# Academic Performance in a 3D Virtual Learning Environment: Different Learning Types vs. Different Class Types

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**Abstract.** The last decade has seen an increasing interest in the use of 3D virtual environments for educational applications. However, very few studies investigated the influence of the learning context, such as class type and learning type, on learners' academic performance. This paper studied the impact of class type (i.e. comprehensive or selective) classes, as well as learning type (i.e. guided or challenge and guided), on students' level of usage of a Virtual Learning Environment (VLE) as well as on their academic performance. The results showed that, unlike class type, there is a significant difference between learners' in their usage of the VLE. Moreover, the results showed that the levels of using a VLE significantly correlated with learners' academic performance.

**Keywords:** 3D Virtual Environment, Learning Analytics, Academic Performance, Guided Learning, Comprehensive Class.

## 1 Introduction

In the traditional classroom, learning is a teacher-centered process. Interactions go from the main source of knowledge who is the teacher to the students. Physical monitoring and tests were typically used to assess the learners' academic performance. The learning process involved students statically interacting with their teachers in the class environment. Advances in technology have led to the creation of many exciting new approaches to student learning. However, despite these advances the traditional classroom model has remained largely unchanged in the last 20 years. In particular, the use of Virtual Learning Environments (VLEs) is underutilized and absent from most classrooms. VLEs offer the promise of experiential and constructivist learning, allowing students to learning by doing. In recent years, the dramatic growth in hardware capacity and drop in prices have made it possible to run 3D Virtual Environments (VEs) on personal computers [1]. With the versatility of VEs, various applications have emerged. These applications include training, entertainment, and learning. A number of studies (e.g. [2], [3]) stress the impact of using VE on learning performance. However, a number of challenges need to be addressed before VLEs become a common learning approach.

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Learning analytics (LA) is a branch of knowledge that uses data collected from a learning situation to uncover the student's current level of understanding and tune the learning process for the individual student. LA was defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" [4]. The definition of LA focuses on the data collection and the context of learning. Although there are many studies that explored different Learning Management Systems (LMS), few studies addressed the influence of different context of learning on the collected data. LA emerges from two converging trends: 1) the evolving use of LMS in educational institutions, 2) the application of data mining techniques to business intelligence processes in organizational information systems. LA has moved beyond analysis of data related to student assessment and activity in a LMS to social network analysis [5], cloud computing [6], and virtual environment [7]. LA applications utilize data generated as a result of learner activities, such as learner participation in discussion board or computer assisted formative assessments [8]. The results of LA could be directed to learners [8], instructors or managers [9].

Many studies have investigated learning in 3D virtual worlds [10] [11]. These studies focused either on factors in the physical world such as student-student or student-teacher interaction [7]; while other studies explored interactions which may reflect the information exchanges between students and the system via the VLE interface, which they called student-system interaction [12]. Few studies explored management factors such as class management or how the learning instructions are presented in VLEs.

To address this gap in the literature, this paper addresses an uncovered topic about the impact of class type, i.e. comprehensive (range of academic abilities) or selective (high academic achievers) classes, as well as learning type, i.e. guided (provided with goal/problem and instructions) or challenge and guided (provided only with the goal/problem) learning type, on students' levels of using a VLE and the influence of level of VLE usage on their academic performance.

In addition, the paper investigates the impact of the level of learners' exposure to the learning material in a VLE on learners' continuous learning performance, on one hand, and the final academic achievement, on the other hand. Exposure to the learning material refers to the amount of time a student spends in the VLE. Continuous learning performance means their progressive learning overtime, often measured via formative assessment. In contrast, academic achievement refers to the final academic student outcome in the form of a mark awarded to the summative assessment task. To achieve these aims, we propose the following research questions:

1. Does learning type (guided learning vs. challenge and guided learning) correlate with learners' exposure to the learning material in VLE?
2. Does class type (comprehensive vs. selective) correlate with the learners' exposure to the learning material in VLE?
3. Does learners' exposure to the learning material in VLE correlate with their continuous learning performance? Moreover, which level of exposure leads to better performance?

