The Pennsylvania State University

The Graduate School

Department of Industrial and Manufacturing Engineering

ELECTROENCEPHALOGRAM DATA ANALYSIS ON E-LEARNING PERFORMANCE

A Thesis in

Industrial Engineering

by

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Submitted in Partial Fulfillment

of the Requirements

for the Degree of

Master of Science

May 2017

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ABSTRACT

E-learning, also known as cyber learning, has become an important part of society. According to the incredible volume of published articles, institutional investment in practice and uptake of web-based education tools in the past decade demonstrates that E-learning practice has achieved a momentum that will make it a central part of future education. The existing body of literature indicates that E-learning is a means of implementing education that can be applied within varying education models (for example, face-to-face or distance education) and educational philosophies (for example, behaviorism and constructivism). However, the quantitative criteria for improving the online learning system remain a mystery. In this study, an experiment was proposed in which the underlying relationship between personality, perceived workload, EEG-detected emotions and learning performance in online learning is addressed. In the experiment, participants were exposed to two kinds of stimuli in the learning of a semaphore flag-signaling system, during which their emotions, NASA-TLX scores and quiz scores were recorded and analyzed.

Based on the analysis performed on the study data, the correlation between personality and perceived workload is observed. It is also concluded that a static learning stimulus is superior to the video form. Relaxation, excitement and focus are revealed to be the most significant emotions in our online-learning setting. A best model of predicting one's learning outcome based on form and emotion data is obtained through symbolic regression. Furthermore, Structural Equation Models involving different number of variables were also considered, indicating that excitement is the strongest mediation factor.

Key Words: E-learning Improvement, Instructional Forms, Electroencephalogram, Personality, Perceived Workload, Learning Performance.

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ACKNOWLEDGEMENTS

I would like to express my appreciation to Dr. Nembhard for all the support he provided during the process of writing this thesis. I am especially appreciative of the Faculty Research Assistant position he offered me at Oregon State University. Dr. Nembhard guided me through the process of determining a topic, performing data analysis, and writing and formatting the thesis. He gave many suggestions on data analysis, which continuously helped in the mapping of the relationship between EEG signals and another measurement. Without his patience and constructive support, it would not be possible for me to finish my thesis. Also, as my reader, Dr. Freivalds provided me with valuable suggestions, all of which helped me to make my thesis a better work.

I would also like to thank my previous lab mate, Chenmu Wang, who graduated from the Department of Industrial and Manufacturing Engineering at Penn State in 2016. Without her great effort in designing the experiment and recording the performance matrices of the EEG, all of the work presented in my thesis would not exist. At the same time, I want to say thank you to the 48 anonymous participants in this study. Only with their participation, time and effort was I able to collect and analyze relevant data. In the process of writing my thesis, my peers from Penn State University and Oregon State University also provided me with valuable suggestions for improving my thesis.

I also would like to thank my parents for their financial and mental support to help me finish my master's degree in the US.

Chapter 1

Introduction

1.1 Background

In the past few decades, a tremendous amount of online education websites have come into our sights, including Khan Academy, Coursera, Code School, Udemy and so forth. All of a sudden, we realize that learning in a traditional classroom is not necessarily more efficient than taking an online course. It is undeniable that online courses give learners the freedom to gain knowledge on any subject, at any time. However, there is a big drawback to online education. Compared to traditional classes, online-learning material is pre-composed and cannot be changed over one learning period. Compared to traditional classroom education, where the instructor can receive real-time feedback from the student, online learning does not give the learner other choices if the learning pace or style does not suit him or her.

Fortunately, the existing body of literature supports the claim that instructional design can help to improve online-learning systems. Additionally, different instructional forms will result in a variety of learning outcomes, among which animation and static graphics are used most often [1, 2]. Furthermore, recent research indicates that online-learning systems could be more intelligent if we design them in the right way; it has been shown that physiological devices such as EEG can help to collect data to reflect a student's reaction to the learning materials. Personality and workload are two additional factors involved in the learning process; they have also been observed to influence learning outcomes. Thus, in this research, it is examined whether two instructional forms, static graphics and animated video, resulted in different learning outcomes, as well as whether EEG waves, personality traits and a perceived-workload survey can be used to accurately detect a student's physiological parameters to predict his or her learning outcomes. If the relationship between the factors mentioned above exists, utilizing EEGs, personality traits and perceived workload are effective quantitative parameters for providing real-time feedback to the learning system. Ways to improve the system will be investigated in the future.

1.2 Online Learning

Although traditional classes and face-to-face interactions are recognized as the primary methods of education around the world, online learning now have a tremendous influence on learning. Online learning, which is also known as e-learning or distance learning, is a learning system that allows students to access course content remotely; a distance-learning course is defined as a course in which more than 80 percent of the course materials are conveyed through the internet [3].

In the mid-1970s, e-mail began to supplement university courses, and computer conferencing first appeared. After that, the first entirely online course and first online program were introduced at the beginning of the 1980s [4]. Having progressed through many years of radio and television learning, the concept of online learning is already more than 170 years old [5]. With the development of modern technology, as well as the widespread use of computers and personal laptops, e-learning has become a way of learning that can be accessed by almost everyone in the world. Today, all kinds of online courses are created and delivered by virtual-only learning communities (e.g., Coursera, Khan Academy), universities (e.g., Penn State University Global Campus) and university-based, non-profit distance-learning programs. In the United States, 6.1 million students took more than one online course in the fall term of 2011, and 31% of all students in higher education took at least one online course [6]. In 2012, the number of students taking at least one online course was 6.7 million, and 32% of higher-education students were involved in online courses [3].

Online courses and programs provide a brand-new way for students to study whatever they want, whenever it suits them, without traveling thousands of miles or quitting their current jobs [7]. Compared to traditional classroom education, where the instructor can get real-time feedback from the students and adjust his or her teaching style accordingly, online training materials are pre-recorded or pre-composed, and no instructor is sitting on the other side of the computer to control the quality of the training. It is the learner's responsibility to pause the video if there is any confusion. If the teaching style used in an online course does not suit a student's learning style, the student has to decide whether he should drop the course or make an attempt to complete the course.

Fortunately, there are many ways to design the E-learning screen to improve the efficiency of learning based on human-factor-related criteria. Per the surveys conducted by Allen and Seaman, the percentage of academic leaders who think the online education is the same as or superior to face-to-face education was 57.2% in 2003; this percentage increased to 77% in 2012 [3]. In a study conducted by Summers and Waigandt, there were no significant differences between the face-to-face study group and online-learning study group in the study of statistics [8]. Online learning can be substituted for face-to-face classes; if properly designed, online courses successfully engage and challenge learners, resulting in a better learning experience and improved student performance [9, 10]. Although many researchers focus on the significance of design in the online learning environment, most of them focus on course design and the development of online communities to achieve higher satisfaction among students; the measurements used in this type of research are mostly subjective [11, 12].

In this study, I examined the effects of two learning methods on student performance. One is static PowerPoint slides, and the other is a human-presented video on the topic of flag semaphore. As an objective measurement, tests were administered after each learning session. I also implemented electroencephalogram statistics as objective mediation factors, and used subjective measurements such as the five-factor personality model and NASA-TLX to understand the relationship among different types of online course materials, brain-wave statistics and learning performance.

1.3 Five Factors Model & NASA-TLX

The five-factor model, also known as the big five personality traits, is composed of five basic dimensions: Extraversion, Agreeableness, Conscientiousness, Neuroticism and Openness to Experience. The foundation of the five-factor model was established in the 1930s, and the initial model was first introduced by Tupes and Christal in 1961 [13]. Rather than describing people in theoretical terms, the five-factor model uses terms that people use to describe others or themselves in daily life. Instead of replacing all of the previous personality instruments, the five-factor model integrated them, resulting in a reliable tool for use any time personality assessment is necessary [14, 15]. A more detailed description of the five-factor model is shown in figure 1-1.

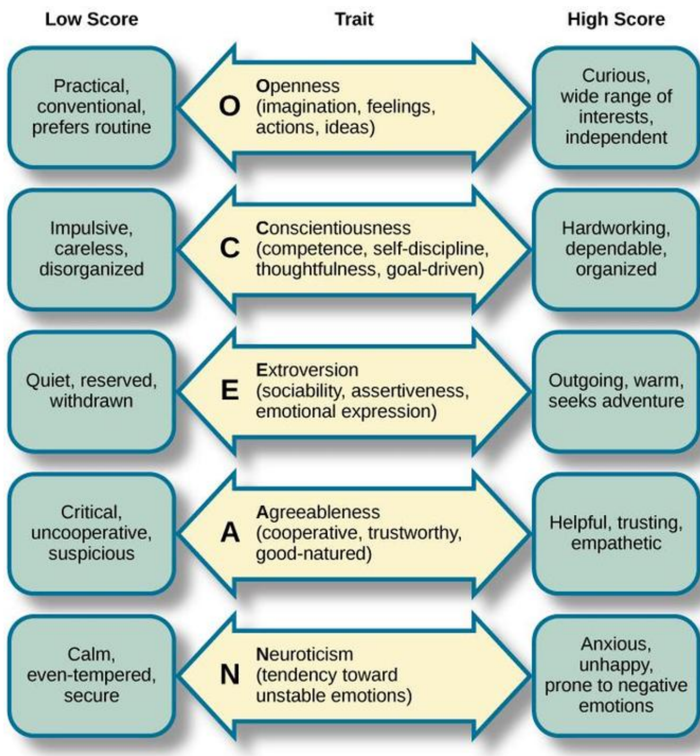

Figure **1-1**: Five Factor Personality Model Dimensions

Another instrument used in our experiment is the NASA-TLX. Like the five-factor model, NASA-TLX is a multi-dimensional tool used to estimate the participant's workload during or immediately following task performance [16]. The six categories of the NASA-TLX are mental demand, physical demand, temporal demand, performance, effort and frustration. Each of the subscales has a 100-point scale with five-point steps, and the six subscales culminate in the task load index. NASA-TLX has been found to be one of the most valid tools for examining participants' workload, including mental workload. It has also proved to be superior in sensitivity and is most acceptable by operators [17]. NASA-TLX is also significantly correlated with some physical measurements, such as blinks [18].

In our study, each subject was presented with a 50-item questionnaire based on the five-factor model personality test. The questionnaire included a series of questions related to specific dimensions of personality. For the task load index, I used computer software to calculate and record the participant's score for each subscale. The task load index and the score of each single dimension in the five-factor model were used in the data-analysis process.

1.4 Electroencephalogram

Electroencephalogram (EEG) is a non-invasive monitoring technology used to detect a participant's brain activity by placing multiple electrodes on the scalp [19]. Regarding EEG signal acquisition, the test can be performed using a wired or wireless headset with different numbers of electrodes. Due to the efforts of medical researchers, EEG has become one of the most common objective and quantitative performance measurements used to understand brain activity in humans. It has been widely applied in the study of many fields, including medical research and psychology [20, 21]. EEG is also recognized as a communication technology in brain-computer interfaces (BCI) and brain-machine interfaces (BMI) [22, 23].

In this study, EEG was specified as an objective mediation factor, through which there is an indirect relationship between instructional forms and learning performance. To reduce the level of possible discomfort and risk to the participants, the wireless Emotiv Insight EEG headset was implemented (Fig 1-2) in this experiment.

Figure **1-2**: Emotiv Insight Electroencephalogram Headset

The headset was composed of five electrodes that correspond to the EEG 10-20 system (Fig 1-3); the positions are AF3, AF4, Pz, T7 and T8. Five emotion measurements were collected and analyzed through Matlab and R in this study; they are relaxation, excitement, focus, interest and engagement.

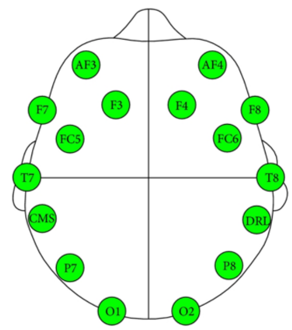

Figure **1-3**: Electroencephalogram 10-20 placement system

1.5 Learning Performance

Learning performance, also called learning outcome, refers to a statement of what a learner is supposed to acquire, comprehend and be able to demonstrate after he finishes the learning process of one specific subject [24]. Learning outcomes can be evaluated with different kinds of devices. From an academic perspective in higher education, the grade-point average (the average of the grades a student received in all courses for one term) is a common assessment of students' learning outcomes. The Collegiate Learning Assessment (CLA) and Collegiate Assessment of Academic Proficiency (CAAP) have also been applied to assess students' learning outcomes [25].

Despite the existence of these comprehensive learning-outcome assessment tools, Marzano et al. acknowledges that traditional teacher-made tests are powerful learning-outcome assessment instruments, specifically because they are highly focused and efficient [26]. Thus, in this study, I administered a pre-designed quiz following the completion of the learning process to evaluate the learning performance of the participant. The quiz covered all of the material the participant learned during each session.

1.6 Organization of the Study

As explained above, this study aims to determine the relationship among instructional forms, personality, mental workload, emotion levels and learning outcomes. The study is arranged as follows.

Chapter 2 presents a review of relevant literature. The first section of the chapter discusses the applications of devices involved in this study on human factors and, specifically, in online learning. The second section focuses on the proven relationship between internal (personal) factors and learning outcomes, as well as external (instructional) factors and learning outcomes. Last, but not least, Chapter 2 addresses analysis methods and the application of EEG in human-computer interactions. Chapter 3 explains the methodology of the experiment. It describes the design of the experiment and participant pool of the study. Chapter 4 serves to provide a comprehensive picture of the data set, within which a variety of mathematical and predictive models were implemented. Chapter 5 presents a discussion, conclusion, and plan for future research.

Chapter 2

Literature Review

2.1 Theoretical Background

As discussed above, there exists both positive and adverse effects of online learning systems. Anderson indicates that, although online learning has the potential to provide humans with effective methods of teaching and learning, it is still in its infancy [27]. Recent literature indicates that instructional design theory can be used to improve online-learning systems, among which the most used forms are static graphics and animated video [28-30]. However, there is a continuing debate on whether animated video is superior to the static form in promoting a learner's achievement. Several researchers pointed out that animation has some advantages compared to static graphics [31, 32]. However, other researchers noted that animated video does not necessarily improve a student's ability to learn the content [33, 34]. One thing we need to be aware of is that most evaluations in the literature examined traditional classroom learning or the learning of movement-based knowledge; the effect of animated video and static graphics on memorization tasks has not been assessed. In addition, several researchers argue that there is a gender difference in the perception of and preferences related to the online-learning environment, which ultimately generates inconsistency in the learning outcomes of males and females [35-37]. Thus, in this work, an experiment was designed to investigate which is the better form for promoting students' learning performance, as well as if there exists a gender effect in the learning process.

The learning outcome is not a consequence generated only by instructional forms and gender differences. Chen and Wang proposed a model relating instructional forms, emotions and learning outcomes, and emotions are believed to be the mediation factors through which different forms impact learning outcomes [38]. In this research, I also employed various statistical-analysis methods to investigate if there is a correlation between instructional forms and emotions and emotions and learning outcomes, as well as to determine if emotions serve as a mediation factor.

Furthermore, the literature asserted that perceived workload and personality are also two important factors in learning. Certain traits in the five-factor personality model are evaluated to be significantly related to students' academic achievement [39, 40]. The relationship between improvement in workload and better performance was also addressed by the literature [41, 42]. In addition, we also need to note that perceived workload and personality are not two independent factors in the learning process; they are correlated with each other, as stated by several online-learning scholars [43]. Thus, the influence of perceived workload and personality on learners' performance, as well as the relationship between workload and personality, are investigated in this research.

2.2 Online Learning Evaluation and Improvement

As the development of modern technology, being able to evaluate the effectiveness of an online-learning system and improve it accordingly is essential for making distance learning a more competitive substitute for traditional classes.

Hew et al noted that the evaluation of the online learning should cover three levels, in specific, are the entire online education program (macro-level), individual online education courses (meso-level) and individual online learners (micro-level) [44]. They claim that, in the meso-level, we should consider if the course objectives, expectations, and evaluation methods are well-designed, communicated to the learner and realized in the course. Similarly, in the micro-level, student satisfaction and changes in attitude should be evaluated. Hew et al. also argue that the learner's work product should be used to evaluate the knowledge gained via the learning process.

In a study conducted by Gazza and Matthias, researchers implemented a survey that was designed to determine the learner's satisfaction level [45]. Student-achievement data were collected as the signal standard to examine if a new online accelerated nursing education program was an improvement over the previous one, and the new curriculum was found to be enhanced. However, Gazza and Matthias echo the statement of Hew et al., stating that additional research and evaluation are recommended to better demonstrate the quality of an online education system. Correspondingly, Rubens straightforwardly notes that satisfaction is not sufficient for the assessment and improvement of an online system; other indicators of learning outcomes or improvement of the learner's performance are needed [46]. In general, the quality of an online-education system is now determined by the satisfaction level of the learner, but other criteria should be considered in future studies concerning the evaluation of online learning systems. Thus, this research focuses on how to promote the online learning system based on a quantitative standard, which is the students' learning outcomes.

2.3 Instructional Design

Instructional design is the art of developing instructional experiences geared at promoting the acquisition of knowledge and skills in an appealing, efficient and effective manner. The instructional-design process consists of a wide range of perspectives, which include determining the needs of the learner, determining the state of the learner, defining the goals and objectives of the instruction, and creating an intervention approach that will assist in transitional processes. Instructors can measure the outcomes of instructional system design casually through direct observation and scientifically through statistical methods. In some cases, it may be difficult to evaluate the outcome of instructional system design, whereby the outcomes remain assumed and hidden completely. An instructor can select one or more instructional-design models to use in a particular learning scenario, whereby most of the models with five phases stem from the ADDIE model. These five phases include analysis, design, development, implementation and evaluation.

