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Rime Elatlassi for the degree of Master of Science in Industrial Engineering presented on April 11, 2018

Title: Modeling Engagement in Online Learning Environments Using Real-Time Biometric Measures: Electroencephalography(EEG) and Eye-Tracking.

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David A Nembhard

Online learning, also known as e-learning, has become an increasingly popular and important component of higher education. Current literature indicates that higher education institutions rely on online learning to meet instructional loads and mitigate increasingly complex course scheduling problems. Students also find it more convenient to finish their college curricula without having to be physically present for traditional in-residence education. With the increasing popularity of distance learning, scholars are more and more concerned with the effectiveness of online technologies in delivering class material and learning outcomes. Specifically, current research seeks to measure the extent to which distance education students are engaged with online material. So far, research has measured student engagement predominantly through self-reporting instruments. However, the accuracy and comprehensiveness of these is debatable.

This study proposes to model student engagement in online environments using real-time biometric measures and using acuity, performance and motivation as dimensions of student engagement. Real-time biometrics are used to model acuity, performance and motivation include Electroencephalography (EEG) and eye-tracking measures. These biometrics have been measured in an experimental setting that simulates an online learning environment. The methodology uses a mixed model ANOVA to investigate whether biometric measures can be used to predict student engagement. Results suggest that eye-tracking and EEG measures can be used to predict acuity, performance and motivation, dimensions of student engagement.

Key words: Online Learning, E-learning, Electroencephalography (EEG), Eye-Tracking, Real-Time Online Engagement

Modeling Engagement in Online Learning Environments Using Real-Time Biometric Measures: Electroencephalography (EEG) and Eye-Tracking.

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Rime Elatlassi

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APPROVED:

Major Professor, representing Industrial Engineering

Head of the School of Mechanical, Industrial, and Manufacturing Engineering

Dean of the Graduate School

I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Rime Elatlassi, Author

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CHAPTER 1: INTRODUCTION

1.1 Background

In the last few decades, online education has become one of the most important pillars of education in the United States and the world in general. Online education, defined as a course(s) offering instructional content exclusively through distance education, gives students the opportunity to take a course(s) anywhere and everywhere (Allen & Seaman, 2016). Because of that, online education enrollment continues to grow. For example, the number of students enrolled in at least one online course increased from 3.7% in 2013 to 3.9% in 2014 while the number of students not taking any online courses continues to drop every year (Allen & Seaman, 2016).

In addition to the convenience, that online education has to offer to students, online education does also offer a number of benefits to educational institutions as well. In fact, it has been reported by literature that traditional educational institutions use online courses in order to meet demand, offer more sections and solve problems such as scheduling and classroom space shortages (Allen & Seaman, 2016).

In addition to courses that offer their entire content exclusively through an online platform, other on-campus classes do still use online platforms to facilitate some of their learning objectives (Wang & Hsu, 2014). Table 1.1 offers a definition of course classifications based on their usage of online platforms as a delivery method (Allen & Seaman, 2016).

Table 1.1 Table describing course classification based on delivery method (adapted from (Allen & Seaman, 2016))

% of Course, Content Delivered through an Online Platform	Course Classification	Description
0%	Traditional	No usage of any online technology. All content is delivered face to face.
1%-29%	Web Facilitated	Course may use a learning management system (LMS) to post items such as syllabi or grades.
30%-79%	Hybrid	Course uses both online and face-to-face delivery where an important percentage of the content is delivered online. Face-to-face classroom time may also be reduced in this case.
>79%	Online	Most or all content is delivered online.

With the convenience and financial benefits that online education offers, an important question is raised: does online education offer comparable quality to face-to-face education? It has been recognized in literature that it is extremely hard, if not impossible, to answer this question as there are no established standards and agreed upon metrics that professionals can use to compare face-to-face and online education (Allen & Seaman, 2016). However, it has been recognized in literature that chief academic officers consider student engagement as a very important metric to consider when comparing online education to face-to-face education (Allen & Seaman, 2016; Rashid & Asghar, \2016).

1.2 Online Learning and Engagement

There is an ongoing debate in literature on whether technology and online platforms positively, negatively or neutrally affect student engagement in online education. On the one hand, some research findings advocate for the belief that the use of online platforms during online education disrupts the learning process and that "digital engagement" is not suitable for education purposes (Mulder, 2016).

However, on the other hand, other research findings indicate that online education increases student achievements (higher GPAs) and direct engagement (interaction with faculty and peers) (Hwang, Wu, Chen, & Tu, 2016). In addition to that, other research outcomes show that knowledge retention in online education is higher than face-to-face education; therefore, student engagement in online education must be higher than student engagement in face-to-face education (Rashid & Asghar, 2016).

In other studies, it was reported that student participation was higher in online education; therefore, the same studies conclude that student engagement must be higher in online education than face-to-face education (Rashid & Asghar, 2016).

1.3 Problem Statement

The problem that current research is struggling with when investigating the topic of student engagement in online education is first, the lack of a clear definition that defines and limits the broad concept of student engagement. Second, because of the absence of a clear definition of what student engagement exactly means, there is also no clear consensus on how to measure student engagement. In some studies, student engagement is measured through metrics such as GPA or class participation. In other studies, student engagement in online education is measured through self-report instruments (Ewell, 2010).

The question that is currently being raised in literature is: are these metrics (GPA, class participation, self-report) valid to measure student engagement? The problem with using metrics such as GPA or class participation is that such measures are one-sided and discriminatory and do not take in consideration other metrics that may be as important when talking about student engagement in online education. Similarly, the problem when using self-report instruments to measure student engagement is their subjectivity and inaccuracy, and therefore inability to measure a complex phenomenon such as student engagement (Wilson & Sasse, 2000). Finally, none of these measures is a real-time measure, but rather tries to capture student online engagement at a later time (typically, after completing a class or an assignment).

In this study, we aim to use real-time biometric measures to model engagement in online learning environments. Based on the reviewed literature, we recognize that engagement has been defined to be composed of several dimensions. Dissimilar terminologies have been used to refer to every composing dimension of student engagement (Christenson, Reschly, & Wylie, 2012; Finn & Zimmer, 2012). In this study, we use acuity, performance and motivation to refer to the three composing dimensions of student engagement in online learning environments.

1.4 Using Biometric Measures to Capture Engagement

1.4.1 Electroencephalography (EEG)

Electroencephalography (EEG) is a signal depiction of micro voltage difference between two cerebral positions plotted over time (Olejniczak, 2006). EEG signals resulting from cerebral neurons are recorded at the scalp through conductive electrodes. To get any detectable EEG signals, it is necessary to have at least 108 neurons generating simultaneous electrical activity as well as a minimum surface area of $6cm^2$ (Henry, 2006).

EEG can be recorded through either wired or wireless headsets. In this study, a wireless headset was used in order to make participants more comfortable and reduce any discomfort. The headset used in this study is the wireless Emotiv Insight EEG headset (figure 1.1). This headset records raw EEG data through five electrodes that are recognized in the 10-20 system as the following positions: AF3, AF4, Pz, T7, and T8 (Herwig, Satrapi, & Schönfeldt-Lecuona, 2003).

Figure 1.1 Emotiv Insight Electroencephalogram

1.4.1.1. Gap Description

EEG has been used in order to understand various human behaviors such as sleep, affective workload, epilepsy and other behaviors. In educational contexts, research has tried to monitor how EEG signals reflect students' mental workload, attention, and reaction to positive and negative feedback (Sun, 2014). In online contexts, previous research has tried to monitor EEG signals behavior when participants were exposed to different online platform designs. However, in general there has been no previous attempts to model student engagement in an online education setting using EEG measures, specifically real-time EEG measures. The aim of this study is to identify EEG measures that are significant to student engagement in online learning, then model student engagement using significant EEG measures.

1.4.2 Eye-Tracking Movements

Eye-tracking is a technique that measures and records eye movements such as saccades, fixations or blinks (Poole & Ball, 2006). Eye tracking techniques aim at helping researchers determine when and where a participant is looking in order to get insights on visual-based information (Rayner, 1998).

Eye-tracking technology has been extensively used in the domain of interface-evaluation in order to determine the efficiency and effectiveness of website design (Poole & Ball, 2006). Additionally, eye-tracking technology has been used in order to gain insights about participants' emotions: for instance, pupil measures has been used to get insights on participants arousal (Bradley, Miccoli, Escrig, & Lang, 2008), gaze maps has been used to understand user preferences in terms of design (Isaacowitz, Wadlinger, Goren, & Wilson, 2006) and fixation durations has been used in order to capture participants' reactions to increasing mental workload (Hendriks, 1996).

1.4.2.1 Gap Description

Eye-tracking technology has been used in an online education context in order to understand certain cognitive and affective states, such as anxiety and relaxation, that students experience when interacting with online material, watching video lectures or taking online quizzes (Poole & Ball, 2006). In addition, gaze maps have been used in order to understand how online class design can be more efficient. However, there has been limited focus on understanding student engagement in online settings through eye-tracking measures. Nor was there any attempt to model student engagement using real-time eye-tracking measures. The aim of this study is to identify eye-tracking measures that may be significant to online student engagement then model student engagement using real-time eye-tracking measures.

1.3 Organization of the Thesis

This study aims at modeling online engagement using real-time biometric measures of EEG and eye tracking. Specifically, we identify two specific research tasks:

1. Determine whether biometric measures are significant to model online engagement.
2. Construct a predictive model of online engagement using real-time biometric measures.

In order to model biometrically model student engagement, two biometric measures were taken into consideration: eye-tracking data and electroencephalography (EEG) measures.

The rest of this study goes as follows: Chapter 2 presents a review of relevant literature. Specifically, Chapter 2 reviews relevant literature that defines engagement, eye-tracking movements and its relevance to engagement and electroencephalography and its relevance to measure engagement.

Chapter 3 explains the methodology that was followed in this study. It describes the experimental factor of this study, the design of the experiment, data collection process, as well as the methods used to analyze data and obtain the desired engagement measurement.

Chapter 4 discusses results obtained in this study. Chapter 5 is a discussion of the previous chapter and the implications of obtained results. In addition to that, the same chapter discusses future research implications of this study.

CHAPTER 2: LITERATURE REVIEW

This chapter presents a summary of relevant literature; specifically, this chapter reviews previous literature to provide a definition of student engagement and the use of biometric measures to capture student engagement and related affective and mental states. Finally, this chapter discusses the efficacy of using self-report instruments in measuring student engagement.

2.1 Theoretical Background

Engagement in online settings has been diversely defined by previous research. Attfield, Kazai, Lalmas, & Piwowarski (2011) defined user engagement in online settings as a combination of emotional, cognitive, and behavioral interaction between the user and an online source. Although this definition is holistic, including various factors contributing towards user engagement, it is broad and difficult to measure. This definition is also open to defining both a onetime user engagement with one source and a long-term relationship between a user and online source. Thus, Attfield et al decorticated user engagement to three main aspects: emotional/affective, cognitive and academic.

In addition to that, (Attfield et al., 2011) also underlined the following characteristics that are associated with user engagement while interacting with an online source:

<u>Focused Attention:</u> When engaged, a user would solely focus attention towards the source he/she is engaged with and exclude any other distractions/ interactions (O'Brien & Toms, 2008). This also means that the engaged user would start adopting a subjective perception of time. In other words, a user would have a biased perception of time depending on how engaged he/she is. Time spent interacting with certain material or sources has also been proved, in previous research, to be an effective indicator of

cognitive engagement. In video games contexts, time spent interacting with a certain game was used as an indicative parameter of players' engagement with the game (Baldauf, Burgard, & Wittmann, 2009).

Positive Affect: Positive affect refers to the type emotions that an engaged user would experience when interacting with an online source. In other words, for a user to be engaged with an online source, intrinsic motivating emotions must be experienced by the user (O'Brien & Toms, 2008) (Jennings, 2000). An example of such affective emotions can include a desire to learn more and explore the online source the user is interacting with or a high level of emotional involvement with the online source.

Endurability: Users tend to remember experiences they were engaged with. Endurability refers to the ability of the user to remember material he/she interacted with as well as user's willingness to interact with the same material again or recommend that experience to other users (O'Brien & Toms, 2010).

User context: User engagement is context dependent; therefore, observing user engagement only through performance would not be sufficient (Law, Roto, Hassenzahl, Vermeeren, & Kort, 2009). Aspects that can affect user engagement can be, but are not limited to personal preferences, likability, personality traits and orientations. Research however is still not able to fully answer how different characteristics might be more or less significant to online users' engagement.

Engagement has also been defined within the video gaming field in various terminologies such as flow, immersion, involvement, attention or cognitive absorption. Immersion has been defined as a progressive experience where all surrounding distractions are gradually being ignored (Nacke, Stellmach, & Lindley, 2011). Definitions of all previously mentioned terminologies (flow, immersion, involvement, attention and cognitive absorption) agree that indications of an engaged user consists of the following: subjective perception of time and discount of outside surrounding distractions. In addition to that, the same literature agrees that users are generally more engaged with tasks that tend to challenge their knowledge or capabilities (Agarwal & Karahanna, 2000; Brown & Cairns, 2004; Jennett et al., 2008; Nacke et al., 2011). Furthermore, it has also been noticed that various definitions of engagement in literature partially or completely overlap while no clear boundaries that definitively distinguish engagement from other similar concepts has been established (Nacke et al., 2011).

2.2 Why Engagement?

The topic of engagement has strongly emerged in previous research as it was found that engagement was strongly related to learning performances. More specifically, previous studies have investigated the performances of highly engaged students in various settings: in online learning settings, in group learning settings, and cooperative learning settings (Admiraal, Huizenga, Akkerman, & Ten Dam, 2011; Raphael, Bachen, & Hernández-Ramos, 2012; Van Schaik, Martin, & Vallance, 2012). It was also proven that highly engaged learners were often associated with higher learning satisfaction (Joo, Lim, & Park, 2011). Even more than that, high engagement was proven to lead to optimal learning and achievements (Egbert, 2004). In online learning environments specifically, it was also proven that engagement was a strong mediator and predictor of class satisfaction (Shin, 2006).

2.2.1 Dimensions of Student Engagement

In recent years, different models of engagement have emerged. Different models use different terminologies, which makes comparison very difficult (Finn & Zimmer, 2012), however all models seem to encompass the following dimensions when modeling engagement: academic engagement, emotional/ affective engagement and cognitive engagement.

Academic engagement refers to student completion of tasks assigned and attentiveness during the learning process. According to literature, there is a minimum threshold of academic engagement needed to help students with the learning process (Finn & Zimmer, 2012). Research has also showed that behaviors such as time spent on task, asking questions, and persistence can all be indicative of academic engagement.

