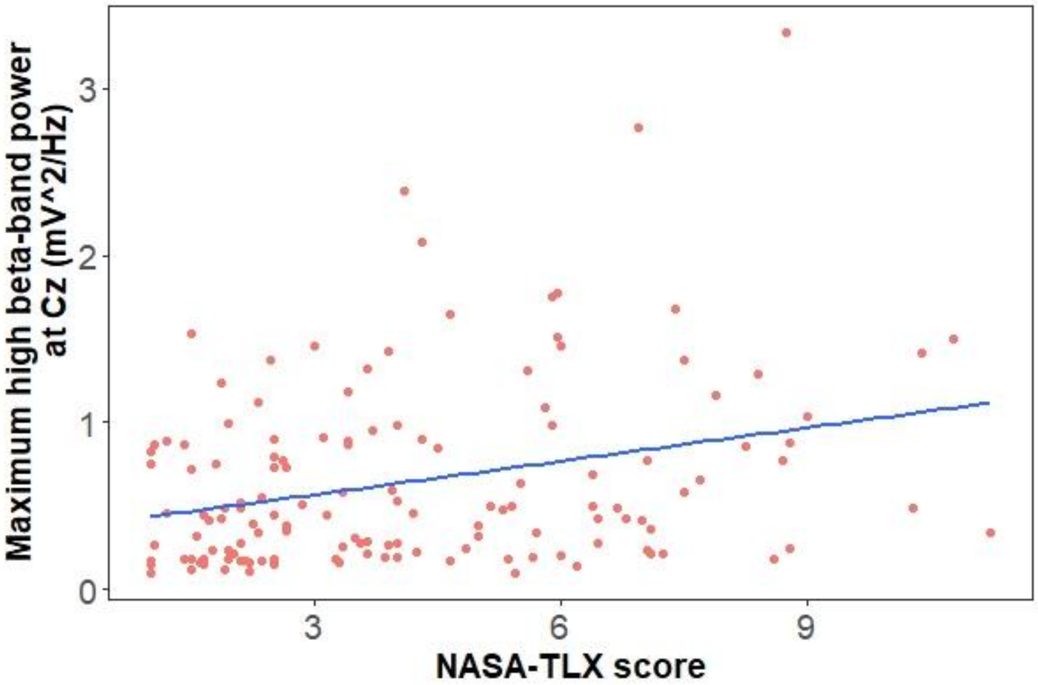

Figure 4.11. Correlation between maximum high beta-band power at Cz and NASA-TLX score