2.3.1 Instructional Media and Multimedia

Instructional media refers to the media channels used by the instructor to pass on information to the learner; in our study, it refers to all the devices and materials used in the learning and teaching process [47]. As such, it involves all the materials, as well as substantial resources, that an instructor can use to implement instructions, thereby facilitating the achievement of instructional objectives by students. Instructional media also serve the purpose of presenting learners with knowledge of learning objectives, motivating and directing learners, and reinforcing learning [48]. Learning can take place through different modes of communication. Chen and Sun assert that these communication platforms are what make up instructional media [31]. The common platforms of instructional media used today are face-to-face interaction, online learning, lessons by radio or television, and deployment of curricular and interactive learning via the internet. Traditional materials used as instructional media include display boards, chalkboards, slides, overheads, printed material (handouts, books and worksheets), charts, videotape or film, slides and real objects. Digital materials used as instructional media include computers, DVDs, real objects or models, CD-ROMs, the internet, interactive whiteboards and interactive video conferencing. According to Sarifuddin, instructional media can be divided into four categories, namely graphic media, 3D media, media projections and media environment [49].

Traditionally, teachers are responsible for presenting and conveying the content of the course, as well as motivating and enhancing students' learning. However, some researchers argue that traditional teaching fails to help students enhance their learning, especially when using single forms such as learning documents or books. In past decades, teachers started to employ a variety of media (mainly PowerPoint slides) in the teaching process, and the media plays an important role in enhancing students' thinking, learning and analysis skills [50]. The instructor and the learners determine the choice of instructional media, whereby the selected media has to be the most efficient to facilitate learning activities or enhance the understanding and comprehension of the learners. These instructional media have common objectives, which include grasping the attention of learners, sparking their interests, supporting their learning activities with living examples as well as visual elaboration and creating a conducive learning environment in the classroom. Furthermore, instructional materials are also instrumental in transforming the learning process into an entertaining, enjoyable experience. According to Chen and Lee, matching the right instructional media with the students is the key to achieving the best results in a classroom setting [32]. Instructors can also educate learners with multimedia tools. Multimedia design combines content from a wide range of materials, such as videos, animations, images, texts, audio and interactive content. Multimedia is an advanced form of media, as it employs more than the rudimentary computer displays used in ordinary media such as texts or hand-produced materials.

The online-learning setting mainly uses digital-media platforms to facilitate learning activities among students as the most effective materials of instructional media. In this case, both the student and the instructor must have access to the internet; once a connection is established, the learning process can be undertaken through interactive video conferencing, online learning portals and DVDs. Additionally, the online-learning setting can also make use of instructional multimedia, which combines most of the other digital-learning materials to enable learners to easily achieve their learning objectives [51]. Furthermore, the use of these digital instructional media and instructional multimedia is very effective in promoting the learning process in an online setting, especially considering the cost-effective nature of online-learning platforms.

Learners also enjoy convenience and comfort in their studies, as they can access their learning material from any place, not necessarily in the classroom as would be the case using traditional instructional media.

The study conducted by Somnuek not only proved that media could improve students' learning outcomes, but it also received a high satisfaction score from the participants. Similarly, in a study performed by Rodgers and Withrow-Thorton, study investigators implemented the Instructional Materials Motivation Survey, which was used to determine the overall motivation to learn of each participant. The study involved three formats of media: video, lecture, and a computer-based form of instruction involving video, sound, and multimedia. The computer-based instruction resulted in an Instructional Materials Motivation Survey score significantly higher than the scores produced by video or lecture. Improvement of the students' achievement with computer-based instruction is seen as significantly better than traditional teaching. The authors argue that the possible reason why computer-based instruction causes higher motivation is that CBI creates a more student-centered, self-directed approach, giving control of the entire learning process to the participants [52]. From the literature discussed above, we can tell that various kinds of instructional media can have different effects on learning motivation and outcomes, thus determining the type of instruction becomes one of the essential keys to improving student learning.

Due to the lack of an instructor presenting material in the distance-learning process, selecting an appropriate instructional form is essential, especially when the learning is asynchronous. Holden and Westfall argue that the effectiveness and quality of instruction in distance learning are determined by instructional design and technologies, which can serve the purpose of improving learning performance [53]. The authors also acknowledge that there is no single best instructional design for distance learning. Generally, we can conclude that instructional design is a key factor in online system design, and content and learning objectives should be considered when selecting an instructional form.

2.3.2 Instructional Form and Cognitive Workload

According to cognitive psychology, cognitive workload refers to the amount of mental effort that one uses as the working memory. Therefore, the cognitive-load theory argues that the choice of instructional design, form, or media plays a critical role in determining the workload of learners [54]. J. Sweller, who developed the cognitive-load theory in the 1980s, identified three different types of cognitive workload: germane, extraneous, and intrinsic. From this perspective, one clear development is that instructors can develop a general framework on the most appropriate instructional form to adopt in regulating the cognitive workload of learners. It is imperative to note that certain instructional forms lead to a higher level of cognitive workload for learners, while others lead to a lower cognitive workload level for learners.

The cognitive-load theory enlightens instructors on some of the broad implications involved with certain instructional designs, thereby guiding them to make the right choice of instructional forms. According to Kort, Reilly and Picard, the right instructional form empowers the instructor to determine and control learning conditions within the classroom, or any classroom environment [55]. In fact, the theory provides instructors with empirically based guidelines for use in decreasing the extraneous cognitive load for their learners during the process of learning. The theory also guides instructors in determining the best type of cognitive workload to adopt given the type and purpose of learning.

Intrinsic cognitive workload refers to the inherent difficulty levels associated with particular forms of instruction. Kalyuga argues that each instructional form has an inherent difficulty associated with it, which the instructor cannot alter in any way, such as calculating 5+5 as opposed to solving a simultaneous equation [56]. However, in order to boost understanding among students when using intrinsic cognitive load, the instructor can break down the schemas into many smaller individual sub-schemas to be taught as individual lessons. After completing all the individual sub-schema classes, the instructor can later bring the sub-schemas back together in a combination that enables learners to follow a series of instructions.

Extraneous cognitive load refers to the workload that learners experience in relation to the style of presentation or instructional form selected by the instructor. Unlike intrinsic workload, extraneous workload is within the control of instructional designers. Therefore, the extraneous load is directly attributable to the instructional materials and instructional form selected by the instructor. For instance, an extraneous cognitive load occurs when the instructor has two or more possibilities of describing or defining an object, item, or formula to learners, such as two ways of defining a rectangle [57]. In such a case, the instructor can define the rectangle to learners in either a figural medium or a verbal medium.

Germane cognitive workload relates to the workload associated with processing, constructing and automating schema. The germane workload is similar to the extraneous workload in the sense that instructors are in a position to manipulate it to meet their classroom demands. O'Connor and Paunonen affirm that germane workload is the most appropriate for learners, as it reduces the extraneous cognitive load learners experience during the learning process. In addition, the germane workload also redirects the attention of learners to cognitive processes with direct relevance to the construction of schemas [58].

Judging from the above perspectives and different types of cognitive workload, it is evident that the choice of instructional form plays a critical role in controlling the cognitive workload. As such, it is advisable for instructors to devise instructional forms that result in a lower level of cognitive workload for their learners, as opposed to those that lead to a heightened level of cognitive workload. For instance, digital instructional forms appear to be less demanding in comparison to traditional instructional forms [59]. Furthermore, instructors should also select teaching models that are far easier for learners to grasp, as opposed to those that make it even more difficult for learners to comprehend. Therefore, by understanding the different types of cognitive workload, instructors can determine the right instructional forms to use in a classroom environment to facilitate better learning among students.

2.3.3 Instructional Forms in Learning

During the past several decades, the use of graphics to improve learning has been acknowledged by many researchers [60, 61]. Graphics are believed to be able to convey the information through two codes, pictorial and verbal, as well as attract the attention of learners. Furthermore, in online-learning circumstances, graphics can work to prompt attention to conceptual learning [28]. However, researchers argue that animation is a more advanced and attractive instructional device, and it is expected to be superior to static graphics in engaging and motivating students; it is also expected to generate better learning gains [29].

With the development of modern technology, instructors now have the choice between the two main instructional forms, which are the static instructional form (uses pictures and drawings) and the animation instructional form (combines both video and audio). The animation instructional form is much better and more advanced compared to the static instructional form. Static instruction is inferior in the sense that it does not generate any behavioral change among the learners, nor does it promote the great acquisition of knowledge. Chamorro-Premuzic and Furnham argued that most of the critics that advise against the adoption of static instructional forms do so because of their failure to inspire discovery among learners, which is a necessary aspect of the teaching process that facilitates real learning [30]. The reason for this assertion is that learners have a great capacity for learning a myriad of things. However, the instructional strategies and designs used by the instructors have to be not only engaging but also stimulating to facilitate this process.

Static instruction is not the most preferred form of learning, as it fails to challenge or enjoin learners. The resulting effect is stagnation of the learners' behavior, slowed transfer of skills and reduced development of critical-thinking skills. Meaningful learning requires relevance brought in by the instructional form, which in turn enables learners to explore the systems and processes involved in learning. In this regard, the animation instructional form is far superior to the static instructional form, as it enables learners to hear and see via animated learning instructions. Chen and Sun affirm that static instructional forms have little impact on the learning process [31]. In fact, several research studies conducted on the use of pictures in the learning process developed a theoretical perspective that affirmed the use of multimedia forms as superior to the use of static forms. In addition, several researchers argue that the influence of different forms is conveyed through changes in a learner's emotions. In a study conducted by Chen and Wang, a model is proposed to show the relationship between forms, emotions and learning outcomes (Figure 2-1), and it is proved that positive emotions are significantly related to better learning performance [38].

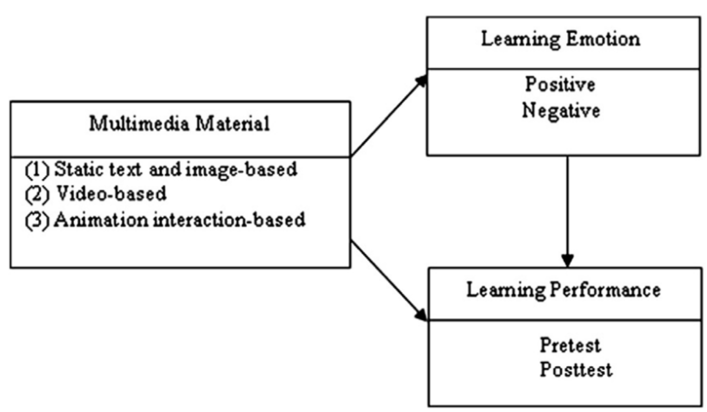

Figure **2-1**: Relationships between Forms, Emotions, and Learning Outcomes

The argument is specifically in consideration of different models of learning, which all point to the superiority of multimedia platforms (animation) as opposed to single-media platforms (static). Recent cognitive theories, such as Schnotz's 'Integrative Model of Text and Picture Comprehension' and the 'Cognitive Theory of Multimedia Learning' developed by Myer, all point to the increased efficacy of the animation instructional form over the static instructional form. In one of her numerous studies, Myer established that a learner sometimes acts as his or her own instructor of skills and knowledge, whereby he or she selects, organizes and actively integrates all of the relevant verbal and visual information received through learning. According to Chen and Lee, the Cognitive Theory of Multimedia Learning assumes three basic perspectives, which are active processing, limited capacity, and dual-channel processing and dual coding [32]. Each assumption derives its findings from a particular theory related to the learning process.

According to Funder, the assumption of active processing draws from the generative theory of meaningful learning, which proposes that, for proper learning to take place, learners must process the information they acquire actively through appropriate selection, organization and integration processes [51]. The assumption of dual coding and dual processing draws from the dual-coding theory and the working-memory model. These two models take into consideration the perception that, in some cases, two different cognitive systems control the processing of information. The limited-capacity assumption draws from the notion that limitations impede the overall processing capacity of information, especially with regard to short-term memory load within each system. These findings largely support the use of animations in learning, as opposed to static images, because of the improved capability of animations to capture the minds and attention of learners. In general, the rationale of if instructional form will have a positive influence on learning and how it occurs was not fully understood. Thus, in this research, I investigated if there exists a relationship between instructional forms and learning outcomes.

The forms that were selected to compare are animation video and static graphics, and emotion is involved as a mediation factor in our model.

2.4 Personality and Learning

Personality refers to the consistent high-level traits that determine the interpersonal relations of an individual with other people or with other groups. On the other hand, learning refers to the processes that facilitate the acquisition of new skills, behaviors, knowledge and understanding by an individual. Learning can be both formal as well as informal. The most common formal type of learning is education. Personality has a great influence on the learning process of an individual. Conversely, the type of learning style that an individual uses to acquire new knowledge and information is directly attributable to his or her personality type. Learning styles are the differences that people exhibit during the learning process in relation to their preferences, strengths and weaknesses [54]. In most cases, these differences pertain to a wide range of elements affecting the process of learning, including the acquisition of new information, comprehension of new information and memorization of new information, in addition to the recollection of the new information.

According to Kort, Reilly and Picard, the process of learning is most effective when the learning style matches the preferences of the learner [55]. Consequently, it is advisable for learners to identify the learning methods that would be most effective on an individual basis, thereby enabling them to acquire knowledge in a much quicker and more effective manner. Similarly, it is advisable for instructors to identify the learning styles that are most effective for their students, a positive pointer that is suitable in promoting the effectiveness of the learning process. The classification of learning styles is attributable to several theories of learning, such as experiential theories, intelligence theories, cognitive styles, sensory modalities of the VARK model and psychological models. One of the most prominent psychological theories is Jung's theory. Briggs Myers popularized Jung's theory by developing a personality type approach that influences learning styles.

2.4.1 Personality Tests

The preference of general attitude is the first learning style developed by Myers in her Jungian approach to personality and learning perspectives. The learning style pitches extraversion (E) against introversion (I) by reflecting the general interests of an individual, exposing where their motivation and interests lie. In this case, the motivation and interests of an introvert are mainly internal, stemming from and driven by his or her inner world. On the other hand, the motivation and interests of extraverts are derived from the outside world, the society that they live in and the people that they interact with [57]. Consequently, the interests of extraverts are normally focused externally. The other category of personality affecting learning styles is people with an intuition (N) preference, whose perceptions of the world and reasoning are broad, as opposed to those with a sensing (S) preference, who perceive and think in a concrete, direct manner.

In other cases, people with the feeling (F) preference have the tendency of being judgmental and responding to events, activities and learning based on the feelings they have, which contradicts the behavior of people with the thinking (T) preference. People with the thinking preference tend to think and react based on logic and reason [56]. The last category of individual defined by Briggs Myers is the judging (J) and the perceiving (P) type. In this case, people with the judging (J) preference exercise a high tendency to comprehend information in a more structured way, making them more likely to prefer systematic and structured learning processes. This preference is opposed to people with the perceiving (P) preference, who are, in most cases, in favor of a less rigid, more heuristic approach to the learning process. In fact, perceiving people tend to prefer the trial-and-error approach in the comprehension of new information.

From the above analysis, it is evident that an individual's personality type, as well as his or her preferences in learning style, has a significant impact in determining the motivation and interest of an individual in relation to the learning process. Consequently, personality also determines the ease with which an individual learner takes in new information, processes new information and recalls new information [58]. Therefore, it is appropriate to note that the personality type of an individual is instrumental in assisting or hindering the learning process, regardless of the format of learning, the environment of learning, or the presentation of learning material. According to Jung, the 16 personality types that determine an individual's learning style, based on his T-F, S-N and E-I dichotomies, along with the J-P relationship, are as follows. The table below shows the different learning styles discussed above.

Table **2-1**: MBTI Personality

Learning Styles			
ESTJ	ISTJ	ENTJ	INTJ
ESTP	ISTP	ENTP	INTP
ESFJ	ISFJ	ENFJ	INFJ
ESFP	ISFP	ENFP	INFP

Another important personality test is the five-factor model, which is also known as the Big Five personality traits. The five-factor model is composed of five dimensions: neuroticism, extraversion, openness to experience, agreeableness and conscientiousness. These five dimensions are posited to be at the top of the hierarchy of universal personality traits, and all the lower-level personality traits can be summarized using the five-factor model (FFM) [15]. Extroversion (E) represents the tendency to seek help from outside circumstance when facing a task or a challenge; a higher extroversion score means the participants are more likely to ask for help instead of working on their own. Agreeableness (A) reflects whether a person tends to adjust his or her behavior and opinions to suit others. A person with a higher score is more likely to agree with others and adapt to the circumstances of a situation. Conscientiousness (C) is the personality related to compliance with rules and regulations. A person with a higher score is more obedient, organized and self-disciplined, while a person with a lower score has a tendency to be messy and insubordinate. The neuroticism (N) score indicates whether an individual is emotional; higher scores indicate that the individual's emotions always change over time. Openness to experience (O) refers to a person's tendency to seek new experiences and challenges. An individual with a higher score is likely to accept novel ideas; he or she may also dream a lot.

2.4.2 Personality and Perceived Workload

Personality and mental workload have a correlational association, whereby the personality type of an individual greatly influences his or her mental workload. According to most research papers, a negative personality increases the mental workload of an individual, while a positive personality reduces the mental workload of an individual [59].

In a study conducted by Rose et al. (2002), researchers identified a correlation between personality and perceived workload by using the five-factor model to identify each participant's personality and NASA-TLX to determine an individual's perceived workload in five different dimensions [43]. The proposed model concerning the relationship between personality, vigilance and workload is shown in Figure 2-1.

