An Experimental Study of Learning Behaviour in an ELearning Environment

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***Abstract*— To achieve an adaptive eLearning system, it is essential to monitor the learner behaviour dynamically to diagnose their learning style. Eye tracking can serve that purpose by investigating the eye gaze movement while engaging in the eLearning environment. In this study, an eye tracking experiment was developed to analyse the pattern of learner behaviour to obtain his learning style as a personalisation aspect in an eLearning system. The electroencephalography EEG Emotive Epoc device was used to disclose learners with more accurate data. In the experiment, we have developed a method to test the hypothesis whether the verbal and visual learning styles reflect actual preferences in an eLearning environment based on Felder and Silverman Learning Style Model. The outcome of this experiment can be used as the starting point for further exhaustive experiments. This paper presents the actual state of our experiment, conclusions, and plans for future development.**

Keywords—eye tracking; eLearning; learning style; EEG;

I. INTRODUCTION

The adaptive eLearning industry is flourishing due to the personalisation of the learning process [1]. Learning Style is one of the main aspects of personalisation from cognitive perspective [2] that raises the need for identifying the student characteristics and preferences, which affect the learning experience [3]. As such, modelling the learner behaviour based on the learning style is helpful in the adaptive eLearning environment and an effective source of needed information. Investigating the eye movement is based on the proposition that the eye movement is related to the person cognitive processes, which reflects the student's attention towards particular keen items [4].

Tracking eye gaze bahaviour whilst looking at the eLearning course screen is achievable with the use of the eye tracker device [5], by getting important data showing the way the learning process is demonstrated in real time. Previous work conducted in this field of using eye tracker in an adaptive eLearning is quite insufficient despite pending research issues [6], such as, the way learning style theories applied in eLearning, and the way learner behave during interaction and collaboration with the eLearning course. This paper is to illustrate our ongoing experiment to develop and improve an adaptive eLearning course that is implanted with eye tracker to help model the learning style with further different angles.

In this paper we used the input dimension which is a part of Felder and Silverman Learning Style Model, including the visual learning style and the verbal learning style. We will test the hypothesis and the correlation of the verbal and visual styles to their preferences and observe the corresponding behaviour in an eLearning environment. To obtain better findings we incorporated the electroencephalography (EEG) technology, to access the learner brainwaves data in order to assess his emotional state during learning such as engagement, focus and boredom. These data output generates an emotional model of learners by retrieving and documenting the neural activity in real time which has become very widely applied type of technology [7].

The effectiveness of an eLearning system does not only depend on the environment but also on the emotional status of the user which was not widely considered in the previous work [8]. Therefore, it has been proposed that intelligent tutoring systems should utilise effective computing in which systems can detect and recognise emotional information. This information can be used to enhance the learning process by avoiding negative emotions such as boredom and disengagement [7]. The data of the learner's emotional state help refine modelling learning styles.

Our experiment was built on the previous work of [8, 9], using the EEG in real time to gather information about learners emotional status combined with the information provided by the eye tracker. We added more features by developing different contents with different levels of difficulties to permit the focus on the learner's behaviour, and to analyse what effects his behaviour if it alters. These collaborated technologies enhance the sources of major data to obtain more clarifications about the eye gaze, fixation, beside the learner emotions such as engagement and motivation. As such, errors will be minimised and wider statistical analysis for the calculated parameters can be implemented.

The remaining of this paper is organised as follows: First, a review is presented for previous studies of learning styles, and previous studies of collaborated technologies in the experiment, such as the eye tracking and the EEG Emotive Epoc. Then, the research questions are listed to be investigated in the designed experiment. The experiment method and architecture discussion are presented next. In the following section the results are discussed. Finally, the paper is concluded in the last Section.

II. RELATED WORK

A. Learning styles

Learning style is one of the main factors of personalisation as a cognitive perspective of the learner. According to Keefe, learning style is the meter of learning modality, and the way of learning is formed by the learner's characteristics [3, 10]. Some of these models are mentioned vastly in the literature due to their effectiveness [11]. Myers-Briggs Type indicator (MBTI) is an effective model and its foundation refers to the Carl Jung's theory. The theory divides types of humans as introverts or extroverts, sensing or intuition, thinking or feeling, and judging or perceiving [12].

