HIGH-PERFORMING ONLINE STUDENT BEHAVIOURS

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ABSTRACT

Research on understanding student high academic performance focused on studying students in a traditional classroom or blended learning environment. This paper presents key online engagement behaviours of students that contribute to achieving high academic performance. The study experimented on three years of data derived from online students' academic performance and online course engagement in a series of six computing courses. Patterns discovered in this study indicate that most of the high-performing students in the online introductory programming courses continue to be high-achieving in their succeeding online computing courses compared to the non-programming courses. The results also show that the more programming experience, the students' performances improve. In addition, students with the highest academic performance engage at least 100% more in online formative learning activities compared to non-high performing students. Their highest activity engagement behaviours were on forum views and quiz activities. Findings of this study will assist educators in identifying critical elements in their content design to help all types of students increase their scholastic performance, better engage online students, and elevate non-high performing students to narrow the gap in students' performance in online courses. Finally, this study can help educational institutions identify what needs to be improved in the current learning analytics tool to better model student behaviours and patterns.

KEYWORDS

Descriptive Learning Analytics, e-Learning, Online Engagement Behaviours, Online Academic Performance

1. INTRODUCTION

Self-motivation and regulation are important for students to achieve high academic performance in a fully online learning and teaching environment. Numerous education research and studies have focused on exploring the factors that differentiate academically high-performing students from low-performing students. To date, studies on understanding students' high academic performances have concentrated on the traditional or blended classroom using self-report instruments (Guo et al., 2019; Kaplan, 2018; Wang & Liou, 2018). However, self-report instruments have been criticized for being limited due to subjectivity. Inaccuracies in self-assessment can be resulted from ingenuine assessments, such as participants altering answers to make them more socially acceptable (Duckworth & Yeager, 2015) being unable to assess themselves accurately (Araujo et al., 2017) exhibiting response bias and having difficulty mapping their answers to the rating scales, and being unable to fully retrieve information from memory (Rosen et al., 2017). Students tend to retrieve distinctive information that is time-bound, but self-reported questions are seldom distinct. With the popularity of online learning and the advancement of data mining techniques, Learning Management Systems (LMS) have been developed and implemented by various online education providers in online courses to automatically record students' engagement and performance data. It is reported that using LMS data to support learning analytics and educational data mining provides a more objective picture of students' learning through data-driven approaches (Liu et al., 2017).

Understanding the online engagement behaviours that contribute to online students achieving high performance will assist online facilitators in continually supporting high-performing students and identifying critical factors to help other students improve their academic performance. Online facilitators can set a guide to online engagement to uplift the performance of non-high performing students. This reasoning is consistent with Dweck (2006)'s work on growth mindset, which is now a synonymous of high expectation. It is hypothesized that students' achievement is strongly affected by what the teacher expects of them, and this has been justified by many education researchers (Campbell et al., 2020; Johnston et al., 2019; Robinson, 2017).

1.1 The Study

The engagement data used in this study were collected from first- and second-year students who were enrolled in a 100% asynchronous online IT degree. Demographics of online students include those who are already working, parents who are unable to go to campus, have disabilities or live or work in a remote area. For them, online learning is more flexible and accessible. Identifying online engagement behaviours of high-performing students using the engagement and performance data recorded through the LMS not only provides a more objective view, but also gives the instructors an insight into how these students' online behaviours differ from the rest of the online students. Identifying these online behaviours can also help instructors highlight these behaviours and encourage changes in practice. Specifically, instructors can suggest specific strategies and provide guidance to non-high performing students on how to adopt these online engagement behaviours. Moreover, personalized learning interventions can be motivated from these behaviours and designed such that students are guided in the development of these positive online behaviours. Results can also help students reflect on their behaviours and learn to self-regulate. Finally, this study will also help educational institutions identify what needs to be improved in the current learning analytics tool to better understand student behaviours and patterns.

This paper presents a longitudinal study investigating online student engagement and academic performance from LMS data of high-performing students enrolled in fully online introductory computing courses. It aims to answer the following research questions:

1. Do high-performing students in introductory online computing courses (programming and non-programming) continue to have high performance in their succeeding computing courses?
2. What are the associations between students' academic performance and engagement behaviours in fully online programming courses?

