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ENHANCING THE MOTIVATION AND LEARNING PERFORMANCE IN AN ONLINE CLASSROOM WITH THE USE OF NEUROMARKETING

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Abstract:

In recent years, the newly emerging discipline of neuromarketing, which employs brain (emotions and behaviour) research in an organisational context, has grown in prominence in academic and practice literature. With the increasing growth of online teaching, COVID-19 left no option for higher education institutions to go online. As a result, students who attend an online course are more prone to lose focus and attention, resulting in poor academic performance. Therefore, the primary purpose of this study is to observe the learner's behaviour while making use of an online learning platform. This study presents neuromarketing to enhance students' learning performance and motivation in an online classroom. Using a web camera, we used facial coding and eye-tracking techniques to study students' attention, motivation, and interest in an online classroom. In collaboration with Oxford Business College's marketing team, the Institute for Neuromarketing distributed video links via email, a student representative from Oxford Business College, the WhatsApp group, and a newsletter developed explicitly for that purpose to 297 students over the course of five days. To ensure the research was both

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realistic and feasible, the instructors in the videos were different, and students were randomly allocated to one video link lasting 90 seconds (n=142) and a second one lasting 10 minutes (n=155). An online platform for self-service called Tobii Sticky was used to measure facial coding and eye-tracking. During the 90-second online lecture, participants' gaze behaviour was tracked overtime to gather data on their attention distribution, and emotions were evaluated using facial coding. In contrast, the 10-minute film looked at emotional involvement. The findings show that students lose their listening focus when no supporting visual material or virtual board is used, even during a brief presentation. Furthermore, when they are exposed to a single shareable piece of content for longer than 5.24 minutes, their motivation and mood decline; however, when new shareable material or a class activity is introduced, their motivation and mood rise.

JEL: I20; I21

Keywords: neuromarketing, facial coding, eye-tracking, motivation, learning performance, online classroom

1. Introduction

Since the COVID-19, higher education is highly dependent on online learning for students. The reasons for the expansion of online learning in recent years are varied but include increased accessibility, advances in communication technologies, increased demand for 'flexible' online or distant learning and the need for institutions to remain competitive by offering students a variety of learning platforms (Skordis-Worrall et al., 2015). More recently, the Covid-19 pandemic forced higher education institutions in the UK and worldwide to urgently suspend face-to-face teaching and replace it with online learning (Adedoyin & Soykan, 2020, Qureshi et al., 2020).

Therefore, it is imperative to consider all the parameters affecting students' motivation and learning performance in online classrooms. The main problem with online learning is a lack of functional group and individual monitoring of how students react mentally and emotionally to the presented material. Effective monitoring and meaningful communication are prerequisites of successful online learning performance (Ferguson & DeFelice, 2010). By addressing this problem, the online learning process can be advanced in several ways. Each student's interest can be measured, and the required changes to the teaching material can be made to better engage the student with effective communication during the online lecture. In this article, we aim to provide insight into how online learners' motivation and learning performance can be analysed and enhanced using neuromarketing. Improving learners' self-regulation, motivation and interaction with their educational experiences is a key concern in online learning. Our study investigates the methods of neuromarketing that can be used during online learning in order to improve students' engagement.

The measurement of neural and physiological signals to gain insight into learners' decisions, motivation, learning, and preferences is referred to as 'neuromarketing' (Lee et al., 2007). The most common method used in neuromarketing is physiological tracking, which includes facial coding and eye movement measurements (eye-tracking) (Lee et al., 2007). The information in an online classroom is primarily available in the fen text and videos (Sungkur et al., 2016). In addition, online students engage in various educational activities, such as attending online meetings, watching video lectures, writing, taking notes and online notes e tests and reading. Learners exhibit varying degrees of involvement when participating in these educational activities, including boredom, annoyance, delight, neutrality and uncertainty. Therefore, it is critical for online teachers to accurately and efficiently detect their online students' engagement status in order to provide customised pedagogical support through interventions (Dewan et al., 2019).

Learner participation has been a critical topic in the education literature since the 1980s, and the issue of participation is particularly relevant to online learning (Bento & Schuster, 2003; Davies & Graff, 2005; Olofsson, 2007; Vonderwell & Zachariach, 2005). Concerns about high drop-out rates in online courses may have sparked this curiosity. In addition, improving learners' motivation and performance by using eye-tracking and facial coding in an online classroom has been acknowledged by many researchers (Rothkrantz, 2016).

