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Title: Effects of Instructional Design and Emotional State on Performance, Mediated by Interest and Attention.

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David A. Nembhard

This study seeks to determine the effect of instructional design and emotional state on performance, considering interest and attention as mediators. To identify this effect, a Structural Equation Model (SEM) is applied to analyze individual performance based on five variables: information representation, emotional state, pupil size, alpha power, and task completion time. The SEM provides a more robust prediction of performance by including behavioral metrics than solely from self-report methods, which may provide biased results. Specifically, eye-tracking and electroencephalography technology were used to measure pupillary response and brain frequency while participants performed tasks on a computer. Results suggest that both instructional design and emotional state have significant effects on performance, but instructional design has the highest influence. Compared to instructions in text, instructions in pictures reduce task completion time, yielding high performance. Experiencing positive emotions, rather than negative emotions, reduce task completion time, improving performance. Interest and attention mediate performance by a significant relationship. This work allows instructors control the conditions of the learning environment in order to improve desired outcomes.

Effects of Instructional Design and Emotional State on Performance, Mediated by Interest and Attention

by

Karina Suarez

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APPROVED:

Major Professor, representing Industrial Engineering

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

Dean of the Graduate School

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

Karina Suarez, Author

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DEDICATION

To the best, the unique, the unconditional: My Family, for their support in all aspects of my life, and most importantly, for trusting in me.

Julián, Luz, Ernesto, Rosa, Sandra, Fernando, Darwin, Juan Carlos: Thank You! This is for you.

1 Chapter I - Introduction

1.1 Background

Individual performance can depend on various factors, such as willingness to do the job (Sandoz, Butcher, & Protti, 2017), accurate directions to achieve the goal (Li et al., 2018), motivation received (Zainuddin, 2018), and emotional atmosphere (Stephens & Carmeli, 2016), etc. The accuracy and facility of task directions are important factors to consider when evaluating performance. The emotional state of the individual has been a trend-topic on the last decade in diverse environments, such as work (Ibrahim, Boerhannoeddin, & Kazeem Kayode, 2017), sports (Campo et al., 2016), and education (Zainuddin, 2018), in the aim of obtaining the best outcomes by motivating the performer and managing their emotions. Similarly, various mediators such as attention (Pashler, Johnston, & Ruthruff, 2001), interest (Nye, Su, Rounds, & Drasgow, 2016), time pressure (J.-E. Kim & Nembhard, 2019), and communication (Macht, Nembhard, Kim, & Rothrock, 2014), have been investigated in order to find the best predictor of performance. The majority of scenarios have traditionally considered subjective scores given from supervisors and peers (Kock, 2017), self-report methods (Parrot & Hertel, 1999) to measure performance, falling into subjectivity when predicting such conduct. It is important to use objective measures for making accurate judgements and avoid biased results. This is the novel approach that the present study pursues by predicting performance through behavioral measures of attention and interest, controlling external factors such as the design of the instructions and the emotions experienced by the performer.

Different theories have been developed around the way of providing directions in the instructional material. There are researchers who claim that learners learn better with textual and pictorial representations instead of only textual information (Park, Flowerday, & Brünken, 2015); other authors sustain that the highest outcome is obtained through animated pictorial learning environments (Park, Knörzer, Plass, & Brünken, 2015); and yet others suggest the use of representational pictures as a way to positively influence performance (Lindner, Ihme, Saß, & Köller, 2018). To investigate and confirm these theories, this study evaluates the effect of two types of formats: textual and pictorial, in order to focus the design efforts on the learning environment that is more comprehensible for the individual and, thus, generates the highest performance.

Emotions have played a critical role in evaluating performance (Fisher, Minbashian, Beckmann, & Wood, 2013) and overall well-being in academic and professional working environments (Dai, 2018). When the individual experiences emotional arousal, their performance can increase up to a specific point in different tasks (M. Yerkes & D. Dodson, 2004). For instance, it has demonstrated that students who experience fewer negative emotions and more positive emotions are more likely to show higher academic self-efficacy (R. E. Mayer & Moreno, 2003). Individual emotions affect the learning process by determining the affect toward a given subject and its post-evaluation. This is: positive emotions arouse positive affect and will contribute to a high performance, while negative emotions arouse negative affect to the subject or content, resulting on a low performance (Kort, Reilly, & Picard, 2001).

1.2 Problem Statements

1.2.1 The role of the instructional design and emotions on performance

The emotional, as well as the design factor, have been analyzed together into the same instructional material, to test the emotions that visual representations transmit to the performer during the learning process (Park, Flowerday, et al., 2015)(Park, Knörzer, et al., 2015). As mentioned in the Background, several representations of information have been analyzed in this matter, such as text, pictures, videos, animations, among the most known. However, to understand the impact of the emotion itself on performance, it is necessary to distinct it from the design of the contents, and vice-versa. Defining what is the factor that mostly influences performance allows to efficiently administer resources by focusing efforts only in the environment that generates the best outcomes.

By testing the instructional design that arouses certain emotions in the learner may let us explore positive and negative effects on performance. But, are emotions significant when performing? Is it a matter of clarity and accuracy of instructions only? To solve these questions, it is necessary to treat the instructional design factor and the emotional factor disjointedly. For this reason, the present study aims to investigate the separate effects of emotions and instructional design features on performance, providing emotional stimulus and visual stimulus to the performer.

1.2.2 Subjective measures to estimate performance

Effects of external or internal stimuli on performance have been commonly evaluated though subjective measures. The most common and easy means to collect performance data is through surveys, checklists or personal forms, since these ways of self-reporting are relatively cost-effective on their administration and facilitate results interpretation (Salters-Pedneault, 2019). However, self-reporting implies subjectivity as the administrator is asking for the individual's perception. When filling out a yearly performance evaluation, for example, the employee is asked what is his or her perception about the job he or she did during the period, taking the risk as administrators to obtain biased information (Paulhus & Vazire, 2007).

To avoid the subjectivity issue, this thesis proposes to measure performance from objective biometrics through electroencephalography (EEG) and eye-tracking technology. EEG and eye-tracking devices have the capacity of providing, respectively, brain frequencies that reflect the level of attention that the individual is investing in the task, and pupil sizes that reflect the level of interest aroused by such task. Biometric measures such as brain power and pupil size provide more reliable data to predict about performance, compared to self-report methods that only allow to infer about this behavior.

1.3 Research Questions

Acknowledging the needs of further analysis in the instructional as well as in the emotional field related to performance, the present study investigates the influence of these factors by examining the following questions:

Q1: Does *instructional design* have effect on *performance*?

Q2: Does *emotional state* have effect on *performance*?

Q3: How do *interest* and *attention* mediate this effect?

By finding the causal relationship among the variables involved, it will be possible to make predictions about performance based on objective behavioral measures, and make improvements controlling external factors.