Emotional/affective engagement refers to the extent to which a student is interested in course material and having either a positive or a negative affective interaction with the tasks and material assigned. Research has shown that emotional/affective engagement is an important moderator between academic engagement and student performances (Finn & Zimmer, 2012). Affective engagement in some contexts in literature also refers to the emotional inclusion that a student feels when interacting with certain classes and subjects. Students that are positively affectively engaged are usually behaviorally incentivized to participate and persist with class material (Finn & Zimmer, 2012).

Cognitive engagement refers to a student’s cognitive and mental abilities of students. It is recognized in literature that cognitive engagement is a function of the brain but also in some contexts, an investment of thoughtful energy in order to understand class material and complex concepts. Research has also shown a positive correlation between cognitive engagement and student performance (Finn & Zimmer, 2012).

In this research, we are referring to academic engagement dimension as performance, emotional/affective dimension as motivation and cognitive dimension as acuity. This research will aim at modeling online engagement using biometric measures. More specifically, this research aims at modeling the three composing dimensions of student engagement (acuity, performance and motivation) using real-time Electroencephalography (EEG) and eye-tracking measures.

2.3. Academic Inclination and Student Engagement

Academic inclination and student engagement are two terms that are often used simultaneously and appear to puzzlingly mean the same concept (Finn & Zimmer, 2012). In fact, both terminologies have been interchangeably used in the National Research Council book *Engaging Schools (2004) (*Council, 2004). In the same book, academic inclination and academic motivation has been defined as the strong desire of a student to succeed in general and in certain class tasks in particular (Council, 2004).

Motivation theories claim that academic inclination is usually sourced from an inner drive to meet the individual's psychological needs (Connell & Wellborn, 1991; Maslow, 1970; McClelland, 1985). Engagement theories, on the other hand, more specifically affective engagement theories, describe engagement as a pattern of actions resulting from external motivators and becoming gradually internalized (Finn & Zimmer, 2012).

2.4 Measuring Student Engagement through Biometric Measures

Assessing user's engagement while performing a task was usually an experience that was measured at the end of the task by assessing user's performances in completing the assigned task. At other times, user's engagement was measured also at the end of the assigned task, but this time through self-report instruments.

However, measuring user's biometric measures in order to assess user's performances has the advantage of allowing researchers to gain a real-time understanding of user's engagement, which was not possible with the previously discussed methodologies (Ikehara & Crosby, 2005). In addition to gaining real time understanding of user's engagement and general behavior, biometric data does allow researchers to assess the affective dimension of user interaction with the assigned task (Ikehara & Crosby, 2005).

2.4.1. Eye-Tracking

Several researches have tried to understand online users' behaviors by monitoring their ocular indices (Granka, Joachims, & Gay, 2004). Previous research was particularly interested in understanding what the user was viewing, for how long, and in what order. In such research, key variables that were included to gain a better understanding of online user' behaviors are fixations, saccades, pupil dilation, and the use of scan paths (Rayner, 1998). Previous research has also noted that eye movement behaviors are different when the reading or browsing task was silent versus aloud (Holmes & O'Regan, 1981; Rayner, 1998). The review presented in this section is factual for silent reading.

When reading, looking at a scene, or even searching for a specific target, a subject will continually make eye movements called saccades (Rayner, 1998). Saccades are rapid eye movements with certain velocities that can go as high as 500 degrees per second (Rayner, 1998). A saccade would typically takes 20 to 50 millisecond to complete (Reichle, Rayner, & Pollatsek, 2003).

During saccades, input from the visual field is reduced due to a phenomenon called saccadic suppression (Matin, 1974; Rayner, 1998) and no visual information is retained during saccades (Ishida & Ikeda, 1989; Wolverton & Zola, 1983). Therefore, no new information is obtained during saccades because eye movement is so rapid that no significant information is actually perceived and processed (Rayner, 1998; Uttal & Smith, 1968).

The duration of a saccade is usually influenced by the size and distance of the area covered. In average, during a reading task, it takes 30 milliseconds to cover a 2 degrees saccade and 40-50 milliseconds to cover a 5 degrees saccade (Abrams, Meyer, & Kornblum, 1989; Rayner, 1998).

Previous research attempted to answer whether cognitive activity is suspended during saccades. Some research findings suggest that for simple tasks, some cognitive activities are interrupted(Rayner, 1998); however, other research findings suggest that during more complex tasks, like reading, lexical processing is not interrupted during saccades(Irwin, 1998).

It is also important to distinguish between saccades and other eye movements such as pursuit, vergence or vestibular. More specifically, pursuit eye movements are much slower than saccades and are following a certain moving target. If the target is moving much faster than the pursuit eye movements, then the human eye may switch to saccades in that case (White, 1976).

Vergence is when movements from both eyes goes inward in order to fixate on a target (Rayner, 1998). Vestibular is when eye movements try to compensate for head and eye movement in order to maintain a certain position (Rayner, 1998). Although pursuit, vergence, and vestibular are very important eye movements, saccades have been proved to be more interrelated to information processing tasks (Collewijn, Erkelens, & Steinman, 1988; Hendriks, 1996; Rayner, 1998).

In addition to that, when analyzing saccades, it is also important to consider the phenomenon of saccade latency. Saccade latency has been proven to be at least 150 milliseconds to 175 milliseconds long (Abrams & Jonides, 1988; Rayner, Slowiaczek, Clifton, & Bertera, 1983; Salthouse & Ellis, 1980; Salthouse, Ellis, Diener, & Somberg, 1981).

Fixations are defined as stable gazes that last anywhere between 200 milliseconds and 250 milliseconds (Rayner, 1998) when reading in English. However, even if researchers define fixations as "stable gazes," eyes are never actually perfectly settled because of constant involuntary movements called nystagmus. It is also not completely clear to researchers why such involuntary movements occur. An example of such involuntary movements are drifts and micro-saccades. Most researchers experimenting with reading tasks consider such involuntary movements noise (Rayner, 1998).

Previous research has found that as a text becomes more difficult, fixation durations increase (Jacobson & Dodwell, 1979; Rayner, Pollatsek, Ashby, & Clifton Jr, 2012). An example of such findings is a study that revealed that participants exhibited longer fixation times when reading sentences with transposed letters versus when reading sentences with normal spelling (Rayner, White, & Liversedge, 2006).

It is also important to note that there is a considerable amount of variation in saccade and fixation time (Reichle et al., 2003). For instance, some saccades would be as large as 15 characters (especially or after regression where the reader is coming back to read a previous line). In the same way, fixation durations are also variant and can sometimes exceed the average time, as previously mentioned. This variability in saccade and fixation total time is mainly due to the difficulty of information processing associated with the task that the person is reading (Reichle et al., 2003).

Pupillometry, a technique measuring user's pupil dilation, has been proven a very promising approach that can give considerable insights about a subject's interest and engagement when interacting with a web source (Oliveira, Aula, & Russell, 2009). However, although eye-tracking movements in general have been widely researched in order to assess user's mental and cognitive states, it has been recognized in literature that pupil size has received much less attention (Oliveira et al., 2009).

Research that has considered pupil size as an indicative variable of user's engagement states that pupil size varies in response to different cognitive, affective and mental states. Specifically, measures of pupil size has been proven an objective biometric measure of user interest and engagement（Aula & Surakka, 2002; Hess & Polt, 1960; Iqbal, Zheng, & Bailey, 2004). Increases in pupil size are found to suggest emotionally interesting and engaging visual stimuli (Hess & Polt, 1960).

To confirm the previously stated finding, in a study carried out on twenty-two participants, researchers asked participants to browse through different shopping sites. Results of this study have shown that sites that were relevant to participants shopping interests elicited increased pupil size (Oliveira et al., 2009).

Research findings confirming the correlation between pupil size and user's engagement has been used to design smart adaptive systems. For instance, a previous research aimed at developing an attention managing system that would allow notifications to show on a computer screen only when users are not highly engaged with any task. To do that, the same research investigated how pupil size correlates with user's engagement when working on a computer. Results showed that pupil size correlated well with user's attention, engagement with the ongoing task, as well as the difficulty (mental workload) of the task. More specifically, pupil size increased as attention, engagement with task and mental workload increased (Iqbal et al., 2004).

In addition to the previous findings confirming the correlation between pupil size and user's engagement, other research findings showed an additional correlation between pupil size and user's affective states. For instance, a study asked forty participants to complete short mathematical questions. After that, participants received either a positive, negative, or a neutral feedback. Results show that different emotions resulting from different type of feedback elicited significant variance in pupil size. Specifically, results showed that pupil size increased significantly more during positive and negative feedback than during neutral feedback (Aula & Surakka, 2002)

Table 2.1 demonstrates how some eye-tracking measures have the potential capability to predict certain cognitive states that the user is experiencing such as anxiety, relaxation, interest or engagement (Ikehara & Crosby, 2005).

Table 2.1 Eye-tracking measures and their potential cognitive connotations.

Eye-Tracking Measures	Cognitive Connotations
Gaze Position, Fixation Duration, Search Patterns	Task difficulty, Anxiety, Relaxation(Andreassi, 2013; Ikehara & Crosby, 2005; Sheldon, 2001)
Pupil Size, Blink Rate, Blink Duration	Task difficulty, Positive/Negative Affective State, Interest, Arousal, Engagement, Mental Effort, Information Processing Speed (Andreassi, 2013; Ikehara & Crosby, 2005; Sheldon, 2001)

It is also necessary to mention that the eye-tracking measures mentioned in table 2.1 are a good predictor of the cognitive states mentioned in the same table only for fixed images (Ikehara & Crosby, 2005). Extracting connotations from eye-tracking measures for moving targets would likely lead to different outcomes.

2.4.1.1 Positive and Negative Factors of Eye-Tracking Sensors

Although eye-tracking data offers a great connotations about the user's cognitive and affective states such as relaxation, anxiety, interest or engagement, eye-tracking data is not able to provide researchers with any information during rest periods when no visual targets are evaluated(Ikehara & Crosby, 2005). In addition to that, pupil size measurements are dramatically impacted by the surrounding environment, the intensity of light and brightness of the target viewed (Ikehara & Crosby, 2005).

2.4.1.2 When and Where to Move Next?

There are two different eye movement activities that research tried to explain: 1) what determines *where* the eyes move during a reading task? 2) What determines *when* the eyes move? Answers to these questions are controversial and there is no one clear answer or consensus to each of the previously stated questions (Reichle et al., 2003). However, there is some evidence that is worth mentioning:

First, there is evidence in research that both activities, that is when and where eyes are moving, are made independently (Rayner & McConkie, 1976; Reichle et al., 2003). In fact, Rayner and Pollatsek (1981) ran two different experiments where they varied the outward aspect of text and found out that the manipulation of the appearance of the text affected saccade durations in the first experiment while fixation durations were not affected. However, in the second experiment, saccade durations were stable but fixation durations were affected (Pollatsek, Bolozky, Well, & Rayner, 1981). Therefore, it was reasonable to deduct from this first evidence that when to move eyes and where to fixate were two independent decisions (Pollatsek et al., 1981; Reichle et al., 2003). However, although it was proven that these two decisions (when and where to move eyes) are independent, it has also been proven that these two decisions can sometimes overlap (Rayner, Kambe, & Duffy, 2000).

2.4.2 Electroencephalography Technology

Electroencephalography (EEG) is a psychological method that has been used as a tool to measure affective states in various applications (Wang & Hsu, 2014). In various cases, different research explored the possibility and effectiveness of using inexpensive non-medical EEG headsets. Results have proven that such commercial headsets effectively measured the affective states of participants (Wang & Hsu, 2014).

EEG is a process where brainwave activity is recorded and has been used in several computer-brain studies to measure the relationship between mental processes and tasks participants were exposed to (Nunez & Srinivasan, 2006; Wang & Hsu, 2014). In this research, EEG measures were described as a "window to brain." EEG measures are recorded by measuring electrical activity through small electrodes that are distributed on the scalp (Nacke et al., 2011; Wang & Hsu, 2014)

EEG has been used to investigate a variety of topics such as sleep disorders, epilepsy, and hyperactivity disorders. Other research focused on using EEG activity to control robots or other outside objects. Additional research used EEG measures to design user-friendly computer interfaces and game environments or even to understand user's behavior in order to develop suitable marketing strategies (Ariely & Berns, 2010; Wolpaw, Birbaumer, McFarland, Pfurtscheller, & Vaughan, 2002). (Clarke et al., 2011; Dupuy, Barry, Clarke, McCarthy, & Selikowitz, 2013; Gola, Magnuski, Szumska, & Wróbel, 2013; Kupfer, Foster, Coble, McPartland, & Ulrich, 1978; Ogrim, Kropotov, & Hestad, 2012; Shi et al., 2012)

Research has been investigating four EEG frequency bands and their potential capability of exhibiting human's affective and cognitive state: theta band (4Hz-8Hz), delta band (0.5Hz-4Hz), alpha (8Hz-13Hz) and beta band (13Hz-30Hz). Theta band has been linked throughout literature to arousal and interest. Delta band has been proven to be linked to sleep and memory workload, alpha band gives indications about mental workload and stress levels, and finally beta group reflects body movements (Penny, Roberts, & Stokes, 1998; Rabbi et al., 2009; Teplan, 2002; Zarjam, Epps, & Chen, 2011)

In addition to the investigation of EEG frequency bands, research is also investigating the role of every lobe in the brain and its functionality (Karnath, Ferber, & Himmelbach, 2001; Perrone-Bertolotti et al., 2015; Petrides, 1994; Price et al., 1994). Studies interested in determining functionalities of every lobe used 3-D brain imaging to detect activated lobes during various tasks such as reading, listening to music or memorizing words (Perrone-Bertolotti et al., 2015). It has been found that the right frontal lobe is linked to functions such as self-awareness, concentration and continued attention. The left frontal lobe however was linked to functions such as habitual responses and reactions to unusual situations. The left frontal lobe was also shown to be linked to word fluency and shown important when verbal communication is involved (Petrides, 1994). Besides research investigating frontal lobes and their functionalities, research has also investigated the functionalities of the temporal lobes (Perrone-Bertolotti et al., 2015). In fact, studies have shown that the right temporal lobe is responsible for a number of functionalities such as nonverbal memory such as memorizing pictures, visuals or routes and directions (Perrone-Bertolotti et al., 2015). The right temporal lobe has also been shown to be linked to nonverbal communication, sound location, and musical awareness (Perrone-

Bertolotti et al., 2015). Left temporal lobe was shown according to research to be responsible for processing verbal memories, speaking functionalities and information retrieval and processing (Price et al., 1994). Finally, the parietal lobe has been linked according to research to various kinds of perception such as vision, hearing and sensing (Karnath et al., 2001)

Various statistical methods have been used in order to analyze EEG recorded data such as Fast Fourier Transform (FFT), Short Time Fourier Transform (STFT); however, there is no consensus on one optimal and efficient method to analyze EEG signals (Nacke et al., 2011; Rabbi et al., 2009). In addition to that, most research focuses on analyzing raw EEG signals or build models based on EEG raw data.