4. Does learning type (guided learning vs. challenge and guided learning) correlate with learners' continuous learning performance.
5. Does learners' continuous learning performance relate to their final academic achievement?

## 2 Literature Review

The learning analytics research community defines learning analytics as the analysis of log files [13], learning resources [14] and learning designs [15] in order to predict and advise people's learning. In order to achieve this goal learning analytics provides a recommendation to predictive models [16] . Learning analytics has many benefits to learning and education administration [17]. Many learning analytics studies investigated the influence of different learning sources (e.g. forum, dashboard, VLE, etc.) on students' academic achievement. In an investigation of the impact of students' performance on some activities that affected their final grade, it was found that students' participation in a discussion forum was the best predictor of their final grades [18]. In [19] data such as login frequency, site engagement, student pace in the course, and assignment grades were used to predict learners' outcome in a course. In [20] the number of discussion messages read and number of discussion replies posted were utilized to predict learner's achievement. [21] used the number of attempts at doing homework, time spent on a problem, and reading of material to predict final grades.

With the emerging use of virtual environments (VEs) in the classroom, learning analytics relies on data sources and logs generated from usage of the VE [7]. Among the studies that used data from VLE to understand learners academic achievement, Agudo-Peregrina et al. [22] studied different interactions in VLEs and its impact on students' academic performance. They investigated three types of interactions associated with learning: student-student interactions, student-teacher interactions and student-content interactions. The results found no relation between the different class interactions or student-content interactions and final academic achievement. Lee et al [23] investigated the impact of a VE-based learning environment on the academic performance of learners with different learning styles. They adopted a classification of learning styles into accommodator learning and assimilator learning. Their results showed that there was no significant difference in the cognitive and affective learning outcomes for students with different learning styles in the VR-based learning environment.

## 3 A VLE Case Study: Omosa

To answer the research questions a VLE was used. This VLE is an ecosystem for a fictitious island called Omosa created to help school students to learn scientific knowledge and science inquiry skills, see Fig. 1. Omosa Virtual World has been implemented using Unity3D. The goal is to determine why the fictitious animals, known as Yernt, are dying out.

The island of Omosa consists of four different locations the learner can visit. In each location there is a virtual agent waiting for the learner's visit. The learner can ask each agent a set of questions (between seven and nine questions). At the end of the session with that agent, the agent will provide the learner with evidence that supports their viewpoint concerning the problems on the island. Learners have to explore the island and visit four different locations. The four locations are the village, the research lab, the hunting ground and the weather station. In the village, the student will meet both the firestick agent and the hunter agent. In the research lab, the students can meet the ecologist agent. In the weather station, the students can meet the climatologist agent. Each agent has a list of questions that the user can ask about the agent and each agent will present an alternative view on why the Yernt are dying out.


(a)


(b)

**Fig. 1.** (a) A Snapshot to the map of Omosa virtual world, (b) A snapshot to one of the four locations the users have to visit

In addition to encountering various agents and getting evidence to determine the possible causes for the Yernt's increased death rates, the students will have to collect multiple notes to get more details and facts that could be used to compare the current and past states of Omosa and deduce the cause of the problem. There are four sets of notes the students can pick up; the first set of notes are rainfall notes located in the weather station that contains information about temperature and rain level readings in different periods. The second set of notes is village field notes located in the village that contains information about the activities of the people in Omosa during the last period. The third set of notes is tree ring notes located in research lab that contains information about the internal structure of the stems of the trees on the island. The fourth set of notes is ecologist notes located in the research lab and they contain notes about the changes in the ecology system of Omosa Island.

After exploring the virtual world and collecting notes, data and evidence from the imaginary island, students are asked to answer a daily question in a workbook. On the last day of exploration, students are required to create a presentation that summarizes their conclusion about what is the cause of the changes in the ecosystem of the island Omosa and what is the reason the imaginary animal Yernt are dying out.