Kolb's model consists of four different learning styles according to the four stages of learning cycle. The model falls into two dimensions: D1 which is Concrete Experience, Reflective Observation, Abstract Conceptualisation, and Active Experimentation; and D2 which is diverging, assimilating, converging, and accommodating [13]. Honey and Mumfords' learning style model divides learning styles into activists, theorists, pragmatists, and reflectors. Another model is Pask's model of Serialist/Holist/Versatilist learning styles [11]. The Herrmann Whole Brain Model, represents learning styles according to the quadrants of the brain along with their functionalities. Finally, Felder and Silverman learning style Model (FSLSM) divides learning styles into four dimensions perception, input, processing, and understanding [14].

In this experiment we focus on two key elements of FSLSM from the input dimension the visual style and the verbal style. The learner can be visual if he prefers to learn with images, charts and videos. Other learner can be verbal if he prefers learning with text or spoken audios.

Several studies in the literature showed that having ELearning environment including texts combined with images and graphs would serve better understanding for the material [15, 16]. However saying that, it is not permanently that contents with text and images combination leads to higher results and better performance. If it did show improvement, that is crucial to many parameters such as the kind of learning concepts and the sum of text and images referential links in between [16, 17]. As such, the learner performance is based on many other characteristics including knowledge foundation and cognitive style [18, 19].

The work of Mousavi et al. exposed the correlation between the cognitive styles and the capability of working memory [20]. The working memory is related to the cognitive style which causes the preference of processing the information in verbal or visual path [21].

Other studies showed that verbal learners perform better when the learning source or material comprises mostly texts, while the visual learner benefits from the combination of the images and texts in the multimedia learning content, and when the content lacks the preferred method the learning achievement declines [22, 23]. The study of Marta et al. proved the existence of varieties of verbal and visual learner's cognitive styles using eye movements as an indicator, which will affect the learning behaviour and performance [24]. Another study using WELSA educational system agreed on the intentional definition of the visual / verbal learning styles, showing that learners spent higher amount of time and more frequent visits on items related to their learning style preferences [25].

B. Other Monitoring Tools

- Eye Tracking

The desired eye movements, fixations and attention maps, shown in Fig. 1-2, are effectively monitored and measured by eye tracking devices. This field is basically recent, especially considering the contribution of the eye communication as an input [26]. Eye tracking devices measures the eye movements based on the infrared and near infrared lighting reflection through the eye pupil, via the retina and the cornea [27].

Researchers have been interested in studying eye movement since the late nineteenth century [28], however, a vital evolution in using eye tracking to Human-computer interaction was in 1958 by Mackworth and Mackworth [29], as they developed a system for learner eye movement recording throughout the conversion of visual scenes.

In the 1980s, researchers conducted real-time eye tracking to human-computer interaction, such as the initial study on learners with disabilities [28].

An improved application aiming to incorporate the eye tracker device is Adele eLearning system, a pioneering work of Pivec et al. [30]. Adele system is a real-time eye-tracking application for tracking the learner behaviour for the research of adaptive interaction. Another study by Hyrskykari et al. [31] developed iDic, a system that identifies potentially difficult situations and provides translation hints if a learner struggles through the reading process. In the study of Wang et al. [32], they used the eye movement to support the learner with feedback to increase his motivation. In the work of Calvi et al. [33], E5Learning prototype was developed with the capabilities to determine the learner preferable subjects and support recognition of emotional status like tiredness or struggling in learning.

Moreover, several studies on eLearning exploited the eye gaze to conduct deeper analysis. In [34] a study was conducted by Nakayama and Shimizu to measure differences in pupil size while engaging in different activities like searching and viewing. Tsianos et al. presented a study that was concerned in the relation between learning styles of imagers, verbalisers, intermediates and the eye gaze pattern [35]. In [36], Xu et al. showed an investigation on the cognitive load of watching videos by exploiting the blink rate, pupil size and fixation data. The study of Biedert et al. in [37] monitored the learner's gaze on the text. If the learner was looking at a particular text location, the system provided illustrations or played audio spontaneously based on Java and JavaScript.