Students' learning in the online classroom is affected by many factors, including communication, emotional engagement, content coverage, students/teacher co-attention, motivation, learning preference and students' interest in the online classroom. Therefore, we conducted neuromarketing research to understand students' motivation and learning performance in the classroom. We perform this research on the following primary research question:

How can Neuromarketing enhance the Motivation and Learning Performance of students in an online classroom?

To answer the question, we conducted neuromarketing research involving students at Oxford Business College, U.K., by using facial coding and eye-tracking. We approach this question from three different perspectives: *teacher* (how many students follow the teacher), *perceptual* (following the teacher's deictic acts) and *conceptual* (following the teacher's discourse). For this research, we use neuroscience technologies, such as facial emotional analysis and eye-tracking, where we capture the students/teacher co-attention, student motivation, student learning performance and student interest. The research was conducted using the participant's web camera and neuromarketing software to capture emotions, attention and motivation. The recording uses a virtual guide (a set of images followed by instructions) assisting the participant in his or her participation in the experiment. The participant was instructed to make sure that no other individuals were present for the duration of the experiment. All participant information was treated in the strictest confidence and data collected from the research were treated in line with standard practice and compliance with UK GDPR (General Data Protection Regulation).

2. Online learning from complex visual content

Learners face many issues when learning virtually in an online classroom. Retention is a serious issue (Glazier, 2016) and can be categorised as one of the most important flaws of the open online learning movement.

Massive Open Online Courses (MOOCs) have proliferated since their appearance in 2008 and continue to have a prominent presence in the higher education industry (Johnson et al, 2015; <u>Sharples et al., 2014</u>).

Robal et al., (2018) report that only 15% of students who start a Massive Open Online Course go on to successfully complete it (Jordan, 2015b). In contrast, the retention rate of students attending traditional (face-to-face) university courses is usually over 80% (Atchley et al., 2013).

The online retention rate is between 10% and 35% is lower than the in-person retention rate (e.g., Patterson and McFadden, 2009; Stover 2005; Terry, 2001).

Students fail for various reasons, for example, their inability of the students to self-regulate (Robal et al., 2018).

Attention loss may be more common in online learning environments. Risko et al. (2012) used three one-hour video recorded lectures on various subjects (psychology, economics and classics) to study this effect. They reported the attention-loss frequency of the participants to be about 43%. A strong negative association was also reported to exist between the test results and attention loss. While watching video lectures, Loh et al. (2016) made use of various probes in order to test learners' loss of attention and, as a consequence, discovered that a positive association exists between media multitasking behaviour and the learners' loss of attention (average frequency of 32%). This led to the conclusion that, by minimising the loss of attention in online learning, we can ultimately improve learning outcomes effectively based on this significant loss of the attention frequencies of the students. Colliot & Jamet (2018) investigated how introducing a teacher's video to an online learning module affected students' learning experiences.

Our research aims to observe the learner's behaviour while making use of an online learning platform. We used these observations to create a framework that can quantify the learner's performance depending upon his/her behaviour and tailor the instructional content to their specific needs. Eye tracking, which is a collection of methods used to make useful observations and capture learners' eye movements, is used in ergonomics, psycholinguistics, psychology, e-learning, advertising and pre-testing to assess the positions and movements of the learners' eyes. El Haddioui & Khaldi (2012) studied the use of such technologies, which allow us to perform eye-tracking to monitor as well as analyse learners' emotions and behaviours while using an e-learning platform. These parameters of emotion and behaviour consist of several factors, which have to be assessed, such as concentration, tension, tiredness, relaxation, and capacity for problemsolving.

2.1 Eye-tracking in self-regulation and interaction of learners

Eye-tracking research methods offer students in the higher education sector a unique opportunity to enhance their interaction and self-regulation skills in the context of online learning. Hyönä (2010) describes how learners' eyes are directed in two ways. Firstly, endogenously to meet task-relevant goals and, secondly, exogenously, by responding to perceptually salient stimuli. Based on these principles, Knight et al. (2014) became the first one to report eye-movement data of learners studying in an online learning environment to determine what eleven first-year higher education students pay attention to and ignore while navigating through online learning tasks. The researchers used the stimulated recall interview data in order to complement and carry out a relatively more comprehensive summary of the learners' task behaviours so that their visual behaviour during the exercise could be explained. They claimed a strong influence of the students' eye movements during text composition, which ultimately influences the status of the learners' cognitive and metacognitive processes.

