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WHEN JUST SHOWING UP ISN'T ENOUGH? THE CASE OF A PROGRAMMING COURSE

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ABSTRACT

Whereas some studies reported there is a strong positive correlation between class attendance and student performance in programming courses, others concluded that attendance has no significant relation with student performance and assessment tasks. Given that students' poor performance in programming is still reported regularly, it would be beneficial to better understand what leads to the mixed effects of attendance. The purpose of this study is to look beyond students' just showing up to class and identify the underlying factors that truly impact student learning and performance in programming courses. Using data from an introductory programming course over four semesters, we found that class attendance and student performance is weakly correlated, but student engagement is a significant factor in predicting student performance. The findings suggest that active engagement from students is a critical factor underpinning student learning and achievement in programming courses.

Keywords

Programming, Class Attendance, Student Engagement, Learning and Performance.

INTRODUCTION

While computer programming is a fundamental course to IT/IS curricula, learning to program can be an incredibly difficult task for most beginners, to the point where the phrases "high failure rate" and "programming course" are almost synonymous. In order to improve the situation, extensive research efforts have been devoted to studying various aspects related to teaching and learning programming. Yet, pass rates were not found to have significantly differed over time (Bennedsen & Caspersen, 2007; Bennedsen and Caspersen, 2019; Dawar, 2023). It appears that introducing students to programming remains to be one of computing education's grand challenges. As pointed out by Bennedsen and Caspersen (2019), the challenge not only persists, but is reinforced.

The challenge does not imply that things cannot improve, especially with persistent and concerted efforts from a community of instructors, learners, and researchers. Among all the studies on programming courses, one particular area of interest is to identify the factors that might impact student performance in programming courses (Luxton-Reilly et al., 2018). For example, in general college settings, class attendance is widely considered as one of the factors that are under students' own control and contribute to student learning (Credé, Roch, & Kieszczynka, 2010; Kassarnig et al., 2017). However, in the case of programming courses, prior studies have reported the mixed effects of class attendance on student performance.

In particular, some prior studies have shown a strong positive relationship between attendance and student programming performance beyond other factors (e.g., Hsu & Plunkett, 2016), whereas others concluded that attendance has moderate or no impact on student performance and assessment tasks (Pudaruth et al., 2013; Veerasamy et al., 2016). One related question is: Why were there such conflicting findings? Given that students' poor performance in programming is still reported regularly, it would be beneficial to better understand the factors behind the mixed effects of class attendance on student performance.

Since mere attendance may not matter at all until too much class time is missed (Durden & Ellis, 1995), other factors such as active participation in class activities and completion of programming assignments could have impact on student performance more than mere class attendance (Bekkering & Ward, 2020). Yet, participation is often confused with engagement. Engagement is about the mental effort that is exerted to master the subject. Participation is about the physical indicators that we can observe that may or may not demonstrate mental efforts. Given that the cognitive load of programming language concept(s) is unusually high, many students especially beginners may choose not to participate or engage in class (Dawar, 2023).

In this study, we look beyond students' just showing up to class and identify the underlying factors that truly impact student learning and performance in introductory programming courses. Using data from an introductory course over four semesters, we found that class attendance and student performance is weakly correlated, but student engagement has a strong positive correlation with performance and is a significant factor in predicting student performance. This study further confirms that the student perspective of learning to program, particularly the extent of their active engagement, is critical for effectively learning programming.

RELATED LITERATURE

Over the past few decades, tremendous amount of research effort has been put into examining various aspects related to introductory programming courses, including teaching tools, pedagogical approaches, student learning, student attitudes, student behavior, and so on (see Luxton-Reilly et al. (2018) for a comprehensive review). Among these research studies that focus primarily on the student, a few have specifically examined the impact of class attendance on the performance in programming courses (e.g., Hsu & Plunkett, 2016; Pudaruth et al., 2013; Veerasamy et al., 2016). However, the findings on the effects of class attendance from these studies have not been consistent with each other, although the general research consensus holds that class attendance improves student performance in higher education (Credé, Roch, & Kieszczynka, 2010; Kassarnig et al., 2017). In particular, Hsu and Plunkett (2016) found there was a significant positive correlation between attendance and student programming performance beyond other factors; Pudaruth et al. (2013) showed a moderate correlation between attendance of lectures and programming performance; and interestingly, Veerasamy et al. (2016) found that formal lecture attendance and final exam performance in programming were negatively correlated.