2.4.2.1 Electroencephalography and Engagement

Although EEG has been widely known as a “window to the brain” as it allows research to get an objective assessment of cognitive, mental, and affective workload of the human brain, research specifically investigating EEG as a tool to measure user’s engagement has not been extensively investigated yet. Specifically, research investigating EEG as measurement of user’s engagement when interacting with an online source or student engagement interacting with online educational material is very scarce. Nonetheless, some studies and results will be discussed in this section.

The existing body of literature suggests that there is a strong correlation between theta frequency band and user’s engagement. For instance, a study conducted to investigate affective ludology, an area of research interested in measuring physiological responses of players when interacting with video games, immersion and engagement were measured while 25 participants were playing video games. Participants in this study were asked to rate their favorite and least favorite games. EEG signals were recorded and results showed that theta band was significantly higher when participants were highly engaged with the game (Nacke et al., 2011). Additional results confirming previous findings come from another study that attempted to investigate the potential differences in EEG between two populations: an adult attention-deficit and hyperactivity disorder (AD/HD) population and a normal population that has never been diagnosed with AD/HD. Thirty-eight participants engaged in a series of tasks while their EEG signals were recorded. Results suggest that AD/HD participants showed a relatively lower frontal theta activity compared to participants that have never been diagnosed with AD/HD. Results of this study suggest that there is a high correlation between theta activity band and engagement (Clarke et al., 2011).

In addition to the evidence presented above about the correlation between theta band activity and engagement, other studies have shown evidence about the positive correlation between beta band activity and engagement. An example of such evidence is a study conducted on 35 participants that were asked to determine whether a visual target was present in a certain matrix. Results of this study suggested that activity in beta band increases prior to correct answers, whereas wrong answers were always proceeded by lower beta band activity. Results of this study suggest that the detection of low beta activity prior to low performances indicates difficulty in sustaining engagement (Gola et al., 2013).

Besides the previous research findings finding correlations between brain waves and different cognitive states, research has also investigated brain lobes involved in certain cognitive states related to engagement . Functional anatomy research proved that left frontal lobe is activated in word tasks where participants were asked to identify similar and contradictory words (Price et al., 1994). In addition to that, Left temporal lobes were proved to be activated during silent and loud reading and were shown in research to be responsible for visual word processing (Price et al., 1994). In other research studies where participants were asked to memorize certain stimuli, researchers were able to detect activity in temporal lobes (Perrone-Bertolotti et al., 2015). Besides, other research that investigated participants' ability to respond to certain stimuli that they were exposed to for the first time were able to notice activity in the left frontal lobe (Petrides, 1994) while activity in the right frontal lobe was attribute to attention and concentration with the task (Petrides, 1994). Parietal lobe, on the other hand was associated with sensing tasks that were given to participants (Karnath et al., 2001). Finally, it is important to also note that there are not enough findings associating one or more lobes with engagement in general or student engagement specifically.

In this research, an Emotiv Insight headset was used. The headset contains five electrodes: AF3, AF4, T7, T8 and Pz. AF3 electrode is located on the left frontal lobe, AF4 electrode is located on the frontal right lobe, T8 is located on the temporal right lobe, and T7 is located on the temporal left lobe. Finally, Pz is located on the parietal lobe. Given the functional anatomy research and its findings that were able to associate every lobe with certain functions, we will refer in this research to every electrode with the function of the lobe it is located on. Specifically, we will refer to every electrode as summarized in table 2.2:

Table 2.2 Table associating every EEG electrode with its locating lobe and function.

Electrode	Lobe	Function
AF3	Frontal left lobe	Verbalized communication
AF4	Frontal right lobe	Sustained attention
T7	Temporal left lobe	Emotional memory
T8	Temporal right lobe	Verbal memory
Pz	Parietal lobe	General perception

Therefore, given results presented in table 2.2, in the rest of this study we will refer to every electrode as presented in table 2.3

Table 2.3 Summary electrode designation to be used in the rest of this study.

Electrode	Designation
AF3	Verbalized communication(AF3)
AF4	Sustained attention(AF4)
T7	Emotional memory(T7)
T8	Verbal memory(T8)
Pz	General perception(Pz)

In summary, the revised body of literature suggests that there are possible correlations between various brain waves, brain lobes and activities that are relate to engagement such as problem solving, word recognition and memory tasks.

2.5 Wonderlic Personal Test (WPT)

Wonderlic Personal Test (1992) (WPT) is a test that aims at measuring one's general cognitive ability (Furnham, Forde, & Cotter, 1998). It is also defined as a personal mental ability test that measures general intelligence and general knowledge (Furnham, Monsen, & Ahmetoglu, 2009). It is a 50-question test where participants are timed and required to complete as many questions as possible in a time frame of 12 minutes.

WPT aims at measuring general intelligence and mental abilities; it allows participants to move from one question to the next on their own pace. Scores for WPT range from 0 to 50 as participants are able to score one point for every correct answer.

Questions included in the WPT are short formatted and include verbal, analogical, and logical questions. All questions are either multiple choice or text entry type of questions. (Furnham et al., 1998). The validity of WPT has been well established in literature (Bell, Matthews, Lassiter, & Leverett, 2002; Matthews & Lassiter, 2007). The body of literature reviewed confirms the validity of WPT. An example is a study conducted on 37 college students that took the WPT. The study shows that WPT scores of the student population strongly correlated with the crystallized intelligence as measured by the Cattell-Horn theory of intelligence, and of the components of general intelligence according to the same theory (Horn & Cattell, 1966; Matthews & Lassiter, 2007). Another example is a study where 67 adults took both the WPT and the Kaufman Intelligence Test (Bell et al., 2002; Kaufman & Kaufman, 1993). Results of this study demonstrated a strong correlation (0.54 to 0.66) between WPT scores and the Kauffman Intelligence Test. It is also worth mentioning that the Kauffman Intelligence Test is also built upon the Cattell-Horn theory of intelligence (Matthews & Lassiter, 2007).

2.5.1 Wonderlic Personal Test and Engagement

Previous research has investigated the correlation between human cognitive abilities and ability to engage in various experiencing. Literature reports that research findings have been able to find promising indications that cognitive abilities are positively correlated with engagement abilities. An example from the existing body of literature is a study conducted on 579 undergraduate students investigated the potential relationship between participants' intelligence and engagement. Engagement in this research has been defined as a deep desire to understand the material participants were interacting with. Low engagement was referred to as surface learning (Von Stumm & Furnham, 2012). Using structural equation models, this research proved a strong association between highly engaged participants and their measured intelligence. The same study has also proved a negative association between surface learning (low engagement) and participants' intelligence (Von Stumm & Furnham, 2012). In addition to the previously mentioned study, other studies confirm the previously discussed findings (Furnham, Swami, Arteche, & Chamorro-Premuzic, 2008(Furnham et al., 2009)

In addition to the previous example extracted from relevant literature showing a positive correlation between engagement and cognitive abilities, other similar studies confirm previous findings. For instance, a study conducted on 101 undergraduate students found that there is a positive correlation between participants' cognitive abilities and participants' engagement (Furnham, Swami, Arteche, & Chamorro-Premuzic, 2008). Additional evidence of the positive correlation between cognitive abilities and user's engagement comes from a study that asked participants to take the Typical Intellectual Scale, a test measuring student engagement in classroom settings. The same study has asked the 212 participants to also take the WPT. Results suggest that there is a strong correlation between the WPT scores and the Typical Intellectual Engagement Scale scores. In addition to that, the same study proved that the WPT and engagement scores were good predictors of students' performances. In fact, the WPT and the Typical Intellectual Engagement Scale scores were able to predict school exam performances six months later (Furnham et al., 2009).

2.6 Self- Report Instruments

One way to try to capture user's engagement is to ask participants to rate their experience and how engaged the person felt through questionnaires and self-reporting surveys. This methodology however is problematic as it is a subjective self-assessment and may not be comprehensively mirroring one's engagement experience and mental state. It has also been noted in literature that self-reporting may also be subject to varying contextual factors (Oliveira et al., 2009).

Additionally, the literature suggests that users participating in various satisfaction questionnaires and other self-report instruments are not always able to accurately report their experience (G. M. Wilson & Sasse, 2000). For instance, a study conducted on 25 participants investigated whether users would notice the difference between high quality videos and low-quality videos. In order to do that, participants were asked to watch two interviews where one was a ‘high quality’ video and the other was a very low quality video. Physiological measurements were measured in order to assess the difficulty/ease participants experienced when watching every video. In parallel, participants were also asked to self-report their perception of the video quality. Results showed that although physiological measurements suggest that participants had more difficulty watching the low quality video, only 16% of participants were able to explicitly report the difference between both videos (G. M. Wilson & Sasse, 2000).

In addition to that, it has also been reported in literature that self-reporting is highly impacted by contextual factors and therefore, users answering self-reporting instruments are usually not just reporting an objective assessment of the material they have been exposed to but are also reporting their affective and cognitive experience as well (G. M. Wilson & Sasse, 2000). This last statement is specifically more relevant when users are interacting with an online source, which is considered a complex environment as it involves so many variables such as content being displayed, brightness, fonts and size, audio quality, speed of display and other variables. This medium’s complexity does not allow users to objectively self-report their affective and cognitive states when interacting with a complex environment and is usually referred to as “mosaic blocking effect” (Gili Manzanaro, Janez Escalada, Hernandez Lioreda, & Szymanski, 1991).

2.6.1 Self-Report Instruments and Engagement

The National Survey of Student Engagement (NSSE) is a U.S. survey that attempts to measure student engagement in order to identify “best learning practices” (Ewell, 2010). The survey was first administered in 2000 and began by targeting 840 institutions. The survey is administered by an independent organization based in Indiana. As a result of administering NSSE for some years, the same institutions generated a publication that aimed at providing students with the best practices to succeed in college, “Seven Principles of Good Practice in Undergraduate Education” (Kuh, 2001).

While the literature discusses the metrics and distribution of the NSSE, other issues about the accountability of student responses are also discussed. In fact, the authors of the survey recognize that although the test is psychometrically validated, it is very hard to make sure that all students’ responses are true and unbiased. They also recognize that the survey does not measure student engagement in real-time, but rather measures a accumulation of how students feel engaged in certain courses (Kuh, 2001).

Australia’s Student Course Experience Questionnaire (SCEQ) is a questionnaire that is used in all graduate level institutions in Australia as a measure of student performances, learning, and engagement with courses as well as a standard to measure different institutions’ performances (K. L. Wilson, Lizzio, & Ramsden, 1997). It was first developed in 1980 in Lancaster University. The same survey is also increasingly used in U.K. graduate level institutions. In addition, SCEQ has been validated as a valid instrument to measure student course satisfaction and engagement (Ramsden, 1991).

In the same fashion that responses to NSSE were judged to be uncertain, responses from graduate students on the SCEQ are also weak and criticized (K. L. Wilson et al., 1997). This is because students’ responses in their nature are subjective, cumulative, and inaccurate. As with NSSE, SCEQ is unable to measure a real-time student engagement, but rather measures a accumulation of student engagement that may also be influenced by a great extent of contextual events.

2.6.2 Self-Report Instruments and Sensing Terminology

In this a study, a self-report instrument was developed in order to capture participants' overall impressions and affective experience with the material assigned. The terminology used in this self-report instrument was extracted from relevant sentiment recognition and analysis literature (Hollenstein, Amsler, Bachmann, & Klenner, 2014; Kim & Hovy, 2004). The verbs used in the self-report instrument (think, feel, find and believe) were extracted from the sensing recognition literature and proven to detect opinions in positive, negative and neutral contexts (Hollenstein et al., 2014). The self-report instrument is composed of a positive and negative pole where the negative pole of the self-report instrument is mirroring the positive part. This is to ensure the reliability and validity of the self-report instrument (Scazufca, Menezes, Vallada, & Araya, 2009). In addition, the self-report instrument is using a seven-scaled Likert scale (Jamieson, 2004). More details about the used self-report instruments are shown in the next chapter.

2.7 Mood Induction Techniques

As the study of cognitive mental and affective states has recently flourished, a new need to induce certain emotions in a laboratory setting has emerged. Eliciting certain emotions through self-instructional procedures is not new and has been first introduced in 1968 (Velten Jr, 1968). However, this last self-instructional instrument is no more effective as it is not using contemporaneous language. A new study has proposed a brief, effective and modern self-instructional procedure to induce various emotions.

A neutral mood induction instrument (Seibert & Ellis, 1991)(See Appendix A) has been used in this study prior to the start of EEG and eye-tracking recordings. The neutral mood induction instrument has been used to bring participants to a neutral emotional state. This would help bring all participants to a relatively similar mental and affective state and would limit variations due to personal emotional states that are not related to this study.

2.7 Summary and Motivating Question

The literature discussed previously suggests that there is enough evidence that both EEG and eye-tracking have the potential to measure various affective and metal states, including real-time online engagement. EEG beta and theta bands have demonstrated a great potential to measure engagement in general as well as real-time online engagement. In addition to that, fixation durations and pupil dilation sizes have also been proven indicative of real-time online engagement. It has also been shown through the literature discussed that eye-tracking measures have also been very relevant in online learning contexts. The same literature also suggests that there is a relationship between participants' engagement abilities and cognitive abilities. These can be measured through the WPT.

After reviewing the discussed literature, we have been able to develop the following motivating question: Can real-time online engagement be predicted through Electroencephalography (EEG) and eye-tracking measures?

CHAPTER 3: METHODOLOGY

This chapter details the methodology followed to predict the three dimensions of real-time online engagement: acuity, performance and motivation. Specifically, this chapter details the objectives of this study as well as the details of the experiment procedure, apparatus used in this experiment, the data collection process, and the statistics extracted from data collected as well as the analysis methodology.

3.1 Objectives

This study was designed to explore how to use biometric measures to predict real-time online engagement. As mentioned in the previous chapter, it was concluded that real-time online engagement is composed of the following three dimensions: 1) acuity; 2) performance; 3) motivation.

Therefore, this study aims at building: 1) a model to biometrically predict the acuity dimension; 2) a model to biometrically predict the performance dimension; 3) a model to biometrically predict the motivation dimension. Biometric measures used to predict real-time online engagement are electroencephalography (EEG) and eye-tracking signals. In addition to the biometric measures, time-on-task (time that the participant *chooses* to spend interacting with the stimulus) was also used to predict dimensions of real-time online engagement.