2. RELATED STUDIES

This section discussed related literature on high-performing students, self-regulated learning, and student engagement data from LMS are used in learning analytics.

2.1 High-Performing Students

Studies have shown a positive relationship between student motivation and academic achievement (Pintrich & De Groot, 1990). It is also indicated that high-achieving students show a refined ability to select and modify study behaviours (Mai et al., 2021), manage their time and use more effective study strategies (Dunlosky et al., 2013) and routinely engage in and adapt skills to pursue these behaviours (Zimmerman & Schunk, 2001). Despite evidence of the association between high performance and effective study behaviours as a primary study strategy, Persky (2018) found in his longitudinal study that high-achieving students relied on re-reading texts and re-watching videos. All these studies revolved around the idea that students perform better if they can fully understand concepts when they self-regulate their learning behaviours. This idea is especially true in an online learning environment where self-regulated learning is critical to students' academic success due to them having limited interactions with peer learners and assistance from the instructors.

A study undertaken by Alqurashi (2022) compared seven aspects of student engagement (i.e., higher-order learning, reflective and integrative learning, learning strategies, quantitative reasoning, and collaborative learning, student–faculty interaction, and effective teaching practices) using survey data collected from senior-level undergraduate students who studied online courses. Their findings showed that low achieving students had significant higher student-faculty interactions than high-performing students. Although this study looked at students' engagement in an online learning environment, the data used were from student survey, which may include inaccuracies in self-assessment of their engagement. Also, the study was not for students who studied fully asynchronous online course and did not explore the engagement behaviours when interacting with online course activities. In this paper, the focus is the monitoring of students' learning process manifested through their online engagement behaviours using engagement and academic performance data captured in the LMS.

2.1.1 Student Engagement and Performance through LMS Data

In an online learning environment, data are often collected from an LMS. An LMS is a critical tool in a fully online learning environment to facilitate the teaching and learning process. In addition to distributing and managing course materials, it also captures students' engagement and performance data that can be further utilized to support the learning analytics and educational data mining. Recent LMS-related research has shifted the focus from exploring interactive and creative functionalities of an LMS to analyzing the LMS data, such as the log data (Henrie et al., 2018) and activity data (Simanullang & Rajagukguk, 2020) to discover patterns of student engagement, evaluate students' academic performance and improve instructors' teaching pedagogical practices. Recent studies reveal that learning analytics (Conole et al., 2011) can be applied to LMS data to visualize student engagement patterns, derive insights from student engagement data for better learning design and improve student learning experience (Henrie et al., 2018; Toro-Troconis et al., 2019). However, empirical data were limited in these studies due to an LMS implemented as a supplement to the traditional classroom teaching or very few fully online courses available for research purpose.

To date, research on understanding student high academic performance has focused on studying students in a traditional classroom or blended learning environment. Nevertheless, few studies have attempted to look at the longitudinal data in online learning and identify the online engagement behaviours of students achieving high academic performance in a fully online learning environment. In this paper, three-year data from six courses were collected from an LMS that stores various online courses having frequent engagement data of different online activities to conduct a longitudinal study to further analyze the online students' engagement behaviours and their association with students' academic performance.

3. WORKFLOW MODEL

The analysis used students' academic performance and online student engagement data. Online engagement behaviours included are the following formative online data activities: forum, quiz, URL, lesson, file, and folder. For empirical experiments, six courses were analyzed, among which three were a series of programming courses and three were a series of non-programming IT courses. The data were divided into two case scenarios, including student academic performance alone, and student academic performance with online student engagement. These scenarios were subsequently used to identify the high-performing students in each course, if they continue to perform well in the succeeding courses, and the relationship of their engagement to the online course to their high performance. For example, Programming 1 is a prerequisite for the Programming 2 course, thus in the experiment, the number of high-performing students in the pre-requisite course that continue to be high-performing in the subsequent courses were identified. The workflow model used in this study comprises of three main phases: data collection, data processing, data exploration and visualizations

