A Study On Eye Fixation Patterns of Students in Higher Education Using an Online Learning System

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ABSTRACT

We study how the use of online learning systems stimulate cognitive activities, by conducting an experiment with the use of eye tracking technology to monitor eye fixations of 60 final year students engaging in online interactive tutorials at the start of their Final Year Project module. Our findings show that the students' visual scanning behaviours fall into three different types of eye fixation patterns, and the data corresponding to the different types relates to the performance of the students in other related academic modules. We conclude that this method of studying eye fixation patterns can identify different types of learners with respect to cognitive activities and academic potentials, allowing educators to understand how their instructional design using online learning environments can stimulate higher-order cognitive activities.

Categories and Subject Descriptors

• **Applied computing~Interactive learning environments**
• *Social and professional topics~Information technology education*

General Terms

Experimentation, Measurement, Performance

Keywords

Eye Tracking, Human-Computer Interaction, Instructional Design, Cognitive Activity, Online Learning

1. INTRODUCTION

The continuous advancement of teaching and learning with the increasing use of technology within the vast selections of modules offered in higher education has been evident over the years. Most examples of the advancement are contributed by the increasing use of online learning systems in the learning environment. The rapid embracing of such technology and its pervasive use in teaching and learning have been brought about by strong supporting changes, ranging from institutional vision and philosophy towards encouraging the use of technology, to the rising focus of building

and developing educators' competencies in using technologies to enhance instructional design.

A common use of learning systems in education is the wide range of multimedia functionalities, which offer many features that can enhance student learning. One study uses computers' multimedia capabilities to lend a sensory component that help reinforce concepts and appeal to a wider variety of approaches to learning [31]. It is highlighted that graphical aspects help students visualize two- and three-dimensional geometric figures and represent mathematical ideas such as the nature of arithmetic versus exponential growth. It is further emphasized that students can make conjectures and experiment with these graphical representations to see the results. Another team of researchers has also explored the use of technology to explore the impact of multimedia resources situated in a national e-learning portal to improve overall science learning experiences [7].

For the School of Information Technology, Nanyang Polytechnic in Singapore, the institution where our empirical research was conducted, the introduction of online learning systems was focused towards online tutorial and problem solving activities. The introduction of online learning systems for teaching and learning of computer programming for students in higher education has benefited both the educators and the students. For the educators, they are able to conduct their lessons using such systems as tools for course material management, assignment submission, setting and conducting of assessment, monitoring of grade performance and student feedback. For the students, their learning deepens with online collaborative work with peers, timely performance feedback, instantaneous access to online course material, and interactive engagement of online assignments. Although a lot has been done to facilitate teaching and learning with the use of technology as a communicative and collaborative channel, very little study has been done on cognitive processes of students as they learn using online tools, particularly in the field of human-computer interaction, on how the instructional design stimulates higher-order cognitive activities.

Learning is also optimized when accompanied by problem solving activities [6], and problem solving induces higher-order cognitive activities learning as it forces students to be active participants in their learning rather than passive information receivers [2]. Online courses such as those provided by lyndaCampus and Codecademy are integrated into various academic modules to heighten the learning experience of the students. However, individual differences among the students would account for a variance in learning outcomes [18, 25]. There is thus a need to address the

diversity in the students' learning approaches, the broad spectrum of individual abilities, and the diversity of socioeconomic and cultural backgrounds [1]. Another study also highlights that learners' cognitive load fluctuates during interaction while using online learning tools [4]. From prior research studies, cognitive activities and deep thinking has corresponded to measurements such as eye fixations, saccades, dwell time percentage, pupil diameter and blink rate [4, 24, 27, 28, 29]. It is unclear, however, as to how these measurements eye movements by learners are related to their learning experiences, and if learning indeed do occurs, how such readings are related to individual academic results in recent past, or use as a predictive method for future academic performances. To our knowledge, no research work has been done to explore these connections. Our study will thus attempt to determine the different patterns of eye fixations and saccades of students learning computer programming from such online learning systems, in particular Codecademy, to their individual academic abilities and performances via grading achieved from related programming modules. The result will seek to help educators understand the effectiveness of the online learning systems towards achieving higher-order cognitive processing, when applied to their students.