1.4 Organization of the Thesis

To determine the relationship among the instructional factor, the emotional factor, attention, interest, and performance, the present study is arranged as follows:

Chapter 2 presents a review of relevant literature regarding the instructional design field, emotions involved in performance, the methods used to assess emotions and performance, and the use of innovative technology as proposal to objectively measure this behavior. The first section of the Chapter discusses the analysis of performance that has been made from the instructional design perspective, in academic and working environments. The second section addresses emotion concepts and how the emotional component is related to performance. Third and fourth sections explain the traditional methods that have been used to measure performance and emotions, and the reliability that objective measures provide in contrast.

Chapter 3 explains the materials used in the study and the experimental methodology applied to test performance. This Chapter describes the design of the experiment, participant pool, measures taken, statistical considerations made for the study, mathematical model applied for inference and prediction, and the data sets obtained.

Chapter 4 provides a comprehensive discussion of the results obtained through the application of structural equation modelling to investigate and predict performance from external stimuli and objective mediators such as attention and interest. Chapter 5 presents the conclusions of the study and suggest a plan for future research.

2 Chapter II - Literature Review

The aim of this thesis is to determine the effects of emotional and instructional stimuli on individual's performance, basing the analysis on behavioral measures such as pupil size and brain power. As mentioned previously, research has shown that individual performance can depend on the accuracy and easiness of directions or on the emotional working environment. Therefore, the facility of task directions, as well as the emotional state of the individual, are important factors to consider when evaluating performance. Since performance is a behavioral response, to make accurate predictions about it and avoid subjectivity, it is important to collect objective data coming from behavioral changes. This is a novel aspect of the present work, wherein performance prediction is made through behavioral measures such as pupil size and alpha brain power, mediating the effect of external stimuli.

Performance predictions are mediated by attention and interest levels. The interest that develops in a particular context depends, among other variables, on the extent to the affect and knowledge experienced in relation to the activity (Hidi, 1990a). An extensive analysis of over 90 studies and 1800 correlations (Nye et al., 2016) suggested interest as a stronger predictor of performance, determining its importance in the analysis of this dimension. Interest has been found positively related to performance though feelings of involvement associated with the task that is being developed (Harackiewicz, Barron, & Elliot, 1998), and the enjoyment generated during the learning session (Hulleman, Godes, Hendricks, & Harackiewicz, 2010). Instructors, therefore, may be able to influence individual interest by designing and implementing features in the learning environment that foster learner's enjoyment and involvement, in the aim to obtain the highest performance outcomes. In the same way, research has shown that performance can be significantly influenced by individual's attention (Land & Tenenbaum, 2013). From its psychological definition, attention is commonly referred as the selectivity of processing (James, 1980); out of all possible objects in the scene, one of them is able to take possession of individual's mind. A focus of attention can facilitate learning and have a positive influence in performance outcomes (Wulf & Su, 2007). Consequently, attention can be also considered as a performance predictor.

2.1 Instructional Design and Performance

Instructing individuals is possible with printed books as well as with computer screens, since comprehension is not highly dependent on the source. Comprehension of contents depends on what kind of information is presented and how is presented to the reader (Schnotz, 2014). Therefore, the level of presentation formats is important when instructing them. Providing the accurate format of instruction supports individual performance; instructions developed without consideration of the message they convey may cause unnecessary cognitive load, leading to poor outcomes (Söderberg, Johansson, & Mattsson, 2010). Text (Hartley, 2004), pictures (Heidig, Müller, & Reichelt, 2015), and video (Bétrancourt & Benetos, 2018), have been studied as the most commonly used presentation formats in instructional design. But what is the format that generates better outcomes?

Theories have been developed around a basic notion that pictorial illustrations can aid readability, facilitate instruction and, ultimately, generate good outcomes. There are researchers who claim that instead of only textual information, combining this with pictures generates a better learning performance (Park, Flowerday, et al., 2015); others maintain that the highest outcome is obtained through animated pictorial learning environments (Park, Knörzer, et al., 2015); and yet others suggest the use of representational pictures as a way to positively influence performance (Lindner et al., 2018). An accompanying function of pictures to describe the textual environment has been analyzed; however further investigation is suggested on the main instructional purpose of each representation to determine if they can substitute each other (Carney & Levin, 2002). As a first step to address this issue, our study evaluates the effect of two levels of information representation in the instructional design: text and pictures.

Instructional design and emotions have been usually analyzed together into the same instructional material. For instance, seductive details, such as additional text or animated pictures, were added to the instructional contents to find that in some cases they may generate a direct detrimental effect on learning performance (Park, Flowerday, et al., 2015); anthropomorphisms, such as geometrical or expressive forms, were used in an instructional environment to arouse learner's attention (Park, Knörzer, et al., 2015); aesthetics were tested in learning scenarios to find a positive impact of different color combinations on learner's emotion and motivation to finish the task (Heidig et al., 2015). Past research has evaluated internal emotions generated by the instructional material itself and their impact on learner performance. However, they have focused exclusively in the design of the learning environment, leaving aside the external emotions that may affect individual performance. To address this issue, the present study distinguishes the impact of external emotional stimuli from the effect of the instructional material's format. Specifically, our work aims to investigate and contrast the effects of emotions and instructional design features on performance.

2.2 Emotions and Performance

Emotions have played a critical role in evaluating performance (Fisher et al., 2013) and overall well-being in academic and professional working environments (Dai, 2018). Before referring to the emotional component influencing performance, it is necessary to first understand how emotions are evaluated. Affective experiences can be described in two dimensions: valence and arousal. Valence refers to how positive or negative an event is, and arousal reflects whether this event is exciting or calming (Kensinger, 2011). Thus, joy and happiness are referred to as positive valence, while anger and fear correspond to negative valence (Frijda, 1986). Through modifications of audiovisual stimuli, it is possible to arouse on the individual emotions with positive valence or negative valence, which will subsequently have an effect on performance. Thus, positive activating emotions, such as enjoyment and hope promote motivation and affect academic performance positively (Reinhard Pekrun, Goetz, Frenzel, & Barchfeld, 2011). Conversely, negative emotions, such as helplessness and frustration, have shown to reduce motivation, increase tiredness, and affect physical and mental ability (Taylor, 2010), implying negative effects on performance.

When learners experience emotional arousal, their performance can increase up to a specific point (M. Yerkes & D. Dodson, 2004). For instance, it has been demonstrated that students who experience fewer negative emotions and more positive emotions are more likely to show higher academic self-efficacy (R. E. Mayer & Moreno, 2003). Individual emotions affect the learning process by determining the affect toward a given subject and its post-evaluation. That is, positive emotions arouse positive affect and will contribute to a high performance, while negative emotions arouse negative affect to the subject or content, resulting on a low performance (Kort et al., 2001). Although the role of emotions in performance has been addressed in educational and working environments, more research on the connections between emotional and motivational variables when instructing the performer is suggested with regard to the influence of emotions on individual achievement (R. Pekrun & Linnenbrink-Garcia, 2014). To attend this gap, the present study investigates the effect of positive and negative emotions when instructing the individual to achieve a task in order to predict performance.