Information gathered by eye-tracking systems shows a person's level of curiosity and centre of attention. These systems enable us to derive useful knowledge about a learner's level of focus, relaxation, tension, problem-solving, learning performance and tiredness. Eye-tracking systems can also provide indirect measurements and eye position monitoring, such as the number and duration of fixations, gaze position, and blink rate. Emotions can be monitored, and the eye-tracking device can offer more customised learning based on the results (Al-Khalifa & George, 2010). The implementation of gaze training as a teaching tool was carried out by Wilson et al. (2011). They implemented gaze training after they had successfully conducted randomised control trials to determine the extent of its usability for testing performance.

The method of monitoring an individual's eye movements is to reflect their attentional behaviour. This is based on the principle that our eyes tend to shift in order to put specific parts of our visual field into high resolution, enabling us to interpret the subject in fine detail in our central direction of gaze. Holmqvist et al. (2011) studied that we usually redirect our attention to that specific point to concentrate our attention on the picture. This mechanism allows eye-tracking technologies to monitor a person's gazing activity over time to provide details about their attention distribution. This urges researchers to make useful and logical speculations about what is being experienced by students while participating in the modern method of synchronous online language learning.

2.2 Facial coding and learning performance

Learning performance can be defined in a variety of ways. For example, it can refer to students' test scores (Ferguson and DeFelice, 2010; Ekwunife-Orakwue & Teng, 2014; Law & Geng, 2019), satisfaction with learning (Ekwunife-Orakwue & Teng, 2014; Yuan et al., 2020), or performance logged in an online learning system (Ekwunife-Orakwue & Teng, 2014; Law & Geng; Yang et al., 2016). Many studies have confirmed that online teaching enhances the learning performance. For example, Shea and Bidjerano (2014)

found that senior high school graduates who chose some online or remote courses from American community colleges had a higher chance of receiving the certificate than their peers who only took traditional face-to-face classroom teaching. Many authors believe that blended learning is superior to traditional face-to-face teaching because it aims to create a learning environment that encourages self-directed learning and claims numerous benefits (Garrison & Kanuka, 2004; Alammary et al., 2014), such as increased learning efficiency, student satisfaction and learning performance.

We are studying that students' actions can be analysed by their movement, eye gaze, posture, touch, pulse, facial expressions and voice pitch. Facial expression is thought to be the most important of these, as studies show that it accounts for 55 per cent of the influence of transmitting messages (Loh et al., 2005). Sun et al. (2017) focussed on using facial expressions to detect emotion in an online learning system. A deep learning approach, known as the convolutional neural network (CNN), was employed to detect emotions in an e-learning system based on facial expressions. They selected three libraries to assess the model's accuracy in detecting emotions to gain further insight. Finally, they explained how to use a professional CNN in an online learning system and implemented an online learning system with an emotion recognition module.

Students' attention and emotions are inextricably linked (Shen et al., 2009). Being alone in front of a screen in an online learning environment is a huge challenge for students. A prototype was proposed by Sharma et al. (2018) to determine students' attention level in real-time by using their facial expressions during an online lecture. They experimented with testing the framework of the prototype. It was found that students' emotions are associated with their levels of attention. Three concentration levels were established by using these data: high, medium, and low.

Shen et al.'s (2009) investigations revealed how learners' emotions undergo a shift during the online learning process and how we can optimise learning environments by using emotion-recognition technologies based on biophysical signals. The circumplex model of impact, which Russell devised, and the learning spiral model devised by Kort were used for their research. There are different methods for studying emotions, but the effects of emotion detection from physiological signals obtained a best-case accuracy of 86.3 per cent. Furthermore, according to the findings of the Emotion Revolution report, the most critical and frequently occurring emotions in learning are engagement and uncertainty.

3. Reliability of Neuromarketing in Research

It is critically important to understand the readiness and motivation of students for online learning. In the late 1990s, Mattice and Dixon (1999) created a study to measure their students' interest in online learning as well as their readiness for effective distance education. The participants of their study were asked about their past experiences regarding distance learning (e.g., time management, desire for formal instruction, job schedules, commuting duration and participation in online courses) and their access to technology. This work was devoid of any sort of study about the self-concept or selfefficacy of the students. The technology index almost depended not only upon the students' access to the internet and email but also on their level of familiarity with these tools. However, their emotions and motivation were entirely overlooked. Irie (2003) examined a representative sample of a survey that has mostly used factor analysis and has been undertaken since 1990 to identify patterns of motivation displayed by Japanese university students. Works published in Japanese are included in the surveys. Two competing sets for motivational concepts highlight the repeating patterns: (a) instrumental and integrative motivation and (b) mastery and performance goal orientation. Unfortunately, these surveys have not been proved helpful in improving students' learning and motivation.