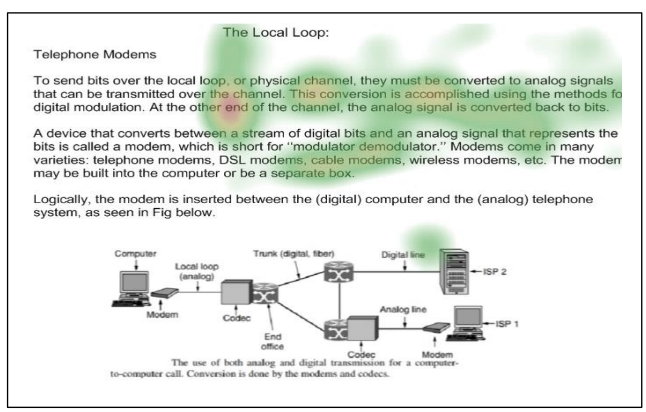

Figure 1. Verbal learner attention map.

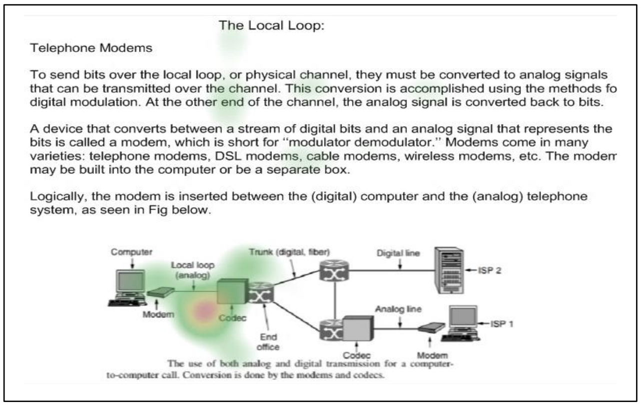

Figure 2. Visual learner attention map.

- EMotive Epoc (EEG)

It is significant for an elearning system to consider the learner's cognitive style in order to enhance their learning achievement [38]. However, only explicit emotions, called academic emotions, are relevant and considered in eLearning systems such as engagement, motivation and focus [8]. The importance of such emotions has encouraged the research on their influence on the learning ability, the performance and the behaviour with the eLearning system [7].

One of the approaches to detect emotions is the EEG technology which has been used in previous studies for nearly 80 years [39]. The study of Iventado et al [40] applied the EEG to extract the learners' emotions to decide the proper time for learning mediate, also to measure feedback. The work of Azcarraga et al [41] showed the EEG had low accuracy representing brainwave data, however adding the mouse improved the accuracy to 92%. The work of ABE conducted by Gonzales-Sanchez et al. in [42] is a compounded system with Emotive Epoc, MIT mind reader, pressure sensors and skin conductance to track learner emotions, to provide a system that reduces the negative emotions. Other studies recorded some setbacks for the Epoc, such as the time needed to set up, the effect of hair thickness on sensors, the inconvenience of wearing the device [43], and the sensitivity to noise [44]. The emotion stimuli IAPS done by Hondrou et al. [39] detected the learner attention and response with the use of a set of different images. IAPS disadvantages had been improved by Lang et al. to detect pleasure, and stimulation [45]. And the study of D'Mello et al [9] using Tobii implanted a dynamic system that automatically reacted if the learner was disengaged and bored, and endeavored to put him back to engagement.

III. INSPECTING EYE BEHAVIOR AND EMOTIONS: OUR EXPERIMENT

A. *Main Research Questions*

The study of D'Mello et al [9] showed the effectiveness of incorporating Tobii eye tracker, to create a dynamic system that automatically reacted to learner disengagement and boredom and steered them back on track. Founded on that, this experiment is organised and designed to investigate the following research issues/ questions:

- Examining the differences between visual learners and verbal learners in the way they gaze at pictures or texts in an e-learning environment, and analysing their behaviour pattern.
- What components are the highest fixated? What are the differences of fixations between the two learning styles?
- What is the learners focus pattern? Do verbal learners differ from visuals in that aspect?
- Do emotions like motivation, disengagement or boredom differ according to learning style, or type of subject?