2. RELATED WORK

The use of eye tracking technology in the study of cognitive processing has seen an increasing amount of interest in recent research works. Most of the literature are based on two theoretical assumptions about the relation between eye movement and cognitive processing, namely the immediacy assumption and the eye-mind assumption, referring to the work of Just & Carpenter [19]. In immediacy assumption, information processing is immediate and occurs when the information is encountered. In eye-mind assumption, the visual information that falls within the focus of attention is also being processed, and the direction of gaze is closely associated with the focus of attention. We have thus conducted our research with these theoretical assumptions in mind.

Before the use of eye tracking technology in educational psychology and educational research, thinking aloud was the method employed in most studies on cognitive processing [3, 5, 16]. In the attempt to understand what happens during learning, some studies have generally used the think-aloud research methodology while readers are involved in text processing. However, this methodology is known to have a limitation of being intrusive. It is suggested that thinking aloud may alter the process of thinking itself, because it requires cognitive resources that should be used in carrying out the primary task of learning [22]. Eye tracking does not have this limitation. It does not interrupt normal reading, and thus will not lead to disruptions in cognitive processing. The eye tracking data collected will completely account for the allocation of visual attention of the learner during task execution, and such measures can be used to draw inferences about cognitive processes.

Prior research works on eye tracking collects fixation duration and gaze duration measurements to draw inferences about cognitive processes [26]. Single fixation duration refers to cases where only a single fixation is made on a word, and gaze duration refers to the sum of all fixations on a word prior to moving to another word. In general, researchers agree that visual attention is related to cognitive processing activities. It is through the interpretation of eye movement data that researchers attempt to understand the relationship of such measures and the underlying cognitive processes.

In our study of students' interaction using a technology enhanced learning environment, we are inspired by the works of Hyönä & Lorch [13], where they have highlighted that the various segments that comprise a text are not given equal processing time. Another similar research paper has also indicated that a text segment that introduces a new topic or a new narrative episode is attended more than the segments that are continuations of the same topic or episode [21]. The conclusive segment at the end of the text has also been found to receive more attention, and the end sentences have been considered as the location of gaze for "wrap up" processing [11]. This inequality of attention was also highlighted in other similar works [9, 10], where it was reported that an increase in cognitive load leads to longer fixation duration and an increase in the number of fixations.

In another of such research work, eye fixations were recorded during the reading of information of three pulley system configurations of increasing complexity [11]. The analysis from the collected data indicated that the readers from the university community often reread the text to process specific information about a component or set of components before building a spatial mental model. Another particularly appropriate measure for our study is suggested by Nielson [23], who has highlighted important findings on the sequence of scanning objects on screen. From his research, he assumes that headlines are examined first, then pictures as well as diagrams and visual examples, followed finally by text. This assumption will also be looked into in our study as well.

An important consideration for our study, as suggested by Kruschke et al. [20], is that the pattern of learning varies across individuals but is relatively stable within individuals. Similar findings have also highlighted differences in pattern of learning, where some participants achieved high accuracy very rapidly in simple tasks, while others learn gradually [30], as well as distinguishing between experts' and novices' eye movement profiles [17] For this study, we will attempt to identify distinctive characteristics in learning among the students.

In analysing the transition of eye fixation patterns, prior works have used various methods towards determining a wide spectrum of pattern types [32]. Methods such as network analysis on the transition of eye fixations have highlighted different combinations of the transition patterns of fixations.

However, to the best of our knowledge, the detailed studies above did not conclude if there were any distinctive connections among the patterns of learning and the performance of the learners in related academic modules. This knowledge is advantageous to both educators and learners, especially in understanding academic performance, and improving on instructional design. Our empirical research in this paper attempts to address this gap.

3. METHODS
3.1 Research Questions
Following the introduction and literature review in the previous sections, we are particularly interested in the following research questions:

Q1. What are the distinctive eye fixation patterns of the students engaging in the online tutorials?

Q2. How are the fixation patterns connected with the students' performances in related academic modules?

3.2 Experiment Setup

A total of 60 final year students from the School of Information Technology, Nanyang Polytechnic, were involved in the experiment. They were at the start of their Final Year Project module, and were selected to complete a series of online tutorials to learn how to program in PHP using an online learning tool called Codecademy. Each student did not have prior knowledge of programming in PHP, and were new to the online learning environment of Codecademy. The students were also selected randomly. English as the medium of instruction was not highlighted as a problem for any of the students.