3.1 Data Collection

The data were collected from student engagement and academic performance reports from the LMS. A total of 804 student academic and engagement data were used in the study. These reports were taken from a series of three online programming courses and a series of three online non-programming courses. For programming courses, three years (2018-2020) of reports were taken from two first year courses and one second year course. For non-programming courses, three years (2019-2021) of reports were taken from two first year courses and one second year course. The data contained a list of students who were enrolled in the courses with de-identified student IDs, their online engagement data, including the number and percentage of forum views and contributions, quizzes attempted and scores (if recorded), files, URLs, lessons, files, folders accessed, and students' academic performance involving summative assessment grades and final course grades. The forums are discussion forums where students can post questions and contribute to answering the questions; quizzes are formative assessments for students to self-check what they've learned; files are content related materials (instructions, additional materials); URLs are links to optional content materials; and folders contain a group of content material files usually containing instructions and files associated to learning activities or assessments. Demographic data of the students were not gathered as a result of previous study (Bretana, Kaushal, Nair, & Cheung, 2020) which discovered that the available demographic characteristics (e.g., age, location, grade point average, gender, degree, full-time/part time study) were not effective indicators of achievement in online programming courses.

3.2 Data Preprocessing

The outcome variable is named as *IsHighPerformance*, which is calculated from *Grade*. A student is considered high-performing if his/her *Grade* has a final raw score of 75 and above. Students can engage with seven types of activities in a course: forum, quiz, assignment, URL, lesson, file, and folder. Assignment is a summative activity while the rest are formative activities. We will only analyze formative activities because these are not required activities. URL, Lesson, File and Folder are formative activities which contains the content materials and does not require contributions from the students while forums and quizzes require students to participate. Each activity has three information types: total engagements of each student in an activity, views of a student, and contributions of a student in an activity as shown in Table 1.

Table 1. Generalized data structure of each activity engagement

Column Name	**Data Type**	**Description**
SP, Year	Nominal	Study Period and Year
Course	Nominal	Course name
Sum<activity>Views	Continuous	Total view count of a student in an activity
SumPercent<activity>Views	Continuous	Total percentage of views of a student in an activity
Sum<activity>Contributions	Continuous	Total contributions of a student inan activity.
SumPercent<activity >Contributions	Continuous	Total percentage of contributions ofa student in an activity
IsHighPerformance	Binary	Target variable

3.3 Data Exploration and Visualizations

Initially, the data sets for all courses were explored by studying the students’ academic performance and then by studying the details of the students’ online engagement and combined academic performance and engagement. These analyses aided in the identification of patterns and descriptive analytics of the data. Next, the academic performance of continuing students, who enrolled in the series of programming courses (2018-2020) and students who enrolled in the series of non-programming courses (2019-2021), was explored. These students’ views and contributions of the formative activities were also explored. Since the focus was on formative activities, summative activities were not included in the analysis of engagement behaviours, that is, viewing of assignment and file submissions were not included in the total count. The reason is that these are required activities and all high-performing students, by default, engage in these summative activities to get a high grade. We are interested in exploring the behaviour patterns of formative activities.

Patterns were explored to identify whether the high-performing students enrolled in the prerequisite programming courses continue to have high performance in the succeeding programming courses, and their engagement behaviours in each of these courses. Results of the data exploration not only led to the understanding of the data, but also reveal the patterns showing whether high-achieving students continue to perform well in succeeding courses. It is important to note that Programming 1 is the prerequisite to both Programming 2 and Programming 3, and it is recommended that students enroll in Programming 1, followed by Programming 2, then Programming 3 in different study periods. However, if there are schedule conflicts, students can take Programming 1, followed by Programming 2 and 3 at the same time. IT Fundamentals is the prerequisite of the System Analysis course, which in turn is the prerequisite of the System Design course. The results and analysis of the data exploration and presented in the next section.

4. RESULTS AND ANALYSIS

The results and analysis in the following subsections explored and visualized the consistency of high-performing students in their series of introductory computing courses, and the associations between students' high academic performance and engagement behaviours in a fully asynchronous online degree.