2.3 Testing and Assessing Emotions

Induction is one of the methods used to test emotions on individuals (Parrot & Hertel, 1999). In 1968, Velten developed an induction procedure to evaluate subject's mood through 60 statements containing contrasting emotions (Velten, 1968). In the experiment, the researcher induced one hundred female students to feel depression and excitement by reading phrases silently and then repeating them aloud for 20 seconds. The procedure was assessed through self-referenced questionnaires with successful results. Since Velten, other authors have tested the procedure with some modifications (Brewer, Deanna/ Doughtie, 1980)(Albersnagel, 1988), specially by changing the number of statements (Seibert & Ellis, 1991). Seibert & Ellis' modification applies 25 statements, instead of the original 60, to elicit temporary positive and negative emotions, and contains current language usage. The adaptation evidenced effective validity results, motivating its application in the present study.

The effect of emotions has been traditionally assessed through self-report methods (Parrot & Hertel, 1999), since they provide flexibility on their administration. One can measure the emotion at different stages of the learning session (Harley, 2016) and make inferences about the stimuli provided. Self-report methods are also cost-efficient and do not require a high expertise in coding or analyzing the results (Salters-Pedneault, 2019). The most known self-reported checklists and questionnaires used to assess emotions are, among others, the Depression Adjective Checklist (DACL), Multiple Affect Adjective Checklist (MAACL), Visual Analogue Scale (VAS), and the Positive and Negative Affect Schedule (PANAS) (Evans, 2004).

The PANAS has demonstrated a reliable and stable measurement scale, making it psychometrically superior over other assessment tools (Tellegen, Watson, & Clark, 1988; Wiseman & Levin, 2011) and widely used in mood induction studies. In the questionnaire, the participant evaluates on a Likert scale (low = 1, high = 5) 20 items related to positive or negative affects. Items such as *enthusiastic*, *excited*, *interested* indicate the individual's momentary feeling of a positive affect (Miller, 2011; Tellegen et al., 1988), derived from positive emotions (Fredrickson, 2004); while *irritable*, *distressed*, or *upset* are items that reflect negative affect (Stringer, 2013) linked to negative emotions (An, Ji, Marks, & Zhang, 2017). The overall score on the 20 items defines what emotion is affecting the participant before starting the assembly tasks. Mean scores for positive and negative affect are 29.7 and 14.8 points, respectively (Tellegen et al., 1988). A high positive affect reflects enthusiasm, alertness, a state of high energy and pleasurable engagement, while a low positive affect is related to sadness and lethargy (Watson & Clark, 1994). Similarly, a high score of negative affect reflects distress and a state of contempt and nervousness, while a low score is associated with calmness.

2.4 Self-reports vs Behavioral Measures on Performance

Self-reports ask for participant's perception when evaluating any feeling or behavior; therefore, biased or even mislead information may be provided (say that one is experiencing any event when it is not) (Paulhus & Vazire, 2007). Performance has been traditionally measured through subjective scores given from supervisors and peers (Kock, 2017), or based on self-report methods (Parrot & Hertel, 1999), since they provide flexibility in use.

Similar to the case of emotions, one can measure goal accomplishment at different stages of the working period by asking the supervisor how was the trainee performance so far, or asking the worker to fill out a survey with his or her auto-evaluation. Although self-report measures can be a first step when assessing performance, we are aware that this is an offline method which results require to be cross-validated with some other real-time measures in order to make reliable conclusions. For this reason, objective data, such as behavioral or physiological (Harley, 2016), are useful to understand the real processes that are taking place inside the human being and may affect their performance.

2.5 Eye-tracking and Electroencephalography Technology to measure Interest and Attention on Performance

Eye-tracking and electroencephalography (EEG) are innovative tools that allow collecting the biometric data required to make behavioral inferences. Eye tracking is a technique in computer interaction that enables researchers to follow human's eye movements, letting them identify where the individual is looking at as they perform assigned tasks (Al-Moteri, Symmons, Plummer, & Cooper, 2017). By definition, EEG is a physiological method that helps to record the electrical activity of the brain, generated by neurons (Mosby's Medical Nursing & Allied Health Dictionary, 2001). This activity is measured by electrodes placed on the scalp surface allowing to analyze which brain areas are actively processing information at a certain time on second timescales. Devices such as EEG and eye-trackers allow researchers to detect changes in brain signals and eye-movements in order to infer about human behavior.

The eye-tracking technique has been used in the last decade across a number of fields to obtain insights about visual patterns. Through eye movements such as saccades, fixations or blinks (Boardman, 2017; Cummins, 2017), fields like aviation, healthcare, sports, technology, instructional design, business and marketing have found constructive information. There is evidence that experts in air traffic control look less at the scenario-specific information than novices (Hasse, Grasshoff, & Bruder, 2012). Studies about the effect of expertise on the gaze patterns in different surgical tasks have concluded that experts look less at the instruments than the novices (Koffskey, Ikuma, Harvey, & Aghazadeh, 2014; Koh, Park, Wickens, Ong, & Chia, 2011), instead they focus more on the task specific area. Regarding sports, research has shown that expert chess players pay more attention on the relative positions of the pieces, rather than the individual pieces, than novice chess players (Blignaut, Beelders, & So, 2008; Reingold, Charness, Pomplun, & Stampe, 2001). In the technological field, the eye-tracking tool has been applied to evaluate computer interfaces and determine the effectiveness of visual design (Poole

& Ball, 2005). In the instructional context, eye-tracking has helped understand certain cognitive-emotional behaviors, such as anxiety or relaxation, that students may experience while visualizing learning material (Hunt, Clark-Carter, & Sheffield, 2015). With eye-trackers help, visual attention has been studied as a crucial factor in consumer behavior, since the act of looking longer or repeatedly at a package has been found as a predictor of the actual purchase.

As noted, there are plenty of functionalities that eye-tracking provides in order to relate human responses to certain behaviors faster and more accurately. One of these functionalities is the capability of measure the pupil diameter of the observer at different stages of the visual task. Pupillary response has provided a good estimation of individual's arousal (Bradley, Miccoli, Escrig, & Lang, 2008); that's why it has been studied as an index of interest (Goldwater, 1972; Hess & Polt, 1960). Interest has been found positively related to performance though feelings of involvement associated with the task that is being developed (Harackiewicz et al., 1998), and the enjoyment generated during the learning session (Hulleman et al., 2010). Given the proven relationship between pupil size and levels of interest, in this study I will use pupil diameters as measures of Interest while performing.