### 3.1 Participants

The reported data is from a classroom study carried out in 2013. The study was conducted in an Australian public secondary school in two science classes: a comprehensive class, and a selective class. Selective and comprehensive classes are types of classes that exist in some states in Australia, including the state of New South Wales where this study was conducted. Selective classes are comprised of students who have sat a voluntary statewide exam in their final year of primary school and achieved at a high level. Comprehensive classes are comprised of students who have not chosen to sit the selective class exam or who did not achieve the level required. Comprehensive classes may also be streamed based on student academic performance or they may have a full range of academic abilities in one class. Nine 50-minute class periods were available. The study was conducted at the end of the first half of the 2013 academic year.

Fifty-five and 45 students from selective and comprehensive classes were invited to participate in the study. Twenty-six students from both selective and comprehensive used the VLE enough to provide data that could be visualized and completed the workbook, and 37 students finished the final presentation slides.

### 3.2 Procedures

Nine 50-minute class periods were available. Each class period was considered a new day in the student's workbook where they were given a task to do. The study was conducted at the end of the first half of the 2013 academic year. The participants were divided into two groups; the first group was given a guided workbook (Guided Learning), while the other group was given an unguided workbook (Challenge and guided Learning). The students were free to navigate the VLE to be able to answer the task in the workbook. Guided Learning (GL) and Challenge and guided Learning (CGL) differ in the level of support or scaffolding provided to the student as s/he tries to solve a problem or achieve a goal. CGL presents the student with the problem but does not assist them in solving the problem. Earlier research on CGL used the term productive failure [24], that reflected that even though students failed initially and needed to go through one or more rounds of trial and error, in the end they were more productive in terms of understanding of the concepts and achieving the intended learning outcomes.

**Guided Learning**

The Guided Learning (GL) group was given a workbook with instructions designed to direct learners while navigating the VLE. The instructions were in the form of a series of checkpoints. In each checkpoint, the learner was asked to go and visit a particular location, ask the virtual character in the target location some questions, and pick up notes in the VLE that contained useful information to help to draw conclusion.

**Challenge and Guided Learning**

The Challenge and guided Learning (CGL) group was given a workbook with no guided instructions. Students had to discover the VLE system themselves and decide where to go to find clues about what happened in the VLE. In addition, learners have to decide whether to talk with virtual characters or not and which questions to ask and which notes to collect. For brevity and clarity, we also refer to this type as unguided in the discussion.

## 4 Materials and Method

### 4.1 Data Collection

To conduct studies on VEs, it is critical to collect participant related data quickly and accurately [25]. Hanna et al [26] provided a taxonomy of techniques to collect data from VEs. In this study, the following three data collection techniques were used.

**Log Files**

Logging users' activities in a VE to interpret their engagement is not new research [27]. Students' navigations across VLE leave a trace of breadcrumbs which may be collected to build a composite picture of activities while learning [28]. To keep track of students' learning activities, three log files for each participant were collected: 1) position log file; 2) virtual agents the user met and which questions were asked and 3) the notes the user picked up. The position log file is used to register the path the user takes while navigating the VE.

**Workbook Marks**

A student workbook was developed to provide learners with information about how to use the Omosa VE. For eight classes/days, the student workbook included assignments and activities to do each day. Learners' answers to the daily assignment were registered; later, answers were coded and marked. The marks awarded for each of the workbooks were used to measure each student's continuous learning.

**Final Presentation Marks**

After completing the daily tasks, students were asked to create presentations using Microsoft PowerPoint. In these presentations, students were asked to conclude their understanding of the learning material by performing scientific inquiry to deduce a reason behind the dying out of the virtual animal. The marks awarded for the presentation were used to measure the learners' final academic achievements.