Pan et al. (2010) studied student motivation by conducting a survey. According to a poll of students at Qingdao Agricultural University's Advanced and Ordinary English classes, most students are driven by intrinsic and extrinsic motives. Furthermore, he studied that students in Advanced English class and those in Ordinary English class have the same level of worry. Furthermore, students in Advanced English class have a more correct attitude than those in Ordinary English class. However, we cannot rely too heavily on the results of this survey because many factors, including students' emotions, learning performance and how it can be improved, are not addressed by this type of survey.

In the college classroom, a conceptual framework for measuring student motivation and self-regulated learning was offered by Pintrich (2004). In contrast to the student approaches to learning (SAL) view, the framework was built on a self-regulatory (SRL) view on student motivation and learning. The implications of the SRL conceptual framework for constructing instruments to measure college students' motivation and learning were examined as well as the differences between the SRL and SAL methods (Pintrich, 2004).

Kerr et al. (2006) developed an instrument based on pre-existing models, such as Felder and Soloman's index of learning styles, Rosenberg's self-esteem scale, Rynearson's metacognitive reading strategies questionnaire, Shea's academic intrinsic motivation questionnaire and Trice's academic locus of control questionnaire. Tech capabilities, autonomous learning, the need for online learning, academic skills and based learning were among the subscales in their initial study (<u>Heijstra and Rafnsdottir, 2010</u>).

The purpose of a study performed by Afzal et al. (2010) was to determine the impact of students' motivation on their academic achievement. A total of 342 students from various Pakistani institutions were chosen for the study. Three-part questionnaires were distributed directly to the target group. The study found that students' motivational characteristics positively influenced their academic achievement, such as extrinsic and intrinsic motivation.

Several surveys have been devised over the years to measure learners' readiness as an indicator of achievement in online programmes. It must, however, be noted that the literature review reveals that the criterion-referenced validity and results of these surveys were unsubstantial. Dray et al. (2011) wanted to create a survey instrument that was more comprehensive than these surveys, and students could use that to measure their preparedness for online learning. They presented the results of a three-phase analysis that included the creation, evaluation and validation of the instrument.

Several online services provide learner preparation assessments in order to help prospective students measure their readiness for online learning (<u>Smith*, 2005</u>) or predict how good they will be learning online (<u>Heijstra and Rafnsdottir, 2010</u>). Even though the traits of effective online students are well known, the question still remains whether colleges and universities should use these characteristics to aid their students in becoming successful. There are many surveys to measure students' readiness for online education, which emphasize the currently available general traits of the learners (e.g. self-directed learning, interpersonal communication abilities and academic locus of control) and basic IT skills (e.g. email, word processing and basic software). Unfortunately, only 20% of online surveys produce correct answers. Consequently, reliable results could not be attained by using these surveys.

Bhatnagar et al. (2014) developed an electronic survey focused on the ten learning outcomes of the unit's conceptual structure as well as the evaluation of the survey items' internal accuracy reliability and construct validity. The survey was completed by teacher education candidates who ranked how well their curriculum met the unit's vision of training educators who are educated, motivated, dedicated and engaging with their students and communities. However, the findings revealed that a set of learning outcomes was not clearly stressed across systems. All these surveys failed to provide actual results because learners were only monitored based on what they said and what they showed. These surveys did not emphasise their emotions, motivation, learning ability, and learning interest in the online classroom.

Thus, the most reliable way to obtain precise information about online learners' interests, motivations, readiness, and performance is to employ eye-tracking and facial coding methods. ET (eye-tracking) tracks where a person is gazing (gaze or focus point), how long they stared at that point, how their eyes change concerning their head, pupil dilation, and how many blinks they make. The order in which their eyes move from one position to another (saccade) may also be measured in addition to fixation (Chae & Lee, 2013).

A diverse range of ET (eye-tracking) tools has been made available to study facial movements. The most commonly used ET (eye-tracking) tools include those that can observe programmed stimuli at specifically chosen points in photographs and images as well as the user's contact with a computer screen. More advanced sensors automatically monitor the head orientation in three-dimensional space about the camera (Zurawicki, 2010). This results in a more subtle calculation procedure with little or no contact between the researchers and their subjects.

Eye monitoring offers unique insights into how people interpret visual information; it reveals unconscious thinking that would otherwise go unnoticed. An eye sensor (wearable or screen-based) illuminates the eye with a light source, resulting in highly visible reflections (Pro, 2017). A camera takes a picture of the eye, which is then used to classify the light source's reflection on the cornea and pupil. Accurate measurements of the eyes' orientation in the space and point of gaze are then made using the internal image-processing algorithms and a physiological 3D model of the retina. During this exercise, participants must go through a calibration process before filming and are instructed to aim at various points on the screen, known as calibration dots. As a result, the eye tracker displays the precise location of the participants' gazes as well as the timing and duration of their fixations and the scan directions of their eye motions (Pro, 2017).