Similar to eye-tracking, EEG has been recognized as a communication tool that can connect the human brain to a computer, allowing researchers the ability to measure some behaviors from brain electric signals (Gandhi, 2014). The electrodes used on EEG work under an internationally recognized system called *10-20 System* that measures the voltage signal generated by brain activity by standardized locations on the scalp: Frontal (F), Temporal (T), Parietal (P), Occipital (O), Central (C), and Zero sites (Z) for an electrode placed on the midline sagittal plane of the skull (Blinowska & Durka, 2006). According to the *10-20 System*, each electrode placement site has a letter to identify the lobe of the brain it is reading the signal from. The position of the electrodes is designated also by a specific number that indicates which side of the head it is analyzing: 2,4,6,8 for the right and 1,3,5,7 for the left, as shown in **Figure 1** (Balasubramanian, Shriya Gullapuram, & Shukla, 2018). For the present thesis, I used a five-channel EEG device which electrodes correspond to positions AF3, AF4, Pz, T7 and T8.

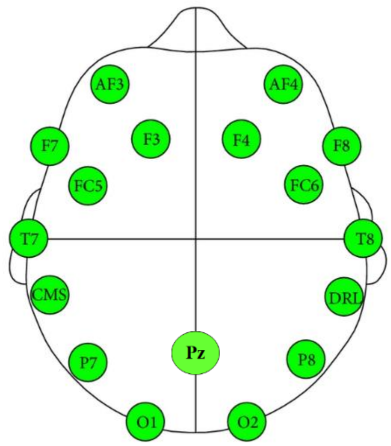


Figure 1: Electroencephalogram 10-20 Placement System

Each of the EEG electrode positions is related to certain brain functions (Sontisirkit, 2013). The five-channel EEG device used in this study provides an estimation of the functions shown in **Table 1**.

Table 1: Emotiv EEG Electrodes and Brain Functions

Electrode	**Brain Function**
AF3	Attention
AF4	Judgement
T7	Verbal Memory
T8	Emotional Memory
Pz	Zero site

The frequency at which the human brain operates is related to aspects of the cognitive processes taking place at a specific time. When the brain is in a certain state, frequency patterns occur in specific frequency bands; these are commonly separated as:

1. Delta, 1 – 4 Hz, associated with the depth of sleep (the stronger the delta rhythm, the deeper the sleep).
2. Theta, 4 – 7 Hz, associated with cognitive workload and memory retrieval.

3. Alpha, 7 – 12 Hz, associated with a relaxed state of mind, attention, and concentration.
4. Beta, 12 – 30 Hz, associated with active thinking, a high alert state of mind.
5. Gamma, >30 - typically 40 Hz, associated with short-term memory matching of recognized objects, sounds, or tactile sensations (Gandhi, 2014).

Although EEG input provides time-domain data that show how a signal changes over time, a frequency-domain analysis will show how that signal's energy is distributed over a range of frequencies (Proakis & Manolakis, 1996). The energy of such signal defines how powerful it is. However, the total power over all time would generally be infinite, and it is of our interest to know the distribution of power per unit time. This measure is obtained through the Power Spectral Density (PSD) function (Stoica & Moses, 2005), that basically shows if the signal is strong or weak at a particular frequency, per time unit. Thus, the inferences and predictions of human behaviors in this study will be based on the power of the brain signals detected by the EEG.

From the five frequency bands mentioned previously, alpha-band oscillations have been found dominant in the human brain, and in a strong relationship with *attentional* demands (W. Klimesch, Doppelmayr, Russegger, Pachinger, & Schwaiger, 1998). Specifically, alpha band activity is associated with functional *attention* (J. Foxe & Snyder, 2011), which comprises suppression and selection of attention (Wolfgang Klimesch, 2012). Evidence also suggests that alpha oscillations can help increase knowledge and find applications for the acquired learning, since they are related to alertness, visual attention maintenance, and ongoing visual processing (J. J. Foxe, Simpson, & Ahlfors, 1998; J. Foxe & Snyder, 2011). I will thus, consider alpha band power as the measurement of attention in this thesis.

2.6 Structural Equation Modelling - SEM

Structural Equation Modelling (SEM) is a set of regression equations that, compared to other linear systems, is more flexible on identifying causal relationships amongst unseen but hypothesized –latent- variables and measured –mediating- variables (Streiner, 2006). The true relationships between these variables are rarely detectable using traditional methods, since the measurement error can be overestimated over the response. SEM first tests for the significance of mediating variables (Nachtigall, Kroehne, Funke, & Steyer, 2003), and then infers on the latent variables; consequently, the relationships among the latent variables reflect their “true correlations uncontaminated by measurement error” (Streiner, 2006). Due to its ability of imputing accurate direct and indirect effects of the mediation process, SEM has been commonly used in the study of performance considering different mediators, for instance: communication (Macht et al., 2014), eye-movement (J. E. Kim & Nembhard, 2019), or time pressure (J.-E. Kim & Nembhard, 2019). In this thesis, SEM determines the mediation of interest and attention in the relationship between instructional design, emotional state, and performance.

3 Chapter III - Materials and Methods

The purpose of this thesis work is to identify the main factor, between instructional design and emotional state, that influences performance, considering behavioural mediators in the relationship. For this purpose, I first model the factors into a 2x2 factorial design, and then analyse all the variables involved in the study into a structural equation model (SEM). The factorial design identifies all possible combinations of factor levels that may affect performance, and the SEM allows to determine the significance and strength of the relationships between factors, mediators and performance. The experiment consists of two practical sessions of emotional induction and task execution, separated by a relaxation time. From these sessions, task completion time, pupil diameter and EEG signals are collected as data input for the statistical analysis of the models.

3.1 Hypotheses

To investigate about performance and suggest general solutions to the problem statements raised in the first section of this thesis, I will address the following hypotheses along the study:

H_1: *Information representation* has effects on *performance.*
H_2: *Emotional state* has effects on performance.
H_3: *Interest* and *attention* mediate the effect of information representation and emotional state on performance.

The referred variables are analyzed in the context of a Structural Equation Model to answer each hypothesis and, consequently, the research questions that originated this study.

3.2 Factorial Design

A 2x2 factorial design is used to model the effect that instructional design and emotional state have on performance. Information representation and emotional state are the two fixed factors considered for the experiment. The participant is considered as a random factor. Other considerations in the design are:

a) Each fixed factor has two levels, as detailed in **Table 2**.

b) The experiment uses eight replications per treatment, to yield 32 observations per participant.

c) The order of treatments as well as the number of participants is randomized (Montgomery, 2017).

d) The significance level used throughout the experiment is α=0.05.

Table 2: Elements of the 2x2 Factorial Design

Factor	Type	Levels
Information representation	Fixed	Text (T), Pictures (P)
Emotional state	Fixed	Positive (P), Negative (N)

3.3 Experimental Sample

36 undergraduate and graduate students (17 males, 19 females; age μ=26.6 years, SD=5.1 years) of Oregon State University were recruited for the experiment. All participants had normal or corrected vision, and did not have prior knowledge of the task. All participants were able to speak, listen, and read in English. Each participant signed a written informed consent before conducting the study, and at the end, monetary compensation was provided.