### 4.2 Visualizing Quantitative Measures of Users' Interactions in Omosa VLE

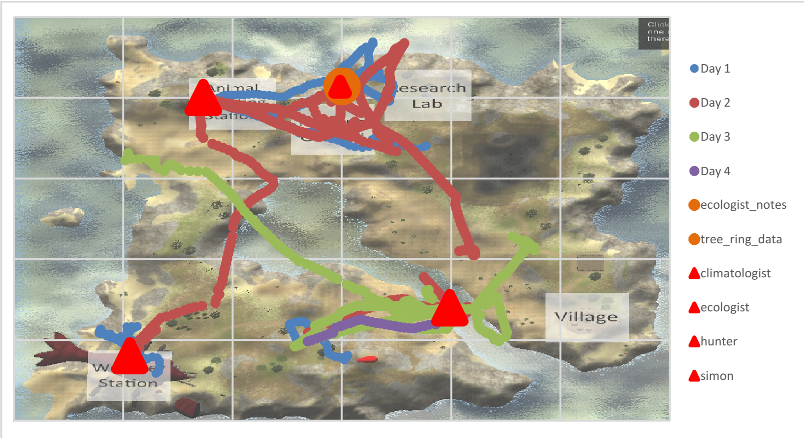
Visualization was used to display the analytics information in a more meaningful way [29] [30]. The aim of this study was to investigate the impact of users' exposure to the learning content of a VE on the progress of their learning performance and later on their academic achievement. The first step is to evaluate users' usage of VLE and rank their interaction. A case-by-case evaluation of the log files that recorded users' activities was conducted. A number of factors were considered to evaluate users' experience. These factors included the numbers of days the learners used the VLE, the navigated distance in the VLE, the number of virtual characters that learners talked with, and the number of objects that were collected. Using these factors, learners' exposure was sorted into three levels: low, medium and high. Figure 2(a, b, c) shows examples for different levels of learner participation. As an example of a high level of VLE usage, Figure 2(a) depicts the distance navigated in each day of the four days and the collected learning notes from Omosa VLE (ecology notes and tree ring data). An example of a learner with a medium level of VLE usage is shown in Figure 2(b). The learner's activity was coded as medium, because the learner visited the VLE only on one day and no learning material in the VLE was collected. Figure 2(c) demonstrates an example of low-level usage of the VLE. This learner was coded as low level because two locations in were not visited and no notes were collected.

## 5 Results

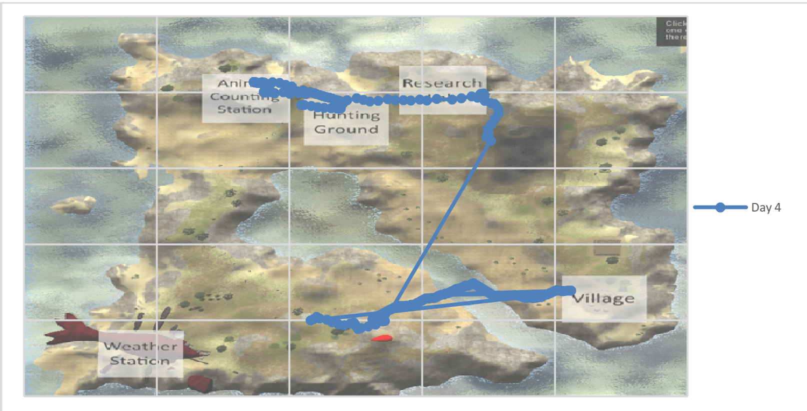
This study aimed to investigate the influence of different class types as well as learning types on learners' level of exposure to the VLE. Additionally, the paper studied the impact of learners' exposure to VLE on learners' continuous learning performance and the final academic achievement. To answer research questions, study variables were tested for normality. The result of Shapiro-Wilk normality test showed that study variables were normality (p-value<0.05).