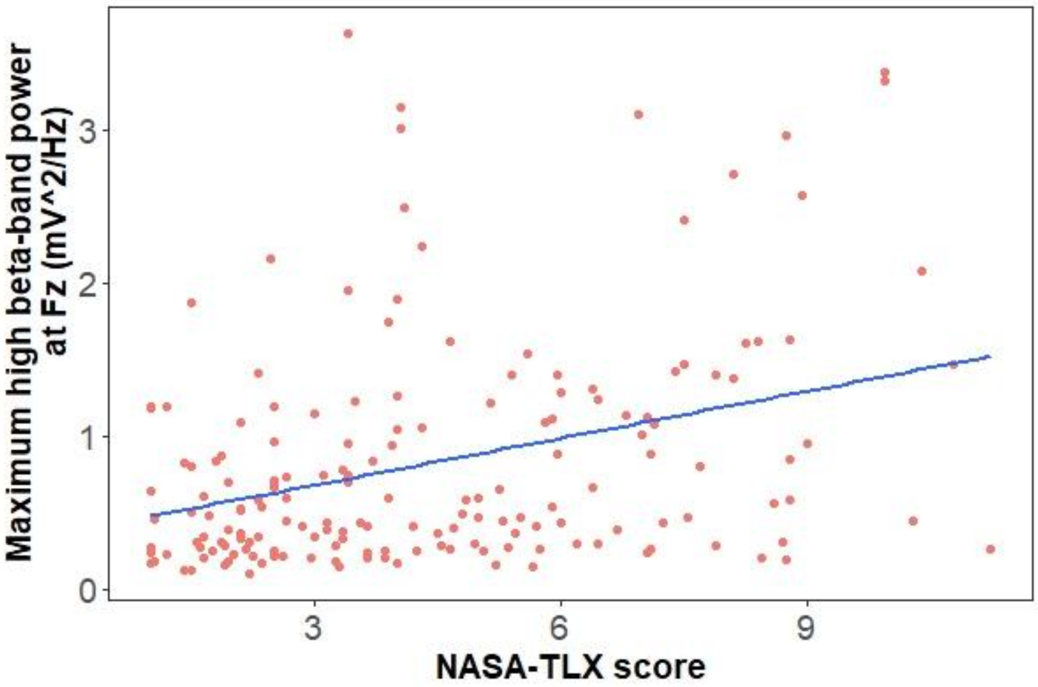

Figure 4.12. Correlation between maximum high beta-band power at Fz and NASA-TLX score

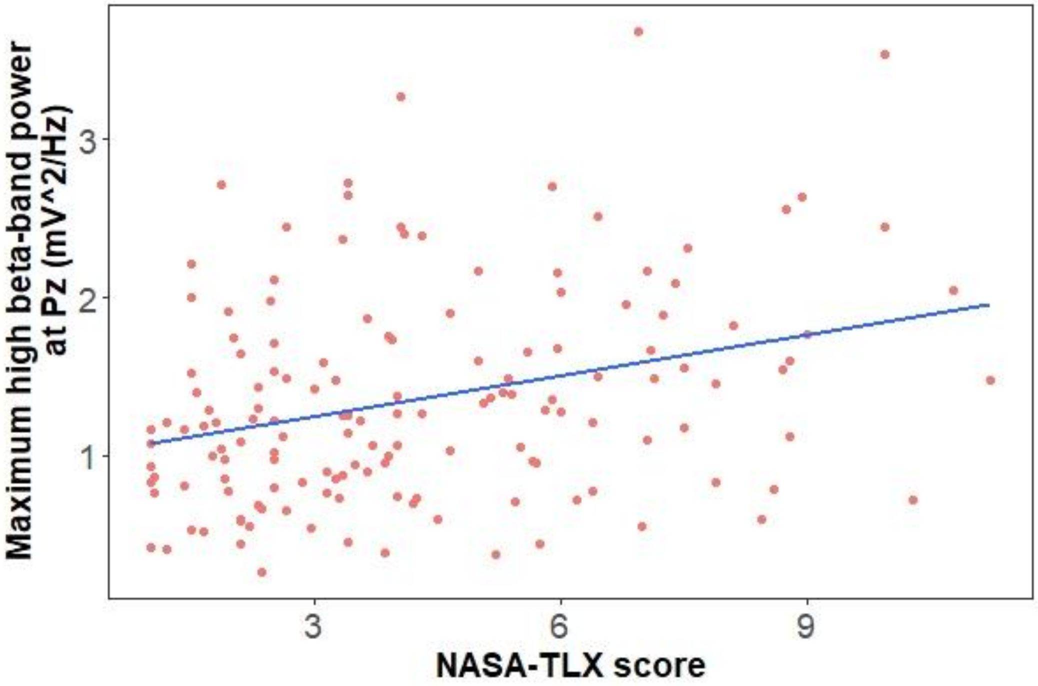

Figure 4.13. Correlation between maximum high beta-band power at Pz and NASA-TLX score