3.4 Experimental Equipment

A Tobii Pro X2-30 eye-tracker and a wireless, five-channel Emotiv Insight EEG headset were used in this study.

Participant's eye metrics were recorded running Tobii Studio Software on a 21.5-inch desktop computer. This computer was also used to conduct the emotion induction procedure on the participant, as well as to perform the assembly tasks on a web page integrated to the eye-tracking software.

The EEG signal was recorded on the Emotiv Pro Software, using a 21.5-inch monitor iMac. The electrodes were positioned as AF3, AF4, Pz, T7 and T8, as referred in Section 2.5. Raw data was collected at a sampling rate of 128 samples per second, and the frequency resolution of the Alpha band was 0.089 Hz. The data was filtered in Matlab, using the Welch periodogram function *[pxx,f] = pwelch (_,fs)* (The MathWorks Inc., 2019), that performs a Fourier Transform and returns a frequency vector *f*, corresponding in this case to the Alpha frequency (8-12 Hz). The sample rate *fs* corresponds to the number of samples per unit time, mentioned before (128). The power spectral density pxx was then integrated to obtain the average power of the Alpha frequency per unit time, through the function *p = bandpower(pxx,f,'psd')* (The MathWorks Inc., 2019). An example of the code used to filter the raw data and obtain the Alpha Power is shown in Appendix A.

3.5 Stimulus and Tasks

3.5.1 Emotional induction and assessment

Since Seibert & Elli's procedure was proven successful in students, using experimental resources more efficiently, this thesis project applies it for emotional state induction (Parrot & Hertel, 1999). The procedure now has 2 modifications:

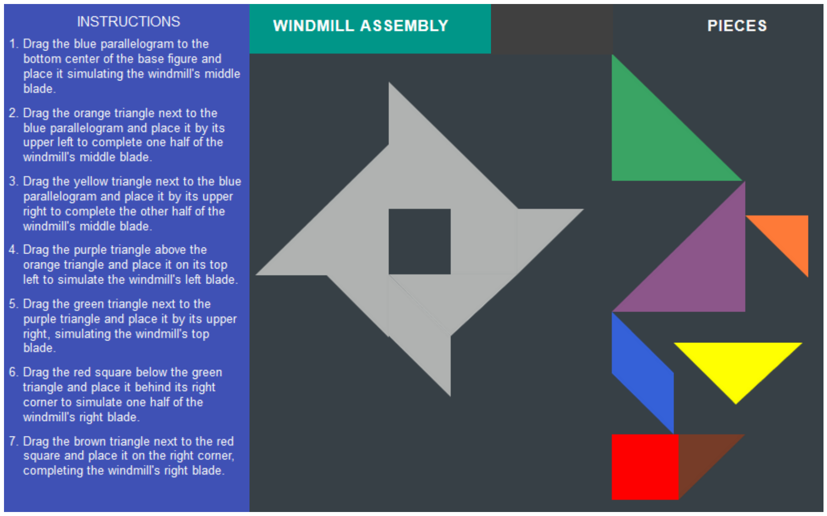
1) Change of the positive statement *Being in college makes my dreams more possible* to *Being in school makes my dreams more possible,* to make it applicable to a broader sample of participants; and

2) Disregard the *neutral scale* statements, since emotional state levels are only positive and negative for this case.

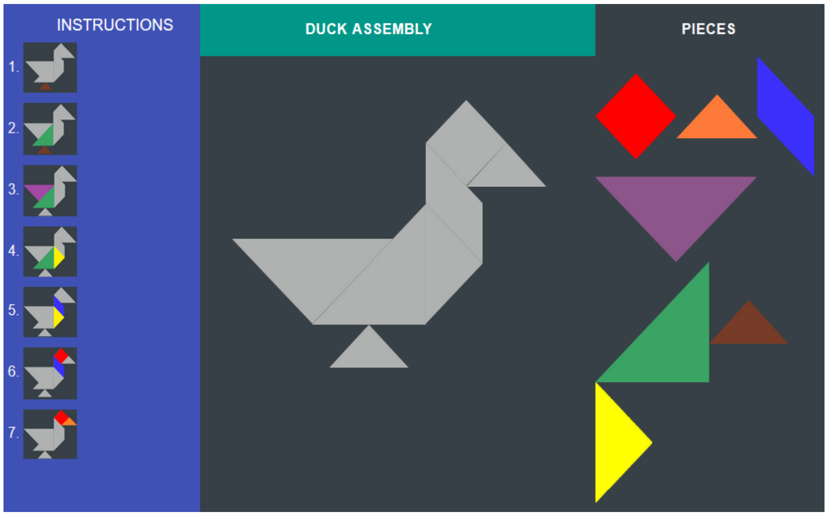
Emotion induction procedures have been traditionally validated through self-reported checklists and questionnaires, where the Positive and Negative Affect Schedule (PANAS) has demonstrated to be psychometrically superior over other assessment tools (Wiseman & Levin, 2011) and widely used in mood induction studies. That is why this thesis uses a PANAS questionnaire to assess participant's emotions before performing the tasks.

3.5.2 Tasks

Each participant completes 32 random tasks (Jashami, Hurwitz, Monsere, & Kothuri, 2019) on a computer, following instructions on the left side of the screen. Each task is associated to a set of instructions (T or P), which order is randomized to appear on the screen as shown on the sequences A-D on Appendix B. **Figure 2** provides examples of the assembly screen with different types of instructions, according to such sequences.



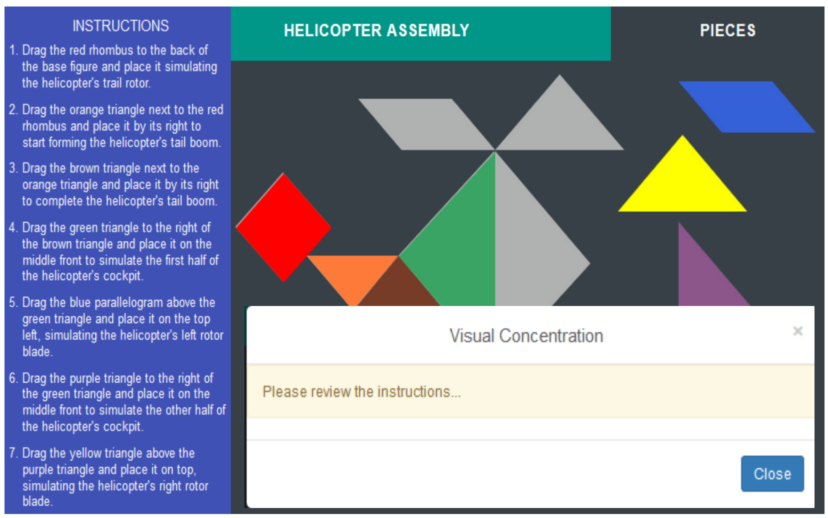
a. Task #9: Windmill, instructions in Text