To answer the first research question about the influence of learning type, the results, see Table 1, showed that there was a significant difference between the students in the guided learning type versus the students in the challenged learning type on the levels of using VLE, [$F(1, 24) = 7.53$, $p < 0.05$, $\eta^2=0.24$]. To further understand which learning type led to more exposure to the learning content of VLE, the mean of each group was calculated. The results, see Fig. 3, showed that average usage of VLE by guided learners was 2.2 and standard deviation was 0.79, while the average of challenge and guided learners was 1.37 and standard deviation was 0.72.

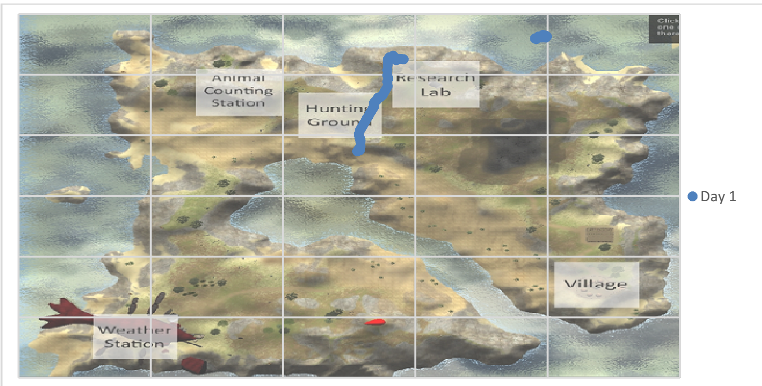
To the second research question about the influence of class type, the average VLE usage for students in the comprehensive and selective classes were 1.7 and 1.67, respectively with standard deviation 0.80 and 1.04, respectively. The result of ANOVA test revealed that there was no significant difference, see Table 2, between students who were in comprehensive or selective classes and their usage level of the VLE.




(a)




(b)




(c)

**Fig. 2.** Visualization of different level of using Omosa, (a) high level of usage, (b) medium level of usage, (c) low level of usage

**Table 1.** Summary of one-way ANOVA to show signifcant difference between learning type and VLE usage (Q1)

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Between Groups | 4.188 | 1 | 4.188 | 7.530 | 0.011 |
| Within Groups | 13.350 | 24 | 0.556 | | |
| Total | 17.538 | 25 | | | |

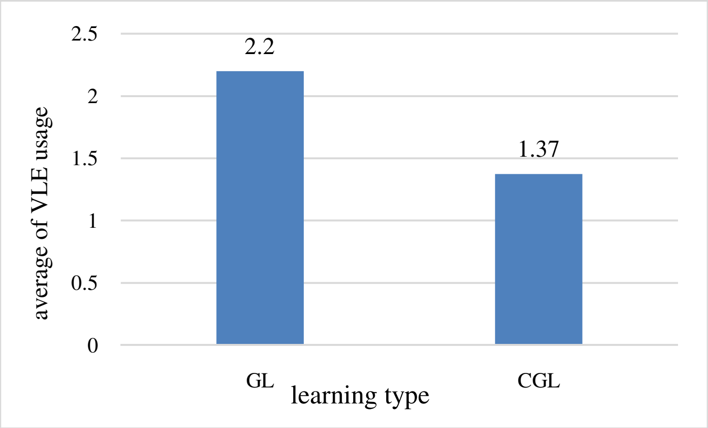



**Fig. 3.** Average of VLE usage for each learning type

**Table 2.** One-way ANOVA to show difference between class type and VLE usage (Q2)

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Between Groups | 0.005 | 1 | 0.005 | 0.007 | 0.934 |
| Within Groups | 17.533 | 24 | 0.731 | | |
| Total | 17.538 | 25 | | | |

**Table 3.** Summary of one-way ANOVA to show signifcant difference between VLE usage and workbook grades (Q3)

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Between Groups | 46.17 | 1 | 46.17 | 9.22 | 0 |
| Within Groups | 250.38 | 50 | 5.01 | | |
| Total | 296.56 | 51 | | | |

To answer the third research question about the impact of learners' exposure to the learning material in VLE on their continuous leaning progress, the results, see Table 3, showed that there was a statistically significant difference between the levels of using VLE on the learning progress as represented in students' workbook marks [$F(1, 50) = 9.22$, $p < 0.01$, $\eta^2$=0.16]. To further understand which exposure level led to higher learning performance, the mean of learners in each level was calculated as demonstrated in Fig. 4. The results showed that the average mark of low exposure students was 3.21 (SD=3.37), 4.33 (SD=3.61) was the average of medium exposure learners and 3.67 (SD=1.70) was the average of high exposure learners.