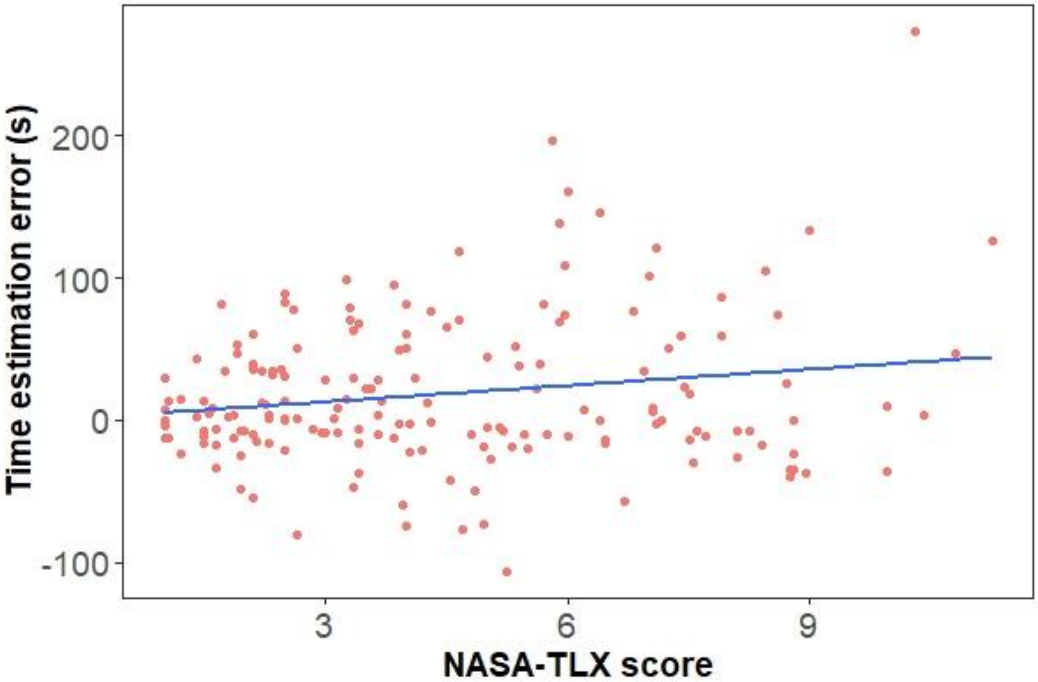

Figure 4.14. Correlation between time estimation error and NASA-TLX score

Chapter 5. DISCUSSION

In this study, I measured the impact of task complexity on time perception in the VRE. Time estimation error was observed to have an incremental trend as task complexity increases as expected. It could be explained that as the jigsaw task became harder, the participants tended to allocate more attention to the jigsaw puzzle and less attention to the time estimation, which may have led to a decreased time estimation accuracy. It is in accordance with the attentional model [12][32] that, a high-complexity task would demand more attentional resources, contributes to fewer available resources that could be allocated to time perception. The phenomenon could be interpreted by the internal clock model of time perception as well [14]. It is harder for an individual to estimate the elapsed time when a high workload task is distracting the person from estimating the time by continuously accumulating time units.

The distinction between the positive and negative values of time estimation error suggests that individuals are more likely to overestimate the elapsed time as the task complexity increases, which is consistent with several studies [33][34][35]. In other words, when an individual performs a challenging task, they may perceive the task to take more time than it actually does. According to the studies on the impact of time perception on satisfaction [21][22], if the individual feels that they are spending more time on a given task, it might decrease their enjoyment of the task and reduce the quality of the user experience. VR application designers should take this into account when designing task complexity levels.

The maximum EEG amplitudes and the maximum high beta-band power at Cz, Fz and Pz were found to be related to task complexity in this study. Larger maximum values were observed as the task complexity increased. This finding supports those of previous studies showing that brain activities become more intense as task complexity increases [41][42]. Beta-band power is known to be associated with visual stimuli and attentional tasks. The increased number of jigsaw puzzle pieces generated a higher demand for attention and visual discrimination, leading to an increase in high beta-band power. The trend in high beta-band power in our result is consistent with previous studies [43][44][45][47]. Since it’s hard to quantify how complex a task is, my result indicates the possibility of using EEG signals to assist task designers to compare the complexity between different tasks.