3.3 The Codecademy Tutorials

The students were to individually complete 13 tasks regarding different programming functions and features of PHP, a popular programming language. These tasks were made available in the form of an online interactive learning module provided by Codecademy. An example of the online learning environment user interface is shown in Figure 1.
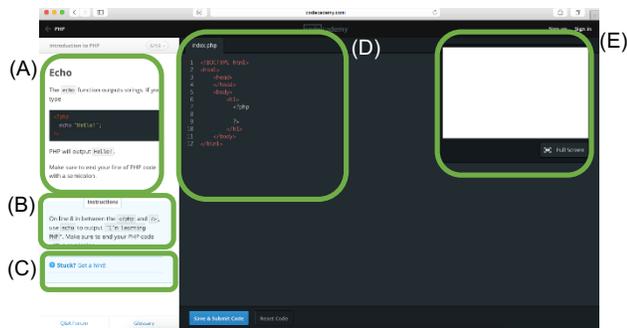

Figure 1: User Interface of Codeacademy

For the online interactive PHP tutorials, the user interface is divided into 5 main blocks. Introduction(A), Instructions(B) and Hints(C) are arranged in sequence on the left column of the screen. The programming Editor(D) is provided at the centre of the screen. A programming Output(E) is displayed on the top right corner of the screen to show the results generated by the program.

The 13 tasks were presented to each student in sequence. Introduction presented the title and fundamentals of the task, followed by Instructions of how to solve the task. Once the students completed each task, they would click the Save and Submit Code button, to proceed to the next task. If a task was done incorrectly, an error message would be displayed at the bottom of the screen, and the student would not be allowed to proceed to the next task. An option for hints was provided for students who were not able to proceed and thus needed some guiding help. Hints were not displayed unless requested for.

Experimental sessions were conducted individually for each student using a setup as shown in Figure 2 and Figure 3, using an eye tracking device from Eye Tribe connected to a laptop in a computer laboratory.

Each data collection session for a student to complete all require tasks lasted from 15 to 30 minutes. At the start of each session, the eye tracking device would be calibrated for each student, before the student proceeded to complete the tasks online. A video screen capture was also recorded while the student proceeded with completing the online tasks. This was to validate eye tracking

records with matching movements and inputs as they complete the online tutorials.

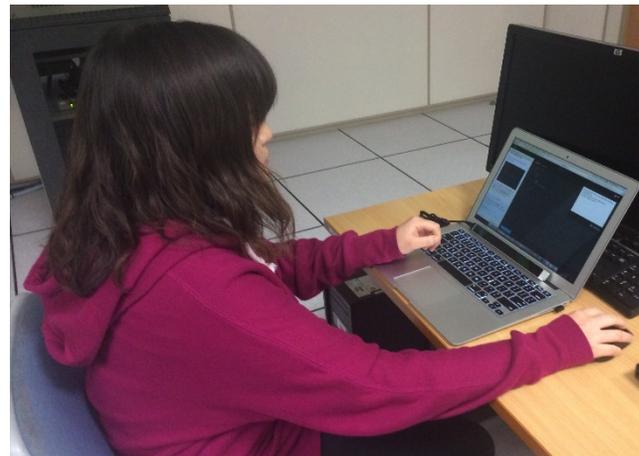Figure 2: Eye Tribe scanner connected to a laptop

Figure 3: A student during an experimental session

3.4 Methodology

Our study focuses on the investigation of eye fixation patterns of students engaging in online learning tool, with the use of eye tracking analysis as the basic method [8, 12]. There are three main eye tracking parameters used in this study, namely the number of fixations, the duration of fixations and sequence of saccades. Fixation plots are generated to reveal the areas of interest of each participant as they progress through their online tutorials. Scan paths that display the series of saccades and the time duration for each fixation are also generated and analysed.

3.5 Data Collection Using Eye Tribe

The Eye Tribe eye tracking device came with a software that helped capture eye movement coordinates, determine fixations, and record a time stamp for each fixation. The records were generated into a text file at the end of each session. After conducting data collection for all students, the text files were retrieved and stored for further analysis.