EEG data collected and explored as a potential predictor of real-time online engagement was collected through the following five channels: AF3, AF4, T7, T8 and Pz. Eye-tracking data collected and explored as a potential predictor of real-time online engagement include pupil dilation and fixation duration.

In order to predict the acuity dimension of real-time online engagement, participants were asked to take the Wonderlic Personal Test (WPT) to measure each participant's general cognitive abilities.

In order to predict the performance dimension of real-time online engagement, participants' performances interacting with the stimulus were measures. In fact, participants were asked to complete several reading tasks (stimulus), and then asked to complete comprehension tasks related to the reading tasks they just were exposed to. Participants' performances in completing the comprehension questions were captured.

In order to predict the motivation dimension of real-time online engagement, participants were asked to complete a self-report instrument after completing their assigned reading tasks. The self-report instrument aimed at measuring the participants' interaction with the reading task they were exposed to by capturing participants' feedback about their level of engagement, interest, intrigue, appeal and interest.

3.2 Experimental Design

To investigate the possibility of using biometrics to measure real-time online engagement, a one-factor experiment was designed with an elicited engagement factor of two different levels: high elicited engagement and low elicited engagement as shown in table 2.1. Electroencephalography (EEG), eye-tracking, and time-on-task were the responses that were collected in order to measure real-time online engagement.

Table 3.1 Table describing the experimental design of this study

Factor	Elicited engagement	
Levels	High	Low
Responses	• Electroencephalography(EEG) • Eye-Tracking • Time on task	

3.3 Hypotheses

After reviewing relevant literature, certain hypotheses were developed about biometrically measuring real-time online engagement. The proposed and hypotheses are listed below:

H1*: Acuity can be predicted through eye-tracking and EEG measures.*

H2*: Performance can be predicted through eye-tracking measures, EEG measures and time on task.*

H3*: Motivation can be predicted through eye-tracking and EEG measures.*

3.4 Stimulus and Tasks

Participants were first given a consent form that gave them general information about the research and the experiment they were about to take part of, specifically, the consent form explained the purpose, process and potential risks involved in this experiment. If the participant chose to move forward, he/she was asked to sign and date the form.

3.4.1 Screening Test:

Participants were asked to complete an initial screening test that asked them about their level of engagement and interest in two distinct themes: Science and Technology and Literature through History. The screening test is shown below in Figure 2.1. The purpose of this screening test was to capture the participant's potential engagement level with the material he/she will be exposed to. Only participants that were "Strongly Interested" or "Interested" in the Science and Technology theme *and* "Uninterested" or "Strongly Uninterested" in the Literature through History theme were selected to continue participating in the experiment.

On a scale of 1-7, rate your interest in reading about the following topics:

How interested would you be in reading about topics within the theme of science and technology? Examples of readings within this theme are: the cognitive process through which brain recognizes human faces, architecture miracles, cosmological theories, and the invention of touchstones.

• 7	• 6	• 5	• 4	• 3	• 2	• 1
Strongly Interested	Interested	Somewhat Interested	Neutral	Somewhat Uninterested	Uninterested	Strongly Uninterested

How interested would you be in reading about topics within the theme of literature through history? Examples of readings within this theme are: the evolvement of poetry styles through history, famous American writers, famous British novels, and renaissance literature.

• 7	• 6	• 5	• 4	• 3	• 2	• 1
Strongly Interested	Interested	Somewhat Interested	Neutral	Somewhat Uninterested	Uninterested	Strongly Uninterested

Figure 3.1 Figure showing initial screening test.

3.4.2 Wonderlic Personal Test (WPT)

Participants that were selected to continue taking part of this experiment were then asked to enter an isolation chamber to minimize any external distractions and asked to complete the Wonderlic Personal Test (WPT). The test was displayed on a 12 inch with a 1920 x 1080-resolution laptop screen as shown in Figure 2.2.

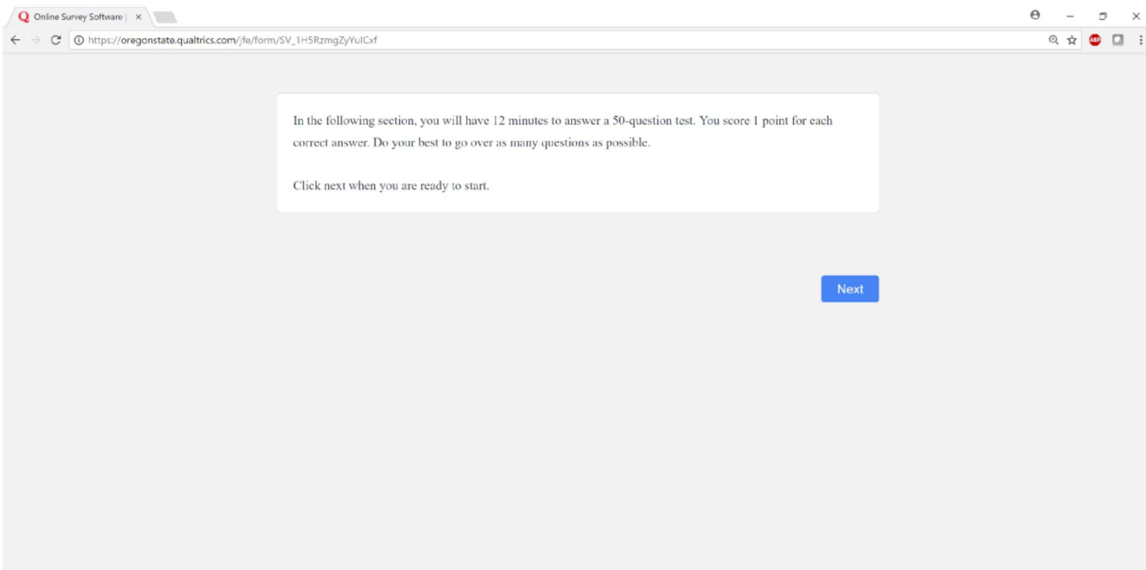

Figure 3.2: Figure showing the instruction page of the Wonderlic Personal Test (WPT).

Participants had twelve minutes to complete the WPT and were able to score one point for every correct answer. Scores were not revealed to participants. The WPT consisted of 50-questions, and participants were asked to answer as many questions as possible. Some of the WPT questions are multiple-choice questions, while other questions were short answer questions. Once the twelve minutes were over, participants were automatically exited from the test. Figure 2.3 shows a screenshot showing one of the WPT questions.

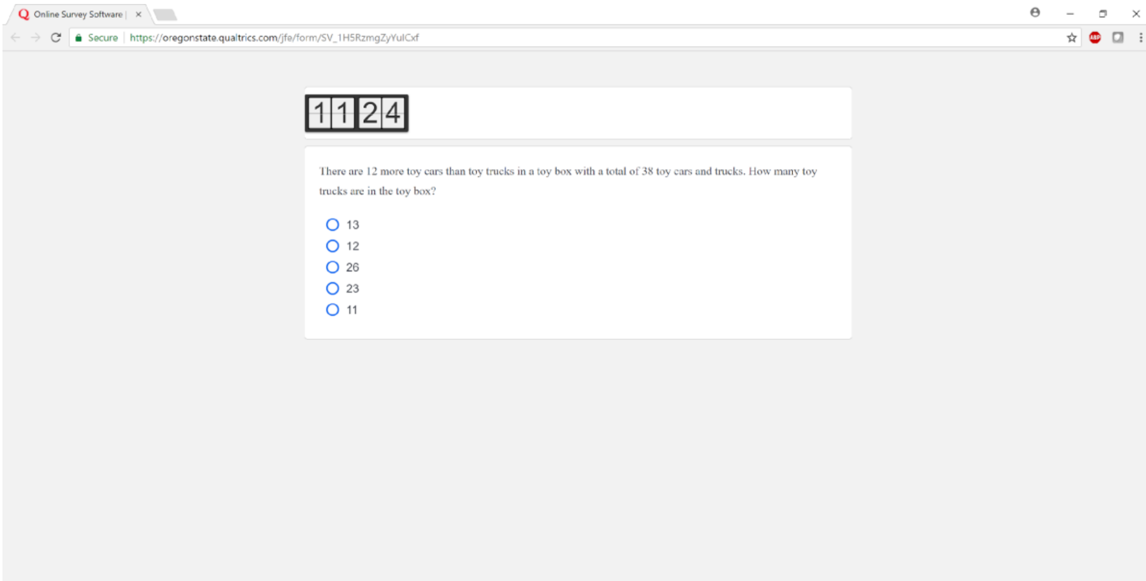

Figure 3.3 Figure showing an example of a WPT question.

3.4.3 Reading Sets

Eight short readings were used in this study to measure participants' engagement levels. Readings used in this experiment were taken from different Graduate Record Examination (GRE) tests. All readings were 122 to 152 words long and addressed one of the following two themes: Science and Technology or Literature through History. An example of one of the readings is shown below.

"Scientists formerly believed that the rocky planets-Earth, Mercury, Venus, and Mars-were created by the rapid gravitational collapse of a dust cloud, a deflation giving rise to a dense orb. That view was challenged in the 1960s, when studies of Moon craters revealed that these craters were caused by the impact of objects that were in great abundance about 4.5 billion years ago but whose number appeared to have quickly decreased shortly thereafter. This observation rejuvenated Otto Schmidt's 1944 theory of accretion. According to this theory, cosmic dust gradually lumped into ever-larger conglomerates: particulates, gravel, small and then larger balls, planetesimals (tiny planets), and, ultimately, planets. As the planetesimals became larger, their numbers decreased. Consequently, the number of collisions between planetesimals decreased."

Every participant got four readings that addressed the theme of Science and Technology and four other readings that addressed the theme of Literature through History. To control the effect of the order in which participants read about every theme, half participants read about the Science and Technology theme first then Literature Through History theme second, while the other half of participants read about the Literature Through History theme first then the Science and Technology theme second.

After every reading, participants were given a multiple-choice comprehension question that they had to answer based on their understanding of the reading they just read. Every question came with four possible answers, only one of them is correct. Participants could spend as much time as they would require completing every reading and answer its accompanying question.

3.4.4 Self-Report Instrument

After finishing every reading set, participants were asked to complete a self-report instrument to report their perceived level of engagement with the reading set they just got exposed to. The self-report instrument consists of eight questions as shown is Figure 2.4.

I think the material I read was engaging

• 7	• 6	• 5	• 4	• 3	• 2	• 1
Strongly Agree	Agree	Somewhat Agree	Neutral	Somewhat Disagree	Disagree	Strongly Disagree

I feel the topic I read was interesting

• 7	• 6	• 5	• 4	• 3	• 2	• 1
Strongly Agree	Agree	Somewhat Agree	Neutral	Somewhat Disagree	Disagree	Strongly Disagree

I found the reading intriguing

• 7	• 6	• 5	• 4	• 3	• 2	• 1
Strongly Agree	Agree	Somewhat Agree	Neutral	Somewhat Disagree	Disagree	Strongly Disagree

I believe the material I read was appealing

• 7	• 6	• 5	• 4	• 3	• 2	• 1
Strongly Agree	Agree	Somewhat Agree	Neutral	Somewhat Disagree	Disagree	Strongly Disagree

I think the material I read was not engaging

• 7	• 6	• 5	• 4	• 3	• 2	• 1
Strongly Agree	Agree	Somewhat Agree	Neutral	Somewhat Disagree	Disagree	Strongly Disagree

I feel the topic I read was not interesting

• 7	• 6	• 5	• 4	• 3	• 2	• 1
Strongly Agree	Agree	Somewhat Agree	Neutral	Somewhat Disagree	Disagree	Strongly Disagree

I found the reading not intriguing

• 7	• 6	• 5	• 4	• 3	• 2	• 1
Strongly Agree	Agree	Somewhat Agree	Neutral	Somewhat Disagree	Disagree	Strongly Disagree

I believe the material I read was not appealing

• 7	• 6	• 5	• 4	• 3	• 2	• 1
Strongly Agree	Agree	Somewhat Agree	Neutral	Somewhat Disagree	Disagree	Strongly Disagree

Figure 3.4 Figure showing the self-report instrument

3.5 Experiment Apparatus

3.5.1 EEG

In order to record brain wave activity, a wireless five-channel headset was used in this experiment. Precisely, the headset used, Emotiv Insight headset, records five brain waves that corresponds to the following channels: AF3, AF4, T7, T8 and Pz. Raw brain wave data from these five channels were captured and recorded.

3.5.2 Eye-Tracking

In order to record eye-tracking activity of participants, a Tobii (X2-30,30Hz) eye tracker was used in this experiment. The Tobii eye-tracker records the right and left eye movements of each participant after an initial calibration.

3.5.3 Presenting Computer

One HP laptop with a monitor of 1920 x 1080 resolution was used to display all tasks and experiment material. All experiment tasks were administered through Qualtrics software through the previously mentioned laptop. The laptop was also connected to a mouse that the participants used throughout the experiment.

3.6 Participants

Overall, 32 participants were recruited to take part of this experiment. Specifically, 16 male and 16 female participants were recruited. Participants were all students at the Oregon State University and all satisfied the following criteria:

1. Have normal or corrected vision.
2. Have functional English capability to understand instructions and learning material

3. Are at least 18 years old
4. Passed initial screening test.

Participants that took part of this experiment received a cash reward for their participation.

3.7 Experiment Procedure

In this experiment, every participant was asked to complete: 1) a cognitive test (Wonderlic Personal Test); 2) the first set of readings and comprehension tasks; 3) the self-report instrument related to the first set of readings; 4) the second set of readings and comprehension tasks; 5) the self-report instrument related to the second set of readings. Every reading set consisted of four readings with a related comprehension question at the end of every reading. Readings of every set were related to a particular theme that elicited either a high or a low engagement.

The order in which participants were exposed to every set of reading (high elicited engagement reading set or low elicited engagement reading) was controlled so that half participants were exposed to high elicited engagement reading set first then low elicited engagement reading set second whereas half of participants were exposed to low elicited engagement reading set first then low elicited engagement reading second.

Before the beginning of every trial, each participant was asked to complete an initial screening test. This test asks participants to rate their perceived level of interest and engagement in two different topics: science & technology and literature through history. Only participants that were highly engaged with the science & technology theme (scored a six or on a seven on a Likert scale) and mediocrely engaged with the literature through history (scored on a two or one on a seven Likert scale) were selected to take part of this experiment.