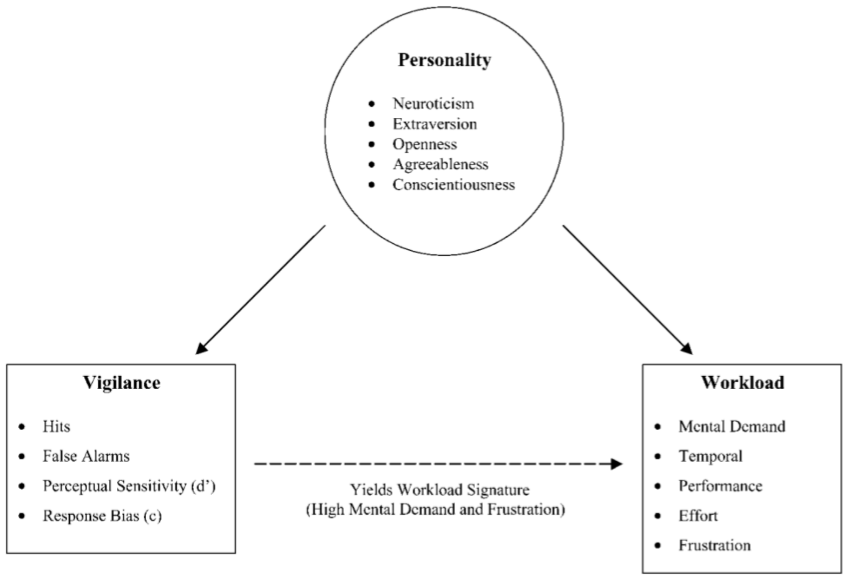

Figure **2-2**: Relationships between Personality, Vigilance, and Workload

Although researchers have found no significant effect of personality on overall perceived workload, the evident correlation between neuroticism and frustration is revealed in Rose's study. The authors claim that participants with higher neuroticism scores—in other words, emotional individuals—experienced an increased frustration level in their study. In this case, it is advisable for an individual to develop the positive aspects of his or her Big Five personality traits in order to improve his or her learning experience. In this research, the relationship between perceived workload and personality is also addressed through statistical analysis.

2.4.3 Personality and Learning

As discussed above, the personality of an individual has a great influence on his or her learning experience. In fact, the personality of an individual plays a critical role in determining his or her learning perceptions and preferences, thereby controlling his or her learning objective overall. According to Chamorro-Premuzic and Furnham (2008), different people have different ways of understanding, processing and demonstrating what they have learned in the classroom context; these differences are responsible for different learning outcomes [30]. O'Connor and Paunonen (2007) note that the evaluation of personality traits can work as the predictor of a learner's academic achievement. They argue that it is certain behavioral tendencies caused by personality traits that affect a person's learning outcomes. Personality works together with cognitive ability in the learning process; while cognitive ability determines what the learner can do, personality reflects what the person will do [58]. In another research study conducted by Chamorro-Premuzic and Furnham, the researchers acknowledge that two personality traits in the five-factor model are significantly related to students' performance in higher education. Neuroticism was a strong predictor of overall exam scores, and extraversion is significantly correlated with final-project marks [39]. Similarly, Duff et al.(2004) also proved that conscientiousness is a significant factor in predicting students' overall GPA, with the ability to predict 34.2% of the variance [40].

In general, it is evident that personality traits are, to some extent, related to academic achievement. However, all the research discussed above, which investigates the relationship between personality and learning outcomes, focuses on traditional classes. The effects of personality on a learner's performance in an online-learning setting remains unknown. Thus, in this research, the five-factor model was introduced as a way to determine the personality, and the relationship between personality and learning outcome is examined.

2.4.4 Other Personal Differences and Learning

Besides personality itself, the literature identifies other personal differences that have an impact on one's learning process, thus yielding different learning outcomes. These factors include gender, age, pacing style and so forth. Lu et al.(2003) note that learners aged 25 and over performed better in online-learning circumstances; it is believed that adult learners experience different motivators and have different learning styles than younger college students who are more familiar with traditional classes [62].

The existing literature also shows that there are gender differences in perception and preference in a telematics learning environment; it is indicated that women are more persistent than men in distance education [35]. The literature also indicates that women and men have distinctively different behaviors in an online-learning setting, according to qualitative research analysis [36]. Furthermore, existing literature also notes that gender differences not only influence learning outcomes, but they also promote an interaction between gender and instructional forms. In the research performed by Wong et al. (2015), a follow-up analysis showed that females gain more benefits than males from animated presentations [37].

Thus, it is advised that the gender effect should be taken into consideration when improving the online-learning system. However, whether there is an overlap between personality traits and other personal differences is not clear in online-education circumstances. Further investigation into gender and age, as well as the joint effect of different factors, is required. In this research, I extracted the gender information from the demographic survey and the relationship between gender and learning performance was evaluated.

2.5 Workload and Learning

As discussed above, mental workload refers to the brain capacity required to perform or complete a given task or task element. In this case, mental workload and learning have a direct correlational relationship. The reason for this assertion is that each learning process occurs in the brain of an individual [31]. Therefore, the individual's learning style determines the level of mental workload as light, moderate or heavy depending on the learning material, instructional form, and individual's personality.

2.5.1 Workload Instruments

Humans are only able to process a limited amount of information at one time [63]. Mental workload is defined as the ratio between an individual's processing ability and the amount of data received; it increases with less information received or a larger number of demands [64].

The NASA Task Load Index (NASA-TLX) is the most common instrument used in measuring mental workload. In fact, it is the most effective measurement tool because of its subjective and multidimensional nature. The NASA-TLX has six subscales that represent the measure of the mental workload of a given task. These six subscales include mental, physical, temporal, performance, effort and frustration. Mental demand is the amount of perceptual and mental activity required to perform a given task; tasks are rated as demanding or easy, complex or simple. According to Chen and Lee (2011), physical demand answers the question of how much physical activity is required to perform a given task, with each individual rating the task as demanding, slack or strenuous [32].

Temporal demand answers the question of how much time pressure a person feels based on the speed at which he or she completes or performs tasks or task elements, a speed that can be either slow or rapid. The overall performance scale indicates the level of success achieved by an individual in performing a given task, rating the performance in consideration of satisfaction levels as either very satisfied with the results or very dissatisfied with the results [51]. The frustration-level scale answers questions regarding the amount of irritation, stress and anger brought about by a project or task in relation to the level of contention, relaxation and complacence felt by an individual when performing the task. Lastly, the effort scale answers questions regarding the difficulties experienced by an individual in performing a given project or task, measured in both mental as well as physical perspectives, and rated as easy, moderate or difficult.

2.5.3 Memorization and Working Memory Capacity

Memorization refers to the process of committing something to memory. Memorization is crucial in the process of learning because it enables an individual to store a significant amount of crucial information in his or her brain. Therefore, memorization refers to the mental process undertaken by an individual in storing a memory and recalling it later, especially with regard to items such as names, experiences, addresses, appointments, telephone numbers, stories, lists, pictures, poems, maps, music, facts, diagrams or any other form of audio, visual or tactical information [55]. The science of studying the memory of an individual falls under the cognitive neuroscience category, an interdisciplinary link between cognitive psychology and neuroscience. Memorization works hand in hand with working-memory capacity, defined as the cognitive function whose main responsibility is to retain, manipulate and use information.

Learners use working memory to store the things they encounter in the classroom in different parts of the brain that have the capacity to take some sort of action. In this regard, working memory is crucial in enabling an individual to focus on a particular task, block out distractions and recognize the objects or events unfolding within his or her surroundings. Jensen affirms that working memory is superior to memorization in the sense that it enables an individual to grasp a phonics-based approach to reading and learning [54]. Working memory is, therefore, a core executive function within the cognitive system of an individual; it operates with a limited capacity, in addition to being responsible for transient holding, processing and manipulation of information. Learners make use of working memory in reasoning and making the right decisions based on their personality and behaviors. The best approach to increasing the capacity of working memory is to focus on subjects or fields that are interesting to an individual, such as hobbies and pastimes.

2.5.4 Workload and Learning

According to Kahneman's theory, workload can influence one's learning by mediating arousal; it is believed that a higher workload may generate higher levels of emotional arousal and attention [65]. Researchers also argue that a student's approach to particular learning tasks will be influenced by his perceptions of the learning environment, which in turn will have an effect on his learning performance [66]. As noted above, the extent of working memory enables students to advance in their learning; that is, an active or extensive working memory leads to faster and better learning, while a slow and less-extensive working memory hampers a student's ability to acquire new knowledge. In a study conducted by Berka et al. (2007), it is observed that workload increases with the working memory load, through which it influences the learning outcomes [67]. Similarly, Wijaya(2012) argued that an improvement in reducing workload is associated with an increase in the learning outcomes; learning outcomes are improved by the improvement of workload, eye fatigue and stress is 18% [68].

Although the relationship between workload and learning is addressed by the literature, the direct and quantitative influence of workload on one's learning performance remains unclear. As Kember et al (1996) noted, workload has the potential to work together with other factors to form interrelationships rather than forming a simple direct relationship. To better understand the role of workload in learning, the influence of perceived workload on learning was assessed via regression in this research.

2.6 Emotions and Learning

According to psychological experts, the emotions of a learner affect his or her learning by determining the attitude of an individual toward a given subject or classroom session. In this regard, it is imperative to note that a positive attitude will contribute to high scores on classroom tests while a negative attitude will equally contribute to low scores on classroom tests. The reason for this assertion is that a positive attitude creates a conducive learning environment, as it boosts the eagerness of a student to acquire new skills, knowledge and expertise from the instructor. Students experience a wide range of emotions that instructors need to harness in order to promote learning capacity and speed. Students with the right emotions will be good and attentive listeners in the classroom, as opposed to students with corrupt or confused emotions, whose minds may stray away from ongoing learning activities in the classroom [56]. Some of the key emotions affecting the learning process include motivation, engagement, interest and excitement.

Motivation sparks positive emotions in the learning process. A student with a high level of motivation will study attentively and learn well in the classroom. On the other hand, students with low morale might even miss classes; if they attend classes, they are likely to spend much of their time disrupting the learning process. Conversely, it is advisable for instructors to develop motivational strategies to boost the learning morale of their students, thereby promoting the learning process [58]. The level of engagement between the instructor and the student determines the effectiveness of the learning process. In a classroom that has active engagement between the two stakeholders in the learning process, achievement of learning objectives is very high. However, in a classroom that has low engagement between the learners and the instructor, the achievement of learning objectives is minimal, if not absent. Consequently, it is advisable for instructors to actively engage their students during every step and stage in the learning process to keep them focused on achieving academic objectives.

Interest is another important emotion that affects the learning process. Learning is a systematic process that takes place in steps and stages. Therefore, a student needs to develop interest in his or her learning activities in order to participate in and follow up on all the steps of learning. In this regard, it is appropriate to assert that a student with deep interest in the learning process will perform better in his or her exams as compared to the student with little or no interest in the learning process. These interests could be in the course, the teacher, the topic or the subject of learning. Paas, Renkl and Sweller (2003) note that a student needs to develop an interest in all of these processes in order to enjoy the learning process and succeed as a student by passing his or her exams [59].

Excitement is an emotion that is similar to interest, as it develops from the level of happiness a student derives from the learning process. It is without a doubt that students taking an exciting class will achieve high scores compared to students taking a boring course [30]. Therefore, it is advisable for instructors to make the learning process as exciting as possible, as it will not only capture the attention of learners but also contribute significantly to the score achieved by each student. Furthermore, learning in an exciting environment makes the learning process not only enjoyable, but also entertaining, thereby making it easier for an instructor to pass on knowledge and for learners to grasp, comprehend and memorize the information they learn in class.

In addition to the emotions described above, there are a variety of other emotions recognized by researchers. Kort et al. (2001) proposed a model representing the relationship between phases of learning and emotions, as shown in Fig 2-2 [55]. The author states that various emotions are stimulated by the learning process.

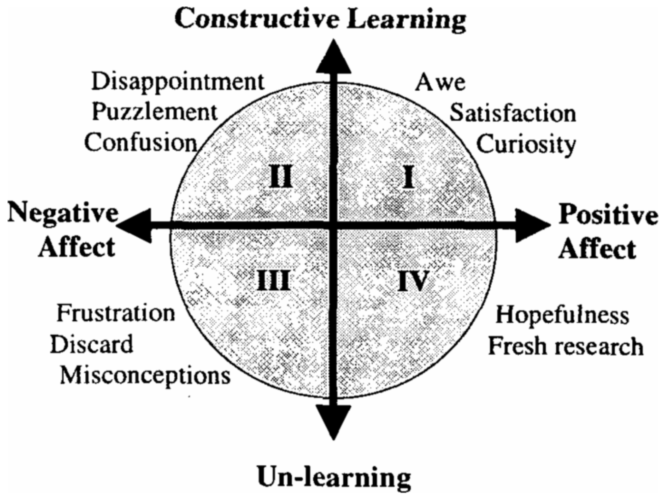

Figure **2-3**: Model Relating Phases of Learning to Emotions

The four quadrants of the graph show the learning phases and their related emotions. The authors argue that the learner will begin with a positive affect and start to gain some knowledge; during this period, he or she will experience emotions like satisfaction and curiosity. Once a learner passes through this phase, the discrepancy between the learning material and the learner's knowledge will emerge, and he or she will experience negative feelings like disappoint and puzzlement. If this kind of discrepancy continues to exist, there will be a time in the learning process that the learner stops learning because he or she does not receive positive-emotion feedback from the experience, and feelings such as frustration occur. However, as knowledge begins to accumulate, the learner will start to experience positive emotions, resulting in the completion of one learning loop. From the above model, we can tell that there are sub-processes in the overall learning process; whether the learner is gaining knowledge is highly related to his emotions. LePine et al. (2004) also note that stress and motivation have an impact on one's learning performance, so they proposed a structural model revealing the impact of previously discussed emotions on learning performance, as shown in Fig 2-3 [69].

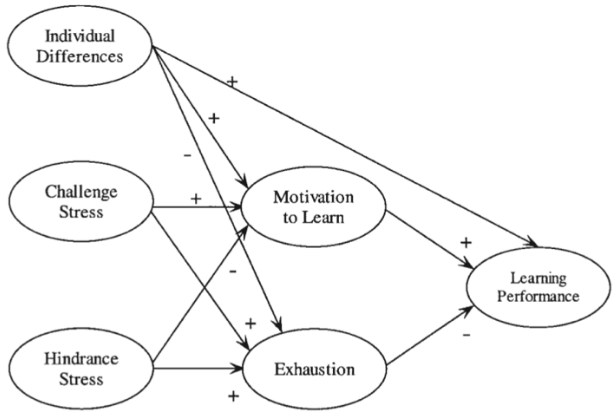

Figure **2-4**: Structural Model of Emotions and Learning Performance

In the statistical-analysis stage, the effects of the emotions in the proposed model are validated. The authors note that challenging stress and motivation to learn will have positive effects on learning performance, while the hindrance of stress and exhaustion will have adverse impacts on learning outcomes. In general, learning is always accompanied by emotions; learning itself can generate various emotions stimulated by the content, design and phase of the learning process. At the same time, the emotions the learner experiences can also benefit or hinder learning. As mentioned above, if emotions serve as a mediation factors which help instructional forms influence the learning outcome is addressed. In addition, the effect of emotion as a single factor is also considered in this research.

2.7 EEG and Learning

The application of electroencephalography became highly popular in recent multidisciplinary research. Electroencephalography (EEG) is a test that is used to measure electrical activity in the brain as a response to the communication between the brain cells. In the past, the evaluation of the learning process was performed using a self-reporting questionnaire survey. However, the subjectivity of the method is recognized, and it is desirable to obtain a more confident measure of flow quantification. The development of EEG gave researchers a tool with which to record objective and quantitative measurements [70].

2.7.1 EEG Technology

Over the past several decades, EEG has been recognized as a new communication tool that can connect the human brain to a computer [71]. It largely benefits the development of research into the relationship between human brain activities and behaviors. Before the emergence of EEG, researchers were only able to evaluate human cognitive performance with qualitative and subjective methods, such as questionnaires and surveys. However, EEG signals can be used to obtain physiological parameters that can be used to study human brain performance objectively and quantitatively [72]. It is believed that EEG waves will show different patterns when the participant's emotional status changes; for instance, EEG can be implemented to detect mental workload, task engagement, vigilance, confidence, distraction and drowsiness [72].

EEG has been widely applied in different fields. In the study conducted by Lal et al., investigators used EEG as a way to detect driver fatigue. Fatigue is described as a mental status between awake and sleep; brainwave activity changes while a person's brain is in a different status. Lal et al. used EEG to detect fatigue, making it possible to successfully study the fatigue behavior of drivers and improve driver safety [73]. Similarly, EEG technology can also be implemented in fire departments and military operations.

2.7.2 EEG and Workload

It is reported that physiological data can be used to determine one's cognitive state. EEG has been widely used in obtaining this type of data [74, 75]. A variety of research studies have been conducted with the purpose of developing an EEG index for workload assessment in tasks such as language processing and memorization, either in a linear or a non-linear way [41].

In a study conducted by Chaouachi et al. (2011), researchers developed a model to predict the participants' mental workload though features extracted from the EEG spectrum. The workload index they developed employed a Gaussian Process Regression model, whose independent variable is the task difficulty. NASA-TLX scores were introduced as the dependent variable. The authors argue that EEG data could be used to successfully build a mental workload index; the reliability of the data has been proven [41]. Similarly, Amin et al. (2014) performed an analysis of workload using EEG measurements in a service environment [42]. The primary purpose of the study was to evaluate the levels of workload experienced by a nurse in a hospital during a regular shift of work. The importance of the proposed analysis is a focus on the safety of the employee and the patients who received nursing care. High levels of mental and physical workload increase the probability of human error; in a hospital environment, human errors may be critical. Consequently, the authors proposed the utilization of EEG to monitor the workload of nurses with the objective of addressing questions about staffing and scheduling decisions. Amin et al. suggested that the data could be used to determine staffing requirements based on the safety level of the nurse's workload. However, it is necessary to determine which level of workload is optimal for the minimization of human errors.

Although EEG has been widely used as a tool to study the relationship between human behavior and mental workload, as well as to determine one's cognitive state, the literature discussed above all requires the training process before EEG works as a classifier for the mental workload. Furthermore, due to the personal difference, the EEG classifier or index has to be trained for each participant. To better understand the relationship between brain activity and human cognitive load, the investigation of building a model that can be applied universally is necessary.

2.7.3 EEG in Learning

According to the literature, perceptual learning, as well as memorization, always happens with the presence of changes in brain activity, and these changes can be recognized by electrophysiological brain activities [76, 77]. One of the fields that EEG has been applied to is evaluating and treating disorders related to the human brain; it is believed that EEG can play a major role in investigating learning and attention problems, mood disorders and other mental diseases [78, 79]. In the study conducted by Chabot et al (2001), the percentage of abnormal quantitative EEGs was found to be much higher in those with generalized or specific learning disorders than in normal children; 32.7% of children with generalized learning disorder have abnormal EEGs, and 38.1% of children with specific learning disorders have abnormal EEGs, while only 5.5% of healthy children have abnormal EEG results [80].