The significant correlation among the maximum EEG amplitude at Cz and Pz, the maximum high beta-band power at Cz, Fz, and Pz, and the NASA-TLX score revealed that certain brain signals tend to increase or decrease simultaneously with the subjective workload assessment in the VRE. The result corroborates the findings of Lecoutre and colleagues [54]. They observed significant correlations between EEG signals and NASA-TLX scores among participants playing a 2D video game, showing that the subjective workload evaluation results and physiological responses are consistent. The positive correlation between time estimation error and the NASA-TLX score in my study suggests that an individual’s time estimation error might reflect his or her subjective workload assessment. My findings demonstrate the possibility of using time estimation for workload assessment, providing support for the findings of previous studies [55][56].

The significant correlation results between time estimation error and the NASA-TLX score, and between the NASA-TLX score and brain signals show the potential for brain signals to be used as indicators of time estimation error. This mediating role of the NASA-TLX score could be tested using other types of statistical analyses that allow researchers to investigate multiple relationships at a time. For instance, structural equation modeling and factor analyses could be performed.

However, my study has several limitations. Firstly, the participants in this study may not fully represent the target group of VR applications. All of the participants in this study were college-aged young adults enrolled at the University of Washington. Future study may aim to recruit participants with different backgrounds, in aspects of age or educational background. Secondly, gender differences were not investigated in the research. Future research might consider the influence of gender on time perception in the VRE. Thirdly, this study employed a commercial VR game that provided near-natural visual stimuli that placed simultaneous physical and mental demands on the participants. Rather than manipulating workload tasks using simplified visual targets and backgrounds, such as the N-back task, the game better simulated real-life situations than the controlled experimental setting did [25]. However, the real-life simulation in this study may have included undetected factors that influenced the quality of EEG signals. Participants' body movements, the vibration of the VR controller, and the electrical interference between the VR HMD and the EEG headset may have influenced the EEG signals. To eliminate noise, further data filtering that compares EEG signals at baseline and during the experiment could be done. Likewise, instead of relying on EEG software, additional data processing techniques such as moving average and wavelet transform (WT) could be applied [57]. Fourthly, the statistical power of the analysis is 0.60, indicating a 40% probability of having Type II error in the result, which could be attributed to the small sample size. Moreover, to control the experiment time and acquire as much data as possible, I designed three blocks for the experiment. However, the design was unbalanced, meaning that the number of times that the low complexity level trial was the first trial in a block was not equal to the number of times that the high complexity level trial was. A more balanced design, such as 2 x 2 or 2 x 4 design, could be used. Finally, only three sensors were used in the experiment. In the future, data from electrodes other than Cz, Fz, and Pz might be analyzed to further investigate the connection between brain signals and time perception in the VRE.

Chapter 6. CONCLUSION

In this study, participants' time perception, brain signals, and subjective workload evaluations were investigated while the participants were performing jigsaw puzzle tasks at two levels of complexity in the VRE. Significant results were obtained to answer the three research questions. 1) Task complexity has a significant impact on time perception in the VRE. Individuals tend to overestimate the time, and the time estimation errors are increased with the task complexity. 2) Task complexity has a positive influence on the maximum EEG amplitudes and the maximum high beta-band power at Cz, Fz, and Pz. Higher task complexity leads to enhanced brain activities, embodied in the increment of the brain signals. 3) A strong correlation was found between the NASA-TLX score and the brain signals, implying the increments in maximum EEG amplitudes and the maximum high beta-band power at Cz, Fz and Pz are accompanied by an increased subjective workload evaluation result. Also, there was a significant correlation between the NASA-TLX score and the time estimation error.

Given the impact of time perception on reaction time, decision-making, and satisfaction, my findings demonstrate the importance of designing a modest task complexity level in the VRE. If this is not possible, VR designers should add a time indicator or other feedback mechanism to help users to estimate the time. The positive correlation result between the NASA-TLX score and time estimation error indicates a promising way for VR researchers to assess users' subjective workload under various conditions by obtaining their time estimation results in the VRE.

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