The text files containing eye movement data were subsequently imported into Tableau Desktop 9.0 to generate fixation plots across different areas. Our research found that the fixation plots can be classified into 3 distinctive patterns (Figure 4.1 – 4.3), which were generated from the students based on the number of fixations, corresponding to the 5 main blocks in Codecademy's user interface, as they complete the online tutorials assigned. This is done by visual observation of the plot patterns generated by the visualisation software.
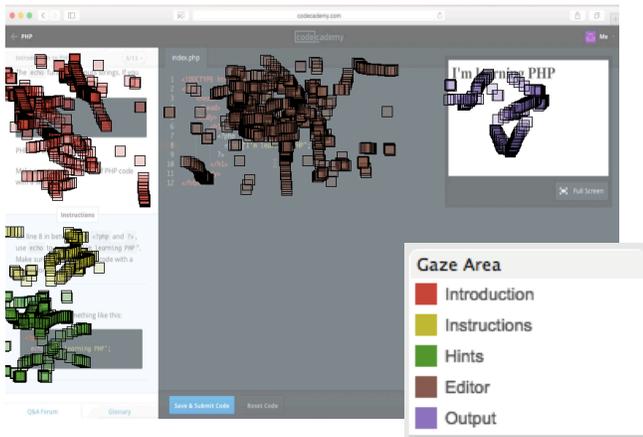
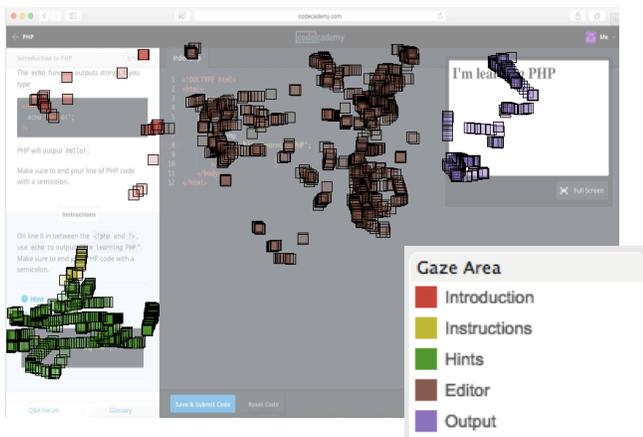**Figure 4.1: Pattern with fixations across all blocks (Type FP1)**

Figure 4.2: Pattern without many fixations on Introduction and Instructions, but a lot on Hints (Type FP2)
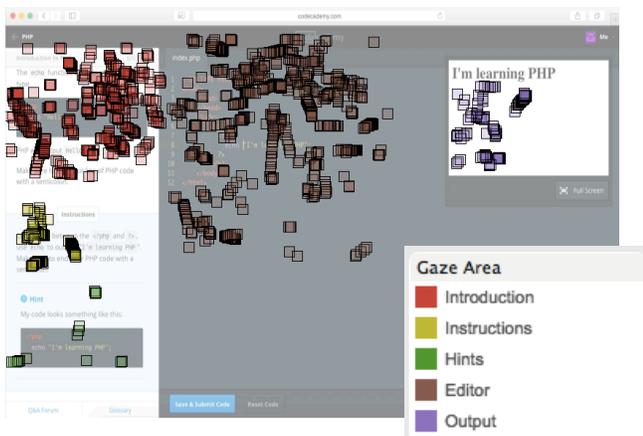

Figure 4.3: Pattern with many fixations on all blocks except Hints (Type FP3)

The first type of pattern (Type FP1) produced a consistent distribution of fixations to all blocks while completing the tasks. Students who displayed this pattern of engagement started by attempting to comprehend the topics as explained in the Introduction, and subsequently tried to complete the tasks displayed in the Instructions block. However, the high count in fixations to Hints suggested that these students had failed in completing the tasks, and had requested for help within the Hints block. This is due to the students finding the tasks too advanced or having misconceptions in the tasks.

Students who displayed the pattern similar to that of the second type (Type FP2), with low count of fixations on Introduction and Instructions but a lot on Hints, may generally had completed the tasks by copying the solutions from the hints. Their fixation plot suggested that they did not value the need to understand the rudiments of the topics, and favoured more towards completing the tasks quickly. It could thus be inferred that since these students appear not to participate in cognitive activities with respect to the understanding of the topics, they had not effectively learned from Introduction or Instructions blocks.

Students who displayed the pattern that corresponded with the third type (Type FP3), with little fixations to Hints, generally completed the tasks by reading through the introduction and instructions. Their fixation plot suggested that they attempted to comprehend the fundamentals of the topics, and followed the instructions accordingly. The low count in fixations to Hints suggested that the learning strategy of these students was to process the requirements within the text of the instructions and to try to produce the solution according to their understanding. These students were thus considered to have higher-order cognitive activities while fixing their attention on learning from Introduction and Instructions throughout their sessions [10, 12].