4.1 Exploring Consistent High Performance of Students in Programming and Non-programming Courses

Table 2 suggests that 52.00% of the high-performing students in Programming 1 continue to obtain high grades in the succeeding programming course. 12.5% of the students who were non-high performing in Programming 1 and enrolled in Programming 2 had a better grade outcome and become high performing in Programming 2. The significant difference between the two percentages (52.00% - 12.50% = 39.50%) indicates that students are more likely to perform high in the successive courses (e.g., Programming 2) if they performed high in prerequisite courses (e.g., Programming 1). Similar observations have existed for students who are high performing in Programming 1 that enrolled in Programming 3 (71.43% continued to be high performing), and Programming 2 and then enrolled in Programming 3 (75% continued to be high performing). Note that 53.33% students who were in the non-high performing category in Programming 2 have performed well in Programming 3. This result is consistent with the experience factor that has been widely studied (Wilcox & Lionel, 2018). Although these studies looked programming experience prior to taking the introductory course, the experience factor can be applied in the study, that is programming experience influence better performance.

Table 2. Academic performances of students in the series of courses

	Prog 1 to Prog 2	**Prog1 to Prog 3**	**Prog 2 to Prog3**	**IT Fund to Sys Analysis**	**Sys Analysis to Sys Design**	**IT Fund to Sys Design**
Continued to be High performing	52%	71.43%	75%	41.38%	68.75%	25%
Non-high-performing to high-performing	12.50%	10%	53.33%	19.15%	22.73%	44.44%

The academic performances of students in the non-programming courses (Table 1) show the percentage of students who have high-performance in pre-requisite that continue to have high performance in succeeding non-programming courses. However, compared to the programming courses, the percentage of high-performing students are lower. For high-performing students in IT Fundamentals that enrolled in System Analysis, 41.83% continued to perform well. For IT Fundamentals to System Design, only 25% continue to perform well. However, from Systems Analysis to System Design, the percentage of students who continually perform high is significant (68.75%). The above results showed that out of six pairs of prerequisites and succeeding courses, five courses were observed that high-performing students in prerequisite courses had a much higher chance of being a high-performing student in the succeeding courses. Only one pair of courses (IT Fundamentals to System Design) showed the opposite trend. Compare to System Analysis and System Design where the contents are more related in the context of software development. IT Fundamentals covers a broad range of IT topics and may not be directly connected to System Design.

Students who are high-performing in the introductory programming courses have a higher chance of getting a high-performing grade in the succeeding programming courses In non-programming courses, it is observed that there is a lower percentage of students continuing to have high-performance if the pre-requisite course contents are not significantly related to the contents of the succeeding courses.

4.2 Online Engagement

Online activities are used to help students progress their learning and prepare them for assessment tasks. The total views of formative activities in programming courses are 108,668 and non-programming courses is

126107. The next highest views are the URL and Quiz. The total views in forum posts are 91% higher than URL and 92% higher than quizzes. For non-programming courses, the total views in forum posts are 99% higher than URL and 86% higher in quizzes. This shows that high performing students significantly views the forum posts. Comparing to non-high performing students, the online engagement data of high-performing students (Figure 1) suggest that the distribution of forum views where the average views of high-performing students for both programming and non-programming courses is more than two-fold (112 % higher) than that of non-high performing students. The active use of forums by high-performing students is consistent with studies from Moström (2011) and Pedrosa et al. (2016) of successful programming students' behaviour in tradition classroom learning that they apply different strategies when they get stuck in programming. One common strategy is through social interaction with peers and teachers. In online learning, one equivalent form of interaction through peers and teachers is through engagement in forums. High-performing students' behaviour of having almost twice activity views than non-high performing is consistent with the self-regulated learner's behaviour of reflection. Viewing helps students to reflect and think about what they are seeing, which help develop their skills and knowledge to analyze what they have just viewed. It is also consistent to studies that indicated that students' viewing activities have direct positive influence on their completing learning tasks (Ma et al., 2015).

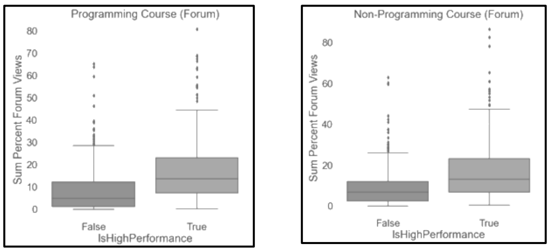

Figure 1. Boxplot of percentage forum views

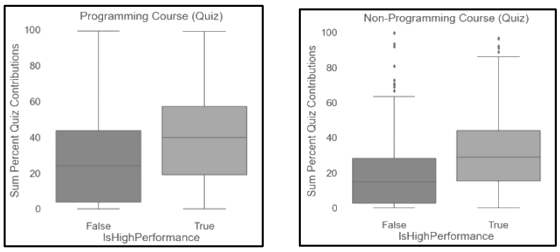

Figure 2. Boxplot of percentage quiz contributions.