B. *Experiment Method Discussion*

- Equipment and Setting

Tobii X120 eye tracker was set-up to collect the eye movement data, that is a real-world stimuli characterised by an accuracy of degrees and integrated into a 17" monitor (1280 x 1024 resolution). The setup is modifiable for learners while maintaining the quality of the extracted eye tracking data [46]. The device has a sampling rate of 60 Hz that will generate minimum 80 ms fixation periods.

OGAMA software was used to record and analyse the data captured by the eye tracker of the learner's gaze, fixations, mouse movement and other details in the system environment. By using this software, the data of each learner will be stored in SQL Express data files for each experiment trial. Each trial is associated with some attributes like handedness, category, and comments beside the other needed ID information. OGAMA records the events timings and parameters, and use the extracted stored data to special features and qualitative and quantitative analysis. Besides some data analysis, gaze plots and learner audio/video recordings will be used to examine the results.

Albeit an enhanced technology, the calibration of the eye tracker does not last for a long time due to changes of the learner head position over time which will affect the precision of eye gaze data [47]. To solve this issue, an experiment might be repeated for the sake of accuracy and higher specification.

The other used device for measuring emotional status is the wireless Emotive EPOC+ neuroheadset. This device provides scientific contextual EEG with high resolution which provides dense array spatial resolution ensuring 'whole brain' measurement. The device does Sequential sampling. Single ADC with resolution of 14 bits 1 LSB = 0.51μV, and bandwidth of 0.2 – 43Hz, digital notch filters at 50Hz and 60Hz. The device setting can be altered by incorporated USB. The device was collaborated with the eye tracker to give details about the time and rate of emotions during the interaction with the learning material.

EPOC setup is complete when the learner wears the Epoc headset and is connected to Bluetooth. Once a working signal is achieved the recording of emotions collaborating with Tobii eye tracker begins.

- Task Description and Procedure

The experiment involves two phases which are the Learner-System Interaction Phase that is concerning with any interaction with the learner to extract data or deliver content, and the Modelling Phase where the interpretation and analysis of data is conducted by the system shown in Fig. 3. There are six learning materials divided to easy and difficult levels, from three different subjects. Chemistry, Networking and Geometry learning materials are developed and presented in texts, images, and charts. To start with, the learner has to fill the ILS (Index of Learning Style Questionnaire) of Felder and Silverman model, then will go through the system and study the learning materials of all the six courses. Results obtained from the ILS will be checked and compared at the end of the easy courses session, and then rechecked with the difficult courses sessions and analysed to endorse our conclusions.

The eye tracker will start to record the screen data describing the learner behaviour with the learning system and will store these data in folders of .oga files with XML layout. These database files, MSSQL Database, will be used for calculations like the fixation, average saccade and other ratios that serve for thorough descriptions and analysis. In addition to the above, video recordings of the experiments will be stored for each experiment.

The learner should wear the EPOC headset, to identify the electrical signals through a sequence of electrodes located on the head. EPOC identifies four kinds of brainwaves delta, theta, beta and gamma. Each of these reflects specific condition of the learner brain, for example Beta reflects the condition of concentration [28].

The learner will start with the easy contents, and then will move to the difficult ones. The time frame is open; they could do the learning courses with a couple of days, a single course must be done in the same time though. In brief, our experiment procedure, learner's task is to study three easy learning materials, followed by three difficult ones. While studying, we will be able to record a learner's eyes gaze data and emotions such as engagement, focus and boredom.

Using the Emotive software associated with the EPOC device, graphs and percentages of real-time data of emotions like focus, engagement and motivation will be generated for each experiment.

For the quality of collected data, the behaviour of the learner would be more normal with neither time restraints on the learning course, nor further instructions for the learning direction during the experiment.

To present a summary of the key findings, for each learner, database tables will be established showing the coordinates of gaze location, fixations, gaze movements videos and gaze heat maps. Moreover, graphs will show how the learner focus changes over time and will detect real correspondences to learner behaviour. All the extracted data will be processed through data mining to classify the learning styles of learners into verbal or visual based on the model of Felder and Silverman, and to conduct further analysis based on that. The technique of data mining will be discussed in more details in future work.