Scan paths were also generated for our study, to observe the sequences of attention focus, as well as the patterns of look-back and rereading behaviours. Such patterns of scanning behaviours were studied extensively [15], where 4 types of reading strategy were identified with their distinctive features. "Fast linear readers" did not make return fixations on previous texts. "Slow linear readers" made many rechecks before moving on. "Non-selective readers" made many look-backs to previous sentences. "Topic structure readers" paid close attention to headings and were also those who produce the most accurate text summaries, a measure of knowledge retention by the participants. These similar findings were again highlighted in another study, where it was found that the quality of recalls of the main ideas presented in the text also correlated with the amount of time spent on look-back and rereading by the participants [14].

Scan plots of the data collected from all the sessions were generated. It was observed that the participants' scan plots largely fell into 3 most profound and distinguished types (Figure 5.1 - Figure 5.3).

For the first type (Type SP1) of scan path in Figure 5.1, it mirrored characteristics similar to "slow linear readers", as students started by placing their attention to headings in Introduction and Instructions, and made many rechecks as they move their attention between the Introduction and Instructions blocks. The darker the shades of the plots around a localized area, the longer is their gaze. For the second type (Type SP2) of scan path in Figure 5.2, it mirrored characteristics similar to "fast linear readers", and is similar to the previous type in terms of its linear scan path sequence. However, these students quickly move their attention to Editor and Output as they complete their tasks without frequent rechecks to headings in Introduction and Instructions. For the third type (Type SP3) of scan path in Figure 5.3, students displayed a significant amount of look-backs to Instructions as the students complete their task on the Editor. This type of scan path resembled that of "topic structure readers".
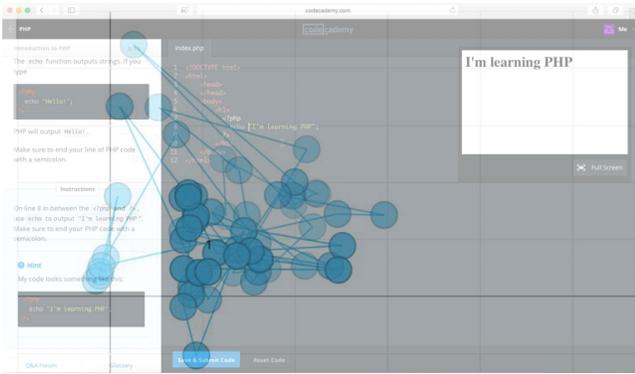
Figure 5.1: Scan path showing characteristics of slow linear readers with darker plots (Type SP1)

Figure 5.2: Scan path showing characteristics of fast linear readers with lighter plots (Type SP2)
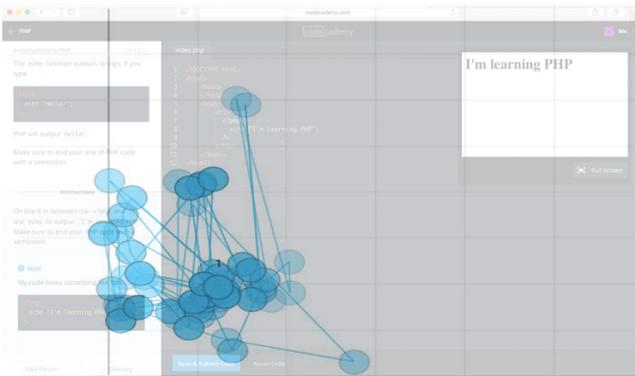

Figure 5.3: Scan path showing characteristics of topic structure readers (Type SP3)

3.6 The Datasets

We conducted Linear Regression analyses using records gathered to form 3 datasets. For the first dataset (snapshot in Table 1), we are able to derive from the eye fixations data the number of counts of Fixation Plot Type (FP1 – FP3) from the set of completed tutorials for each student.

Table 1: Excerpt of data showing counts of Fixation Plot Type for tutorials completed by each student.

	FP1	FP2	FP3
Student01	4	2	7
Student02	3	4	6
Student03	6	3	4
… …			
Student59	2	3	8
Student60	3	7	3

Similarly, in the second dataset (snapshot in Table 2), from the eye fixations data, we again derived the number of counts of Scan Path Type (SP1 – SP3) from the set of completed tutorials for each student.

Table 2: Excerpt of data showing counts of Scan Path Type for tutorials completed by each student.