As discussed by Robins, Rountree, and Rountree (2003), acquiring and developing knowledge about programming is a highly complex process. It involves a variety of cognitive activities, and mental representations related to program design, program understanding, modifying, debugging (and documenting). Margulieux, Catrambone, and Schaeff (2018) compared the domain difficulty of three courses, namely, computer programming, chemistry, and statistics, and found computer programming to be the most difficult of the three, due to the complexity of the content to be learned, especially in terms of mapping problem solving procedures to solving problems. Therefore, we could argue that programming has characteristics that might affect how factors such as class attendance impact student performance and learning differently.

Mere attendance may not matter until too much class time is missed (Durden & Ellis, 1995), but is a better predictor than SAT, high school GPA, study habits and skills (Credé, Roch, & Kieszczynka, 2010). However, as pointed out by Bekkering and Ward (2020), once in class, being active matters. Participation in class is a combination of coming to class and paying attention once there. Yet, participation is about the physical indicators that we can observe that may or may not demonstrate mental efforts that are considered as engagement. Student engagement has been linked to improved achievement, persistence and retention (Kuh et al., 2008), with disengagement having a profound effect on student learning outcomes and cognitive development (Ma et al., 2015).

Student engagement is the energy and effort that students employ within their learning community, observable via any number of behavioral, cognitive or affective indicators across a continuum (Bond et al., 2020). In particular, behavioral engagement includes indicators such as participation, effort and time on task (Hospel, Galand, & Janosz, 2016); cognitive engagement is defined as student's level of investment in learning. It includes being thoughtful and willing to exert the necessary effort for comprehension of complex ideas or mastery of difficult skills (Fredricks, Blumenfeld, & Paris, 2004); and affective or emotional engagement focuses on the extent of positive (and negative) reactions to teachers, classmates, academics, or school (Bond et al., 2020; Fredricks & McColskey, 2012).

Self-report survey measures are the most common methods for assessing student engagement, because they are often the most practical and easy to administrate in classroom settings. However, self-reports may not reflect their actual behaviors or strategy use (Fredricks & McColskey, 2012). For example, students may not answer honestly under some conditions; the measures generally contain items that are worded broadly, rather than worded to reflect engagement in particular tasks. Instead, some studies have used observational techniques to examine students' engagement and note behaviors, such as asking and answering questions, requesting clarifications, and exchanging ideas as measurement of engagement (Fredricks & McColskey, 2012; Zhoc et al., 2019).

STUDY CONTEXT AND DATA DESCRIPTION

We collected data from an introductory Java programming course offered in face-to-face delivery mode at a regional state university. It is one of the required courses for undergraduate students majoring in Information Systems (IS), and other majors in the College of Business can take it as an elective. IS majors must receive a letter grade of C or higher to pass the course. The course has been taught by the same instructor over the last four years, and class size is relatively small, ranging from 12 to 21 students. The attendance and engagement data were collected over a period of four semesters.

The data sample comprised 64 students. The instructor used the Attendance function in the Learning Management System (LMS) to track the attendance of each class session. The number of questions related to the course material a student asked, the number of questions a student responded, the number of clarifications requested, and the number of assignments and quizzes completed on time were used to measure student engagement. Each of these engagement activities was counted as one point, whether it occurred in class, outside the classroom, in person, or online via emails or discussion board in the LMS. The student engagement score was the sum of all the points that a student has earned. The overall course grade, as the weighted average of all grading components on a standard 0-100 percentile scale, was used to measure student performance in the course.