Eye monitoring allows researchers to monitor and record the respondents' eye movements in real-time as they complete a survey during survey pretesting. Face monitoring, in particular, makes it possible for the researcher to examine and keep track of the focal point and duration of the respondents' gaze while reading and responding to questions (Galesic & Yan, 2011). In addition, this functionality allows us to spot questions that are either difficult to understand or have some other flaws.

4. Motivation of students and effects on learning performance in an online classroom

Students' attention in class is primarily due to teachers' direct supervision of lectures. Despite this, a significant number of students lose focus, even though they are under close observation. This dilemma is exacerbated in the online learning world by the lack of human oversight. It necessitates a method for assessing and identifying a student's lapses in concentration during the online learning session. Webcams are one technical affordance for detecting such a lack of attention. In recent years, researchers have started using webcams to carry out eye monitoring, collect the all-important gaze data and incorporate these data for sophisticated machine learning systems to diagnose inattention or lack of focus.

Online learning is defined as a form of self-regulated learning by Schacter and Szpunar (2015), who suggest a methodological structure for optimising learning from instructional videos. Students must track their performance, recognise learning problems and react to these judgments to self-regulate their learning; in other words, students must consciously build and interrogate mental models when studying metacognition regarding the learning process. Al-Awni's (2016) research aimed to increase student engagement in online learning platforms by extracting facial features' mood variations. They thought that analysing a student's moods during an online lecture based on their emotional states would provide useful insights that could be used to increase the effectiveness of information distribution in online learning. A neural network model was used to teach the algorithm to recognise facial feature sets and predict individual facial expressions. Mood trends and, as a result, the extent of a student's participation in an online learning environment were estimated using different variations of interrelated facial expressions in particular time frames.

El Haddioui & Khaldi (2012) emphasised observing the online behaviour of learners and developed a framework to build clusters of the learners depending upon their behaviours, which could then be used to tailor the instructional content by using these data to fit the learners' needs. Face monitoring consists of a collection of several methods for capturing and observing eye movements. This technology has been employed in various disciplines, such as psycholinguistics, psychology, e-learning, ergonomics and advertising pre-testing to assess the movement and position of the eyes. They efficiently made use of eye-tracking technologies to monitor and analyse the emotions and behaviour of learners on an online platform. These emotions and behaviours of the learners include tension, level of concentration, relaxation, tiredness and problem-solving.

Ekman (1993) has thoroughly studied facial features and their relationship to emotions in a number of publications, and he is widely considered one of the most important contributors to facial attribute-based emotion research. While a facial acting coding scheme may provide details about immediate facial emotional responses, there is also a need to determine a general mood based on different action units, which differ from person to person and situation to situation. Facial characteristics (forehead, eyebrows, nose, mouth, and so on) are the basic characteristics that are often used in face recognition systems because their gestures aid in the creation of speech on the human face (<u>Bailenson et al., 2001</u>).

The use of eye-tracking to study learning ability has dominated the literature. For example, Knight et al. (2014) studied how students use their eye movements to handle incoming input during learning activities and how linguistic influences, such as the number of sentences, the difficulty of the text and the learner's context awareness, affect eye movement patterns when the content is written. Barrios et al. (2004) described that AdELE (Adaptive E-Learning) is a platform for adaptive online learning that uses eye-tracking and content tracking technologies. This platform consists of a user profiler, a dynamic context library combining fine-grained real-time eye tracking with synchronous content tracking and an integrated multimedia learning environment. The platform ensures that the information given is relevant, accurate, and reliable and adapts to the needs of the users, their level of knowledge, and the real-time monitoring of their behaviour.

Mason et al. (2016) validated and expanded the results about the importance of these eye-tracking technologies for educational purposes, such as the promotion of strategic processing as well as learning from an illustrated text by using an eyemovement modelling example in higher education. They observed that those learners who studied the model's visual behaviour were found to have a much more integrated image and text analysis.

Colliot & Jamet (2018) researched to see how introducing an instructor video to an online learning module affected students' learning experiences. A total of 43 undergraduates were given the option of learning the content of a pedagogical manual with or without the use of an instructor video on the projector. According to the eyetracking results, students were found to have consumed 25% of their time while watching the instructor film. These findings reveal that the video lecture of the teachers should be used in online learning so that social cues can be enhanced without causing any sort of interruption.