C. RESULTS

It is essential to keep in consideration, when studying the learners' behaviour, that some learners have moderate learning style, i.e. they have no significant preference to being verbal or visual. As such, for the quality of output, it is desirable to exclude those learners with moderate learning styles and inspect the learners with clear significant preference of learning style as proposed in the study of Koć-Januchta et al in [24]. Rather than recruiting large number of participants, the designed experiment focused on the variations of variables through the different courses with various complexity levels, to

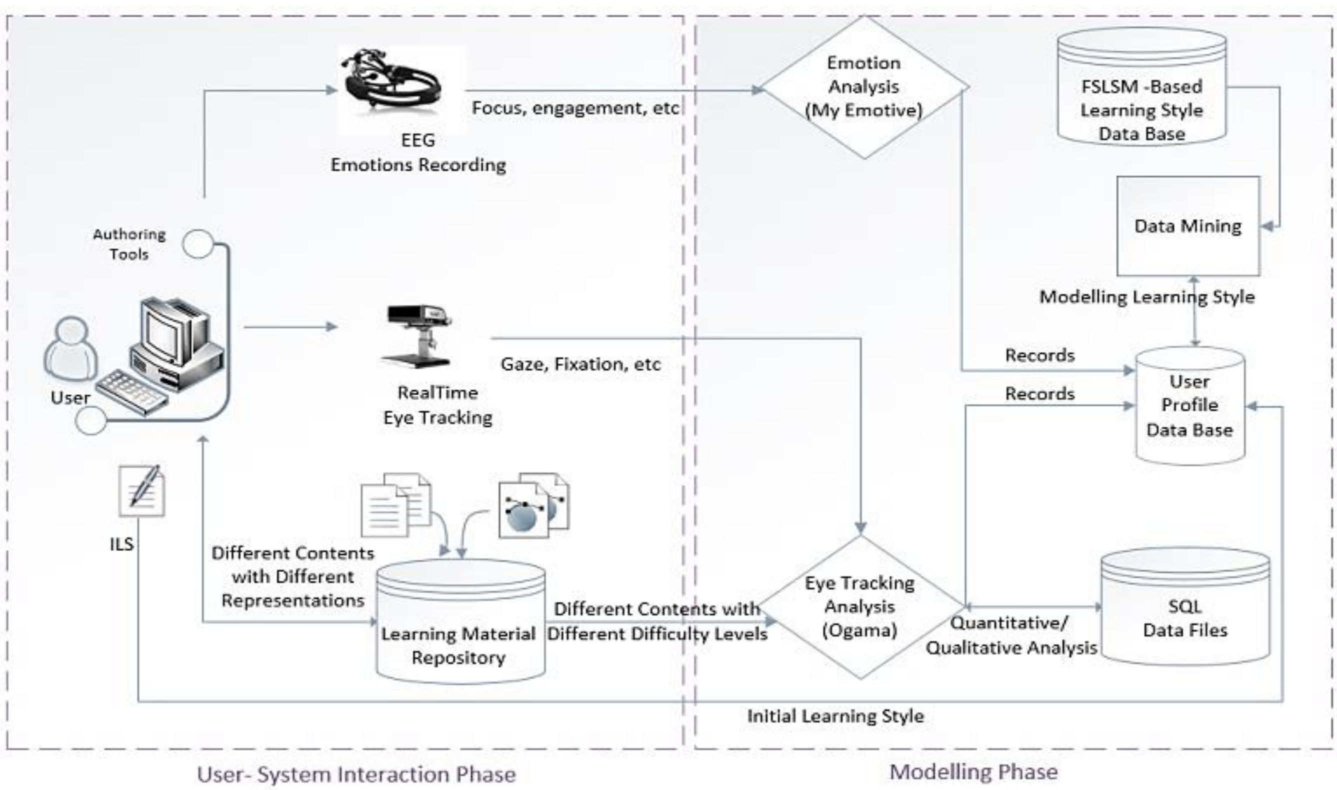

Figure 3. Experiment system architecture.

be related to the learner parameters and characteristics such as cognitive style, eye movements, and emotions in order to enhance the compactness of investigating each learner's behaviour.