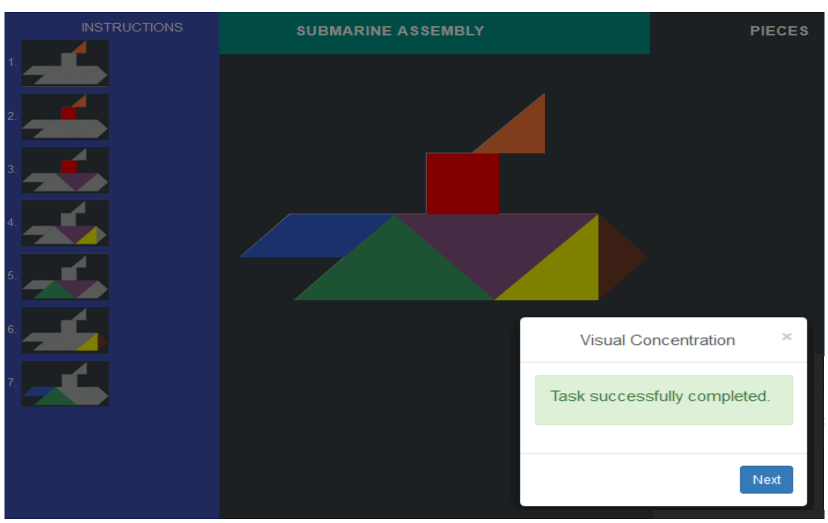
b. Task #18: Duck, instructions in Pictures

Figure 2: Examples of assembly tasks

As a way to ensure that the participant follows the instructions, the assembly platform was designed to display a warning alert when the participant tried to move a piece arbitrarily. Another alert was displayed to indicate that the task was successfully completed, allowing the participant to continue to the next one. Examples of the referred messages can be seen in Figure 3.



a. Alert of following instructions



b. Alert of successful task completion

Figure 3: Alerts displayed by the assembly platform

3.6 Experimental procedure

The experiment started inducing participants to a specific emotion by reading 25 statements, either positive or negative, such as: *"Being in school makes my dreams more possible", "I bet things will go well for the rest of the day"*; or *"Academic life is harder than I expected", "I doubt that I'll ever make a contribution in the world"*. Participants were instructed to experience each statement, as it would apply to them personally, and repeat it aloud. When they finished the 25 statements, their emotion was assessed by an online PANAS questionnaire.

Afterwards, participants performed the 1st task, following instructions on the screen. At the end of the 16th task, a 3-minute break was provided to let participants relax before eliciting the next emotion. At the end of the second emotion induction procedure, a new assembly session started with 16 new tasks to complete. A graphical summary of the experimental procedure is shown on **Figure 4**.

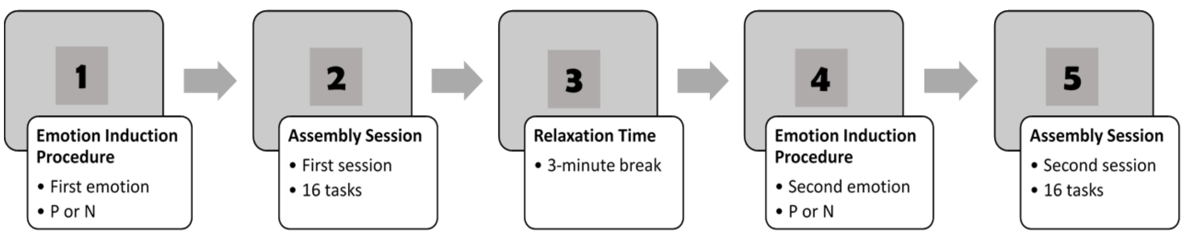


Figure 4: Summary of the experimental procedure

3.7 Measures

Three measures are recorded automatically while the assembly sessions are taking place:

1) Task completion time, through the assembly platform;

2) Pupil diameter, though the eye-tracking device; and

3) Alpha band power, from the EEG alpha band records.

To estimate the parameters in SEM, all variables of the regressions require to be numerical. Since the independent variables of this study are categorical, they were coded appropriately before running the model, as shown in **Table 3: Codification of Independent VariablesTable 3**.

Table 3: Codification of Independent Variables

Independent Variable	Level	Code
Information Representation	Pictures	1
	Text	0
Emotional State	Positive	1
	Negative	0

To identify the changes in pupil diameter and alpha power measures from a reference point, I calculated the mean of these variables for each participant in 32 trials, and subtracted each recorded value from the mean. This way, I obtained relative measures that will provide more accurate effect estimations.

3.8 Experimental Model - SEM

In this thesis, I apply SEM to examine the mediation of interest and attention in the relationship between instructional design, emotional state, and performance. **Table 4** provides the notation for the variables in the referred SEM.

Table 4: Notation for Structural Equation Model

Variable		Abbreviation
X_1	Information Representation	InfoRep
X_2	Emotional State	Emotion
X_3	Pupil Diameter	Pupil
X_4	Alpha Power	AlphaP
Y	Completion Time	Time

Coefficients are estimated through the following relationships (Werner & Schermelleh-Engel, 2009):

$$Y = \lambda_1 X_1 + \lambda_2 X_2 + \beta_{21} Y_2 + \beta_{31} Y_3 \qquad (1)$$

$$Y = \beta_3 X_3 + \beta_4 X_4 \qquad (2)$$

$$X_3 = \beta_{13} X_1 + \beta_{23} X_2 \qquad (3)$$

$$X_4 = \beta_{14} X_1 + \beta_{24} X_2 \qquad (4)$$

The model is specified in R as in equations (1) to (4) (Fox, 2006), and estimated parameters are obtained through the *sem* function (Ihaka & Gentleman, 1996). An example of the code developed in R for the calculation of the estimates is shown in Appendix C.

InfoRep and Emotion are independent variables that correspond to factors information representation and emotional state, respectively. Interest is measured through the participant's pupil diameter, and corresponds to the variable Pupil. AlphaP represents the variable alpha power that evaluates the changes of attention level. Performance is measured in terms of task completion time per participant, this is the reason why it is termed Time in the model. The analogy used for this variable is the faster the task is completed, the better the performance (less time = higher performance). **Figure 5** shows the proposed SEM that links all mentioned variables.