Detecting the reading ability of online university students usually is tricky and time-consuming. Zhan et al. (2016) used eye-tracking sensors to monitor temporal and spatial human eye movements. Key markers for detecting reading skills include pupils, blinks, focus, saccade and a decline in learners' concentration and motivation. A multifeature regularisation machine learning mechanism was used to create a computational model based on empirical eye-tracking data. The model accurately guessed an individual learner's reading ability within twenty minutes, which has clear benefits in terms of saving time and improving accuracy.

Sungkur et al. (2016) proposed a real-time tracking scheme that uses image recognition and eye identification techniques to provide an overview of the different current techniques that lead to the development of the learning method. A multipronged eye monitoring technique has been imagined to represent such a versatile mechanism. The eye tracker device works by firstly recognising the user's pupils and then detecting their iris and pupil motions. Following that, data on the users' eyes and the motions of their pupils are scrutinised, and diagrams are created to aid in assessing the attention and behaviour of the user. The planned device is economical and can be employed for any device or laptop that has a standard web camera.

5. Materials and Methods

5.1 Participants

Out of the 2000 undergraduate students studying at Oxford Business College, only a sample of 297 undergraduate students (both genders, ages 18-50) was taken for this study because they met the study's criteria. For example, they participated in the research via computers and not mobile phones, watched the video until the end, and controlled excessive head movement).

The research lasted five days, and the Institute for Neuromarketing, together with OBC's marketing team, forwarded video links via email, a student representative from OBC, the WhatsApp group and a newsletter specially created for that purpose. In order to keep the research as realistic as possible, students were randomly assigned to a video link lasting 90-seconds (n=142), and another group of students was provided with a video link lasting 10-minutes (n=155). The professors in the two videos were different to achieve compatibility with real life where students have several teachers per module. The videos were divided into two separate links for improved accuracy, to avoid poor quality calibration and prevent student fatigue and/or lower levels of responsiveness when watching the second video. The study was conducted in accordance with the regulations of OBC'S Research Ethics panel. In accordance with the Declaration of Helsinki (Mundial, 2019), all of the participants were informed about the study and gave their written

informed consent in digital form prior to enrolling in the study. Their data were treated according to standard practice and in compliance with UK GDPR (General Data Protection Regulation).

5.2 Materials

The study used two pre-recorded videos from best lectures at OBC. In collaboration with OBC's marketing team, the Institute for Neuromarketing recruited students to participate in the research. These students were invited to participate and sent a participation link to a video lecture based on the experimental group they were randomly assigned to. In the 90-second video, participants watched the lecture with the lecturer talking on the screen, while in the 10-minute video, the lecturer shared his screen with the content but kept his camera on in the upper right-hand corner of the screen.

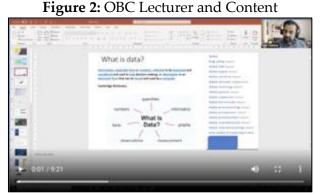
To participate in this research, access to a computer with an embedded web camera was required. In this instance, mobile phones were not available to ensure strong scientific validation of results.

The self-service online platform Tobii Sticky was used to measure eye-tracking and facial coding. According to the results, Sticky's average gaze error in a real-world (non-lab) environment is 1.6 to 1.8 degrees (~5% of screen width and 7% of screen height) on a laptop.



Figure 1: OBC Lecturer

Copyright: Institute for Neuromarketing



Copyright: Institute for Neuromarketing

5.3 General Procedure

After receiving a link to a pre-recorded online lecture, participants were also given a set of images with instructions to ensure compliance with the technical requirements before starting the eye calibration. During the 90-second online lecture, participants' gazing activity was monitored over time for details on their attention distribution and emotions were analysed through facial coding, while in the 10-minute video, only emotional engagement was analysed.

6. Results

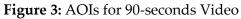
6.1 90-seconds Video

In the 90-second-long video, the main goal was to evaluate students' listening attention and elicited emotions during an online lecture where no visual material was presented. Students' gazing activity was monitored over time to generate data on their attention distribution, while their elicited emotions were analysed based on the facial coding data.

6.2 Listening Attention

When spending the longest periods of time looking and fixating on the lecture, students were mostly focused on the professor; however, their mouse-clicking behaviour and the relatively small number of fixations and short amount of time spent looking at other AOIs (areas of interest) suggests that students' listening concentration levels dropped during the lecture and visits to other AOIs were used to "restart" their concentration (Figure 5).