	SP1	SP2	SP3
Student01	2	3	8
Student02	3	3	7
Student03	6	6	1
… …			
Student59	1	3	9
Student60	4	5	4

The third dataset (snapshot in Table 3) is a collection of the academic grades of all programming project modules in which the students were enrolled during their course of study. As a third (final) year student, all students will have completed 4 semesters of project modules (Proj01 – Proj04).

From the grades score of the 4 project modules, we further aggregated the score to obtain the average score (ProjAve). We also recorded the students' Grade Point Average (GPA) of all academic modules which the students obtained by the end of Year 2 (Yr2GPA).

Table 3: Excerpt of data showing results of students' past grades from project modules and their GPA.

	Proj 01	Proj 02	Proj 03	Proj 04	Proj Ave	Yr2 GPA
Student01	79	67	77	79	75.50	3.72
Student02	92	84	75	78	82.25	3.68
Student03	63	55	63	64	61.25	1.74
… …						
Student59	73	61	91	78	75.75	2.73
Student60	72	80	73	70	73.75	3.56

4. RESULTS

This study seeks to understand how the fixation plot and scan path are related to the project and academic grades of the students, we used SPSS Statistics version 22 to run regression analysis on the datasets collection mentioned in the previous section. For this study, the multiple regression model used are having three independent variables, namely FP1 – FP3 for fixation plot analysis, and SP1 – SP3 for scan path analysis. The following sections will show the effects of both fixation plot and scan path on project average and end of Year 2 GPA scores, by deriving the coefficient of the three independent variables for the linear regression analyses.

4.1 Fixation Plot and Project Average

Table 4 below shows the coefficients of the independent variables FP1 – FP3 effect on the project average (ProjAve).

Table 4: Coefficients of the independent variables FP1 – FP3 effect on the project average (ProjAve).

Coefficients^{a,b}

Model	Unstandardized Coefficients		Standardized Coefficients	Sig.
	B	Std. Error	Beta	
1 FP1	3.730	.336	.195	.000
FP2	6.206	.351	.370	.000
FP3	6.574	.147	.534	.000

a. Dependent Variable: ProjAve

b. Linear Regression through the Origin

The Adjusted R Square value for this analysis is 0.996, which means that our linear model fits a set of observations very well. From the results above, it can be seen that FP3 has the highest standardized coefficient value that contributes positively to the prediction of project average scores of the pool of students. It can also be seen that FP1, having the lowest standardized coefficient value, provides the least in the prediction of the students' project average grades. The randomness of the residual vs fitted plot below shows that regression analysis is not biased.
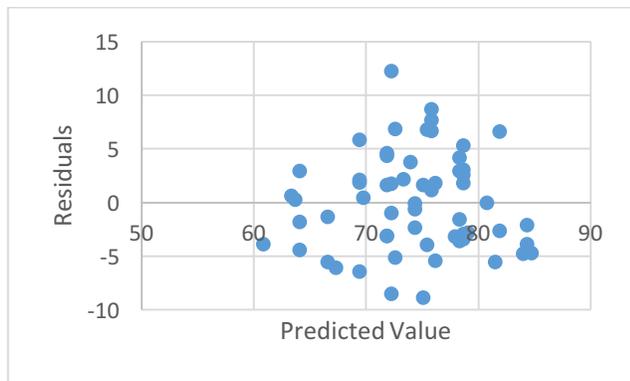

Figure 6: Residual vs Fitted Plot for Fixation Plot Type effect on Project Average

4.2 Fixation Plot and GPA

Table 5 below shows the coefficients of the independent variables FP1 – FP3 effect on the end of Year 2 GPA (Yr2GPA).

Table 5: Coefficients of the independent variables FP1–FP3 effect on the end of Year 2 GPA (Yr2GPA).