The fourth research question asked whether there is a correlation between guided/unguided learning in the VLE and learners' academic performance. Although the results did not show a statistically significant difference between guided and unguided students in their workbook grade, see Table 4, the mean grade of unguided learning students was higher than that of guided students.

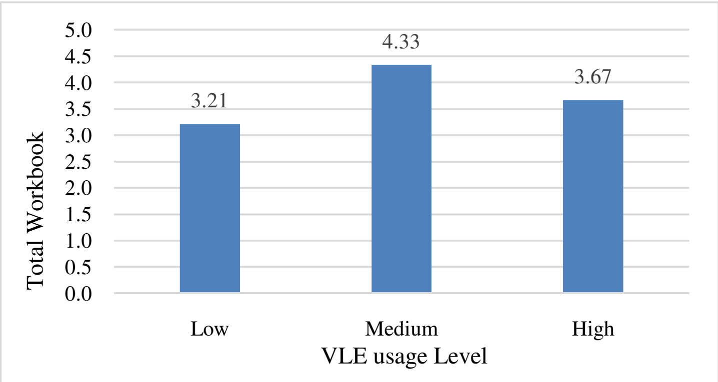



**Fig. 4.** Average workbook grade for each VLE usage

**Table 4.** Summary of one-way ANOVA to show signifcant difference between learning type and workbook grades (Q4)

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Between Groups | 26.496 | 1 | 26.496 | 3.082 | 0.092 |
| Within Groups | 206.35 | 24 | 8.598 | | |
| Total | 232.846 | 25 | | | |

Finally, the fifth research question inquired whether there is a relation between the learners' continuous performance based on their daily workbook marks and their final academic achievement as shown in the presentation mark. A paired T-test was used to determine whether there was a significant difference between the average values of learners' scores for the workbook and their scores in the final presentation. The results, see Table 5, showed that there was no significant difference between students' workbook results and presentation result.

## 6 Discussion

This study aimed to investigate the influence of different class types (comprehensive vs. selective) as well as learning types (guided learning vs. challenge and guided learning) on the learners' level of exposure to the VLE. In addition, the paper investigated the impact of the different level of learners' exposure to the learning material in a VLE on 1) learners' continuous learning performance, and 2) learners' final academic achievement.

The first research question asked whether different learning types, guided learning or challenge and guided learning, correlates with VLE usage level. The results showed that there was a significant difference between the students who had guided learning versus the students who had challenge and guided learning on VLE usage level of these students. This result reveals the importance of learning type to stimulate learners to explore the learning material included in a VLE. In this study, guided learning may direct learners to explore the VLE more and encourage them to follow the instructions to talk with virtual characters or pick up the virtual notes. A number of studies (e.g. [31]) investigated the effect of guided and unguided learning to stimulate users' attention and the level to explore VE content more. This finding is consistent with other studies that suggested that discovery learning with guidance can be more effective than discovery learning with no guidance in enabling students to apply their knowledge to new problems [32]. Another study on discovery learning suggested that discovery learning accompanied by guidance in the form of coaching is more effective than unguided discovery learning [33]. Goo et al. [34] proposed that the tasks in a VE which begin with unguided followed by guided learning style was more effective to simulate users than the tasks which begin with guided followed by unguided learning style.