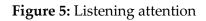


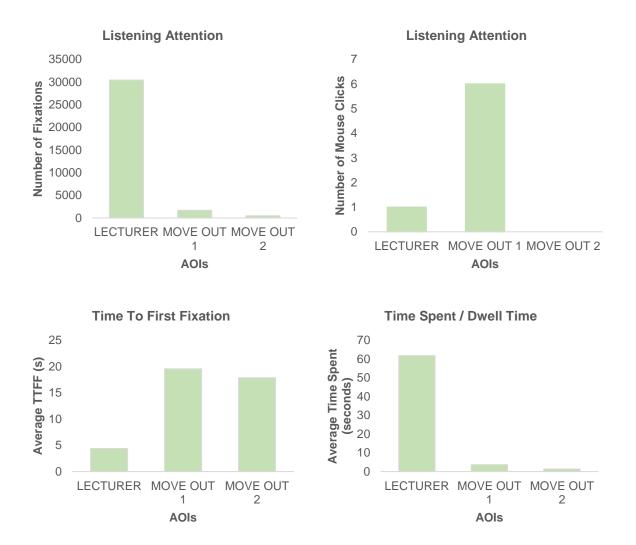
Note: AOIs were selected to study listening attention in students – Lecturer, Move Out 1, Move Out 2. **Copyright:** Institute for Neuromarketing.

Figure 4: Heat Map for 90-seconds Video



Note: Colour gradient overlay visualisation showing general distribution of gaze points. **Copyright:** Institute for Neuromarketing.





Data indicate the number of fixations for each AOI, number of mouse clicks within each AOI, average time to first fixation for each AOI, and average time spent looking at each AOI.

6.3 Emotion analysis

During the online lecture, students mostly elicited neutral emotions and sadness (Figure 6). They also showed unpleasantness towards the lecture being presented (Figure 7) and relatively higher intensities of negative emotions compared to positive ones (Figure 8). With the increase in aversiveness as time passed by and higher intensities of negative emotions, it is possible that students had difficulties focusing on the lecture due to the lack of accompanying visual material presented on the screen.

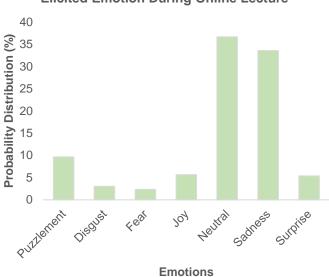


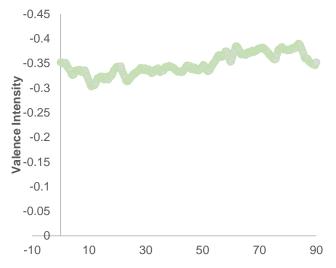
Figure 6: Elicited emotions during online lecture

Elicited Emotion During Online Lecture

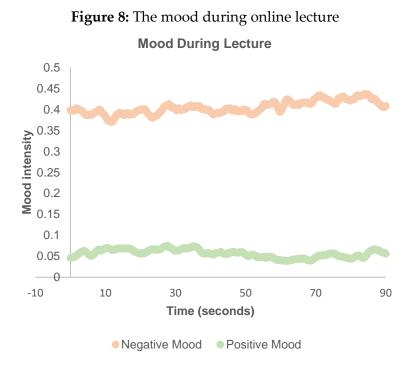
Data indicate the probability distribution of elicited emotions during online lecture.

Figure 7: Emotional valence during online lecture

Emotional Valence During Lecture



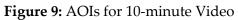
Data indicate valence intensity throughout the online lecture. Positive values are associated with pleasantness and attractiveness, while negative values suggest unpleasantness and aversiveness.

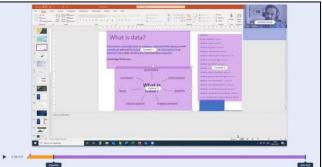


Data indicates the intensity of positive and negative emotions elicited during the online lecture.

6.4 10-minute Video

In the 10-minute online video lecture, the main goal was to evaluate elicited emotions based on facial coding data during an online lecture where visual material was presented and the lecturer's camera was kept on in the upper right corner of the screen.

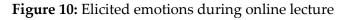


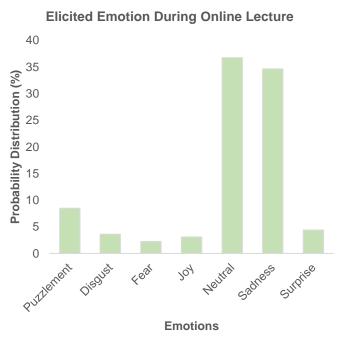


Note: 4 AOIs were selected to study emotional activity in students – Lecture Focus, Content 1, Content 2, Content 3. **Copyright:** Institute for Neuromarketing.