3.7.1 Consent Form

Once every participant arrived, he/she received a consent form that provides detailed explanation of the experiment they were about to take part of. Specifically, the following information was provided:

- Information about the purpose of this research study
- The procedure of this experiment: a detailed explanation of the steps that the participant would go through to complete this experiment.
- Possible risks that may be involved if the participant chooses to take part of this experiment: it was explained to participants that there are no major risks involved in this experiment besides the fact that the EEG headset may cause some discomfort while wearing it.
- An explanation that data collected and recorded from this experiment (Wonderlic, EEG, eye-tracking, task performance, self-report data) is going to be saved and used for research purposes
- An explanation that all data collected is going to be saved under anonymous codes and that the identity of every participant is going to be confidential.
- Finally, an explanation that participating in this experiment is completely optional and that every participant has the right to withdraw from the experiment at any time.

- An explanation that the participant will have to complete a screening test, and depending on the results of this test, the participants will be either chosen to take part of the rest of the experiment or not.
- If the participant agrees to move forward and take part of the experiment, the participant then signed and dated the consent form, which was then collected by the student researcher.

3.7.2 Initial Screening Test

After reviewing the consent from, every participant was then asked to take an initial screening test. Only participants that were "Strongly Interested" or "Interested" in the Science and Technology theme *and* were *at the same time* "Uninterested" or "Strongly Uninterested" in the Literature Through History theme were selected to continue participating in the experiment. Participants that were chosen to take part of this experiment were then invited to come inside an isolation chamber to continue the experiment.

3.7.3 Wonderlic Personal Test (WPT)

A 50-question Wonderlic test (WPT) followed, where participants had twelve minutes to complete this test. Before proceeding with the test, an instruction page was displayed that explained the duration of the test (twelve minutes total) and that the test consists of 50 questions total. Every participant was also provided with a white paper and pencil that can be used as scratch paper during the WPT.

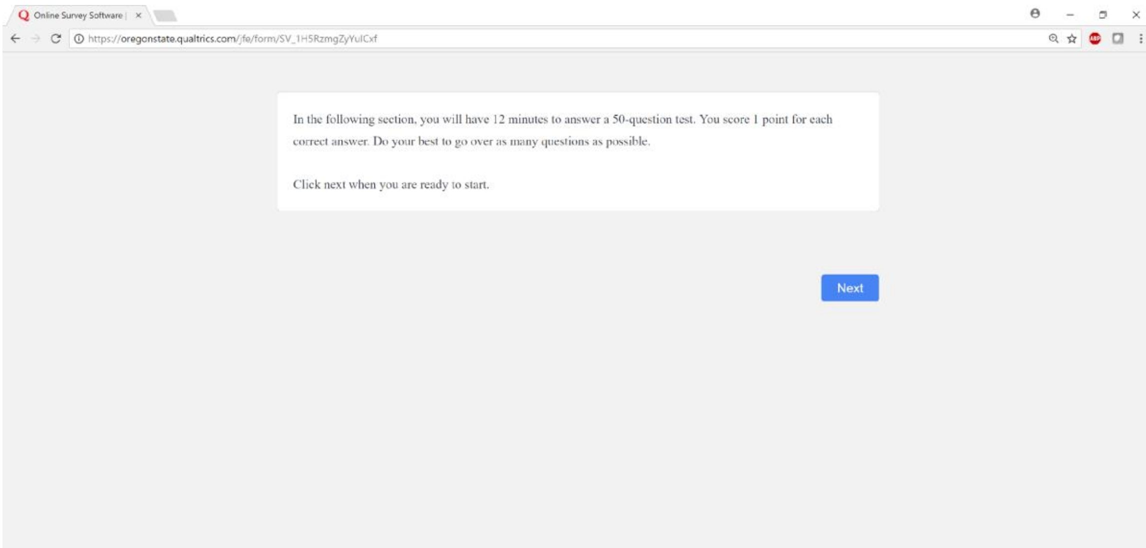

Figure 3.5 Figure showing the instruction page preceding the WPT.

3.7.4 Calibrating the EEG and Eye-Tracker

After every participant finished taking part of the Wonderlic Personal Test, student researcher helped participants put on the EEG headset, turn on the eye tracker, calibrate both EEG, and eye tracker.

3.7.5 Stimulus

Participants were then required to complete four readings about either the theme of Science and Technology or the theme of Literature through History. At the end of every reading, participants were asked to answer a corresponding question. The order in which every participant read about every theme (Science and Technology or Literature through History) was controlled: half participants (sixteen participants) read about Science and Technology theme first then Literature through History theme second. While the other half of participants (sixteen participants) read about Literature through History theme first then Science and Technology theme second.

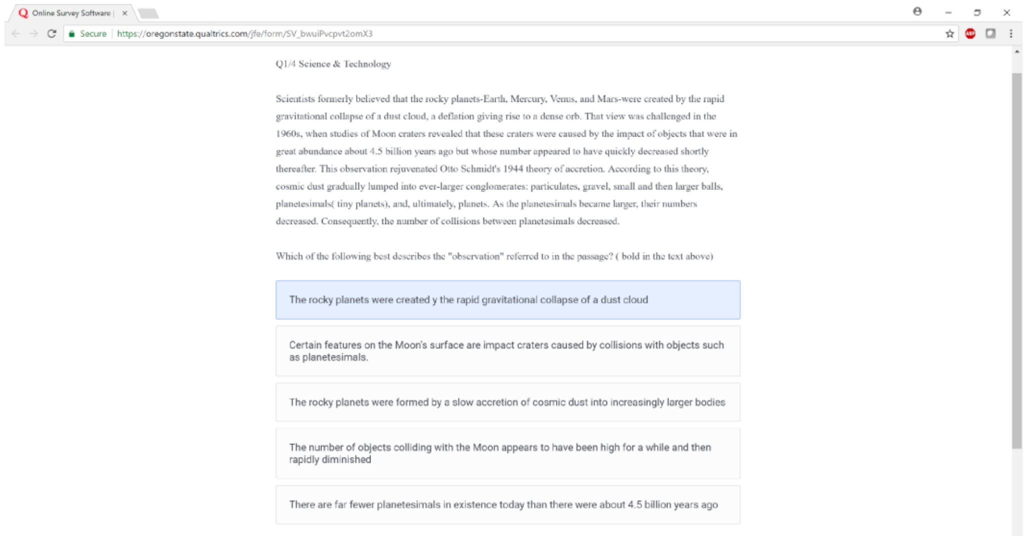

Figure 3.6 Figure showing an example one of the Science and Technology readings

3.7.6 Self- Report Instrument

At the end of every theme, participants were asked to complete a self-report, asking them about their perceived level of engagement while completing the readings just read. Figure 2.7 shows the self-report instrument that was presented to every participant at the end of every reading set.

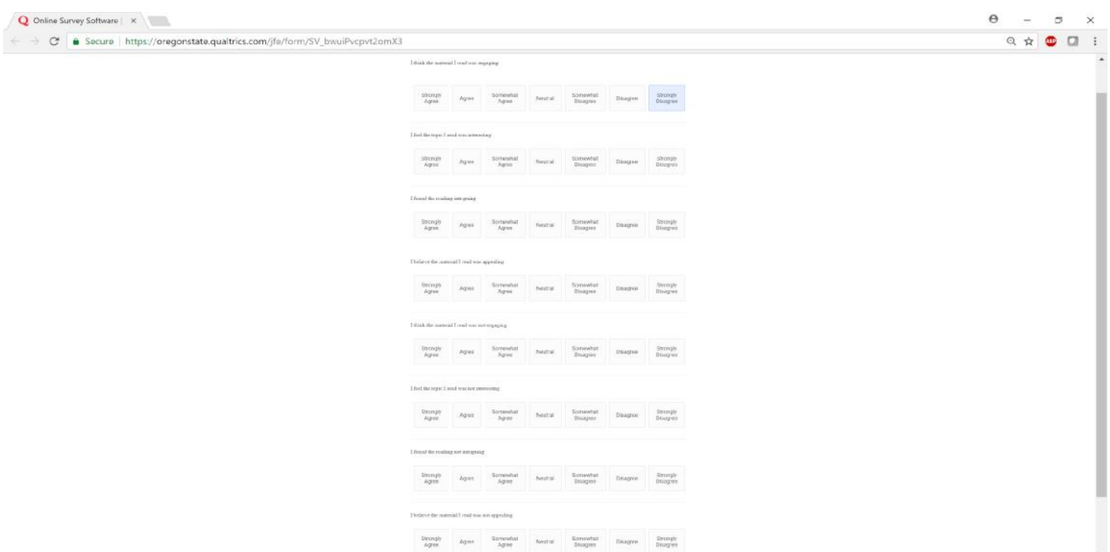

Figure 3.7 Figure showing the self-report instrument displayed after every reading set

3.8 Data Recording

One HP laptop, the same laptop used to display stimulus to participants, was used to capture and record eye-tracking data. Tobii (X2-30,30Hz) installed on the same laptop allowed for recording and then exporting the eye-tracking data. EEG data was recorded on a separate Lenovo laptop. Emotiv ControlPanel allowed the recording then the export of EEG data.

3.9 Predicting the Three Dimensions of Real-Time Online Engagement

As described in the previous experiment procedure, different data was collected to predict the three dimensions of real-time online engagement. Below is a summary of how the collected data set were used to predict every dimension.

3.9.1 Acuity

To predict the first dimension of real-time online engagement, acuity, cognitive ability was set as a dependent variable. Cognitive ability was measured through the Wonderlic Personal Test (WPT). The independent variables are EEG and Eye tracking measures.

3.9.2 Performance

To predict the second dimension of real-time online engagement, performance was set as a dependent variable. Performance was measured by capturing participants' performances answering reading tasks related questions. The independent variables are EEG measures, eye-tracking measures and time on task.

3.9.3 Motivation

To predict the third dimension of real-time online engagement, motivation was set as a dependent variable. Motivation was measured through the self-report instruments that were administered at the end of every reading set. The independent variables are EEG and eye-tracking measures.

3.9.3.1 Calculating Scores from the Self-Report Instrument

In order to extract a score from every completed self-report, the following methodology was followed: the Likert scale of the negative pole questions were reversed as described in Figure 3.9. Then, the scores of all questions were summed up. Therefore, the scores from all taken self-reports ranged from a minimum of eight to a maximum of fifty-six.

I feel the topic I read was interesting

• 7	• 6	• 5	• 4	• 3	• 2	• 1
Strongly Agree	Agree	Somewhat Agree	Neutral	Somewhat Disagree	Disagree	Strongly Disagree

I feel the topic I read was not interesting

• 1	• 2	• 3	• 4	• 5	• 6	• 7
Strongly Agree	Agree	Somewhat Agree	Neutral	Somewhat Disagree	Disagree	Strongly Disagree

Figure 3.8 Figure showing how the Likert scale is reversed for all negative pole questions before summing up all scores.

3.10. Glossary of Used Parameters

Table 3.2 provides a summary of all parameters used in this study as well as a description of every parameter, its units and range.

Table 3.2 summarizes all variables collected during this study, their units, range and description.

Variable Name	Unit	Range	Description
Acuity	Points	0-50	Variable measuring general cognitive abilities of participant
Performance	Point	0-1	Score obtained when answering the comprehension questions that appeared at the end of every reading. A participant scored 1 point for every correct answer
Motivation	Points	8-56	Measures participant's motivation through a self-report taken at the end of every reading set.
Elicited Engagement	Unitless	High Low	Engagement level with regard to a theme/reading set
Time on Task	Seconds	12-226	Variable measuring the total time that a participant chooses to spend per every reading set
EEG	Microvolts^10	58-809	Variable measuring the electric activity on participant's scalp
Eye Tracking *Fixation Duration*	Milliseconds	10-896	Variable measuring total duration of every fixation
Eye Tracking *Pupil Dilation % change*	Percentage	0-100	Variable measuring the % change in both right and left pupil diameters

3.11 Collected Data

All participants took one Wonderlic Personal Test (WPT), two reading sets and two self report instruments. Every reading set consisted of four readings with a question at the end of every reading. While completing every reading set, Electroencephalography (EEG) and eye-tracking measurements were recorded. EEG signals were recorded through *five different channels*. Eye-tracking signals recorded consisted of *total fixation duration* and *pupil dilation*. Therefore, in total, there were 32 WPT data sets, 1280 EEG data sets, 512 eye-tracking data sets, 256 performance data sets and 64 self-report data sets.

3.12 Data Statistics

In order to analyze the total fixation duration, the average, minimum and maximum of every trial set was computed. In the same fashion, in order to analyze the pupil size, minimum, maximum, average, and percentage change of every trial were calculated. Additionally, to analyze EEG data, average, minimum and maximum of every trial were computed. The rest of collected data (WPT scores, self-report scores, performance scores, time-on-task were used in the same format as they were collected with no manipulations.

3.13. Observed Data Outliers

After the data collection was over, collected biometric data was graphed in order to detect the existence of any outliers.

3.13.1. Eye-Tracking

While participants were completing the assigned reading tasks, eye-tracking data was recorded. Specifically, the total fixation duration and pupil dilation size of both the right and left eye were recorded. Among the 512 data sets collected, four outliers were observed. An example of an observed outlier is shown in Figure 3.10. These outliers were removed and replaced by the mean of the rest of the data sets in order to assure the balance of the data to be analyzed.

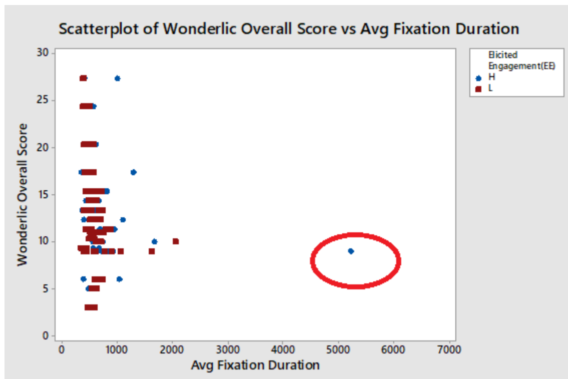

Figure 3.10 Figure showing outlier in total fixation duration

3.13.2 Electroencephalography (EEG)

While completing the reading tasks, EEG signals were recorded. EEG recordings came through five channels: AF3, AF4, T7, T8 and Pz. The EEG signals were recorded in **µ**V*10.

As mentioned above, there was a total of 1280 EEG data set. Out of this data set, three data outliers were observed. An example of an observed outlier is shown in figure 3.11. The outliers observed are believed to be a result of a technical issue with the recording EEG headset and not a true reflection of the participants' EEG activity. To assure the balance of data, these outliers were deleted then replaced by the mean of the rest of the data.