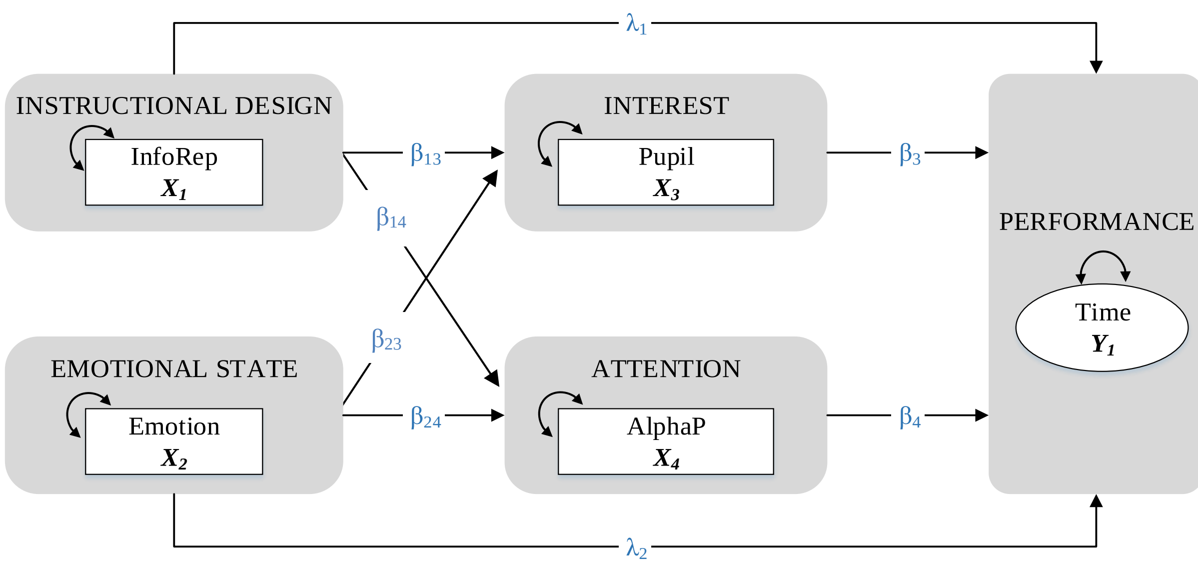


Figure 5: Proposed SEM for analysis of Performance

The statistics to evaluate model fit in the proposed SEM are given in terms of goodness of fit index (GFI), and Bentler Comparative Fit Index (CFI) (Parry, 2017). The CFI is normalized to have a range of 0-1, with results typically greater than or equal to 0.90 as statistically significant; and the GFI is considered significant when greater or equal to 0.95.

4 Chapter IV - Results and Discussion

4.1 PANAS Scores

Participants' mean score in the PANAS evaluation was 34.9 (*SD* = 7.5) for positive affect, and 18.4 (*SD* = 4.0) for negative affect. PANAS mean scores have been stated as 29.7 and 14.8 for positive and negative affect, respectively (Tellegen et al., 1988). Equal or higher scores than 29.7 reflect enthusiasm, alertness, a state of high energy, while scores equal or higher than 14.8 are associated with a state of distress and nervousness. Research in the educational field applied PANAS to evaluate emotional traits related to outcomes, finding that positive and negative affects may in fact predict performance (Merz & Roesch, 2011). Hence, the results of the present experiment reflect that the technique applied to induce positive and negative emotional states was effective and well oriented to the evaluation of performance.

4.2 SEM Results

The proposed SEM is considered a relatively good fit to the data (*GFI* = 0.98, *CFI* = 0.95) (Parry, 2017). **Table 5** summarizes the results from fitting the proposed SEM for analysis of performance. A graphical representation of these results is shown in **Figure 6**, wherein only statistically significant relationships are presented for clarity.

Table 5: Parameter estimates for SEM

Relationship	Parameter	Estimate	*p-value*
Information Representation → Time	λ_1	-0.51	<0.001*
Emotional Valence → Time	λ_2	-0.11	<0.001*
Information Representation → Pupil Diameter	β_{13}	0.37	<0.001*
Emotional Valence → Pupil Diameter	β_{23}	0.09	0.001*
Information Representation → Alpha Power	β_{14}	-0.05	0.012*
Emotional Valence → Alpha Power	β_{24}	0.01	0.649
Pupil Diameter → Time	β_3	-0.21	<0.001*
Alpha Power → Time	β_4	0.06	0.011*

**Significant relationships, p-value < 0.05*

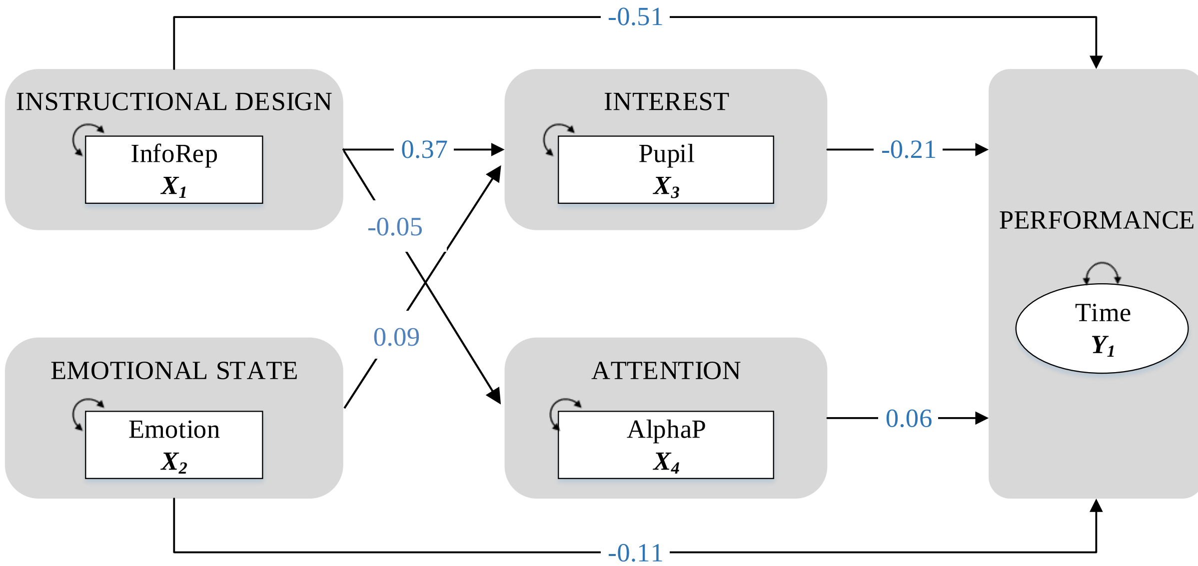


Figure 6: Results of SEM for Analysis of Performance

The relationship between information representation and task completion time showed to be significant (*p-value* < 0.001). Recalling **Table 3**, it is possible to infer that varying the design of instructions from text to pictures to train the participant on performing a task, decreases completion time ($\lambda_1 = -0.51$), yielding high performance. This result confirms the findings of positive cognitive influence of pictorial representations on student's performance (Lindner et al., 2018), and benefits on learning when information is graphically represented (Schnotz & Bannert, 2003).