Apart from the clinical application of EEG in investigating learning disorders, research has also been performed in human-computer interaction to understand the correlation between EEG signals and learning outcomes. In the study of Skrandies and Klein (2015), researchers designed an experiment involving two levels of mathematical problems; the participants were asked to solve the problems before and after learning about the mathematic roles. The increase of mean EEG frequency in simple tasks and the decrease of mean EEG frequency in hard problems were observed [81]. Similarly, in the experiment done by Zoefel et al. (2011), an increase in the amplitude of the upper alpha frequency band was also accompanied by the improvement in cognitive performance [82]. Nevertheless, understanding human learning with EEG is still under investigation; both studies discussed above used average EEG amplitudes, which have proved to be illustrative. However, the use of average EEG amplitudes can eliminate some features of EEG, as it is a time series of data. Thus, further investigation involving other statistics should be conducted.

2.7.4 EEG Statistics and Analysis

Brainwaves contain an extensive range of frequencies, and EEG tracks and records human brain activity by extracting different frequency bands via electrodes placed on the human scalp; both positions and the frequency band could help us to understand human brain activities. Sontisirkit (2013) suggested that each of the EEG sensor positions is related to certain brain functions, as shown in Table 2-2 [83].

Table **2-2**: Emotiv EEG Sensors and Brain Functions

Sensor	Brain Function	Sensor	Brain Function
AF3	Attention	FC6	Left Body Controller
AF4	Judgment	T7	Verbal Memory
F3	Motor Planning	T8	Emotional Memory
F4	Motor Planning for left upper	P7	Verbal Understanding
F7	Verbal Expression	P8	Emotional Understanding
F8	Emotional Expression	O1	Visual Processing
FC5	Right Body Controller	O2	Visual Processing

Aside from the position of the sensor, researchers have been paying intensive attention to four typical frequency bands: delta (0.5 - 4 Hz), theta (4 - 8 Hz), alpha (8 - 13 Hz) and beta (13 - 30Hz) [84]. Delta waves can be found at the frontal head, and they are related to deep sleep as well as working-memory workload; theta waves are related to drowsiness or arousal; the alpha band reflects mental workload, stress and fatigue; and the beta group reflects human foot and left-hand movement. [72, 83, 85-87]. Since different frequency bands represent different human brain activities, Rabbi et al.(2009) argue that researchers typically use frequency-split technology, such as Fast Fourier Transform (FFT), Short-Time Fourier Transform (STFT) and Wavelet Transform to decompose the original EEG signal into various frequency bands as discussed above [72]. Based on the frequency bands, three classic features can be calculated: Power Spectral Densities (PSD), 5-level wavelet decomposition-based features, and Spectral Coherence (SPC) [85, 88]. In addition to the traditional time-frequency analysis methods discussed above, other statistical analyses were also applied in previous research. Berka et al. (2007) constructed an EEG metric for task engagement based on the application of stepwise regression on absolute and relative power spectral variables [67].

In general, a variety of statistical analysis methods have been applied to EEG investigations over the past several decades, but most of the literature focuses on investigating human brain activities and behavior based on raw EEG data, or on building models individually. Based on the applications of EEG on helping understand human brain activity in learning, I introduced EEG as a tool to record the emotion in this research.

2.8 Summary

The literature discussed previously demonstrates that there is a relationship between each two of the factors discussed above. First, it is evident that instructional media have an impact on one's perceived workload in the learning process, through which they can impact learning outcomes. Second, it is proved that there exists a relationship between personality and learning performance. However, what kind of a relationship it is and how personality traits can influence one's learning outcomes is still unclear. Furthermore, the literature also points out that personality has a relationship with perceived workload; specifically, in the literature examined, researchers acknowledge that personality traits in the five-factor model are quantitatively related to the subscale workload in NASA-TLX. Similarly, the impact of emotion on one's learning is also noted. Aside from these factors, other factors such gender and age are also proved to benefit or hinder one's learning process. To present a clearer view of the relationship of proposed factors, a summarized model is presented in Figure 2-4.

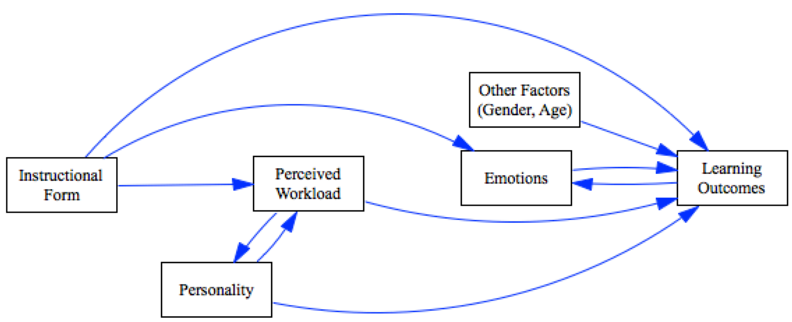

Figure **2-5**: Relationship of Proposed Factors

Chapter 3

Methodology

3.1 Objectives

The study was designed to determine the underlying correlation among personality, mental workload, EEG-detected emotion levels and online-learning performance, which will be further used to develop an objective and quantitative model to evaluate online-learning system design. Specifically, I developed two forms of semaphore learning material—one static and the other a video—as our stimulus. Five dimensions (extraversion, agreeableness, conscientiousness, neuroticism and openness to experience) in the five-factor model, six dimensions (mental demand, physical demand, temporal, performance, effort and frustration) in NASA-TLX and five emotion measurements (relaxation, excitement, focus, interest and engagement) are involved in our study.

3.2 Experimental Design

To address the purpose of this study, a two-factor experiment was designed, with a form factor of two different levels and a three-level letter group factor. The form factors are the material presented to the participants; the two stimuli are static PowerPoint slides and an animated teaching video. The other factor is composed of three levels, which is the letter group sequence. In the experiment, every participant was required to learn six sets, with each set containing four semaphores.

At the beginning of the trial, the participant will be asked to do a five-factor-model personality test. After learning every two sets of semaphores, the participant is required to take a NASA-TLX test, as well as a quiz covering all the material he learned in the previous session. In the process of the entire experiment, the participant's EEG data will be recorded and stored via Matlab.

3.2.1 Hypothesis

Based on the literature review discussed above, I developed the following hypothesis. However, since the experiment failed to separate the NASA-TLX corresponding to different instructional forms, the relationship between form and NASA-TLX cannot be investigated. Furthermore, since over 90 percent of our participants are Penn State University graduate students, the data is not sufficient to perform analysis on the age effect. The proposed hypotheses are listed as below.

H1: Two different forms of stimuli will directly result in variations in learning performance.

H2: There is a correlation between gender and learning outcomes.

H3: EEG-detected emotions will be different when a participant is stimulated by the static slides versus the teaching video.

H4: There is a correlation between NASA-TLX and personality if the instructional form factor is controlled.

H5: Different emotion levels during the learning process will cause different learning consequences.

H6: Different perceived workload will have effect on one's learning performance.

H7: There exists a correlation between personality and learning outcomes if the instructional form factor is controlled.

In general, the study focus on developing a comprehensive picture concerning the factors and human brain activities involved in an online-learning setting. A detailed model stating the possible relationships among the factors is presented in Figure 3-1.

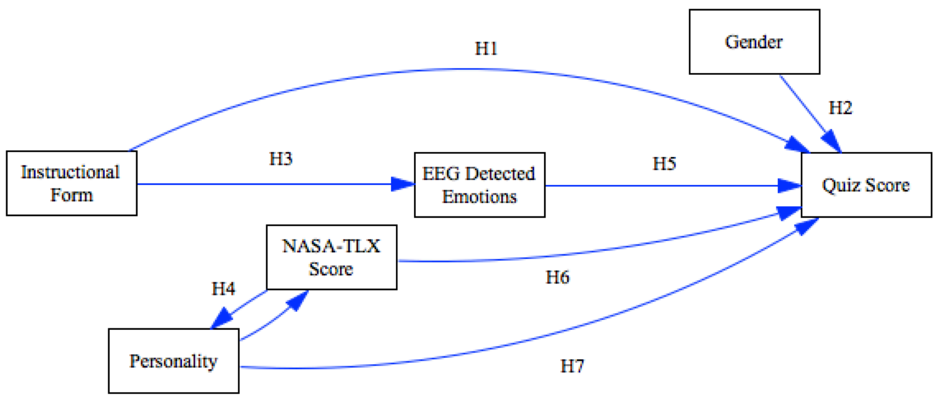

Figure **3-1**: Proposed Online Learning Model

3.2.1 Stimulus and Tasks

As mentioned before, the semaphore flag-signaling system was employed as our experimental material. The semaphore flag-signaling system is a telegraphy system that conveys information based on the waving of a pair of hand-held flags in a particular pattern. Semaphores have been advanced and widely used in the maritime industry since the 19th century. An example is shown in Figure 3-2.

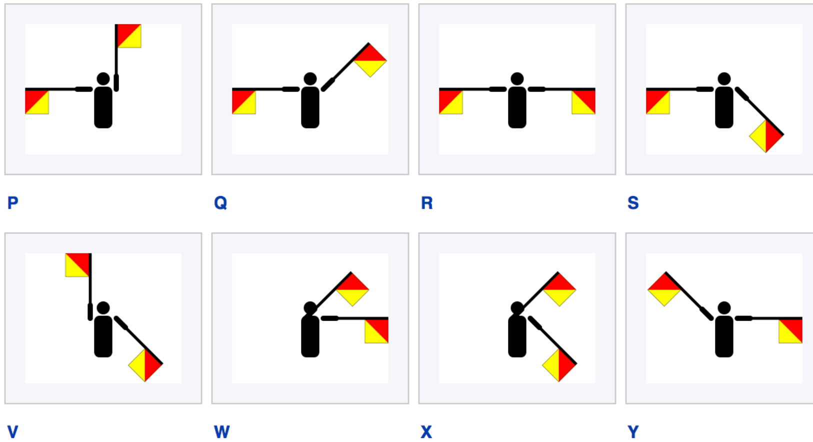

Figure **3-2**: Semaphore Flag Signaling System

In this study, the current flag semaphore system was utilized, which uses two short poles with square flags. The signalman holds the flags in different positions to signal letters of the alphabet and numbers. The signalman holds one pole in each hand and extends each arm in one of eight possible directions. Except for in the rest position, the flags do not overlap. The flags are red and yellow since I am using the flag-signaling system that is usually utilized in the sea. Two types of commonly used instructional media, static pictures and animated videos, were introduced to investigate if various forms have an effect on the participant's mental workload, emotions and learning outcomes. In the static pictures form, a picture of a man holding the flags and the corresponding English letter will be presented, while in the animated video, there will be one person showing the English letter in semaphore from the start position to the end; an example is shown in Figure 3-3.

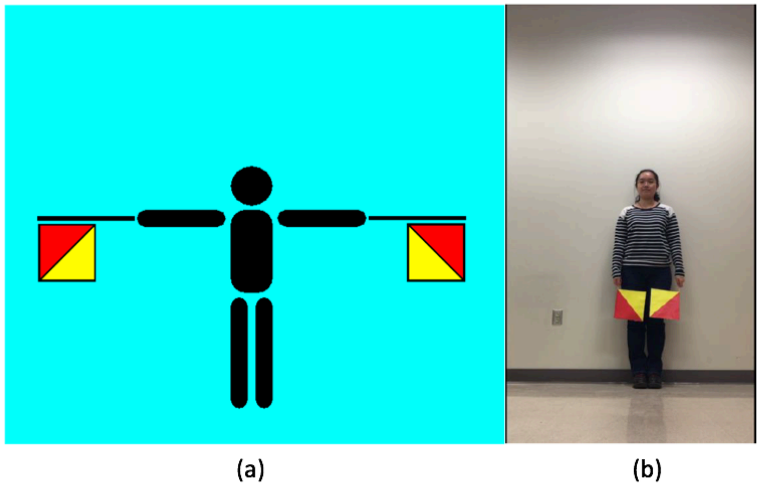

Figure **3-3**: Static Instruction (a) and Video Instruction (b) Example

During the entire learning process, the participant will be asked to go through three sessions of semaphore learning; each session will contain two set of semaphores, one in static form and another conveyed by video, with four letters in each set. The six total sets of semaphore combinations are shown in Table 3-1.

Table **3-1**: Experimental Trials Combinations

Form	Static			Video		
Letter group	GXQU	FZKD	JOEM	HBVL	SCPW	YATN

Half of the participants started with the static form, while the others started with the animated video. To assure the influence of the letter group in further data-analysis stages, the participants were divided into six different groups. Different treatments for each group are shown in Table 3-2.

Table **3-2**: Experimental Treatment Groups

Groups	Stimuli Sequence					
1	Static GXQU	Video HBVL	Static FZKD	Video SCPW	Static JOEM	Video YATN
2	Static FZKD	Video SCPW	Static JOEM	Video YATN	Static GXQU	Video HBVL
4	Static JOEM	Video YATN	Static GXQU	Video HBVL	Static FZKD	Video SCPW
5	Video HBVL	Static GXQU	Video SCPW	Static FZKD	Video YATN	Static JOEM
6	Video SCPW	Static FZKD	Video YATN	Static JOEM	Video HBVL	Static GXQU
7	Video YATN	Static JOEM	Video HBVL	Static GXQU	Video SCPW	Static FZKD

During the process, the participants were also asked to do a demographic survey and a five-factor model test (Big Five Personality Test) at the beginning of the experiment. The population survey was used to gather the personal information such as gender, age and if he or she has background on semaphore signaling system. In the experiment, a 50-item five-factor model test was introduced to determine the personality of the participant, which is shown in Appendix A. After finish each session, the participant was asked to take a NASA-TLX test, as well as a quiz which covers the letter learnt in the learning process, the quiz will require the participant to draw the correct position of a corresponding semaphore letter, which is shown in Figure 3-4.

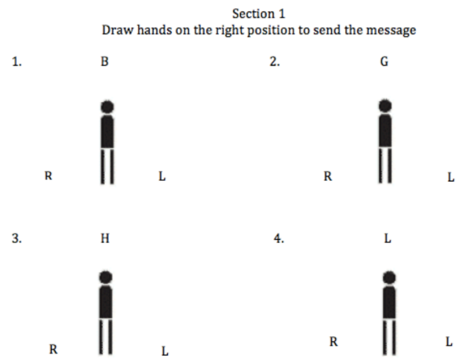

Figure **3-4**: Example Quiz Answer Sheet

3.2.2 Participants

Overall, 48 participants (26 males, 22 females) were recruited for this experiment. They all ranged in age from 19 to 35 with a mean age of 25.0 (standard deviation=3.17 years). All the participants are students at The Pennsylvania State University, University Park. All participants are qualified according to the following criteria:

1) Undergraduate and graduate students at The Pennsylvania State University, University Park.

2) Aged 18 years or older.

3) No working knowledge of semaphore flag signals; a conceptual understanding was acceptable, but no specific knowledge of signal-to-letter correspondences was allowed.

4) Have sufficient English ability to understand the instruction in the learning material.

All participants received cash compensation for their participation.

3.2.3 Experiment Apparatus

EEG

As mentioned above, a wireless, seven-electrode, five-channel Emotiv Insight EEG headset was used in the experiment; the corresponding positions are AF3, AF4, Pz, T7 and T8. There are five emotions recorded: relaxation, excitement, interest, focus and engagement. The EEG was sampled at nine per second.

Presenting Computer

One Lenovo Windows 10 computer with a 17-inch monitor was employed to complete the survey session as well as present the experimental material; the course materials were given via the PowerPoint software installed on this computer. OBS studio was installed on this machine to control the screen camera and web camera, which are used to record the screen and guarantee the timestamps are consistent on two computers. It is also responsible for recording the subjects' facial expressions, which can be used to exclude the EEG amplitude changes resulting from changes in facial expression or head movement. The PC was connected to a keyboard, mouse and additional monitor.

Recording Computer

One Dell Windows 7 laptop was used to record the EEG data through Matlab. In addition to Matlab, the Emotiv software suites were also installed to help better understand the brain activity of the participants. Emotiv ControlPanel and Testbench were used to assure the quality of the signal, as well as capture and monitor EEG waves in real time.

3.2.4 Experiment Procedure

Upon arrival, a consent form and brief description of the experiment were given to each participant. The participants received the following information:

- The procedures and the possible risks of the experiment.
- He/she agreed to participate in the experiment, as well as the research use of data recorded during the experiment (personal information, FFM and NASA-TLX data, head movements, facial expressions and EEG waves). Each participant signed the consent form, but he/she retained the right to withdraw from the study at any time.
- Descriptions of the survey, learning task and quizzes he/she needed to complete during the experiment.
- A statement indicating that all of the information he or she provided is confidential, and that he or she will finish the experiment with his or her best effort.

After reviewing all of the information provided, each participant was presented with the demographic survey, which collected personal information such as gender, grade level, nationality, native language and any previous knowledge of the semaphore signaling system. A 50-item five-factor-model test was followed by the demographic survey (Appendix A). Upon survey completion, in order to ensure the participant had a better understanding of the details of the learning process, an example of the experiment material that the participant would be exposed to was presented, in which both static PowerPoint slides and animated video were included. The participant was informed that no note taking would be allowed during the learning, and that he could begin the quiz only after the quiz instruction slide appeared.

As all of the possible questions were answered, the participant was required to put on the Emotiv Insight headset with the help of the investigator, and was asked to make five different facial expressions (neutral, smile, frown, clench, surprise) for calibration of the Emotiv

ControlPanel software. The calibration session was followed by three sections of learning, in which the participant was required to learn four semaphores via the static form and another four semaphores via animated video. The task was system-paced, with each semaphore appearing twice for eight seconds each time. At the end of each learning section, there was a two-minute rest followed by a quiz and a NASA-TLX test. After finishing all three sections, the participant was free to take off the headset and leave; no participant was asked to visit for a second trial. A detailed flow-process diagram is shown in Figure 3-5.