**Table 5.** Summary of Paired Samples T-Test between workbook and presentation grades (Q5)

| | Paired Differences | | | | | t | df | Sig. (2-tailed) |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Deviation | Std. Error Mean | 95% Confidence Interval of the Difference | | | | |
| | | | | Lower | Upper | | | |
| workbook - presentation | 0.875 | 4.17172 | 0.73746 | -0.62906 | 2.37906 | 1.187 | 31 | 0.244 |

The results of the second research question inquire whether there is a relationship between learners' class type and their usage level of the VLE. The results showed that there is no significant difference in exploring the VLE between students in comprehensive and selective classes. These findings along with the finding of the first research question suggest that what really matters in discovery learning is how the learning material is presented to the learners regardless of their academic ability.

The third research question investigates the impact of learners' exposure to the learning material in VLE on their continuous learning progress. The results showed that learners' with a low level of exposure to VLE content had the poorest average marks in their daily workbook. The learners demonstrating a medium level of exposure to VLE achieved the highest mark. An unexpected result was the finding that students with highest VLE usage did not achieve the highest workbook scores.

To further understand the result of high VLE usage students, a qualitative analysis of the high VLE usage students (level 3) showed that some of these students outwardly used the VLE; however their usage does not reflect real engagement at a cognitive level with the learning content. For example, some students superficially navigated around the VLE; however, these traversals were aimless and did not explore the learning material. Other students in this level asked many questions of the virtual character, however, many of these questions were repeated and hence asking questions did not build towards an increase in their understanding of the situation. The finding highlights the importance of estimating the student's meaningful usage of VLE so that their activity builds towards the learning target.

Many research studies reported the positive impact of VLE on learners' academic performance compared to traditional learning [31]; however, research studying the relation between guided/unguided learning in a VLE have reported mixed conclusions. Although our study did not show significant differences between guided and unguided learning in VLE, many studies [35] reported that although learners preferred unguided VLE, learners who have the guided VLE (teacher-demonstrated based or TDB) learning significantly outperformed their peers who had unguided learning (Student Co-navigated Based or SCB). Another study [36] indicated that students who received the Guided Inquiry Learning approach performed significantly higher than those who received the tutorial approach.

The finding related to the last research question suggested that learners' continuous learning performance in daily assignments is consistent with their final academic achievement. This confirms the value of early monitoring of learner performance and possible automated intervention via alerts and encouragement to change behaviour or recognition of achievement to encourage continued performance.

## 7 Conclusion and Future Work

This study aimed to investigate the relationship between class type, comprehensive or selective, as well as learning type, guided or challenge and guided, and the level of exposure to the learning content in VLE, on one hand, and on the continuous academic performance and final learning achievement, on the other hand. The results showed that class type had no significant relationship with learners' level of using the VLE, while learning type had a significant relationship with learners' level of using the VLE. Learners who had the guided learning experience showed more willingness to use the designed VLE.

Our findings promote active student participation as a lever to improve the learning outcomes. In other words, learners' engagement with the learning content of VLEs is a fundamental element in continuous academic performance and final achievement. However, this participation should be monitored to be sure that it is moving the learner toward the learning goal and not just aimless exploration. This finding necessitates the implementation of a run-time LA that measure learners' positive participation in the content of VLEs.

Among the findings of this study, learners' usage of VLEs was found to correlate with their continuous academic performance and their final achievement. The Challenge and Guided Learning activities are based on Kapur's productive failure theory [37], which has an "idea generation and exploration" phase (Challenge) and a "consolidation" phase (Guided Learning). What is reported in this paper is only looking at learner behaviors in the virtual environment in the first phase. In other work looking at the results for the second phase, both learning type conditions showed the same learner behaviors.

As future work, an objective evaluation of the learners' level of exposure to the learning content of VLEs is needed to be designed. This objective evaluation will help in monitoring learners and drawing a picture of their behaviour in early stages of learning. Understanding student performance and behaviour will potentially allow teachers and/or the VLE to provide just-in-time support according to the needs and context of the learner.

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