Coefficients^{a,b}

Model	Unstandardized Coefficients		Standardized Coefficients	Sig.
	B	Std. Error	Beta	
1 FP1	.029	.033	.037	.386
FP2	.296	.035	.424	.000
FP3	.312	.015	.608	.000

a. Dependent Variable: Yr2GPA

b. Linear Regression through the Origin

For this analysis, the Adjusted R Square value is 0.978, which also signifies the strength of the relationship between the model and the response variables. FP3 is shown again to have the highest standardized coefficient value of 0.608, suggest that it provides the most effect for the students' GPA performance. Likewise, 0.37 for FP1 may suggest the lowest in contribution towards the prediction of GPA grades. However, since the p-value for SP1 is 0.386, and since it is over the common alpha value of 0.05, it also indicates that it is not statistically significant. Figure 7 shows the randomness of the residual vs fitted plot.
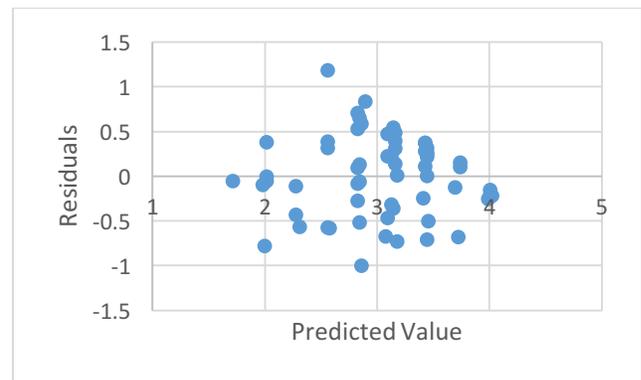

Figure 7: Residual vs Fitted Plot for Fixation Plot Type effect on GPA

4.3 Scan Path and Project Average

Table 6 below shows the coefficients of the independent variables SP1 – SP3 effect on the project average (ProjAve).

For this analysis, it is again noted that the Adjusted R Square value is 0.996. the standardized coefficient for SP3 is highest at 0.54, suggesting that students with scan path type associated to Topic Structure Readers may also have the highest retention of knowledge and skillsets, and thus lead to higher project average scores. The standardized coefficient of SP1 is the lowest at 0.195, suggesting that it contributes the least in prediction towards project performance. Figure 8 shows randomness of residual vs fitted plot.

Table 6: Coefficients of the independent variables SP1 – SP3 effect on the project average (ProjAve)

Coefficients[a,b]

		Unstandardized Coefficients		Standardized Coefficients	
Model		B	Std. Error	Beta	Sig.
1	SP1	3.758	.364	.195	.000
	SP2	6.220	.358	.371	.000
	SP3	6.543	.142	.540	.000

a. Dependent Variable: ProjAve
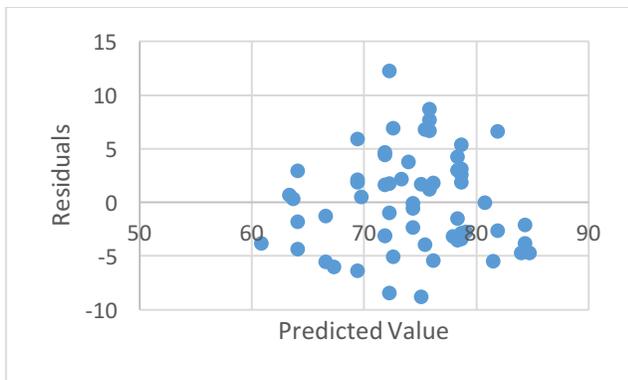
b. Linear Regression through the Origin

Figure 8: Residual vs Fitted Plot for Scan Path Type effect on Project Average

4.4 Scan Path and GPA

Table 7 below shows the coefficients of the independent variables SP1 – SP3 effect on the end of Year 2 GPA (Yr2GPA).

Table 7: Coefficients of the independent variables SP1–SP3 effect on the end of Year 2 GPA (Yr2GPA)

Coefficients[a,b]

		Unstandardized Coefficients		Standardized Coefficients	
Model		B	Std. Error	Beta	Sig.
1	SP1	.035	.035	.044	.330
	SP2	.290	.035	.416	.000
	SP3	.312	.014	.620	.000

a. Dependent Variable: Yr2GPA

b. Linear Regression through the Origin

The linear regression report for this analysis also shows a high Adjusted R Square value of 0.976. Similarly, from the above table,

SP3 has the highest standardized coefficient of 0.620, which implies that it strongly supports GPA performances. It can also be seen that for SP1, with a p-value of 0.330, it is not a significant variable to affect students' end of Year 2 GPA performance. Figure 9 below shows the randomness of the residual vs fitted plot.
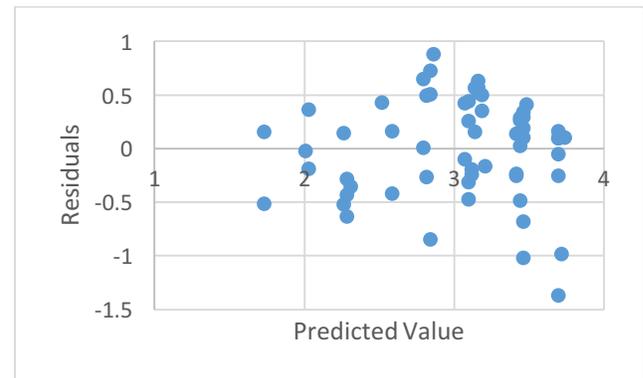