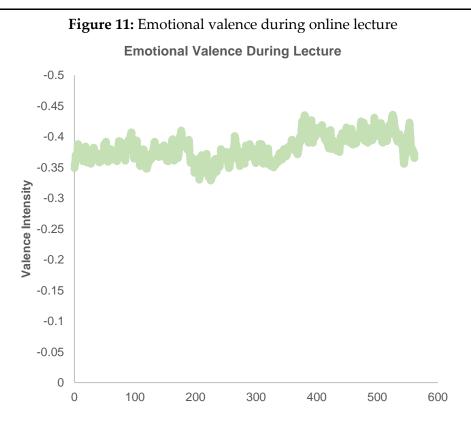
6.5 Emotion Analysis

During the 10-minute online video lecture, students mostly elicited neutral emotions and sadness (Figure 10), implying that students should be exposed to a greater number of slides or introduced to other didactic materials (e.g. virtual boards) during long lectures in order to increase their mood and enhance their learning performance. They also subconsciously showed unpleasantness towards the lecture being presented (Figure 11). However, the intensity of this unpleasantness dropped with the change of visual material and/or when a student discussion activity was presented. Throughout this online video lecture, students also elicited relatively higher intensities of negative emotions when compared to positive ones (Figure 12), but the change of visual material resulted in a slight increase in the intensity of positive emotions.

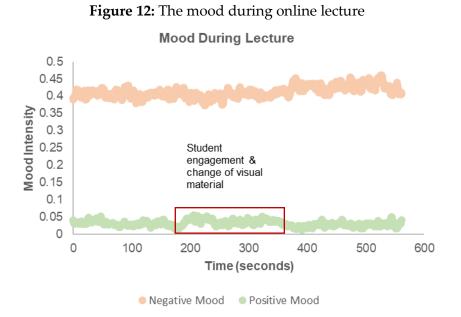




Data indicate the probability distribution of elicited emotions during the online lecture.



Data indicate valence intensity throughout the online lecture. Positive values are associated with pleasantness and attractiveness, while negative values suggest unpleasantness and aversiveness.



Data indicate the intensity of positive and negative emotions elicited during the online lecture.

7. Discussion

In the present study, we investigated ways of enhancing students' motivation and learning performance with their educational experience in online learning. Students' gazing activity over time was monitored for details on their listening attention distribution, while elicited emotions were analysed based on their facial coding. The results suggest that, even during a short lecture, students tend to lose their listening concentration when no accompanying visual material or virtual board is utilised. Moreover, their attention also drops following exposure to one shareable piece of content for longer than 5.24 minutes; however, with the introduction of new shareable material or a class activity, their motivation levels and mood increase.

8. Conclusion

Understanding how different students learn educational information during an online study session necessitates a thorough examination of their behaviour and emotional condition throughout the lecture. This study was conducted to watch and evaluate students' behaviour and motivation in order to understand what was causing their emotional detachment during an online class. The findings may aid in a better understanding of the entire ecosystem of an online learning environment in which increased student engagement and motivation are top priorities. Neuromarketing is a great help in this regard to study the behaviour and emotional engagement of students during an online class. Studies can be performed during the online learning session, depending on the student's and online learning administrator's preferences. Facial expressions and eye-tracking may be used to determine a student's mental state since facial characteristics vary over time and offer the greatest representation of what the student is thinking. Because student engagement during unsupervised learning is crucial to enhancing learning capacity, it is important to understand the issues that students expreience in an online learning environment.

The findings of this study demonstrate that facial expressions and eye-tracking data extracted using a web camera and Tobii Sticky platform may be utilised to actively derive students' emotional status during material delivery in an online learning system. Students' listening and emotional engagement during the study can give useful information on methods to improve the online learning experience. The resulting data may be utilised to enhance online learning in the future to engage learners more actively in real-time when an inattentive mood is recognized.

8.1 Recommendations

In the future, OBC should continue using teachers' recorded video lectures; however, it is essential to remember that giving a long lecture without shareable visual material will result in decreased learning performance, as recall and retention increase when information is presented using both auditory and visual channels (Paivio, 2013), and

visual information is essential for the processing and remembering verbal information (Mayer and Moreno, 2003). Therefore, in order to retain students' attention during long lectures, it is advised to change shareable visual content approximately every 4-5 minutes, introduce a class discussion, or use a virtual board.

Despite scientific literature suggesting that surveys have not proved useful for improving students' learning and motivation, they should be used in conjunction with neuromarketing data to gain further insights into learning motivation levels during online video lectures.

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Conflict of Interest Statement

The authors declare no conflicts of interests.

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