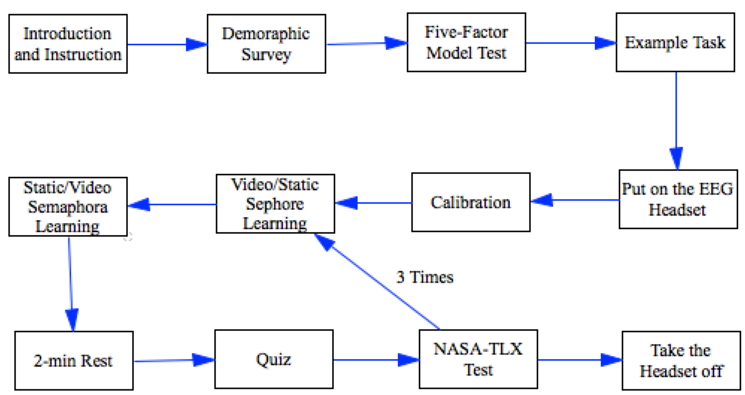

Figure **3-5**: Procedures of Experiment

Chapter 4

Data Analysis

4.1 Preliminary Data

As mentioned above, all of the participants took the five-factor-model test at the beginning of the experiment, the NASA-TLX and three quizzes. In total, there are 48 data sets of the five-factor model and 288 NASA-TLX test score data sets. After reviewing all of the quizzes, I sorted the scores based on the static form and the animated video. Thus, there are 288 data sets for learning outcomes derived from the static form and the animated video, and 144 for each individual form. In addition, I recorded five EEG-detected emotions. Since each participant completed six trials in total, 144 EEG data sets for each emotion in a single instructional form were obtained. In total, 1,440 data sets of EEGs have been analyzed.

Five-Factor Model

In the five-factor model, the scores of the participants are divided into five dimensions; the range of each scale is between 0 and 40, at intervals of 1. The five dimensions are shown as follows. Extroversion (E) represents the tendency to seek help from outside circumstances while completing a task or facing a challenge; a higher score means that participants are more likely to ask for help rather than working on their own. Agreeableness (A) reflects if the person tends to adjust his or her behavior and opinions to suit others. A person with a higher score is more likely to agree with others and adapt to his or her circumstances. Conscientiousness (C) is the personality trait that is strict with rules and regulations. A person with a higher score tends to be organized, self-disciplined and obedient, while a person with a lower score will likely be messy and insubordinate. The neuroticism (N) score indicates whether the individual is emotional;

higher scores indicate that the participant's emotions always change over time. Openness to experience (O) is the personality trait related to seeking new experiences and challenges; individuals with high scores are likely to accept novel ideas and may dream a lot.

There was one set of personal data, for participant No. 24, missing in the recorded data. To maintain the balance of the data and assure further data analysis, the individual's five-factor score is represented by the mean of all other participants, by each dimension correspondingly. The distribution of the five-factor-model test scores after the data modification are displayed in Figure 4-1.

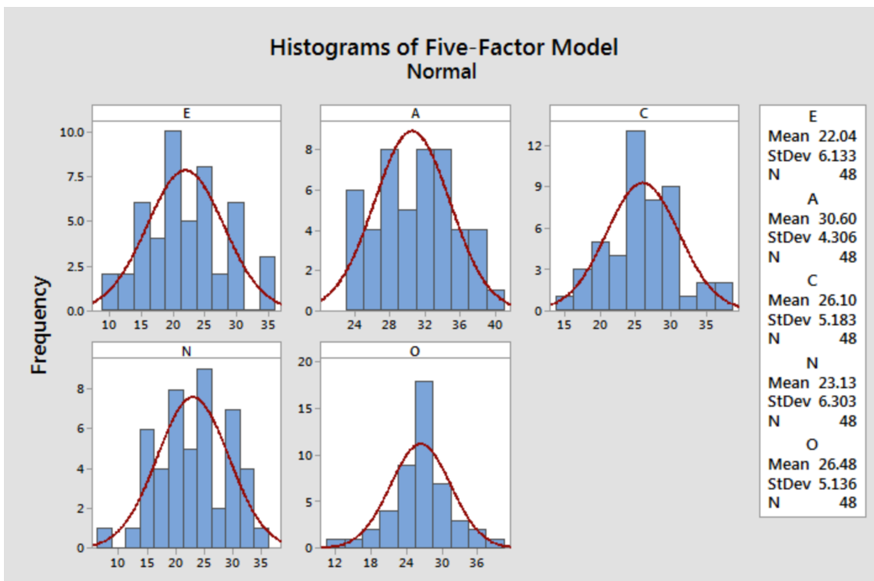

Figure **4-1**: Normal Distribution Histogram of Five-Factor Model Test

NASA-TLX Test

The NASA-TLX data was composed of six dimensions with a score range of 0 to 100 in each dimension. The dimensions are stated as follows. Mental demand, which illustrated how much mental and perceptual activity was required, allowing us to evaluate if the task was easy or demanding psychologically. Physical demand, similarly, estimates the amount of physical movement or activity needed for the task. Temporal demand evaluates the level of the pressure derived from the time pace of the task. Overall performance works as an assessment of how successful the participant is in accomplishing the task. Frustration level serves the purpose of evaluating the emotional status of the individual, indicating whether he or she is irritated, stressed, or experiencing related emotions. The last dimension, effort, is a scale for determining how hard the person should work to accomplish the task. The distribution histogram of the NASA-TLX test scores by each dimension is displayed in Figure 4-2.

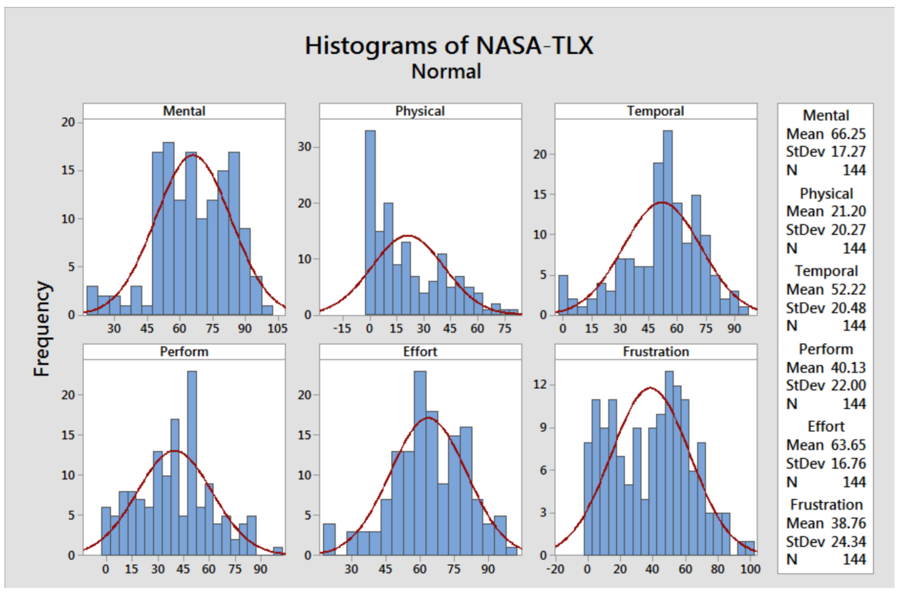

Figure **4-2**: Normal Distribution Histogram of NASA-TLX Test

Learning Outcomes

As noted above, each participant took a test covering the material conveyed in the static form and animated video. For the purpose of better understanding the effects of static and dynamic instructional forms, I separated the scores according to instructional style. They are rated for each quiz and separate form within a 40-point range with five-point steps. Due to one missing individual file in the raw data, participant No. 48, and the importance of the balance of the data, his score was calculated by averaging all other participants' quiz scores by each semaphore set (four semaphores in a certain form). The distribution histogram of the learning outcomes by different instructional types is displayed in Figure 4-3.

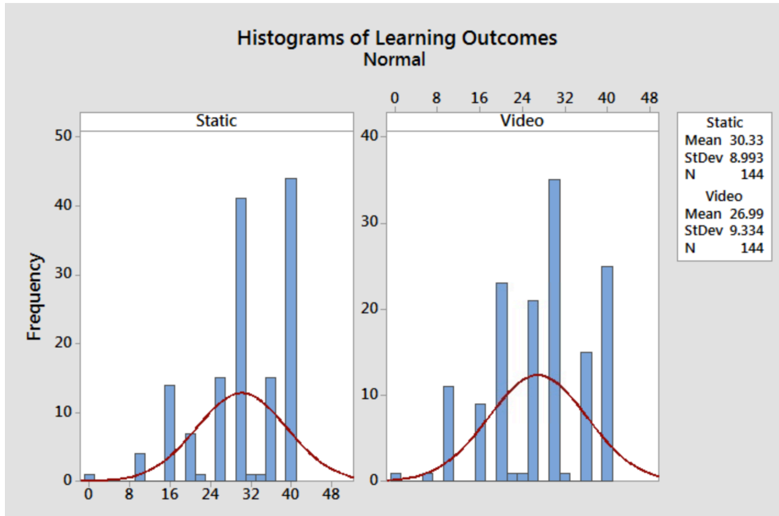

Figure **4-3**: Normal Distribution Histogram of NASA-TLX Test

As we can conclude from the histograms, the five-factor-model test data, as well as NASA-TLX scores and learning outcomes, all have good normality. Similarly, the mean of recorded EEGs in each emotion stimulated by a single instructional form also showed ideal normality.

4.2 Normalization and Statistics

Each individual learned six sets of semaphores (three in static and three in dynamic form) in total, and there were five emotions detected by EEG (relaxation, excitement, focus, interest and engagement) recorded in each trial, with a total number of 48 participants; I have in total 1,440 data sets of EEG waves.

Since EEG data varies across the sample pool, it contains many individual differences. To avoid giving individual differences more weight than the actual changes caused by the form in the EEG data, rendering us unable to recognize the effect of the stimulation of instructional forms, I normalized the EEG for further data analysis. However, due to the lack of baseline EEG recordings, I was unable to normalize the data with the EEG data of the participants in their rest state. Instead, I calculated the mean EEG for each participant in six trials, and normalized the data according to the individual mean. Since EEG is an example of non-periodic time series data, it is difficult for us to recognize the pattern from the time series data itself. An example of the EEG waves is shown in Figure 4-4.

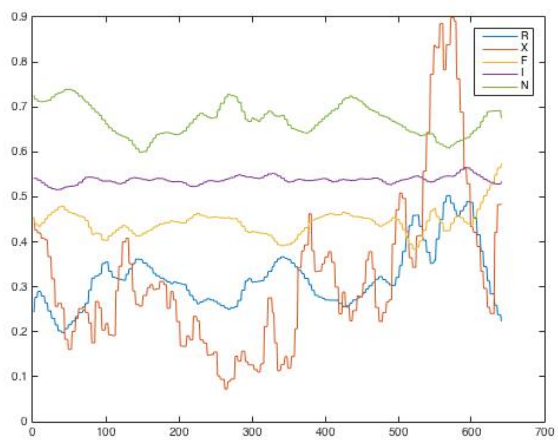

Figure **4-4**: Five-Emotion EEG Waves Example

Hence, ten statistics of each EEG wave were introduced to illustrate the features of the brain wave and conduct further analysis. Based on the graph of an EEG wave, I first recognized min, max, mean, median, range and standard deviation as the statistics of the measurement. These six statistics are widely used in different levels of data analysis, and they served to illustrate the overall level and the variation of each EEG wave. Apart from the basic statistics, as a time series data, every participant reached the peak and valley value at a different time point, which is highly related to their emotional changes. In this case, the time point at which the peak and valley values appeared was also extracted from the EEG wave.

By observing the EEG data, we can also tell the EEG data have the potential to illustrate the change of one's emotions during the overall time interval. To include this feature in the statistics, I fitted a linear-regression model to each set of EEG data, and the slope of the linear regression model was treated as a parameter regarding the change of the participant's emotions. Another important feature of the human brain is that a reaction time exists between receiving the stimuli and human activities. In this study, I assumed that this kind of delay, specific by the term latency, also exists. The issue of latency was addressed by implementing the linear piecewise regression model. The piecewise regression model, also known as segmented regression, fits the data sets with multiple linear regressions with each two neighboring fitted lines connected to each other; it enables the researchers to recognize the change point hidden in the data. The free-knot spline approximation Matlab toolbox invented by Bruno Luong was used in this study. The maximum number of knots were pre-determined to four to assure the data would not be overfitted by the regression model, and the latency time was specified by the position of the second knot adjacent to the beginning point. An example of the EEG-fitted piecewise regression model is presented in Figure 4-5.

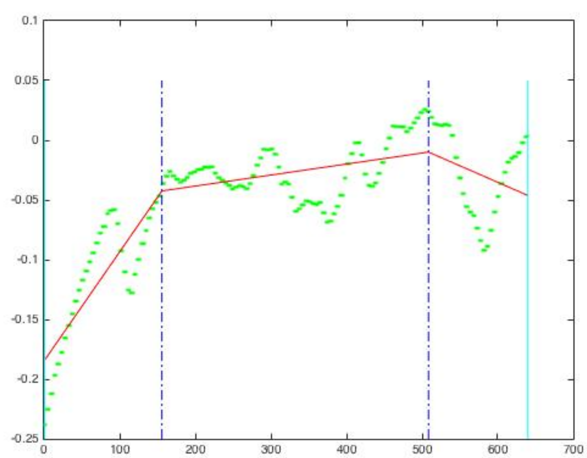

Figure **4-5**: Emotion EEG Piecewise Regression Fitting Example

Overall, the statistics calculated by each trial are maximum EEG amplitude, the time spent to reach the peak value, minimum EEG amplitude, the time spent to reach the valley value, mean, median, standard deviation, range, the slope of the fitted linear regression model and latency. A Matlab code example is included in Appendix C.

4.3 ANOVA and Correlation

4.3.1 One-way ANOVA Analysis

To test hypothesis one, an ANOVA was conducted to recognize if the factors result in significantly different consequences in learning outcomes. Minitab was used to conduct the ANOVA analysis.

Score vs. Form

To test hypothesis one, a one-way ANOVA analysis was used in recognizing if the two forms influenced the learning outcomes. The independent variable is the instructional form, the static type is coded by 1, and the video is presented by 0. The dependent variable is the score that participants got when exposed to various kinds of stimuli. The consequence of ANOVA analysis is shown in Figure 4-6 and Figure 4-7.

One-way ANOVA: Scores versus form

Method

Null hypothesis	All means are equal
Alternative hypothesis	At least one mean is different
Significance level	α = 0.05

Equal variances were assumed for the analysis.

Factor Information

Factor	Levels	Values
form	2	0, 1

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
form	1	803.3	803.34	9.56	0.002
Error	286	24025.6	84.01		
Total	287	24829.0			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
9.16546	3.24%	2.90%	1.88%

Means

form	N	Mean	StDev	95% CI
0	144	26.986	9.334	(25.483, 28.489)
1	144	30.326	8.993	(28.823, 31.830)

Pooled StDev = 9.16546

Figure **4-6**: One-way ANOVA: Scores vs. Form

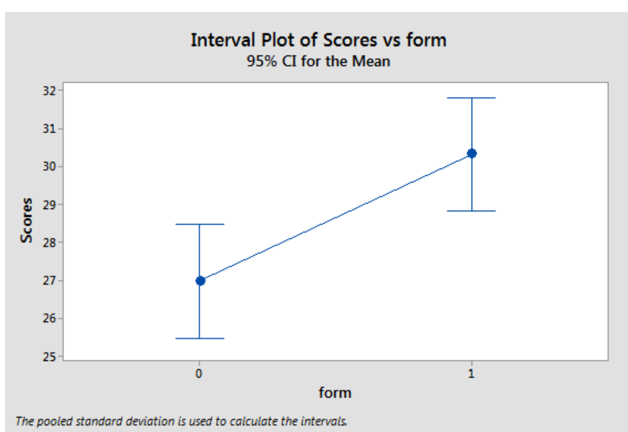

Figure **4-7**: Interval Plot of Scores vs. Form

From the above consequence of ANOVA analysis, we can conclude that the learning outcomes stimulated by static and dynamic form are significantly different (p=0.002). The dynamic structure yields a confidence interval of the performance equal to [25.483, 28.289] with the mean of 26.986, while the static results in a higher score confidence interval, [28.823, 31.830] with an average of 30.326. Compared to the dynamic form, learning outcomes stimulated by the static form are 3.34 points higher. Since the scores range from 0 to 40, learners exposed to the static form achieved a better learning outcome—8.35% higher than the scores of participants who learned via animated videos.

Score vs. Gender

Some researchers argue that online-learning outcomes are better in female gender groups. Based on the fact that most of the participants are enrolled in graduate school at Penn State University, I was unable to assess the effects of education level on performance in this online-learning setting. Nevertheless, to test hypothesis two, I conducted another ANOVA analysis to evaluate the gender effect, in which male is coded with 1 and female with 0. The consequence of this ANOVA analysis is shown in Figure 4-8. In this ANOVA analysis, the p-value of gender effect is 0.826, which is much higher than 0.05. Thus, we can conclude that the gender effect does not exist in this learning setting.

One-way ANOVA: Scores versus gender

Method

Null hypothesis	All means are equal
Alternative hypothesis	At least one mean is different
Significance level	α = 0.05

Equal variances were assumed for the analysis.

Factor Information

Factor	Levels	Values
gender	2	0, 1

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
gender	1	4.2	4.222	0.05	0.826
Error	286	24824.7	86.800		
Total	287	24829.0			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
9.31664	0.02%	0.00%	0.00%

Means

gender	N	Mean	StDev	95% CI
0	132	28.788	10.040	(27.192, 30.384)
1	156	28.545	8.658	(27.077, 30.013)

Pooled StDev = 9.31664

Figure **4-8**: One-way ANOVA: Scores vs. Gender.

4.3.2 Correlation Coefficient

In addition to the ANOVA analysis, correlation analysis was also conducted to recognize other relationships among the factors involved in the proposed learning model. First, I ran the correlation analysis using 50 statistics calculated in the previous session against form, as well as the learning scores. I also calculated the correlation coefficient between personality, NASA-TLX scores, EEG emotions and learning outcomes. The significance level was pre-determined to 0.1 in all the correlation coefficient calculations.