Table 1 presents the descriptive statistics for the variables. Statistical tests were undertaken to determine the relationships between variables. The level of significance was set at $p \leq 0.05$. Kruskal-Wallis tests were also conducted to assess the differences in course grades across three levels of student engagement scores. Three different levels were recognized:

(1) Low level of engagement: ≤ 8 points
(2) Medium level of engagement: 9 to 23 points
(3) High level of engagement: ≥ 24 points

	Attendance	Course Grade	Engagement Score
Mean	55.85	72.36	17.93
Median	53.70	73.61	16.67
Standard Deviation	28.62	14.55	14.82
Minimum	7	29.81	6
Maximum	100	95.27	33

Table 1. Description Statistics for Variables (n = 64)

PRELIMINARY RESULTS AND DISCUSSION

Spearman rank-order correlation analysis revealed that there was weak correlation ($r_s = 0.27$) between attendance and course grade. However, the analysis found a strong correlation ($r_s = 0.86$) between engagement score and course grade.
A Kruskal-Wallis test found a statistically significant difference in the course grade across three segments of student engagement. Table 2 shows the number of students and median course grades for each of the engagement levels. We can see that the high level of engagement group had a higher median course grade than the medium level of engagement group, which in turn had a higher median course grade than the low level of engagement group.

	n	Median Course Grade
Low level of engagement	17	60.44
Medium level of engagement	33	72.89
High level of engagement	14	83.24

Table 2. Difference in Median Course Grade Across Engagement Levels ($p = 0.009$)

In addition, we used ordinary least squares (OLS) regression to assess if attendance and/or engagement predict student performance (i.e., course grade). Initial analyses were conducted to ensure it meets the assumptions of linearity in parameters, normality, absence of multicollinearity and homoscedasticity of errors. We start with a zero-order model (Model 1) that simply examines the effect of attendance, and Model 2 examines the effect of both attendance and engagement. Then, in Model 3, we introduce the control variables including gender, the number of credit hours taken during that semester, and self-reported hours worked per week at any paying job. The Model 3 contains all of the variables including attendance, engagement, and all the control variables. Such design allows us to look into how controlling for certain factors may explain away any initial difference in the results. Table 3 contains the results showing that, in all of the models, attendance does not make a statistically significant contribution to predict course grade, and engagement does make a statistically significant contribution to predict course grade at 1% significance level. Such results suggest that student engagement is an important factor underpinning student performance in programming course. Given that programming typically involves high cognitive load with abstract thinking and building problem-solving skills, it requires students to engage with the conceptual contents instead of passively consuming information. Just showing up in the class without actively and mentally engaging in learning activities may not be enough, especially for novice programming students.

Independent and Control Variables	Model 1	Model 2	Model 3
Attendance	0.838 (0.336)	0.910 (0.327)	0.774 (0.292)
Engagement		1.209*** (0.401)	1.188*** (0.398)
Gender (Male)			-0.942 (0.129)
Credit hours taken			-0.151 (0.788)
Hours worked/week			0.211 (0.468)
Intercept	21.401*** (0.545)	35.114*** (1.621)	38.725*** (2.003)
Adjusted R^2	0.032	0.225	0.241

Table 3. OLS Regression Models Predicting Course Grade

*p < .05; **p < .01; ***p < .001, using a two-tailed t-test. Unstandardized coefficients reported with standard errors in parentheses.

LIMITATIONS AND CONCLUSION

This research has several limitations. Student engagement in programming course was measured in terms of quantity rather than quality of the engagement. Nevertheless, engagement is widely recognized as a complex and multifaceted concept. There is a variety of methods for measuring and assessing engagement, each with strengths and limitations (Fredricks & McColskey, 2012). The data sample is relatively small. In the future, we intend to gather other related information such as GPA as a control variable, and look into utilizing software tools to automate the capture and measurement of student engagement. Importantly, if engagement can be monitored as semesters progress, it can be used to identify students at risk of failing and underperforming.

Programming is generally regarded as difficult for students to learn and challenging for instructors to teach. This research provides evidence of how just showing up in class isn't enough for student learning in programming courses. Instead, actively engaged in learning activities contributes positively to student performance and learning outcomes. It supports earlier studies conducted in other types of courses and disciplines demonstrating the critical importance of engagement in student learning, achievement, and retention. The positive impact of engagement on student learning in programming courses may also inform that the instructors of programming should embrace active learning principles in their course design to explore student engagement and promote active learning.

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