The quiz is significantly higher in contributions for both programming and non-programming courses (57,393 total contributions for programming courses and 76,211 for non-programming). Forum contributions is significantly lower (90% lower for programming and 92% lower in non-programming courses). Other activities have zero contribution because students these formative activities provide content to the online student but was not designed for interaction with them. For quiz contributions (Figure 2), the percentage difference in the average quiz contributions in programming courses of high-performing students is 44% higher compared to non-high performing students, while for non-programming courses the percentage difference is 112%. We've also seen that students who were high performing for all programming courses (Programming 1, Programming 2, and Programming 3) have a 159% difference in contribution and 198% difference in views. For non-programing courses (IT Fundamentals, System Analysis and System Design), students who were consistently high performing in these three courses have a 170% difference in views and 105% in contribution.

The quiz formative activity is the online activity where high-performing students contribute the most in programming courses and non-programing courses. This behaviour of having high contributions to formative activities such as quizzes in coding is consistent with the studies that high-performing students in programming education have been consistently active in practice as their study progresses (Hassinen & Mäyrä, 2006; Mai et al., 2021; Pedrosa et al., 2016).

4.2.1 Statistical Significance

Student's t-test has been performed to evaluate statistically if the mean values of online engagement between high performance and non-high-performance students are equal. Table 3 shows that all p-values of two online engagement data sets of both programming (8.99e-11 for forum views and 2.69e-9 for quiz contributions) and non-programming courses (9.83e-16 for forum views and 5.33e-15 for quiz contributions) are much lower than 0.05, indicating a rejection of the null hypothesis, i.e., the online engagement is statistically significantly different between high-performing and non-high performing students.

Table 3. P-values of the students' t-test on two different online engagement

	Programming Courses	Non-Programming Courses
Sum Percentage Forum Views	8.99e-11	9.83e-16
Sum Percentage Quiz Contributions	2.69e-9	5.33e-15

5. CONCLUSION AND RECOMMENDATION

The study presented in this paper analyzed three-year engagement and academic performance data of students enrolled in a 100% asynchronous online IT courses. Students' academic performance and online engagement data were collected from the LMS to provide a more objective data and explore the relationship between online engagement behaviours and academic performance. The data were further analyzed to discover the patterns of online engagement behaviours of high-performing students. The study revealed that an average of 54.5% of high-performing students in the introductory programming courses continued to have high performance in the succeeding programming courses. High-performing students in the first programming courses have a higher chance (61.43%) of maintaining the high performance in Programming 3 than Programming 2. The study also showed that as students get more programming experience, that is after they have completed Programming 2, more than fifty percent of the non-high-performing students became high-performing in Programming 3. For non-programming courses, high-performing students in their first course (IT Fundamentals) has a lower percentage of achieving a high performance in the succeeding courses. Students who are high performance in System Analysis has a higher chance (46.025) of having consistent high performance in System Design. As the results indicated a continuity of high-performing students in an introductory course and the succeeding courses especially for programming courses, their online engagement behaviours were further explored.

The online engagement data of high-performing students is consistent with self-regulated learner behaviours. The average forum views of high-performing students for both programming and non-programming courses was 112 % higher than that of non-high performing students. In the quiz activity contributions, the average contributions of high-performing students for programming courses were 44% higher while 112% higher for non-programming courses comparing to non-high performing students. Online students use the online equivalent medium or tool to manifest the face-to-face student behaviours (e.g., social interaction with peers and teachers in face-to-face and the equivalent discussion forum tool in online learning as a form of social interaction).

Though this study utilized a data-driven approach based on learning analytics to understand the online engagement behaviours of high-performing students studying at a 100% asynchronous online IT courses, the study was limited to the data available through the LMS. Viewing of content videos is an activity that has been excluded due to the transition from one video tool to another which resulted in the inability to access the older data. For future directions, we aim at further analysing the data collected in this study to identify the predictive factors that contribute to students' high performance and the continuity of their high performance and extending this study by understanding the mindset of these high-performing students when engaging and learning online.

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