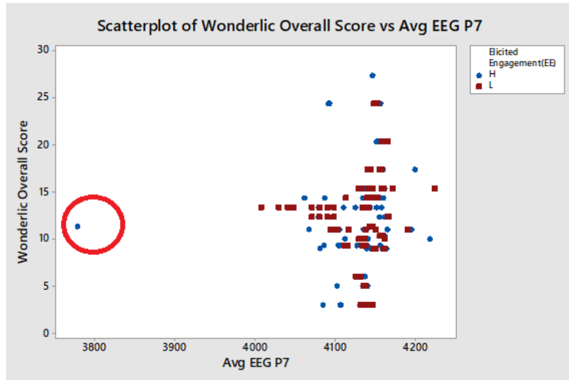

Figure 3.11 Figure showing an EEG outlier that was later replaced

3.14 Mixed ANOVA

Because of the nature of repetitive measures that were taken from participants, a mixed ANOVA analysis was conducted in order to test differences between biometrics and real-time online engagement. Minitab was used in this study in order to conduct the mixed effect ANOVA analysis.

The model that was used to analyze all three dimensions of engagement is under the form of equation 3.1 where i ranges from 1 to 3 where Y_1 corresponds to the acuity dimension, Y_2 corresponds to the performance dimension and Y_3 corresponds to the motivation dimension

$$
\begin{gathered}
Yi = \\
\alpha 1 Participants + \beta 1 Elicited\ Engagement \\
\gamma 1 Avg.AF3 + \delta 1 Avg.AF4 + \varepsilon 1 Avg.T7 + \zeta 1 Avg.T8 + \theta 1 Avg.Pz + \\
\gamma 2 Min.AF3 + \delta 2 Min.AF4 + \varepsilon 2 Min.T7 + \zeta 2 Min.T8 + \theta 2 Min.Pz + \\
\gamma 3 Max.AF3 + \delta 3 Max.AF4 + \varepsilon 3 Max.T7 + \zeta 3 Max.T8 + \theta 3 Max.Pz + \\
\rho 1 Avg.Fixation\ Durations + \tau 1 Avg.Pupil\ \%\ change + \\
\rho 2 Min.Fixation\ Durations + \tau 2 Min.Pupil\ \%\ change + \\
\rho 3 Max.Fixation\ Durations + \tau 3 Max.Pupil\ \%\ change + \\
Time\ on\ Tak + \beta 0
\end{gathered}
$$

Equation 3.1 Mixed ANOVA Model for the Three Dimensions

3.14.1 Acuity

To test the first hypothesis; ***H1**: Acuity can be predicted through eye-tracking and EEG measurements;* a mixed ANOVA was conducted where acuity was the dependent variable while EEG and eye-tracking measures were the independent variables. The model described in equation 3.1 was used to analyze *acuity, Y*.

3.14.2 Performance

In order to test the second hypothesis; ***H2**: Performance can be predicted through eye-tracking measurements, EEG measurements and time on task;* a mixed effect ANOVA analysis was conducted where performance was the independent variable while EEG, eye-tracking and time on task were the independent variables. The model described in equation 3.1 was used to analyze *performance, Y2*

3.14.3. Motivation

In order to test the third hypothesis; ***H3**: Motivation can be predicted through eye-tracking and EEG measurements;* a mixed ANOVA analysis was conducted where motivation was the independent variable while the EEG and eye-tracking measures were the independent variables. The model described in equation 3.1 was used to analyze *motivation, Y3.*

CHAPTER 4: RESULTS

This chapter describes the results obtained after applying the methodology detailed in the previous chapter. Specifically, this chapter exhibits a summary of the data collected and results of the mixed ANOVA.

4.1. Summary of Data Collected

As summarized in the previous chapter, there are 32 *Acuity* variables, *EEG* variable, 512 *eye-tracking* variables, 256 *performance* variables, 64 motivation variables. Table 4.1 shows a summary of all data sets collected by showing the mean, maximum, minimum of every data set collected.

Table 4.1 Table summarizing data sets collected

Measure	Mean	Standard deviation
Acuity	13	5
Performance	0.27	0.44
Motivation	34	13.08
Verbalized communication (AF3)	417	3.26
Sustained attention (AF4)	436	23.09
Emotional Memory (T7)	407	6.81
Verbal Memory (T8)	418	3.84
General Perception (Pz)	412	5.39
Fixation Duration	54	13.80
Pupil Dilation	0.89%	0.02

4.2 Mixed ANOVA Results

To test the three hypotheses presented in the previous chapter, a mixed ANOVA was conducted to recognize if any of the biometrics result in significantly different consequences in acuity, performance or motivation. Minitab was used conduct the mixed ANOVA analysis.

4.2.1 Acuity

A mixed ANOVA was run in order to test for the first hypothesis; *H1: Acuity can be predicted through eye-tracking* and *EEG measures*. In order to satisfy the non-correlation assumption, a principal component analysis was run

4.2.1.2 Principal Component Analysis for Acuity Dimension

In order to run a mixed ANOVA a principal component analysis was run on all independent variables in order to mitigate any correlations that might exist between independent variables. The matrices obtained from the principal component analysis are shown in table 4.2

Table 4.2 Table summarizing the matrices obtained after running the principal component analysis on independent variables for acuity dimension

Independent variable	*PC1*	*PC2*
Pupil % change	0.707	-0.707
Avg. General Perception (Pz)	0.707	0.707

To run the mixed ANOVA, acuity was the dependent variable. On the other hand, the matrices obtained from the principal component analysis (PC*1* and *PC2*) were the independent variables. *Participants* was considered a random factor and *Elicited Engagement* was considered a fixed factor.

As shown in table 4.3, PC1 was shown to be significant (*p*=0.003). However Elicited Engagement was shown not to be significant (*p*=0.503). Results and coefficients are shown in table 4.3(complete mixed ANOVA model is in appendix 6.1)

Table 4.3 Reduced mixed ANOVA model for the acuity dimension

Model	**Variance**	**Coefficient**	***p*-value**
Random:			
Participants	24.41		≤0.001
Fixed:	4.56		
Elicited Engagement		0.097	0.503
Independent Variables:			
PC1		0.42	0.152
PC2		0.89	0.003
Total	28.96		

R-sq= 84.41%

From the above results of the mixed ANOVA analysis, we can conclude that PC1 was significant, therefore pupil percentage change and *average Pz(general perception) are significant.* However, *Elicited Engagement* was not significant. The R-square of this model is equal to 84.41%.

4.2.2 Performance

A mixed ANOVA was run in order to test for the second hypothesis; *H2: Performance can be predicted through eye-tracking measures, EEG measures and time on task*.

In order to satisfy the non-correlation assumption, a principal component analysis was run.

4.2.2.1 Principal Component Analysis for Performance Dimension

In order to run a mixed ANOVA a principal component analysis was run on all independent variables in order to mitigate any correlations that might exist between independent variables. The matrices obtained from the principal component analysis are shown in table 4.4

Table 4.4 Table summarizing the matrices obtained after running the principal component analysis on independent variables for performance dimension

Independent variable	*PC1*	*PC2*	*PC3*	*PC4*	*PC5*
Avg. Emotional Memory(T7)	0.67	-0.056	-0.18	0.07	-0.709
Avg. General Perception(Pz)	0.66	-0.060	-0.043	0.32	0.67
Max Fixation Duration	-0.17	-0.29	-0.93	-0.042	0.101
Time on Task	0.17	-0.68	0.22	-0.66	0.097
Min General Perception (Pz)	-0.22	-0.66	0.204	0.67	-0.14

To run the mixed ANOVA, acuity was the dependent variable. On the other hand, the matrices obtained from the principal component analysis (PC*1*, *PC2*, *PC3, PC4* and *PC5*) were the independent variables. *Participants* was considered a random factor and *Elicited Engagement* was considered a fixed factor. As shown in table 4.5 *PC4* and *PC5* were shown to be significant. Coefficients and p-values are shown in table 4.5(complete mixed ANOVA model is in Appendix 6.2)

Table 4.5 Reduced mixed ANOVA model for the performance dimension

Model	**Variance**	**Coefficient**	***p*-value**
Random:			
Participants	0.29		0.001
Fixed:	0.52		
Elicited Engagement			≤0.001
Independent Variables:			
PC4		0.104	0.022
PC5		-0.37	≤0.001
Total	0.81		

R-sq=80.01%

As shown in table 4.5 *PC4* is shown to be significant (*p*=0.022) in addition to that, PC5 was also shown to be significant (*p*≤0.001). Last, Elicited Engagement was also shown to be significant(*p*≤0.001). The R-square of this model is 80.01%.

4.2.3 Motivation

A mixed ANOVA was run in order to test for the third hypothesis; *H3: Motivation can be predicted through eye-tracking and EEG measures*.

In order to satisfy the non-correlation assumption, a principal component analysis was run.

4.2.3.1 Principal Component Analysis

In order to run a mixed ANOVA a principal component analysis was run on all independent variables in order to mitigate any correlations that might exist between independent variables. The matrices obtained from the principal component analysis are shown in table 4.6.

Table 4.6 Table summarizing the matrices obtained after running the principal component analysis on independent variables for motivation dimension

Independent variable	*PC1*	*PC2*	*PC3*	*PC4*	*PC5*
Avg. Emotional Memory(T7)	0.095	0.69	0.706	-0.046	-0.093
Avg. General Perception(Pz)	0.068	0.705	-0.705	-0.047	0.008
Max Fixation Duration	0.56	-0.13	-0.037	-0.723	-0.36
Time on Task	0.58	-0.015	0.046	0.043	0.81
Min General Perception (Pz)	0.57	-0.048	-0.044	0.686	-0.44

To run the mixed ANOVA, acuity was the dependent variable. On the other hand, the matrices obtained from the principal component analysis (PC*1*, *PC2*, *PC3, PC4* and *PC5*) were the independent variables. *Participants* was considered a random factor and *Elicited Engagement* was considered a fixed factor. As shown in table 4.5 no independent variable was shown to be significant. Coefficients and p-values are shown in table 4.7. The R-square of this model is 77.91%(complete mixed ANOVA model is in appendix 6.3)

Table 4.7 Reduced mixed ANOVA model for the motivation dimension

Model	**Variance**	**Coefficient**	***p*-value**
Random: *Participants*	0.305		0.001
Fixed: *Elicited Engagement*	0.23		≤0.001
Independent Variables: *PC1*		0.104	0.408
Total	0.54		

R-sq=77.91%

4.3 Results Summary

Table 4.8 summarizes the R-square values of random effects and fixed effects of the acuity, performance and motivation dimensions.

Table 4.8 Table summarizing mixed effect ANOVA results

Engagement	**Random Effects R^2**	**Fixed Effect R^2**
Acuity	84.24%	84.41%
Performance	55.97%	80.01%
Motivation	56.23%	77.9%

CHAPTER 5: CONCLUSION AND DISCUSSION

This chapter provides a summary of the findings discussed in this research study. Specifically, this chapter compares previous research findings measuring real-time online engagement using eye-tracking measures with this study's findings predicting the three dimension of real-time online engagement using eye-tracking measures. In addition to that, this chapter also compares previous attempts in measuring real-time online engagement using electroencephalography (EEG) with this study's findings in predicting the three dimensions of real-time online engagement using EEG measures. Lastly, this chapter discusses this study's limitations and future research paths.

5.1 Eye-Tracking Measures and Real-Time Online Engagement

Throughout literature, there has been several attempts to measure online user's engagement by monitoring users' eye-tracking measures. First, it is important to note that literature and previous research that attempted to understand users' behavior in general and in particular, users' engagement was not conducting research related to an academic context or online learning. These research efforts focused on understanding whether eye-tracking behavior is significantly different when online users are highly engaged, and then comparing that same eye-tracking behavior when the users are less engaged

More specifically, these research efforts focused on eye-tracking data such as fixations and pupil size in order to gain a better understanding of users' online engagement. The same type of data (eye-tracking and pupil size) was also focused on in this research. Other data such as gaze maps were used in literature to gain a better understanding of where users were looking and the order of their eye movement while browsing various news and shopping sites. However, such information would not be as valuable and indicative in the context of this research as the task that was given to participants was a reading task.

Saccades were also used in some research to gain a more understanding of users' behavior trying to find certain information on online news pages. In these studies, measuring saccades lengths gave researchers a hint on the search effort that users had to make in order to find certain information on a shopping or news page for instance. Using saccades in this current study was also not relevant, as the task that was presented to the participants was a reading task where participants were not searching for certain information, but rather reading and understanding a certain subject they were more or less interested in.

In accordance with previous research findings, this study has been able to prove that eye-tracing measures, specifically fixations and pupil size are both significantly different when participants were highly engaged versus when participants were less engaged. In fact pupil percentage change, a variable measuring the amount of change in pupil dilation size since calibration time, was shown to be significant in predicting all three dimensions of real-time online engagement. In addition to that, fixation duration was also shown to be significant to predict the second dimension of real-time online engagement: performance.

The results summarized in the previous paragraph and detailed in the previous chapter as well come in accordance with previous research findings that linked eye-tracking behaviors to various cognitive and mental states. Specifically, as mentioned in chapter two, fixation duration was linked by previous research to the level of task difficulty, concentration, relaxation and anxiety In addition to that; pupil size was linked by previous research to task difficulty, various negative and positive affective states, interest, arousal, mental effort and information processing.

5.2 Electroencephalography (EEG) Measures and Real-Time Online Engagement

In previous literature, there has been various attempts to investigate the indications that EEG frequency bands would provide about humans' affective and cognitive states. Specifically, previous research has investigated whether the theta band, alpha band, beta band and delta band would behave significantly differently in distinct cognitive and affective bands.

The theta band was found in previous research to be significantly different when participants were in positive versus negative affective states in contexts such as playing video games. It was also found to be significantly different when participants were paying more attention to the material they were interacting with.

The context in which the EEG frequency bands were investigated in previous research rarely focused on the subject of engagement or even real-time online engagement. In addition to that, contexts in which previous research reported its findings were more related to video gaming or moving visual target tasks, which is different than tasks that were presented in this study that consisted of reading tasks within an academic educational context.

Because of the difference in the investigative nature of previous research and the current study, it was difficult to compare the outcomes of this study with previous research findings. However, it was possible to see some accordance in what this study found and what was previously reported in literature regarding the significance of the theta and beta band frequencies in scenarios where participants were highly attentive or in higher affective states.

This research therefore confirmed to a certain extent some previous research findings as EEG measures were significantly different when participants were highly or less engaged. In fact, this study proved that EEG measures were capable of predicting all three dimensions of real-time online engagement: acuity, performance and motivation.

5.3 Limitations and Future Research

The findings of this research were successful in showing the significance of using biometrics measures in predicting real-time online engagement. However, this research could also be improved in various aspects. First, a more stable EEG headset would improve the outcomes of this research, the stability of the data, and would potentially reduce the calibration time that was needed in this research. The headset that was used in this study, Emotiv Insight, is a wireless headset that was relatively easier to use and put on participants. However, the signal of the headset was unstable and very hard to calibrate. In addition to that, the signal quality was sometimes interrupted during the data collection phase.