Figure 9: Residual vs Fitted Plot for Scan Path Type effect on GPA

5. DISCUSSION

The analysis from this research has enabled us to understand that there are strong relations among different types of eye fixation measurements and behavioural patterns in association with the level of engagement in learning and the type of learners and their traits towards learning. The results also suggested that students who display different visual scanning behaviours have significantly achieve different scores in their GPA and project grades. This may give rise to early detection of students who may need more help and assistance in learning well before the assessments at the end of the semesters.

We can further suggest that although the approach towards learning among the students varies, we found that students who are identified as engaged learners using the online learning system, are also high achievers in related academic modules. This finding indicates that the students exhibit consistent learning traits across modules conducted in the traditional methods of teaching, and modules using online learning as a teaching tool. Therefore, by capturing eye fixation measurements, educators may be able to identify, even before any form of assessments, students who may need more help in achieving better academic performance. Educators can also use the findings as a measure of how effective the instructional design of their online tutorials are in enhancing learning with higher-order cognitive activities.

The limitations of this research study lie in the dependencies of the results with the particular online UI of CodeAcademy. However, as these UI features, namely onscreen blocks of Introduction, Instructions, Hints, programming Editor and Outcome are generally found in other Integrated development environments (IDEs) for programming, our findings and insights remain useful and applicable.. Other communicative and collaborative channels, such as forum discussions and synchronous or asynchronous chat features, may provide richer insights on the visual scanning behaviours and traits of the students. In such cases, more variations of eye fixation pattern types may arise, which could expand the understanding of cognitive processing of different groups of learners.

In order to deepen the understanding of the relationship between eye fixation behaviours and cognitive activities, a more general

approach towards determining fixation plot and scan path types should also be done to handle a larger variation of patterns [31]. Methods such as network analysis on the transition patterns of eye fixations may result in more combinations of fixation plot and scan path.

Another concern about the data collected is the inference of cognitive activities and meaningful learning primarily from the capturing of eye movement of the learners. During the course of data collection, it is observed that students could also be in deep thoughts while looking elsewhere, for example an open window, a ceiling fan etc. Although these actions can also be moments contributing to higher-order cognitive activities of the learners, the Eye Tribe sensor did not capture them. Other types of detection techniques, such as neuroimaging technique using Electroencephalography (EEG) may be combined together with eye tracking sensor data to increase the accuracy of the results.

6. CONCLUSION

This study has shown that online learning systems stimulate cognitive activities, and that different students have displayed different levels of engagement patterns through eye fixations. These eye fixation patterns are also able to characterize different types of learners, from the analysis of the dataset from eye tracking technology that monitored the eye fixations of 60 final year students engaging in online interactive tutorials at the start of their Final Year Project module. Our findings further suggest that the students' visual scanning behaviours fall into three different types of eye fixation patterns, with the data which corresponded to the different types of learners having strong relations to the performance of the students in other related academic modules. the study thus concludes that this method of analysing eye fixation patterns can identify different types of learners with respect to their cognitive activities and academic potential, and also allow educators to understand how their instructional design using online learning environment can stimulate higher-order cognitive activities.

For practical usage, the findings from this study have potentials of allowing educators to understand the behaviours and attributes of their students through the use of online learning tools. Although this study uses the modest size of a datasets from the selected final year students, it has nonetheless produce insights on the possibilities of assessing and monitoring students' learning progress and performance apart from relying on traditional assessment tools such as test and examination papers.

For future works, educators and researchers can also perform research studies by providing different sets of instructional design to facilitate online learning by different learners, and analyse the patterns of other neuroscientific measurements of the students. The measurements can be further studied to correlate with other behavioural and/or academic performance metrics, to understand how best to conduct online teaching and learning. It will be most apparent for MOOCs, which are Massive Open Online Courses designed for worldwide engagement, students' demographical data, time zones, language competencies etc., may also affect online engagement behaviours.

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