Emotional state and task completion time variables also showed a significant relationship in the model (*p-value* < 0.001). Discrete emotion categories (positive or negative) have demonstrated to offer the richest and most useful information when determining the influence of the emotional state on performance in competitive environments (Lazarus, 2000). In the academic field, positive achievement emotions such as enjoyment or pride were shown to facilitate performance attainment (Reinhard Pekrun, Elliot, & Maier, 2009). Our results confirm this findings, showing the influence of positive emotions on performance by reducing task completion time ($\lambda_2 = -0.11$).

Pupil diameter increased when instructions were shown in pictures (β_{13}= 0.37, *p-value* < 0.001), and participant experienced positive emotions (β_{23}= 0.09, *p-value* = 0.001). Since dilation responses to stimuli are interpreted as an index of interest (Goldwater, 1972), these results suggest an increase of interest when pictorial representations and positive emotions are present. Research in the field has shown that individuals are in general more interested in image-rich contents rather than textual or bullet points (Tangen et al., 2011); therefore, our findings in this matter were the expected. Profound meta-analyses have concluded that an increased level of interest leads to high performance (Hidi, 1990b)(Harackiewicz & Hulleman, 2009), in support of our findings regarding pupil diameter and task completion time. When pupil size increased, and therefore the index of interest was higher, the time it took to complete the task was reduced ($\beta_3 =$ -0.21; *p-value* < 0.001), leading to better performance.

The second behavioral variable I consider in this model, alpha power, was affected by the type of information representation but not by the valence of emotions. A pictorial representation of instructions demanded a lower alpha power investment in the task, reducing the attentional effort by the participant ($\beta_{14} =$ -0.05; *p-value* = 0.012) (Boxtel, Tsuchiya, & Koch, 2010). In contrast, task completion time showed to increase at the same time than alpha power, suggesting that extended periods of attention increase the time recorded to complete the task ($\beta_4 =$ 0.06; *p-value* = 0.011).

5 Chapter V - Conclusions

This study modeled performance as a function of instructional design features and emotional stimuli, and considered behavioral mediators such as interest and attention to explain this relationship. Findings suggest that instructional design and emotional state affect performance, and that interest and attention mediate this relationship. Even when both factors, instructional and emotional, evidenced significant effects, information representation showed the highest influence on performance, by arousing participant's interest. A pictorial representation of instructions improves performance since they increase participant's interest in the task and demand less attention effort from the performer.

Emotional state has a positive effect on performance when guiding the participant to experience positive emotions, since they arouse the interest in the task. However, participant's level of attention is not influenced by emotions. Performance improves when arousing participant's interest, not by demanding focused attention. Demanding higher levels of attention may have a detrimental effect on performance since focusing in the task for extended periods increase its completion time.

Overall, the highest parameter estimations correspond to the relationships between information representation, interest, and performance, revealing that the design of the learning environment is the factor that mainly influences performance; therefore, the visual perception of the instruction is important to obtain higher outcomes when executing a task. Even when the influence of the emotional state was significant on the majority of variables in the model, the low estimated parameters for these relationships make us consider alternative ways of analysis to improve the estimations. Since the procedure applied for measuring emotional state was based on induction and assessed through a self-report method, the researcher guided the participant to feel a certain emotion, and trusted on their evaluation of the feeling, instead of measuring itself. For future research, through EEG metrics, the mood that the participant comes in for the study could be directly evaluated, link this mood to a positive or negative scale and test on performance, to determine improvement on estimations.

Including more variables for measuring the effect of both factors in the model may be potentially explored in the future. For instance, by increasing the number of frequency bands analyzed, one may check how significant are behaviors like cognitive workload or active thinking on performance; or if performance depends also on gaze patterns related to interest in the instructional material.

The results of this work not only contribute to improve basic instructional environments by suggesting the design features that foster high performance, but offer guidelines to the industry on how to increase productivity by providing accurate directions and managing emotions in individuals.

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Appendices

Appendix A: Example of the Matlab code used to calculate Alpha Power

```
% Doing the calculations for the 5 channels:
for i = 1:5
            x = EEG_rawdata(:,i);
            fs = 128;

% Performing the Fourier Transformation and PSD
estimation through Welch Periodogram

[pxx, f] = pwelch(x,hann(length(x)),0,length(x),fs);

% Calculating power in the Alpha range 8-12 from
previous estimation pxx

AlphaPower = bandpower(pxx,f,[8 12],'psd');

power_table(k,participant) = array2table(AlphaPower);


end
```

Appendix B: Randomization of treatments to appear on the assembly screen

		Sequence A	Sequence B	Sequence C	Sequence D
Assembly Task		Treatment	Treatment	Treatment	Treatment
1	Tree	PT	NT	PP	NP
2	Fish	PP	NP	PT	NT
3	Car	PT	NT	PP	NP
4	Spinning top	PP	NP	PT	NT
5	Dog	PT	NT	PP	NP
6	Cow	PP	NP	PT	NT
7	Horse	PT	NT	PP	NP
8	Boat	PP	NP	PT	NT
9	Windmill	PT	NT	PP	NP
10	Swan	PP	NP	PT	NT
11	House	PT	NT	PP	NP
12	Ship	PP	NP	PT	NT
13	Airplane	PT	NT	PP	NP
14	Microscope	PP	NP	PT	NT
15	Tortoise	PT	NT	PP	NP
16	Sea Lion	PP	NP	PT	NT
Relaxation time					
17	Flamingo	NT	PT	NP	PP
18	Duck	NP	PP	NT	PT
19	Helicopter	NT	PT	NP	PP
20	Submarine	NP	PP	NT	PT
21	Rabbit	NT	PT	NP	PP
22	Rocket	NP	PP	NT	PT
23	Camel	NT	PT	NP	PP
24	Turtle	NP	PP	NT	PT
25	Chicken	NT	PT	NP	PP
26	Person	NP	PP	NT	PT
27	Chair	NT	PT	NP	PP

28	Cat	NP	PP	NT	PT
29	Candle	NT	PT	NP	PP
30	Goat	NP	PP	NT	PT
31	Eagle	NT	PT	NP	PP
32	Train	NP	PP	NT	PT

Appendix C: Example of the R code used in the parameter estimation of the proposed SEM

```
install.packages("sem")
install.packages("semPlot")
library(sem)
library(semPlot)

rm(list=ls(all=TRUE))
opt <- options(fit.indices = c("GFI","AGFI","SRMR","CFI"))

data=Data3
cov.data<-cov(Data3)


Model1 <- specifyModel(text="
                       InfoRep  -> Pupil,   b1, NA
                       Pupil    -> Time,    b2, NA
                       Pupil   <-> Pupil,   NA, 1
                       Time    <-> Time,    NA, 1
                       InfoRep <-> InfoRep, NA, 1
                       ")

fit1<-
sem(SEM,data=Data3,orthogonal=FALSE,test="Satorra.Bentler")
fit1
summary(fit1,standardized=TRUE)


fitmeasures(fit1,c("GFI","AGFI","SRMR","CFI"))

semPaths(fit1,"std")
```