Forms and EEG Detected Emotions

To test hypothesis three, which addressed the relationship between forms and emotions, I calculated the correlation coefficient and p-value to determine the possible relationship between forms and 50 EEG-detected emotion statistics. There were five emotions found to be significantly correlated with the instructional form factor. A summary of the correlation is shown in Table 4-1.

Table **4-1**: Correlation of Form and Emotions

Form with	P-value	Correlation Coefficient
Excitement Standard Deviation	0.025	-0.132
Excitement Range	0.033	-0.125
Interest Time to Peak	0.034	0.125
Engagement Max	0.036	-0.123
Engagement Mean	0.072	-0.106

From the table above, it is evident that excitement and engagement are the two emotions that have a negative correlation with forms. The static structure tends to yield a smaller variation in excitement, and it results in a higher value in engagement. Since the types are coded by 0 and 1, and the range of engagement max and engagement mean falls within 0 and 1, the effect of the form of the change in one's engagement counts more than 10%. However, when the participant was exposed to a static form instead of a dynamic form, the longer it took for the interest level to reach its peak value.

Scores and EEG Detected Emotions

For a similar purpose, to test hypothesis five, I calculated the correlation coefficient and p-value of performance scores and 50 EEG emotion statistics to determine the possible relationship between them. After calculating the correlation coefficient, it is evident that 14 emotion statistics are significantly related to test scores. A summary of the statistics, as well as the p-value and correlation coefficient, is shown in Table 4-2.

Table **4-2**: Correlation of Emotions and Learning Performance

Scores with	P-value	Correlation Coefficient
Relaxation Minimum	0.081	-0.103
Relaxation Slope	0.018	-0.138
Excitement Minimum	0.007	-0.158
Excitement Standard Deviation	0.017	0.140
Excitement Range	0.018	0.140
Excitement Latency	0.056	-0.113
Focus Standard Deviation	0.054	0.113
Focus Range	0.098	0.098
Interest Minimum	0.070	0.107
Interest Mean	0.018	0.139
Interest Median	0.022	0.135
Interest Slope	0.042	0.120
Engagement Maximum	0.045	-0.118
Engagement Standard Deviation	0.092	-0.100

Although the emotions do not necessarily result in varying scores, the table above successfully points out the relationship between emotions and performance ratings. The higher score is present together with the larger variation in excitement and focus (Standard Deviation and Range), the greater the overall interest level (Minimum, Mean and Median) and the steeper the positive change in interest. Conversely, high-level valley value and severe changes in relaxation, larger valley value in excitement, and greater peak value and variation in engagement are observed to correlate with a lower performance score.

Personality and NASA-TLX

As stated in chapter 3, hypothesis four focuses on the relationship between perceived workload and personality. To investigate the relationship between personality and NASA-TLX score, the correlation coefficient was calculated by each dimension in personality and NASA-TLX. Table 4-3 shows the p-value, and the correlation coefficient is given in Table 4-3.

Table **4-3**: P-value of Personality and NASA-TLX

	Mental	Physical	Temporal	Perform	Effort	Frustration
E	0.003	Not Sig	Not Sig	Not Sig	Not Sig	Not Sig
A	0.005	0.027	0.014	0.003	Not Sig	0.000
C	Not Sig	0.042	0.057	0.055	0.008	0.055
N	0.000	0.023	0.043	0.012	0.000	Not Sig
O	Not Sig	Not Sig	Not Sig	0.001	0.048	0.001

From these two tables, we can conclude that personality scores derived from the five-factor model are correlated to the NASA-TLX, which indicates that different personalities have a different capacity for handling the workload. It is recognized that all five dimensions in the five-factor model are at least related to one scale in NASA-TLX. The correlation of extroversion (E) and mental demand are observed to be significant (p=0.003, b=0.176). It tells us that extroverted individuals prefer to seek help from others while facing a challenge they regard as difficult, compared to those who are more introverted. It was also observed that participants who like to gain new experiences were more satisfied with their performance, but at the same time, they indicated that the task required more effort and resulted in a higher frustration level, in comparison to individuals with lower scores.

Table **4-4**: Correlation Coefficient of Personality and NASA-TLX

	Mental	Physical	Temporal	Perform	Effort	Frustration
E	0.176	Not Sig	Not Sig	Not Sig	Not Sig	Not Sig
A	-0.163	0.131	-0.144	-0.176	Not Sig	-0.207
C	Not Sig	0.120	0.112	0.113	0.156	0.113
N	0.370	-0.134	0.120	0.148	0.304	Not Sig
O	Not Sig	Not Sig	Not Sig	0.198	0.117	0.193

Among all the five-factor dimensions, agreeableness, conscientiousness and neuroticism are mostly related to perceived workload. Those participants who are more obedient to rules and regulations (high conscientiousness score), as well as more emotional (high score in neuroticism), were observed to gain higher perceived workload across the six dimensions. However, overall, those who can adjust themselves to their environment (high score in agreeableness) obtained lower scores in NASA-TLX. Among all the relationships addressed in the table above, the strongest correlations are neuroticism against mental workload, and neuroticism against the amount of effort spent on the task. This indicates that emotional individuals are potentially much more likely to feel the stress in a system-paced online-learning setting.

However, with only the correlation coefficient, the relationship between personality and perceived workload cannot be well-investigated. Further analysis is required to have a comprehensive view of the relationship between personality and workload.

4.4 Stepwise Regression Modeling

With the ANOVA and correlation studied in the previous section, we can recognize some of the one-to-one relationships among the factors involved in the proposed model. Nevertheless, ANOVA and correlation failed to recognize the joint effects of several factors in the model. In this case, stepwise regression modeling was applied, which is a process of building a model by successively adding or excluding variables based solely on the t-statistics of their estimated coefficients, to create a mathematical model that can involve several dependent variables and recognize significant terms in the model. The significance level is predetermined as 0.1 in all stepwise regression models.

4.4.1 Form Included Model

To test hypothesis one and five together, first, I introduced a model involving the form. The form is already recognized as an influential factor in the ANOVA analysis stage. The result of the stepwise regression model is shown in Figure 4-9. From the graph below, we can recognize the significant terms in a comprehensive model of predicting learning performance; the factors are form, relaxation maximum, relaxation mean, relaxation median, relaxation standard deviation, relaxation range, excitement standard deviation, excitement latency, focus mean, focus standard deviation and focus latency. The stepwise regression determined that there are only three emotions that are highly related to learning performance, specifically relaxation, excitement and focus. Among all the emotion factors, relaxation mean, relaxation range, excitement standard deviation and focus standard deviation can influence the score positively, while others will set back the student’s learning performance.

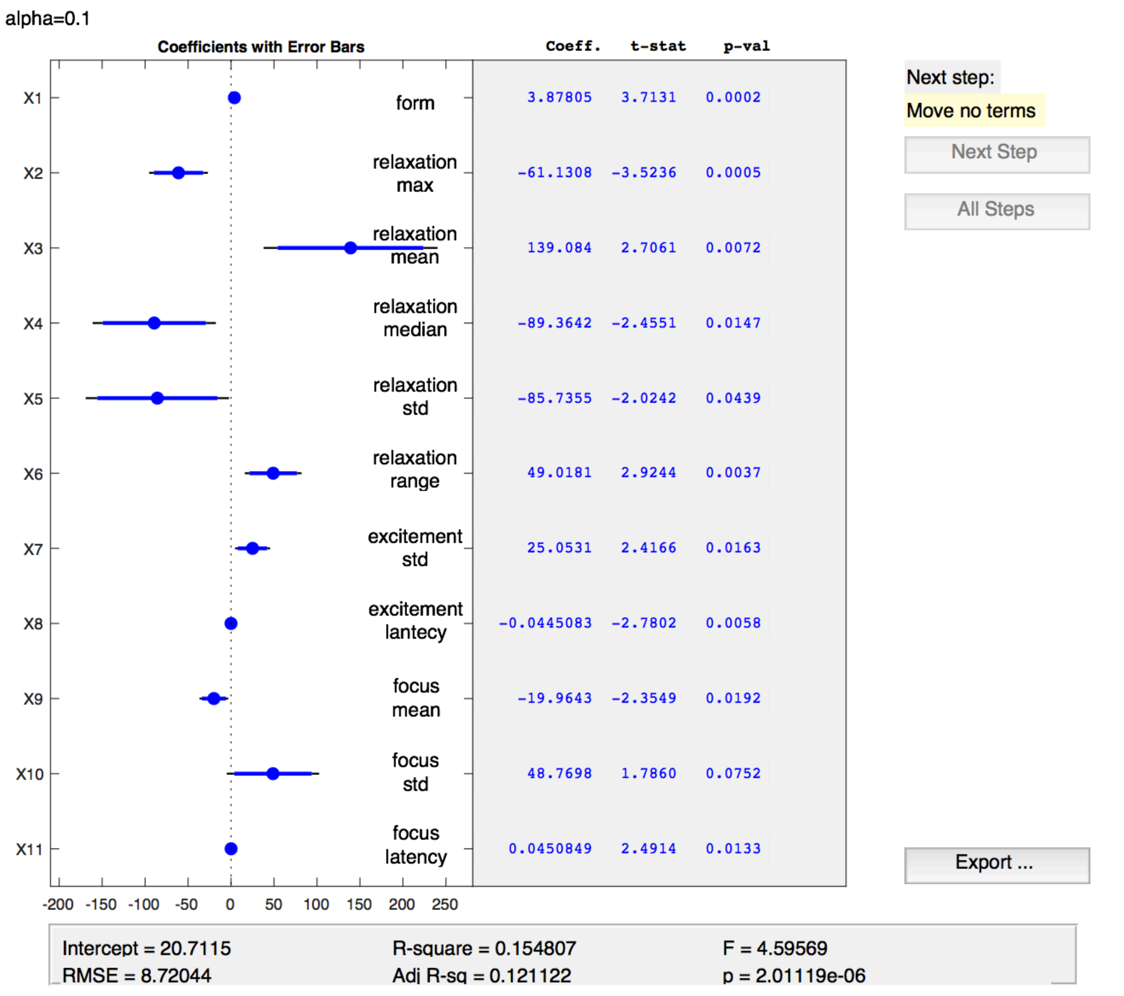

Figure **4-9**: Stepwise Regression: Form and Emotions against Scores

4.4.2 Form Excluded Model

Although the form is recognized as a significant factor in influencing the student's learning performance, how the form influences the learning consequence is not clear. Besides, the correlation between a single emotion and the learning outcomes were addressed in the analysis stage, but the overall impact of the emotions working together is not revealed. Thus, to avoid the substantial impact of structure in eliminating potential emotion statistics, as well as to examine if emotions can work as a predictor for the learning outcomes, I performed stepwise regression modeling without the form presented in the model. The result of the stepwise regression model is shown in Figure 4-10.

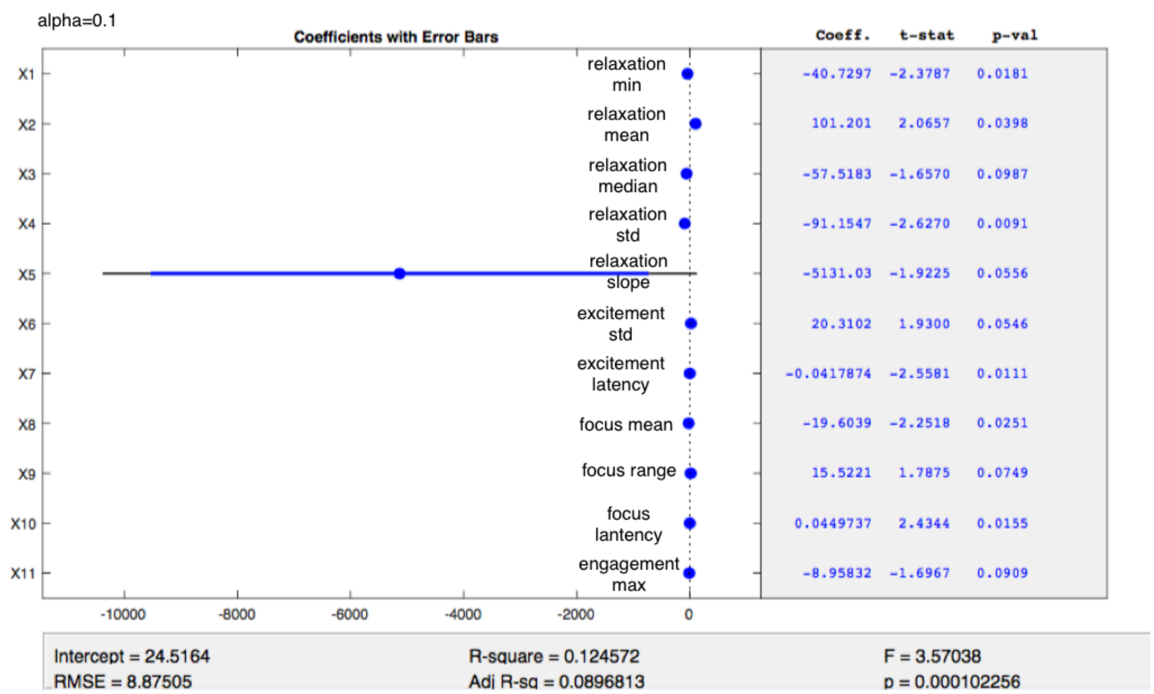

Figure **4-10**: Stepwise Regression: Emotions against Scores

This stepwise regression yields factors that are very similar to the previous one; however, in this model, the relaxation slope is involved instead of relaxation standard deviation, as well as focus range rather than focus standard deviation. One more emotion statistic, the engagement max, is recognized in this model.

4.4.3 Form, gender, personality and NASA-TLX

Similarly, as stated in hypotheses six and seven, perceived workload and personality also have the potential to influence learners' achievement. Thus, in addition to EEG-detected emotions, another stepwise regression was performed to investigate the possible relationship between form, gender, personality and NASA-TLX against learning performance. The result is shown in Figure 4-11.

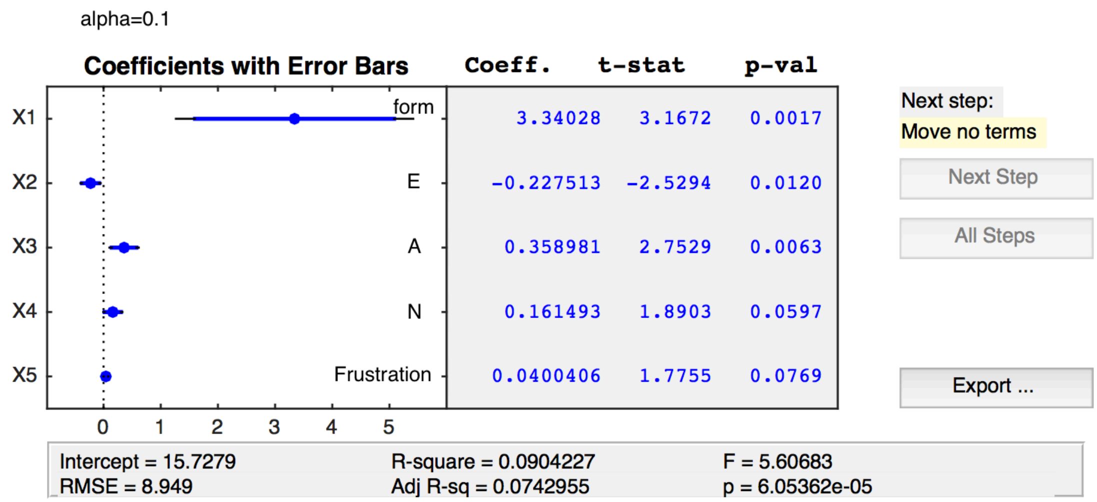

Figure **4-11**: Stepwise Regression: Form, Gender, Personality and NASA-TLX

From the stepwise regression above, we can tell that the extraversion, agreeableness and neuroticism are highly related to learning performance. It is shown that introverts, people with high environment adjustability and emotional individuals will receive higher scores on the quiz. Regarding mental workload, the frustration level is observed to be related to learning performance.

4.5 Symbolic Regression Modeling

Symbolic regression, different from the pre-determined structure of linear or non-linear regression models, allows different operators, as well as constants and variables, to enter the model. Symbolic regression works to recognize every candidate solution, which is usually called a tree, and finalize the searching process when the best model with the highest fitness is obtained

[89]. The fitness of the model is testified by R-square, which is the same in linear and non-linear regression model. The fitness of the model is testified by the R-square, which is the same in linear and non-linear regression models. An example of a symbolic regression tree is presented in Figure 4-12.

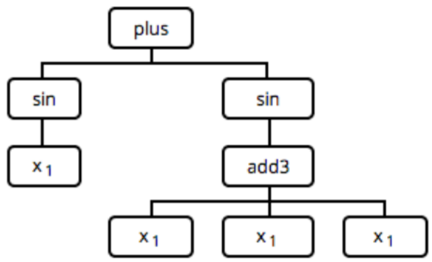

Figure **4-12**: Example of a tree (gene): f(x1) = sin(x1) + sin(3x1)

Compared to the stepwise regression I used to recognize the significant terms in a previous analysis, symbolic regression provides an opportunity for me to not be trapped by a single form of the regression. For a similar purpose of utilizing stepwise regression modeling, a symbolic regression analysis was conducted through the Eureqa software to test hypothesis one and five; the results are shown as follows.

4.5.1 Form Included General Symbolic Modeling

By running the symbolic regression in Eureqa software, a best general model using EEG emotion statistics to predict the learning-performance score is obtained. The general model is in the following form. This model achieves a better ability to predict 24.7% of the variance compared to the linear regression model (R^2=0.155).