EEG and Eye-tracking data was collected during the time that participants were reading and then answering the comprehension questions that were presented at the end of every reading task. This was designed this way because of the time and inconvenience of turning the EEG recording and eye tracking recorder on and off after every reading task (especially if repeated eight times, after every reading task). In future research, we hope to be able to collect EEG and eye-tracking recordings during reading tasks and during evaluation tasks separately in order to be able to compare the EEG and eye-tracking measures using reading and evaluation tasks.

EEG and eye-tracking data collected and analyzed in this study is in the form of time series. In order to analyze the collected data, average, minimum, maximum, and sometimes percentage change was calculated. However, in future research we are hoping to use time series specific analysis tools in order to accurately represent and analyze the EEG and eye-tracking measures.

This research is also opening the gate towards more research in the domain of acuity and its correspondence with biometric measures. In fact, there is scarce research about the topic of acuity and its correlation with biometric measures, specifically, EEG measures. We hope that in the future, we will be able to investigate more on this topic.

In this research, real-time online engagement was predicted using biometric measures. In fact, biometric measures were proved to be able to predict the three dimensions of real-time online engagement. However, we are still not fully able to dictate how these dimensions could be used separately or combined to predict real-time online engagement. Although this research was conducted and perceived within an academic educational context, where real-time online engagement could be measured within an online learning setting, we do also recognize that the outcomes of this research could also be indicative and open future research gates to other contexts such as online browsing, video game design and other related contexts.

6.APPENDICES

6.1. APPENDIX 1: Complete mixed ANOVA model for acuity dimension

Mixed Effects Model: Wonderlic Overall Score versus … gagement(EE)

Method

Variance estimation	Restricted maximum likelihood
DF for fixed effects	Kenward-Roger

Factor Information

Factor	Type	Levels	Values
Participant	Random	32	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32
Elicited Engagement(EE)	Fixed	2	H, L

Variance Components

Source	Var	% of Total	SE Var	Z-Value	P-Value
Participant	24.390860	84.24%	6.628583	3.679649	0.000
Error	4.564370	15.76%	0.436647	10.453216	0.000
Total	28.955230				

-2 Log likelihood = 1234.632311

Tests of Fixed Effects

Term	DF Num	DF Den	F-Value	P-Value
PC1	1.00	250.82	2.07	0.152
PC2	1.00	251.13	8.94	0.003
Elicited Engagement(EE)	1.00	219.06	0.45	0.503

Model Summary

S	R-sq	R-sq(adj)
2.13644	84.41%	84.22%

Coefficients

Term	Coef	SE Coef	DF	T-Value	P-Value
Constant	13.274844	0.883201	28.38	15.030377	0.000
PC1	0.417096	0.290025	250.82	1.438135	0.152

PC2	0.893401	0.298815	251.13	2.989816	0.003
Elicited Engagement(EE)					
H	0.097330	0.145070	219.06	0.670918	0.503

Marginal Fits and Diagnostics for Unusual Observations

Obs	Wonderlic Overall Score	Fit	Resid	Std Resid		
15	3.000000	13.611095	-10.611095	-2.000242	R	
98	24.330000	13.133837	11.196163	2.114505	R	
99	24.330000	12.698526	11.631474	2.194617	R	
100	24.330000	12.726448	11.603552	2.189191	R	
101	24.330000	13.705731	10.624269	2.003122	R	
102	24.330000	13.645426	10.684574	2.014225	R	
103	24.330000	13.636567	10.693433	2.015859	R	
104	24.330000	13.669192	10.660808	2.009844	R	
225	11.330000	6.943059	4.386941	0.934853		X
226	27.330000	8.598946	18.731054	3.819360	R	
227	27.330000	9.645975	17.684025	3.504294	R	
228	27.330000	10.131224	17.198776	3.372608	R	
229	27.330000	9.816152	17.513848	3.428524	R	
230	27.330000	9.116044	18.213956	3.629392	R	
231	27.330000	9.074052	18.255948	3.642087	R	
232	27.330000	8.993326	18.336674	3.666716	R	
233	27.330000	13.786986	13.543014	2.553582	R	

R Large residual
X Unusual X

Conditional Fits and Diagnostics for Unusual Observations

Obs	Wonderlic Overall Score	Fit	Resid	Std Resid	
41	17.330000	10.764525	6.565475	3.331605	R
81	12.330000	19.181851	-6.851851	-3.431211	R
89	20.330000	14.956426	5.373574	2.690832	R
97	14.330000	22.348101	-8.018101	-4.041902	R
113	20.330000	15.800860	4.529140	2.269669	R

121	15.330000	7.027821	8.302179	4.172010	R
137	9.330000	13.609377	-4.279377	-2.148284	R
161	5.000000	10.417907	-5.417907	-2.713667	R
185	11.000000	15.058913	-4.058913	-2.037370	R
193	15.330000	10.103119	5.226881	2.621778	R
201	9.000000	13.227966	-4.227966	-2.127289	R
225	11.330000	22.860865	-11.530865	-6.237235	R
233	27.330000	13.432287	13.897713	6.961291	R
241	11.330000	16.515252	-5.185252	-2.596392	R
249	11.330000	16.515252	-5.185252	-2.596392	R

R Large residual

6.2 APPENDIX 2: Complete mixed ANOVA model for performance dimension

Principal Component Analysis: Avg EEG T7, Avg EEG Pz, ... Min EEG Pz

Eigenanalysis of the Correlation Matrix

Eigenvalue	1.7474	1.1263	0.9705	0.8306	0.3253
Proportion	0.349	0.225	0.194	0.166	0.065
Cumulative	0.349	0.575	0.769	0.935	1.000

Eigenvectors

Variable	PC1	PC2	PC3	PC4	PC5
Avg EEG T7	0.675	-0.056	-0.186	0.070	-0.709
Avg EEG Pz	0.660	-0.060	-0.043	0.321	0.676
Max Fixation Duration	-0.171	-0.296	-0.933	-0.042	0.101
Time on Task	0.176	-0.684	0.226	-0.663	0.097
Min EEG Pz	-0.222	-0.661	0.204	0.671	-0.147

Mixed Effects Model: Performance versus PC1, PC3, PC4, ... ement(EE)

Method

Variance estimation	Restricted maximum likelihood
DF for fixed effects	Kenward-Roger

Factor Information

Factor	Type	Levels	Values
Participant	Random	32	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32
Elicited Engagement(EE)	Fixed	2	H, L

Variance Components

Source	Var	% of Total	SE Var	Z-Value	P-Value
Participant	0.282112	56.92%	0.080785	3.492143	0.000
Error	0.213559	43.08%	0.020419	10.458610	0.000
Total	0.495672				

-2 Log likelihood = 428.074184

Tests of Fixed Effects

Term	DF Num	DF Den	F-Value	P-Value

PC1	1.00	128.71	1.43	0.234
PC3	1.00	239.24	2.09	0.149
PC4	1.00	246.56	6.56	0.011
PC5	1.00	232.61	15.76	0.000
Elicited Engagement(EE)	1.00	220.12	458.86	0.000

Model Summary

S	R-sq	R-sq(adj)
0.462125	80.41%	80.02%

Coefficients

Term	Coef	SE Coef	DF	T-Value	P-Value
Constant	1.078125	0.098236	29.28	10.974898	0.000
PC1	0.061683	0.051550	128.71	1.196576	0.234
PC3	0.051586	0.035664	239.24	1.446438	0.149
PC4	0.120545	0.047064	246.56	2.561271	0.011
PC5	-0.357152	0.089971	232.61	-3.969654	0.000
Elicited Engagement(EE)					
H	0.625100	0.029182	220.12	21.421067	0.000

Marginal Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
57	4.000000	2.148509	1.851491	2.687068	R
58	4.000000	2.059396	1.940604	2.807606	R
59	4.000000	2.062317	1.937683	2.803452	R
60	4.000000	2.130020	1.869980	2.703332	R
161	0.000000	1.419281	-1.419281	-2.054725	R
163	0.000000	1.385891	-1.385891	-2.006166	R
164	0.000000	1.407675	-1.407675	-2.032887	R
185	0.000000	1.517086	-1.517086	-2.191298	R
186	0.000000	1.566019	-1.566019	-2.255422	R
187	0.000000	1.555387	-1.555387	-2.247383	R
188	0.000000	1.463546	-1.463546	-2.113539	R

R Large residual

Conditional Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
58	4.000000	3.060521	0.939479	2.166493	R
59	4.000000	3.063442	0.936558	2.159752	R
60	4.000000	3.131145	0.868855	2.005415	R
129	3.000000	2.101682	0.898318	2.071287	R
202	3.000000	2.115811	0.884189	2.038372	R
207	0.000000	0.887033	-0.887033	-2.046371	R

R Large residual

Mixed Effects Model: Performance versus PC3, PC4, PC5, ... ement(EE)

Method

Variance estimation	Restricted maximum likelihood
DF for fixed effects	Kenward-Roger

Factor Information

Factor	Type	Levels	Values
Participant	Random	32	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32
Elicited Engagement(EE)	Fixed	2	H, L

Variance Components

Source	Var	% of Total	SE Var	Z-Value	P-Value
Participant	0.265763	55.21%	0.075123	3.537684	0.000
Error	0.215580	44.79%	0.020550	10.490293	0.000
Total	0.481343				

-2 Log likelihood = 425.377854

Tests of Fixed Effects

Term	DF Num	DF Den	F-Value	P-Value
PC3	1.00	237.39	2.68	0.103
PC4	1.00	250.64	5.51	0.020
PC5	1.00	234.84	16.93	0.000
Elicited Engagement(EE)	1.00	221.42	456.09	0.000

Model Summary

S	R-sq	R-sq(adj)

0.464306	80.16%	79.84%

Coefficients

Term	Coef	SE Coef	DF	T-Value	P-Value
Constant	1.078125	0.095641	30.41	11.272627	0.000
PC3	0.058044	0.035439	237.39	1.637833	0.103
PC4	0.106315	0.045291	250.64	2.347394	0.020
PC5	-0.367439	0.089303	234.84	-4.114538	0.000
Elicited Engagement(EE)					
H	0.625933	0.029309	221.42	21.356250	0.000

Marginal Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
57	4.000000	2.186663	1.813337	2.668136	R
58	4.000000	2.103431	1.896569	2.780557	R
59	4.000000	2.106006	1.893994	2.776920	R
60	4.000000	2.149339	1.850661	2.714234	R
161	0.000000	1.431844	-1.431844	-2.103378	R
162	0.000000	1.396657	-1.396657	-2.052126	R
163	0.000000	1.397314	-1.397314	-2.052472	R
164	0.000000	1.433828	-1.433828	-2.100046	R
185	0.000000	1.536789	-1.536789	-2.251924	R
186	0.000000	1.579964	-1.579964	-2.308575	R
187	0.000000	1.581878	-1.581878	-2.318315	R
188	0.000000	1.481035	-1.481035	-2.169887	R

R Large residual

Conditional Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
41	2.000000	1.184194	0.815806	2.005865	R
58	4.000000	3.060993	0.939007	2.154279	R
59	4.000000	3.063568	0.936432	2.148387	R
60	4.000000	3.106902	0.893098	2.049680	R
129	3.000000	2.105046	0.894954	2.052985	R
149	1.000000	0.129425	0.870575	2.010117	R

202	3.000000	2.116689	0.883311	2.025985	R
207	0.000000	0.877110	-0.877110	-2.012944	R

R Large residual

Mixed Effects Model: Performance versus PC4, PC5, … ngagement(EE)

Method

Variance estimation	Restricted maximum likelihood
DF for fixed effects	Kenward-Roger

Factor Information

Factor	Type	Levels	Values
Participant	Random	32	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32
Elicited Engagement(EE)	Fixed	2	H, L

Variance Components

Source	Var	% of Total	SE Var	Z-Value	P-Value
Participant	0.274950	55.97%	0.077315	3.556230	0.000
Error	0.216288	44.03%	0.020569	10.515134	0.000
Total	0.491237				

-2 Log likelihood = 423.212758

Tests of Fixed Effects

Term	DF Num	DF Den	F-Value	P-Value
PC4	1.00	251.49	5.30	0.022
PC5	1.00	237.56	17.49	0.000
Elicited Engagement(EE)	1.00	222.28	451.94	0.000

Model Summary

S	R-sq	R-sq(adj)
0.465067	80.01%	79.77%

Coefficients

Term	Coef	SE Coef	DF	T-Value	P-Value
Constant	1.078125	0.097145	30.55	11.098155	0.000
PC4	0.104595	0.045419	251.49	2.302869	0.022
PC5	-0.374619	0.089584	237.56	-4.181745	0.000

Elicited Engagement(EE)					
H	0.622718	0.029292	222.28	21.258772	0.000

Marginal Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
57	4.000000	2.096775	1.903225	2.763076	R
58	4.000000	2.057646	1.942354	2.816545	R
59	4.000000	2.059624	1.940376	2.813754	R
60	4.000000	2.105261	1.894739	2.748656	R
161	0.000000	1.423561	-1.423561	-2.069907	R
162	0.000000	1.402627	-1.402627	-2.039943	R
163	0.000000	1.401565	-1.401565	-2.037804	R
164	0.000000	1.464438	-1.464438	-2.122447	R
185	0.000000	1.595934	-1.595934	-2.311716	R
186	0.000000	1.595071	-1.595071	-2.306963	R
187	0.000000	1.651637	-1.651637	-2.391425	R
188	0.000000	1.552287	-1.552287	-2.246764	R

R Large residual

Conditional Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
57	4.000000	3.096406	0.903594	2.071066	R
58	4.000000	3.057277	0.942723	2.159530	R
59	4.000000	3.059255	0.940745	2.154996	R
60	4.000000	3.104893	0.895107	2.051220	R
129	3.000000	2.111943	0.888057	2.034092	R
202	3.000000	2.110554	0.889446	2.036980	R

R Large residual

Mixed Effects Model: Performance versus PC4, PC5, ... ngagement(EE)

Method

Variance estimation	Restricted maximum likelihood
DF for fixed effects	Kenward-Roger

Factor Information

Factor	Type	Levels	Values
Participant	Random	32	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32
Elicited Engagement(EE)	Fixed	2	H, L

Variance Components

Source	Var	% of Total	SE Var	Z-Value	P-Value
Participant	0.274950	55.97%	0.077315	3.556230	0.000
Error	0.216288	44.03%	0.020569	10.515134	0.000
Total	0.491237				