Once the learner starts the learning process, database, graphs and videos will be created showing how his eye gaze is located over time and how items are fixated Fig. 4-5. The collected data will help calculate key metrics to understand the learner cognitive activities. Some of these metrics are fixation duration and gaze duration as indicators of difficulty in interpreting information. Gaze percentage is another dynamic metric due to its association with the importance of an object. Also, the percentage of fixation of an area of interest will be considered as an indicator of attention [28, 48].

In addition, real-time graphs will be developed showing percentages of the learners' emotions during learning like excitement, engagement, and interest. The correspondences of these emotions with the learning behaviour will be detected to enhance the quality of data used for modelling and analysing learning styles in an advanced phase.

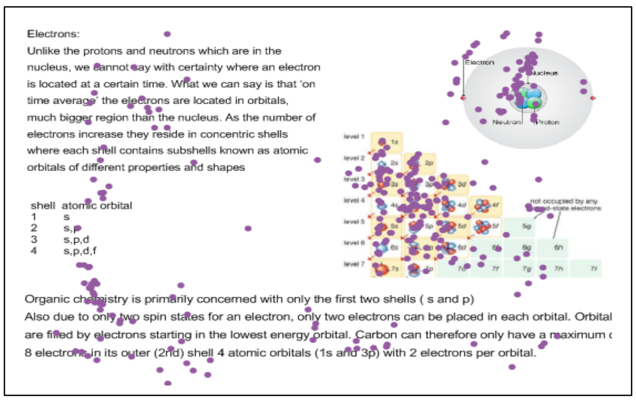

Figure 4. Visual learner gaze fixation.

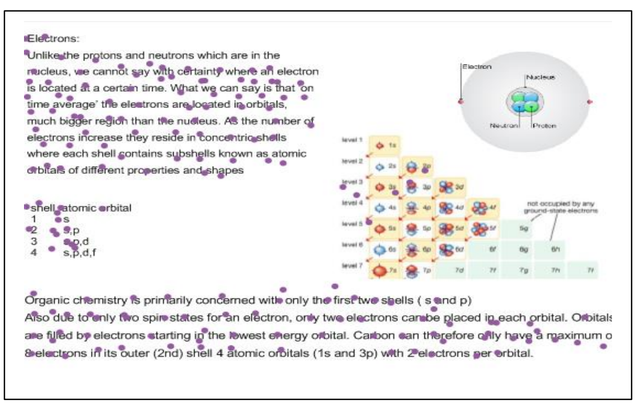

Figure 5. Verbal learner gaze fixation.

IV. CONCLUSION

As established in the literature, learning behaviour reflects cognitive style [3]. We aim to exploit this by using parameters such as eye gaze and fixation duration to draw the pattern of learners after classifying them into visual and verbal learners.

Our experiment is prepared to investigate similar aspects to those performed in literature. However our implemented eLearning system provides different subjects with different levels of difficulty for each participant. Also, the EEG technology will be applied and with the eye tracking to obtain bigger data and add more dimensions for learning styles analysis. The earliest tests described in this paper have mainly focused on eye gaze, and fixations related to learner behaviour. Nevertheless, eye gaze and fixation can also be contingent on other dynamic influences other than the subject material like the emotional status. Hence, it is desirable to anticipate the emotional factors as well, beyond the eye gaze and mouse movement in modelling and analysing learning styles.

Our developed experiment exploits the mentioned technologies overhead on learners' behaviour to enhance accuracy and quality of the resulted data and reduce the potential errors. In contrast with most previous studies being general, our experiment aim is to use the emotions to exclude the time when the learner is not focusing on learning, which will increase the precision of the analysed data. We need to check whether our integrated technologies and chosen variables and parameters would lead to significant results successfully and effectively. Consequently, we will claim that our method is operative and efficacious for the purpose of studying and analysing learning styles. Our primary experiment design in this paper is to achieve this aim.

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