Score = a + b****Relaxation Range*** + c****Form*** + d*sin (e****Relaxation Range***) + (f****Relaxation Std**Focus Mean*** - g****Relaxation Std***)/ (***Excitement Std**Focus Std***) - h****Focus Mean**Focus Std***

In my study, specifically, the constant and coefficient in the above model are:

Score = 28.5519500706561 + 10.8123245154737* ***Relaxation Range*** + 2.35512899642659* ***Form*** + 4.40650345806098*sin (32744.1377797268* ***Relaxation Range***) + (2.6012026337684* ***Relaxation Std*** * ***Focus Mean*** - 0.36978321786234* ***Relaxation Std***)/ (***Excitement Std*** * ***Focus Std***) - 877.085759461998* ***Focus Mean*** * ***Focus Std***

In this model, the significant terms recognized are much like what was discovered through the linear regression. However, different from linear regression indicating that each single factor will have either a positive or a negative impact on one's learning outcomes, the symbolic regression revealed that there existed some levels of interaction among the factors. The model above illustrates that the static form and lower variation in relaxation will result in a higher quiz score, which is consistent with the coefficient calculated through a stepwise regression model. Nevertheless, there are interactions between relaxation standard deviation and focus mean, excitement standard deviation and focus standard deviation, and focus mean and focus standard deviation addressed by the model.

4.5.2 Form Excluded General Symbolic Modeling

For the same purpose in previous linear regression modeling, to avoid over-weighted influence of form, another symbolic modeling was performed. Three emotions enter the symbolic regression model with six statistics in total. It achieved a higher R-square in regression fitness (R^2=0.161) compared to the linear regression model (R^2=0.125).

Score = a + b/ (c + ***Focus Mean***) + d/ (***Relaxation Max*** - e) + -f/(***Relaxation Mean*** + ***Excitement Std***) + g****Focus Std***/(***Relaxation Std*** + ***Excitement Std*** - h)

In this study specifically, the constant and coefficient in the above model are:

Score = 30.905 + 0.008/ (0.085 + ***Focus Mean***) + 0.002/ (***Relaxation Max*** - 0.161) + - 0.160/(***Relaxation Mean*** + ***Excitement Std***) + 0.218* ***Focus Std*** /(***Relaxation Std*** + ***Excitement Std*** - 0.260)

When comparing the symbolic regression model with the linear regression model, it is found that the effect of individual emotion statistics is consistent in these two models. In other words, when focus mean, relaxation max and relaxation standard deviation increase, the score decreases. Similarly, the individual with higher relaxation mean and focus standard deviation tends to obtain a higher score on the quiz.

4.6 Structural Equation Modeling

After recognizing the significant terms in the 50 emotion statistics, in order to examine the direct and indirect relationship of the factors in the comprehensive model, I ran three levels of structural equation models to better address the issue.

4.6.1 Three-Factor Two-Link Model

In this section, a simple structural equation model is introduced to address the relationship shown in Figure 4-13 below. In this example, the form is determined as the independent variable, and the score is the dependent variable; the bio-stat refers to the EEG-recorded emotion statistics, which serve as a mediation factor. The purpose of this model is to disclose which emotion statistics can successfully form this loop.

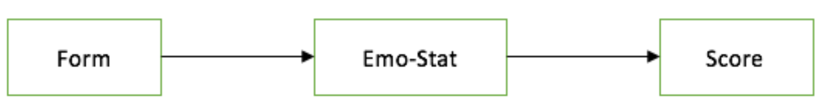

Figure **4-13**: Two-Link Structural Equation Model

After fitting all of the significant terms, it was recognized in the previous analysis that four structural equation models are specified in the form stated above; the models are shown in Figure 4-14 through Figure 4-17. The four emotion statistics are the excitement minimum, excitement standard deviation, excitement range, and engagement maximum; the results of the SEM modeling are listed in Table 4-5 through Figure 4-8.

Excitement Minimum

Table **4-5**: Two-Link Structural Equation Model of Excitement Minimum

Goodness-of-fit index = 0.7209389					
Parameter Estimates					
	Estimate	Std Error	z value	Pr(>|z|)	
b1	-11.506	4.185	-2.749	5.978e-03	Score <--- Stat
b2	0.023	0.008	3.050	2.294e-03	Stat <--- Form

The first emotion statistic that is proved to be significant in the SEM is the minimum of the excitement. According to this SEM model, the static form will result in a higher value in the minimum of the excitement (p=0.002, b=0.023), which indicates that the participant's excitement tends to drop to a very low value during the process. However, maintaining the excitement level causes a poorer learning performance (p=0.006, b=-11.506).

Figure **4-14**: Two-Link Structural Equation Model of Excitement Minimum

Excitement Standard Deviation

Table **4-6**: Two-Link Structural Equation Model of Excitement Standard Deviation

Goodness-of-fit index = 0.7204033					
Parameter Estimates					
	Estimate	Std Error	z value	Pr(>|z|)	
b1	23.140	9.406	2.460	1.389e-02	Score <--- Stat
b2	-0.015	0.003	-4.500	6.795e-06	Stat <--- Form

Figure **4-15**: Two-Link Structural Equation Model of Excitement Standard Deviation

The SEM model above illustrates that, compared to dynamic form, the static form causes a smaller variation in one's excitement level (p=0.000, b=-0.015), while a higher excitement variation results in a better performance.

Excitement Range

The third SEM model works together with the SEM of excitement standard deviation to indicate the excitement is more stable if the participant's learning is stimulated by the static form (p=0.000, b=-0.045). At the same time, the smaller the changes in excitement level, the higher the score will be (p=0.014, b=7.289).

Table **4-7**: Two-Link Structural Equation Model of Excitement Range

Goodness-of-fit index = 0.7205229

Parameter Estimates					
	Estimate	Std Error	z value	Pr(>|z|)	
b1	7.289	2.976	2.450	1.432e-02	Score <--- Stat
b2	-0.045	0.010	-4.274	1.918e-05	Stat <--- Form

Figure **4-16**: Two-Link Structural Equation Model of Excitement Range

Engagement Max

Table **4-8**: Two-Link SEM of Engagement Max

Goodness-of-fit index = 0.7227673					
Parameter Estimates					
	Estimate	Std Error	z value	Pr(>|z|)	
b1	-10.506	5.090	-2.064	3.899e-02	Score <--- Stat
b2	-0.026	0.006	-4.202	2.644e-05	Stat <--- Form

Figure **4-17**: Two-Link Structural Equation Model of Engagement Max

With the model of the maximum of engagement, we can conclude that the static form yields a lower engagement peak value, and the lower peak value of the engagement produces a better learning performance.

4.6.2 Four-Factor Five-Link Model

Overall speaking, the two-link SEM model succeeds in finding the significant mediation factors through which the form indirectly casts an effect on the learning outcomes. We can also conclude from the previous analysis that the instructional form itself potentially influences the quiz score directly. Thus, the SEM model, which involves the relationship between form and score, as well as the emotions involved, is considered as shown in Figure 4-18.

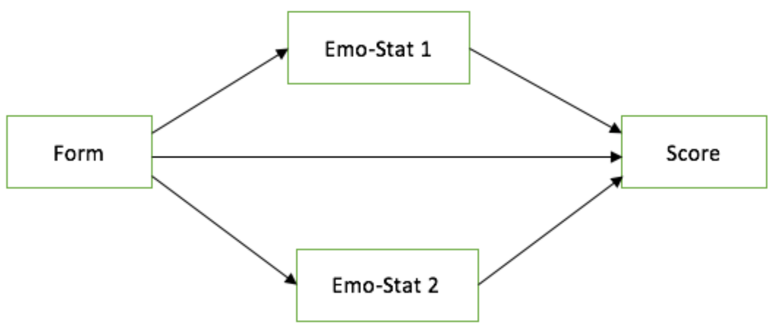

Figure **4-18**: Five-Link Structural Equation Model

In this model, every two out of the four emotions will be examined by fitting the SEM model; the SEM model will be seen as a successful unless all of the regression coefficients in the model have a significant p-value. The only successfully fitted model is illustrated by Table 4-9 and Figure 4-19.

Table **4-9**: Five-Link Structural Equation Model

Goodness-of-fit index = 0.7178503					
Parameter Estimates					
	Estimate	Std Error	z value	Pr(>|z|)	
b1	-9.177	4.148	-2.212	2.695e-02	Score <--- Stat 1
b2	17.923	9.467	1.893	5.834e-05	Score <--- Stat 2
b3	0.023	0.008	3.050	2.295e-08	Stat 1<--- Form
b4	-0.015	0.003	-4.500	6.795e-06	Stat 2<--- Form
b5	3.825	0.555	6.886	5.720e-12	Score <--- Form

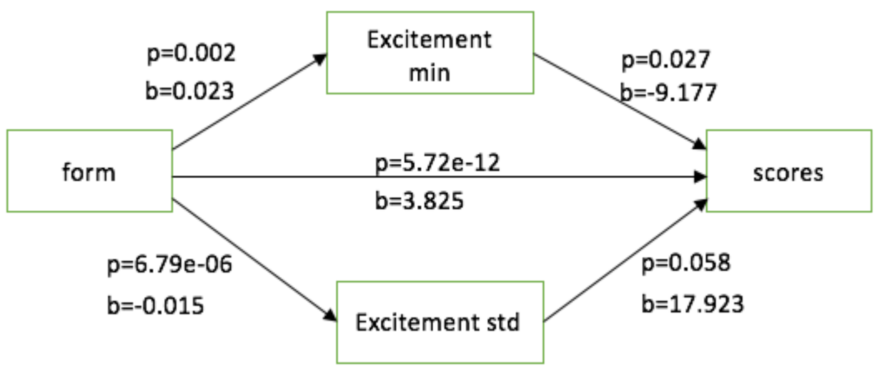

Figure **4-19**: Five-Link Structural Equation Model

According to the above SEM model, excitement played a major role in the influence of instructional form. However, the statistics extracted from the time-series data still have a limit on representing the individual's excitement level over a period of time; therefore, further analysis on the effect of the excitement emotion in learning is required.

Chapter 5

Conclusion and Discussion

5.1 Instructional Form and Learning Outcomes

As mentioned in the literature review, there exists a variety of literature noting that animated video generates high learning gains compared to static instructional forms in online learning. In a meta-analysis comparing animated and static graphics, which was composed of 61 studies and 7,000 subjects, investigators argued that animation is significantly superior to static graphics [90]. This assertion is consistent with what Hoffler and Leutner(2007) found in their meta-analysis, in which 26 studies and 76 pair-wise comparisons are contained [91]. The meta-analysis they conducted revealed the significant advantage of animation in 21 studies. However, there are two pair-wise comparisons indicating that static graphics are superior to animated video.

The superiority of animation is also found in other studies. Wong et al.(2009) compared static graphics and animation in the learning of human motor skills, and the animation form turned out to result in higher levels of student engagement and motivation, allowing students to achieve higher scores [92]. However, the authors also noted that this benefit only occurs when students are learning non-movement-based objectives; the advantage of animation is eliminated once the material became non-movement-based content. Similarly, Hoffler and Leutner also pointed out that the superiority is evident, specifically when the depicted action is highly related to the learning objective [91] .

In order to investigate my first hypothesis, which focuses on revealing the relationship between various instructional forms and learning outcomes. In this research specifically, I compared the effect of static graphics and animated video in online learning performances.

ANOVA analyses were introduced in the analysis stage. In this study, static graphics were proved to be advanced compared to the dynamic instructional form in the learning of semaphores. We need to note that, in the literature discussed above, there are several levels of animation defined, as well as different knowledge types [90, 91]. The reason animation does not show its advantage in this study is because the learner only needs to memorize the final position of each letter in semaphore. In other words, the learning objective is a single static picture instead of a memorization task composed of a series of body actions, under which circumstance animation loses its advantage of showing a dynamic process, and static instructional form is sufficient for this particular task. Furthermore, based on the features of the learning objective, the animated video actually spent less time showing the final position than the static picture, which is another potential explanation for the inferiority of animation in my study.

Hence, as mentioned by many researchers, there are different levels in both the content and the animated video, and these factors also interact with other factors—for instance, the learner's cognitive style [90]. As Holden and Westfall (2006) asserted, there does not exist a single best instructional model for distance learning, and detailed instruction on using instructional forms to improve learning outcomes requires further investigation [53].

5.2 Emotions and Learning Outcomes

As addressed early in the literature review, there are a variety of emotions involved in learning; these emotions are generated by the learning content and learning materials, affecting the learning outcomes of the learner. These emotions include motivation, engagement, excitement, interest and so on [55, 59, 69]. This relationship was also proved statistically by LePine et al. (2004); investigators asserted that challenge stress and motivation to learn will benefit learning performance, while hindrance stress and exhaustion will have an adverse impact on one's learning. However, none of the literature discussed implemented the widely used five-factor model of personality as the classification rule of different personality traits.

It was proposed in hypothesis five that emotions are directly related to learning outcomes; in hypothesis three, it was proposed that emotions serve as mediation factors through which instructional forms influence learning achievement. This study successfully revealed that there is a relationship between emotions and one's learning performance. The stepwise linear regression and symbolic regression served the purpose of recognizing significant factors as well as predicting each learner's performance score. Relaxation, excitement and focus are recognized as the three factors that had the most influence on learning achievement in my study. The general symbolic regression model, which involves the form and the three emotion statistics, is recognized as the best prediction model for one's learning outcomes, with an R-square of 0.247. We need to note that there are several levels of interactions involved in the model, which failed to appear in other models, and this model achieves the highest predicting ability. This indicates that there is a potential for the learning process to be influenced by the interactions among different emotions rather than various independent feelings.

A comprehensive model was also presented, through structural equation modeling, relating form and emotion to learning outcomes. In this study, excitement is recognized as the strongest emotion that works as a mediation factor in linking the instructional form to learning achievement. As addressed above, in the SEM model, I only considered the effect of a single factor. Thus, there is the potential that some significant emotion interactions in online learning are not revealed by the analysis method utilized. Thus, further statistical analysis on determining the significant terms in emotions are expected.

5.3 Personality and Perceived Workload

According to recent papers, there exists a relationship between personality and perceived workload [59]. Similarly, as shown in the study conducted by Rose et al. (2002), although there does not exist a strong correlation between overall five-factor-model test scores and NASA-TLX, the relationship between subscales is found to be significant [43].

In this study, the relationship between perceived workload and personality was also addressed, stated as hypothesis four. In contrast to those studies, my data failed to show the significant relationship between neuroticism and frustration; however, other subscale correlations are found in my study. First, there exists a positive relationship between extroverted personality and high mental workload. Second, those who are good at adjusting themselves to their environment will experience less perceived workload in all dimensions except physical demand. The conscientious personality, referring to those participants who are stricter with rules and regulations, experienced higher levels of mental, physical and temporal demand, and yielded higher scores in performance satisfaction and effort spent. Last, but not least, individuals with higher levels of openness to experience are more satisfied with their performance; at the same time, they state that they spent more effort on the task and experienced higher levels of frustration.

This study indicates that there is a strong correlation between the terms in the five-factor model and NASA-TLX, but shows an inconsistency with the conclusion of the research completed by Rose et al. There is the potential that the correlation between the two factors is influenced by other undefined variables under a variety of learning settings, and the possible interaction with other factors involved in online-learning circumstances needs to be investigated.

5.4 Personal Differences, Personality, Workload and Learning Outcomes

Many researchers argue that females can gain more benefits than males in an online-learning setting, although their attitude toward online-education systems is comparatively negative [35-37]. In order to investigate the gender effect, I proposed hypothesis two, that learning outcomes will be significantly different in two gender groups. However, my study failed to discover this kind of gender difference in an online-learning setting. It needs to be noted that personal differences can have different impacts in different online settings, such as the level of animation in a video. In this online setting specifically, there are many other factors involved that might eliminate or outweigh the gender effect.

I also took the impact of perceived workload and personality in learning into consideration, stated as hypotheses six and seven. Hypothesis six states that different workloads will cause different learning outcomes, while hypothesis seven focuses on the impact of personality on learners' achievement. Consistent with the research discussed in the literature review, three personality traits in the five-factor model, as well as frustration in NASA-TLX, are observed to have effect on one's learning performance. Similarly, it is also observed that the significant terms are different from what the literature addresses. In this study, introversion, agreeableness and neuroticism are proved to be significant in predicting one's learning outcomes. We need to note that, according to different tasks and various standards of academic achievement, the significant factors revealed in the literature are not the same as the ones revealed in my study [39, 40]. Thus, there is potentially an interaction among the learning content, objectives and personality traits involved in the learning process. Further investigation of the relationship between personality and learning outcomes in different learning circumstances needs to be addressed.

5.5 Limitations and Future Research

According to the above discussion, we can tell this study successfully revealed relationships between the factors in the proposed model. However, this research also several limitations that can be improved. First, due to the design of the experiment, there is only one NASA-TLX after learning via two different instructional forms; therefore, I am not able to separate the perceived workload by the corresponding instructional form, thus sacrificing the investigation into the relationship between form and NASA-TLX. I also recorded emotions directly with the performance-matrices recording function provided by Emotiv, without recording the raw data bands of EEGs. I recommend that other researchers record the raw EEG data in the future so that more information can be extracted from both the emotion recordings and the raw EEG bands. On the data-analysis side, although this study succeeded in addressing the relationship between each two factors, an overall picture of the relationship between personality, perceived workload, emotions and learning performance needs to be investigated in the future.

In the literature discussed above, it is also acknowledged that improving the user's satisfaction is another import aspect of improving the online-education system. Thus, in the future study, I will include a questionnaire to determine the learner's satisfaction level as another independent variable. The purpose of this questionnaire is to testify if I can improve the online-learning system based on both the user's satisfaction and learning outcomes. Furthermore, many researchers argue that pacing style is another import factor in online learning, and it is proved to interact with other factors in online learning. The pacing-style factor will also be considered in future research.