-2 Log likelihood = 423.212758

Tests of Fixed Effects

Term	DF Num	DF Den	F-Value	P-Value
PC4	1.00	251.49	5.30	0.022
PC5	1.00	237.56	17.49	0.000
Elicited Engagement(EE)	1.00	222.28	451.94	0.000

Model Summary

S	R-sq	R-sq(adj)
0.465067	80.01%	79.77%

Coefficients

Term	Coef	SE Coef	DF	T-Value	P-Value
Constant	1.078125	0.097145	30.55	11.098155	0.000
PC4	0.104595	0.045419	251.49	2.302869	0.022
PC5	-0.374619	0.089584	237.56	-4.181745	0.000
Elicited Engagement(EE)					
H	0.622718	0.029292	222.28	21.258772	0.000

Marginal Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
57	4.000000	2.096775	1.903225	2.763076	R
58	4.000000	2.057646	1.942354	2.816545	R
59	4.000000	2.059624	1.940376	2.813754	R
60	4.000000	2.105261	1.894739	2.748656	R
161	0.000000	1.423561	-1.423561	-2.069907	R

162	0.000000	1.402627	-1.402627	-2.039943	R
163	0.000000	1.401565	-1.401565	-2.037804	R
164	0.000000	1.464438	-1.464438	-2.122447	R
185	0.000000	1.595934	-1.595934	-2.311716	R
186	0.000000	1.595071	-1.595071	-2.306963	R
187	0.000000	1.651637	-1.651637	-2.391425	R
188	0.000000	1.552287	-1.552287	-2.246764	R

R Large residual

Conditional Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
57	4.000000	3.096406	0.903594	2.071066	R
58	4.000000	3.057277	0.942723	2.159530	R
59	4.000000	3.059255	0.940745	2.154996	R
60	4.000000	3.104893	0.895107	2.051220	R
129	3.000000	2.111943	0.888057	2.034092	R
202	3.000000	2.110554	0.889446	2.036980	R

R Large residual

6.3. APPENDIX 3: Complete mixed ANOVA model for motivation dimension

Mixed Effects Model: Performance versus PC1, PC2, PC3, ... ement(EE)

Method

Variance estimation	Restricted maximum likelihood
DF for fixed effects	Kenward-Roger

Factor Information

Factor	Type	Levels	Values
Participant	Random	32	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32
Elicited Engagement(EE)	Fixed	2	H, L

Variance Components

Source	Var	% of Total	SE Var	Z-Value	P-Value
Participant	0.314985	56.66%	0.088558	3.556832	0.000
Error	0.240953	43.34%	0.023025	10.464883	0.000
Total	0.555938				

-2 Log likelihood = 459.519221

Tests of Fixed Effects

Term	DF Num	DF Den	F-Value	P-Value
PC1	1.00	248.75	0.58	0.447
PC2	1.00	184.98	0.00	0.952
PC3	1.00	145.40	0.11	0.736
PC4	1.00	229.46	0.01	0.921
PC5	1.00	232.09	0.45	0.503
Elicited Engagement(EE)	1.00	219.89	420.03	0.000

Model Summary

S	R-sq	R-sq(adj)
0.490870	77.99%	77.46%

Coefficients

Term	Coef	SE Coef	DF	T-Value	P-Value
Constant	1.078125	0.103848	30.40	10.381713	0.000
PC1	-0.021422	0.028106	248.75	-0.762180	0.447

PC2	0.003643	0.060658	184.98	0.060051	0.952
PC3	0.023568	0.069869	145.40	0.337320	0.736
PC4	-0.008518	0.086262	229.46	-0.098745	0.921
PC5	0.070595	0.105256	232.09	0.670697	0.503
Elicited Engagement(EE)					
H	0.636904	0.031077	219.89	20.494662	0.000

Marginal Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
57	4.000000	1.706425	2.293575	3.188849	R
58	4.000000	1.714672	2.285328	3.173814	R
59	4.000000	1.646029	2.353971	3.294480	R
60	4.000000	1.690408	2.309592	3.194161	R
161	0.000000	1.612944	-1.612944	-2.224042	R
162	0.000000	1.602323	-1.602323	-2.230066	R
163	0.000000	1.598503	-1.598503	-2.226402	R
164	0.000000	1.601842	-1.601842	-2.228902	R
185	0.000000	1.735280	-1.735280	-2.354148	R
186	0.000000	1.721994	-1.721994	-2.335993	R
187	0.000000	1.713252	-1.713252	-2.333752	R
188	0.000000	1.710432	-1.710432	-2.320380	R

R Large residual

Conditional Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
57	4.000000	3.017680	0.982320	2.136372	R
58	4.000000	3.025927	0.974073	2.118705	R
59	4.000000	2.957284	1.042716	2.302176	R
60	4.000000	3.001663	0.998337	2.170334	R
132	3.000000	2.011125	0.988875	2.209001	R

R Large residual

Mixed Effects Model: Performance versus PC1, PC3, PC4, ... ement(EE)

Method

Variance estimation	Restricted maximum likelihood
DF for fixed effects	Kenward-Roger

Factor Information

Factor	Type	Levels	Values
Participant	Random	32	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32
Elicited Engagement(EE)	Fixed	2	H, L

Variance Components

Source	Var	% of Total	SE Var	Z-Value	P-Value
Participant	0.311277	56.44%	0.087292	3.565948	0.000
Error	0.240228	43.56%	0.022925	10.478862	0.000
Total	0.551505				

-2 Log likelihood = 455.723677

Tests of Fixed Effects

Term	DF Num	DF Den	F-Value	P-Value
PC1	1.00	249.89	0.62	0.432
PC3	1.00	176.20	0.14	0.712
PC4	1.00	229.95	0.01	0.924
PC5	1.00	232.86	0.45	0.503
Elicited Engagement(EE)	1.00	220.44	421.30	0.000

Model Summary

S	R-sq	R-sq(adj)
0.490130	77.98%	77.54%

Coefficients

Term	Coef	SE Coef	DF	T-Value	P-Value
Constant	1.078125	0.103275	30.61	10.439325	0.000
PC1	-0.021770	0.027644	249.89	-0.787500	0.432
PC3	0.024761	0.066865	176.20	0.370316	0.712
PC4	-0.008272	0.086100	229.95	-0.096075	0.924
PC5	0.070522	0.105083	232.86	0.671109	0.503
Elicited Engagement(EE)					

H	0.636895	0.031029	220.44	20.525698	0.000

Marginal Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
57	4.000000	1.714412	2.285588	3.139489	R
58	4.000000	1.722587	2.277413	3.125521	R
59	4.000000	1.654047	2.345953	3.244358	R
60	4.000000	1.696890	2.303110	3.164657	R
161	0.000000	1.613958	-1.613958	-2.233546	R
162	0.000000	1.603623	-1.603623	-2.239393	R
163	0.000000	1.599271	-1.599271	-2.235837	R
164	0.000000	1.603098	-1.603098	-2.238249	R
185	0.000000	1.734414	-1.734414	-2.361849	R
186	0.000000	1.721608	-1.721608	-2.344664	R
187	0.000000	1.712552	-1.712552	-2.341872	R
188	0.000000	1.710540	-1.710540	-2.329772	R

R Large residual

Conditional Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
57	4.000000	3.018063	0.981937	2.136008	R
58	4.000000	3.026239	0.973761	2.118688	R
59	4.000000	2.957698	1.042302	2.302048	R
60	4.000000	3.000541	0.999459	2.175927	R
132	3.000000	2.010491	0.989509	2.213625	R

R Large residual

Mixed Effects Model: Performance versus PC1, PC3, PC5, ... ement(EE)

Method

Variance estimation	Restricted maximum likelihood
DF for fixed effects	Kenward-Roger

Factor Information

Factor	Type	Levels	Values

Participant	Random	32	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32
Elicited Engagement(EE)	Fixed	2	H, L

Variance Components

Source	Var	% of Total	SE Var	Z-Value	P-Value
Participant	0.310725	56.50%	0.087015	3.570916	0.000
Error	0.239214	43.50%	0.022776	10.503136	0.000
Total	0.549939				

-2 Log likelihood = 452.660771

Tests of Fixed Effects

Term	DF Num	DF Den	F-Value	P-Value
PC1	1.00	250.89	0.62	0.430
PC3	1.00	177.90	0.14	0.706
PC5	1.00	233.84	0.46	0.500
Elicited Engagement(EE)	1.00	221.36	423.91	0.000

Model Summary

S	R-sq	R-sq(adj)
0.489096	77.98%	77.63%

Coefficients

Term	Coef	SE Coef	DF	T-Value	P-Value
Constant	1.078125	0.103173	30.68	10.449728	0.000
PC1	-0.021792	0.027585	250.89	-0.789977	0.430
PC3	0.025142	0.066618	177.90	0.377411	0.706
PC5	0.070793	0.104832	233.84	0.675298	0.500
Elicited Engagement(EE)					
H	0.636748	0.030926	221.36	20.589113	0.000

Marginal Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
57	4.000000	1.715999	2.284001	3.140961	R
58	4.000000	1.724218	2.275782	3.126882	R
59	4.000000	1.661308	2.338692	3.221338	R
60	4.000000	1.698201	2.301799	3.166791	R

161	0.000000	1.614597	-1.614597	-2.237509	R
162	0.000000	1.604047	-1.604047	-2.243097	R
163	0.000000	1.599479	-1.599479	-2.239254	R
164	0.000000	1.603492	-1.603492	-2.241916	R
185	0.000000	1.735004	-1.735004	-2.365943	R
186	0.000000	1.722488	-1.722488	-2.349028	R
187	0.000000	1.706903	-1.706903	-2.330040	R
188	0.000000	1.711313	-1.711313	-2.334018	R

R Large residual

Conditional Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
57	4.000000	3.017966	0.982034	2.140687	R
58	4.000000	3.026185	0.973815	2.123252	R
59	4.000000	2.963275	1.036725	2.277779	R
60	4.000000	3.000168	0.999832	2.181138	R
132	3.000000	2.009844	0.990156	2.219403	R

R Large residual

Mixed Effects Model: Performance versus PC1, PC5, ... Engagement(EE)

Method

Variance estimation	Restricted maximum likelihood
DF for fixed effects	Kenward-Roger

Factor Information

Factor	Type	Levels	Values
Participant	Random	32	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32
Elicited Engagement(EE)	Fixed	2	H, L

Variance Components

Source	Var	% of Total	SE Var	Z-Value	P-Value
Participant	0.307960	56.35%	0.086143	3.574984	0.000
Error	0.238571	43.65%	0.022691	10.513799	0.000

Total	0.546531

-2 Log likelihood = 449.193961

Tests of Fixed Effects

Term	DF Num	DF Den	F-Value	P-Value
PC1	1.00	251.88	0.62	0.430
PC5	1.00	234.41	0.45	0.505
Elicited Engagement(EE)	1.00	221.35	427.29	0.000

Model Summary

S	R-sq	R-sq(adj)
0.488437	77.97%	77.71%

Coefficients

Term	Coef	SE Coef	DF	T-Value	P-Value
Constant	1.078125	0.102741	30.79	10.493637	0.000
PC1	-0.021767	0.027539	251.88	-0.790402	0.430
PC5	0.069825	0.104655	234.41	0.667192	0.505
Elicited Engagement(EE)					
H	0.637408	0.030836	221.35	20.671053	0.000

Marginal Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
57	4.000000	1.751519	2.248481	3.076897	R
58	4.000000	1.757127	2.242873	3.069988	R
59	4.000000	1.695980	2.304020	3.159127	R
60	4.000000	1.734768	2.265232	3.099667	R
161	0.000000	1.599919	-1.599919	-2.221089	R
162	0.000000	1.589624	-1.589624	-2.227002	R
163	0.000000	1.584808	-1.584808	-2.222679	R
164	0.000000	1.589373	-1.589373	-2.226372	R
185	0.000000	1.737033	-1.737033	-2.375984	R
186	0.000000	1.727972	-1.727972	-2.363358	R
187	0.000000	1.705545	-1.705545	-2.335373	R
188	0.000000	1.721734	-1.721734	-2.353881	R

R Large residual

Conditional Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
57	4.000000	3.024796	0.975204	2.126650	R
58	4.000000	3.030405	0.969595	2.116001	R
59	4.000000	2.969257	1.030743	2.265959	R
60	4.000000	3.008045	0.991955	2.164238	R
132	3.000000	2.009923	0.990077	2.222123	R

R Large residual

Mixed Effects Model: Performance versus PC1, ... ited Engagement(EE)

Method

Variance estimation	Restricted maximum likelihood
DF for fixed effects	Kenward-Roger

Factor Information

Factor	Type	Levels	Values
Participant	Random	32	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32
Elicited Engagement(EE)	Fixed	2	H, L

Variance Components

Source	Var	% of Total	SE Var	Z-Value	P-Value
Participant	0.305957	56.23%	0.085563	3.575797	0.000
Error	0.238178	43.77%	0.022604	10.536982	0.000
Total	0.544135				

-2 Log likelihood = 446.959362

Tests of Fixed Effects

Term	DF Num	DF Den	F-Value	P-Value
PC1	1.00	252.87	0.69	0.408
Elicited Engagement(EE)	1.00	222.06	440.59	0.000

Model Summary

S	R-sq	R-sq(adj)
0.488035	77.91%	77.74%

Coefficients

Term	Coef	SE Coef	DF	T-Value	P-Value
Constant	1.078125	0.102428	30.83	10.525663	0.000
PC1	-0.022778	0.027469	252.87	-0.829218	0.408
Elicited Engagement(EE)					
H	0.640298	0.030505	222.06	20.990119	0.000

Marginal Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
57	4.000000	1.743631	2.256369	3.094035	R
58	4.000000	1.740886	2.259114	3.097260	R
59	4.000000	1.731917	2.268083	3.108232	R
60	4.000000	1.742833	2.257167	3.094965	R
161	0.000000	1.614178	-1.614178	-2.244849	R
162	0.000000	1.585476	-1.585476	-2.226090	R
163	0.000000	1.582541	-1.582541	-2.224455	R
164	0.000000	1.585785	-1.585785	-2.226265	R
185	0.000000	1.738522	-1.738522	-2.383207	R
186	0.000000	1.734648	-1.734648	-2.377454	R
187	0.000000	1.731198	-1.731198	-2.372413	R
188	0.000000	1.718004	-1.718004	-2.353844	R

R Large residual

Conditional Fits and Diagnostics for Unusual Observations

Obs	Performance	Fit	Resid	Std Resid	
57	4.000000	3.019296	0.980704	2.140066	R
58	4.000000	3.016552	0.983448	2.145920	R
59	4.000000	3.007583	0.992417	2.165817	R
60	4.000000	3.018499	0.981501	2.141756	R
132	3.000000	2.012422	0.987578	2.218171	R

R Large residual

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