Appendix A

50-item FFM Test

Rating	I…	Rating	I…
	1. Am the life of the party.		26. Have little to say
	2. Feel little concern for others.		27. Have a soft heart
	3. Am always prepared.		28. Often forget to put things back in their proper place.
	4. Get stressed out easily.		29. Get upset easily.
	5. Have a rich vocabulary.		30. Do not have a good imagination.
	6. Don't talk a lot.		31. Talk to a lot of different people at parties
	7. Am interested in people.		32. Am not really interested in others.
	8. Leave my belongings around.		33. Like order.
	9. Am relaxed most of the time.		34. Change my mood a lot.
	10. Have difficulty understanding abstract ideas.		35. Am quick to understand things.
	11. Feel comfortable around people		36. Don't like to draw attention to myself.
	12. Insult people.		37. Take time out for others.
	13. Pay attention to details.		38. Shirk my duties.
	14. Worry about things.		39. Have frequent mood swings.
	15. Have a vivid imagination.		40. Use difficult words.
	16. Keep in the background.		41. Don't mind being the center of attention.
	17. Sympathize with others' feelings.		42. Feel others' emotions.
	18. Make a mess of things.		43. Follow a schedule
	19. Seldom feel blue.		44. Get irritated easily.
	20. Am not interested in abstract ideas.		45. Spend time reflecting on things.
	21. Start conversations.		46. Am quiet around strangers
	22. Am not interested in other people's problems		47. Make people feel at ease.
	23. Get chores done right away.		48. Am exacting in my work.
	24. Am easily disturbed.		49. Often feel blue
	25. Have excellent ideas.		50. Am full of ideas.

Appendix B

Five Factors & NASA-TLX data

Participant #	E	A	C	N	O	Mental	Physical	Temporal	Perform	Effort	Frustration
1	16	24	25	24	27	64	23	59	32	59	53
1	16	24	25	24	27	65	25	68	48	72	65
1	16	24	25	24	27	63	23	67	32	65	59
2	30	37	27	8	32	30	9	4	9	48	4
2	30	37	27	8	32	39	5	58	10	48	7
2	30	37	27	8	32	18	4	55	20	18	6
3	22	28	30	27	28	54	38	43	70	60	30
3	22	28	30	27	28	57	35	58	60	53	28
3	22	28	30	27	28	60	38	61	84	58	54
4	26	29	26	20	28	57	69	69	23	63	59
4	26	29	26	20	28	75	77	72	38	76	84
4	26	29	26	20	28	82	80	81	22	76	70
5	16	26	30	30	24	87	14	75	81	81	68
5	16	26	30	30	24	80	12	74	60	80	71
5	16	26	30	30	24	78	10	65	33	78	72
6	24	23	26	17	24	67	1	49	72	50	22
6	24	23	26	17	24	68	1	41	50	58	10
6	24	23	26	17	24	69	0	56	33	67	13
7	30	32	28	25	31	65	3	31	2	50	0
7	30	32	28	25	31	56	0	59	50	66	50
7	30	32	28	25	31	59	0	30	1	44	4
8	25	28	25	27	20	69	11	73	50	65	12
8	25	28	25	27	20	67	18	52	33	65	17
8	25	28	25	27	20	78	21	85	58	79	29
9	34	34	27	24	27	89	0	74	34	90	50
9	34	34	27	24	27	84	0	59	25	90	40
9	34	34	27	24	27	95	0	69	37	83	43
10	20	32	31	31	25	65	21	15	8	75	5
10	20	32	31	31	25	95	48	88	49	97	75
10	20	32	31	31	25	88	54	91	48	97	63
11	22	29	24	20	12	50	10	50	65	35	15

11	22	29	24	20	12	59	9	25	71	39	19
11	22	29	24	20	12	59	14	15	1	35	10
12	22	24	24	19	27	72	21	41	32	21	7
12	22	24	24	19	27	72	8	32	13	47	38
12	22	24	24	19	27	76	12	48	10	55	31
13	24	27	34	31	30	89	1	75	73	76	60
13	24	27	34	31	30	74	0	63	46	61	49
13	24	27	34	31	30	77	1	59	48	60	53
14	20	36	38	25	26	50	5	70	51	62	49
14	20	36	38	25	26	51	8	71	50	81	49
14	20	36	38	25	26	49	13	70	61	78	50
15	19	33	22	14	25	25	0	0	41	28	1
15	19	33	22	14	25	50	1	1	56	54	1
15	19	33	22	14	25	59	1	11	57	60	3
16	29	33	28	16	24	74	35	49	51	74	78
16	29	33	28	16	24	68	39	54	13	60	60
16	29	33	28	16	24	83	60	62	50	75	71
17	15	33	37	32	31	79	50	54	51	65	10
17	15	33	37	32	31	74	49	35	51	49	10
17	15	33	37	32	31	69	24	30	41	55	9
18	22	33	17	16	17	80	1	95	36	76	54
18	22	33	17	16	17	59	1	72	2	72	16
18	22	33	17	16	17	72	1	71	3	61	43
19	21	28	32	22	22	55	40	74	41	79	55
19	21	28	32	22	22	84	40	75	55	85	60
19	21	28	32	22	22	55	44	59	27	64	54
20	28	38	28	25	32	74	44	38	30	75	64
20	28	38	28	25	32	64	54	76	40	65	59
20	28	38	28	25	32	75	59	69	46	78	84
21	20	24	24	12	25	78	28	89	40	80	27
21	20	24	24	12	25	86	45	79	41	83	22
21	20	24	24	12	25	86	68	80	43	83	38
22	21	26	22	21	23	20	20	20	10	19	30
22	21	26	22	21	23	30	31	30	30	30	30
22	21	26	22	21	23	19	20	19	21	20	20
23	29	37	20	22	25	65	5	40	55	60	20
23	29	37	20	22	25	54	60	36	19	69	26

23	29	37	20	22	25	64	65	39	21	78	25
24	11	32	17	33	34	84	0	71	14	94	6
24	11	32	17	33	34	85	1	81	5	90	3
24	11	32	17	33	34	86	1	55	32	54	14
25	13	28	28	23	26	57	15	55	33	53	39
25	13	28	28	23	26	51	11	51	31	46	43
25	13	28	28	23	26	48	4	45	29	45	32
26	22	39	30	21	28	50	27	26	3	51	33
26	22	39	30	21	28	35	53	18	7	34	15
26	22	39	30	21	28	49	44	30	12	30	31
27	12	32	36	19	37	58	36	63	70	63	65
27	12	32	36	19	37	64	38	60	63	66	71
27	12	32	36	19	37	64	39	60	54	82	56
28	21	27	18	31	28	65	60	68	61	49	49
28	21	27	18	31	28	51	32	25	50	61	49
28	21	27	18	31	28	48	35	46	35	68	45
29	15	28	21	23	27	79	23	35	85	84	69
29	15	28	21	23	27	81	49	49	81	70	59
29	15	28	21	23	27	80	49	65	80	83	64
30	21	34	24	15	28	59	40	56	83	60	19
30	21	34	24	15	28	58	39	44	31	47	14
30	21	34	24	15	28	55	45	46	36	48	10
31	18	36	31	24	26	55	19	51	38	63	39
31	18	36	31	24	26	59	19	54	49	66	55
31	18	36	31	24	26	66	21	56	38	68	52
32	19	26	31	20	20	84	5	54	16	79	50
32	19	26	31	20	20	84	5	55	1	80	44
32	19	26	31	20	20	89	5	49	16	99	55
33	36	24	24	35	39	97	0	55	81	64	79
33	36	24	24	35	39	94	4	53	42	93	71
33	36	24	24	35	39	98	3	56	98	77	93
34	24	32	30	32	26	76	10	50	58	62	78
34	24	32	30	32	26	77	16	36	5	77	55
34	24	32	30	32	26	85	26	71	12	93	99
35	24	36	31	31	27	90	10	56	60	86	23
35	24	36	31	31	27	86	16	75	63	80	19
35	24	36	31	31	27	89	12	33	50	82	17

36	17	34	22	30	21	70	19	48	50	63	44
36	17	34	22	30	21	65	20	50	38	62	38
36	17	34	22	30	21	64	20	51	40	66	43
37	16	32	31	31	30	88	1	49	84	90	25
37	16	32	31	31	30	50	0	85	51	49	33
37	16	32	31	31	30	23	1	50	35	48	50
38	26	29	20	26	26	85	14	30	39	62	14
38	26	29	20	26	26	83	11	41	66	58	35
38	26	29	20	26	26	73	12	33	38	59	35
39	25	26	19	18	30	90	11	6	58	57	84
39	25	26	19	18	30	92	11	59	2	68	43
39	25	26	19	18	30	81	5	66	20	77	40
40	29	33	23	16	24	85	56	79	31	69	75
40	29	33	23	16	24	75	30	69	31	75	60
40	29	33	23	16	24	79	34	65	26	79	59
41	31	37	27	32	31	86	1	50	13	66	6
41	31	37	27	32	31	80	1	51	15	75	11
41	31	37	27	32	31	81	2	53	15	76	14
42	18	32	26	23	16	50	11	1	10	40	0
42	18	32	26	23	16	54	10	0	27	50	4
42	18	32	26	23	16	49	4	0	21	45	1
43	21	29	20	17	26	46	7	48	46	46	41
43	21	29	20	17	26	59	3	53	53	52	52
43	21	29	20	17	26	50	8	55	48	52	53
44	34	35	27	18	36	55	34	18	70	59	58
44	34	35	27	18	36	50	50	35	61	54	40
44	34	35	27	18	36	54	54	45	84	63	63
45	11	32	25	24	19	69	15	59	50	68	29
45	11	32	25	24	19	55	20	49	26	55	10
45	11	32	25	24	19	56	15	55	41	61	13
46	14	28	26	20	26	78	49	74	49	74	61
46	14	28	26	20	26	42	42	71	38	55	45
46	14	28	26	20	26	40	40	65	46	60	44
47	18	24	16	15	26	56	1	54	75	53	74
47	18	24	16	15	26	52	1	58	50	62	54
47	18	24	16	15	26	55	0	57	30	57	51
48	27	30	25	25	29	53	1	57	29	41	1

48	27	30	25	25	29	62	0	56	38	56	0
48	27	30	25	25	29	67	0	64	48	59	1

Sample Emotion Statistics Data

Relaxation Max	Relaxation Median	Relaxation Range	Excitement Std	Excitement Latency	Focus Mean	Focus Latency
1.73E-01	4.38E-02	1.86E-01	1.62E-01	5.50E+01	1.35E-02	2.40E+01
2.07E-01	-3.44E-03	3.26E-01	1.60E-01	6.50E+01	-4.69E-02	1.30E+01
1.61E-01	8.94E-04	3.09E-01	1.96E-01	2.30E+01	-9.27E-03	2.90E+01
1.03E-01	5.73E-02	7.46E-02	6.44E-02	1.70E+01	3.69E-02	3.60E+01
2.97E-02	-9.56E-03	8.45E-02	1.39E-01	2.00E+01	2.69E-02	1.90E+01
5.21E-02	-5.51E-02	2.18E-01	1.61E-01	2.60E+01	-5.47E-02	2.50E+01
2.11E-02	2.11E-02	4.02E-03	1.50E-01	7.00E+01	-1.82E-02	6.50E+01
2.11E-02	2.11E-02	0.00E+00	3.03E-01	4.10E+01	-3.37E-02	4.10E+01
2.11E-02	2.11E-02	6.94E-02	2.25E-01	8.40E+01	6.38E-02	9.10E+01
1.19E-01	-1.03E-03	1.95E-01	1.83E-01	3.70E+01	-7.59E-02	2.60E+01
1.43E-01	5.10E-02	4.24E-01	2.55E-01	1.11E+02	-1.39E-02	4.10E+01
1.43E-01	2.06E-02	3.57E-01	2.76E-01	1.30E+01	9.62E-02	4.10E+01
1.26E-01	-9.44E-02	4.29E-01	2.46E-01	1.32E+02	4.72E-02	1.03E+02
1.26E-01	1.26E-01	3.11E-01	2.19E-01	2.70E+01	6.41E-02	6.30E+01
1.26E-01	4.57E-02	3.62E-01	2.32E-01	9.10E+01	-7.49E-02	9.60E+01
2.87E-01	6.18E-02	3.13E-01	1.80E-01	2.30E+01	-7.31E-02	8.80E+01
1.24E-01	-6.32E-02	2.96E-01	1.84E-01	4.40E+01	-6.31E-02	4.30E+01
2.87E-01	-4.91E-02	5.48E-01	1.97E-01	3.10E+01	4.77E-02	4.60E+01
2.02E-01	7.18E-02	2.91E-01	7.53E-02	1.08E+02	-3.85E-02	6.10E+01
1.21E-01	-7.57E-02	3.93E-01	2.16E-01	2.40E+01	-1.23E-03	6.80E+01
2.02E-01	1.72E-01	4.60E-01	1.71E-01	4.80E+01	1.91E-02	8.30E+01
1.02E-01	3.52E-02	1.91E-01	9.35E-02	2.20E+01	-2.13E-02	4.50E+01
1.02E-01	-2.83E-02	3.48E-01	1.84E-01	1.03E+02	5.89E-02	1.01E+02
1.02E-01	1.02E-01	3.76E-01	2.02E-01	2.20E+01	-1.21E-02	2.10E+01
1.73E-02	1.73E-02	0.00E+00	1.29E-01	4.00E+01	2.69E-04	3.30E+01
1.73E-02	1.73E-02	0.00E+00	2.64E-01	5.00E+01	-5.02E-02	7.20E+01
1.73E-02	1.73E-02	2.06E-01	2.27E-01	4.80E+01	3.11E-02	5.10E+01
1.17E-01	-6.52E-04	3.28E-01	1.50E-01	8.40E+01	2.10E-02	1.30E+01

1.17E-01	-3.53E-02	4.39E-01	1.86E-01	3.30E+01	-5.29E-03	4.10E+01
1.17E-01	1.10E-01	3.26E-01	1.35E-01	1.00E+02	-1.30E-01	1.90E+01
2.11E-01	3.08E-02	3.30E-01	1.80E-01	7.40E+01	1.01E-01	6.20E+01
2.11E-01	1.54E-02	5.12E-01	1.35E-01	3.90E+01	-1.16E-01	3.70E+01
2.11E-01	-5.61E-02	4.48E-01	1.69E-01	1.05E+02	1.73E-01	2.60E+01
1.47E-01	2.95E-02	2.65E-01	1.45E-01	3.70E+01	-2.29E-02	2.00E+01
1.51E-01	-6.00E-02	4.23E-01	2.14E-01	5.90E+01	9.58E-02	3.70E+01
1.51E-01	5.55E-02	3.90E-01	1.50E-01	1.39E+02	-1.78E-01	4.80E+01
3.53E-03	3.53E-03	1.92E-02	1.43E-01	1.10E+01	2.08E-01	1.50E+01
3.53E-03	3.53E-03	0.00E+00	1.28E-01	3.90E+01	-9.59E-02	1.50E+01
3.53E-03	3.53E-03	1.05E-01	8.78E-02	1.80E+01	-1.22E-01	2.10E+01
1.42E-01	4.05E-02	1.53E-01	1.90E-01	1.08E+02	1.15E-01	2.50E+01
3.13E-01	-7.39E-02	4.84E-01	1.35E-01	1.40E+01	-2.92E-02	2.70E+01
1.59E-01	-3.57E-02	3.01E-01	6.18E-02	6.20E+01	-1.07E-02	2.40E+01
1.06E-01	1.06E-01	0.00E+00	9.23E-02	4.70E+01	-6.20E-02	4.70E+01
1.06E-01	1.27E-02	2.51E-01	1.58E-01	4.20E+01	-1.27E-02	4.60E+01
1.00E-01	-1.26E-01	3.79E-01	1.87E-01	1.24E+02	2.47E-02	7.30E+01
1.62E-01	1.43E-01	2.90E-01	1.67E-01	3.50E+01	-5.89E-02	3.50E+01
1.62E-01	-1.60E-02	4.30E-01	2.04E-01	5.30E+01	-5.92E-02	6.10E+01

Appendix C

Example Matlab Code for 10 statistics

```
for k=1:48

    my_field= strcat('p',num2str(k));

    %This function put the 'p'name with the number of the loop to create

    %the enumeration for the name of the individual existent matrices.

    Matrixprueba{k,1}(:,:)=eval(my_field); %Read the sting value as a variable.

end

for k=1:48

[m,z] = size(Matrixprueba{k,1});

for c=1:z % number of columns

    counter=1;

    for L=1:m

        if or(Matrixprueba{k,1}(counter,c) >= 0,Matrixprueba{k,1}(counter,c) < 0)

        TempMat(counter,2)=[Matrixprueba{k,1}(counter,c)];

        TempMat(counter,1)=counter;

        counter=counter+1;

        end
    end

    TempMat=sortrows(TempMat,[2,1]);

    Solutions{k,1}(1,c)=TempMat(1,2);%Min

    Solutions{k,1}(2,c)=TempMat(1,1)/m;%location of the minimum

    TempMat=sortrows(TempMat,[-2,1]);

    Solutions{k,1}(3,c)=TempMat(1,2);%Max

    Solutions{k,1}(4,c)=TempMat(1,1)/m;%location of the max
```

```
    m=length(Matrixprueba{k,1});

    y=Matrixprueba{k,1};

    [r,m,b]=regression(z,y);

    Solutions{k,1}(5,c)=mean(TempMat(:,2));%Average/mean

    Solutions{k,1}(6,c)=median(TempMat(:,2));%Median

    Solutions{k,1}(7,c)=std2(TempMat(:,2));%Stdev

    Solutions{k,1}(8,c)=maximum-minimum; %Range

    Solutions{k,1}(9,c)=m; %Slope


    y=h(1:m,1);

    x(1:m,1)=1:m;

    pp=BSFK(x,y,2);

    knot=pp.breaks(1,2);

    Solutions{k,1}(10,c)={knot}; %Latency


    clear TempMat

end

end
```

Example R Code for Structural Equation Model

```
library(sem)

rm(list=ls(all=TRUE))

opt <- options(fit.indices = c("RMSEA","GFI", "AGFI", "SRMR","NFI", "NNFI", "CFI",
"RNI", "IFI",  "AIC", "AICc", "BIC", "CAIC"))

dat.sem <- read.csv('table',header=F)
dat.model1<-dat.sem[,c(1,7,52)]


dat.cov <- cov(dat.model1)

Model1<-specifyModel()
V7 -> V52, b1, NA
V1 -> V7, b2, NA
V1 <-> V1, NA, 1

sem1<- sem(Model1,dat.cov,288)
summary(sem1)
```

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