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RESEARCH ARTICLE

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Evaluating Students' Performance Relative to Their Time Investment in an Asynchronous Online Class

ABSTRACT

COVID-19 lockdowns led to increased adoption of online teaching with courses that have an asynchronous format. It is recognized that some students could be online without dedicating all of their time to the class. This study aims to investigate whether there exists any association between the hours students invest in online classes with the point scores they achieve. Data on semester participation hours and total point scores were gathered in CNST 440-540, an asynchronous online class at Eastern Michigan University from the winter semester of 2016 to the winter semester of 2021. Statistical modeling revealed a modest but significant relationship between student online time and actual point scores.

Introduction

The COVID-19 pandemic had a profound effect on various sectors of the economy, as well as every aspect of human existence, not just in developing countries but internationally (Bacher-Hicks et al., 2021). Due to this situation, most schools, colleges, and universities worldwide switched from face-to-face instruction to virtual formats. Adapting to and combating the infection through online education is seen as effective for controlling and limiting the spread of the virus (McGrail et al., 2020). Social limitations such as virtual learning and "shelter-at-home" advising have made it more difficult for children and adolescents to participate in physical education, sports, and other school- or community-based organized physical activities. Additionally, parental constraints such as working from home or losing childcare make it challenging to develop strategies to keep their children physically active (Bates et al., 2020; Lee et al., 2021). Shifts toward online learning affect adolescents' overall attitude toward learning, motivation to study, and academic performance (Aguilera-Hermida, 2020). As a result, it is vital to evaluate the impact of students' time spent in online classes on their academic success measured in terms of grade points at the end of the semester. Hence, this study aims to determine whether there is any discernible relationship between the actual number of hours (i.e., participation hours) that students invest in online classes and the overall point scores that they achieve.

Background Literature

The COVID-19 pandemic has had tremendous impacts on the lives of many people. Over 200 countries have been affected by the pandemic, which has wreaked havoc on the education sector. Schools, institutions, and other learning facilities were closed, and the closure had a negative effect on the student population directly and indirectly. As a result, there have been tremendous changes in every aspect of our lives and education. Traditional face-to-face educational practices have been significantly disrupted as a result of social alienation and constrained mobility rules, for instance. Moreover, due to the implementation of numerous new standard operating procedures, reopening schools once restrictions have been eased has become a significant challenge (Pokhrel & Chhetri, 2021).

Byun & Slavin (2020) found that pupils in sixth and seventh grades in South Korea place a high value on academic achievement, and the coronavirus's unfavorable repercussions have had detrimental impacts on students' grade point average (GPA). It is likely that changes in the environment caused by COVID-19 will have negative impacts on many students' academic achievement. Many stressors are already being experienced by South Korean students particularly due to high academic expectations, such as those imposed by parents who place immense pressure on their children to achieve high scholastic accomplishment and performance (Shin & Wong, 2013).

Using a questionnaire, Elhadary et al. (2020) compared the academic achievement of pure science students against that of social science students to draw conclusions. Another questionnaire was created and distributed to the professors of the two fields in which it was used. The study found that a variety of factors, including anxiety (60.3%), social difficulties (41.8%), and Internet connectivity, had a negative impact on both student and instructor motivation, with anxiety being the most detrimental (43.2%). The e-learning platform, on the other hand, has garnered positive responses from students (65.0%) and teachers (48.8%) so far.

Student performance in online courses was shown to be poorer, on average, than in physical courses in a study of over 230,000 students enrolled in over 168,000 parts of the various subjects throughout four years (Bettinger et al., 2017). On the other hand, other major schools of thought have differing viewpoints and observations, and many have found little to no difference overall. To put it another way, there is a whole universe of students who benefit from online education and see their academic performance improve due to this kind of instruction.

Therefore, it is possible to expect that the value of virtual classrooms in this era will be reflected in improved student performance, particularly considering the COVID-19-mandated modifications to teaching delivery and procedures. Another researcher examined the sequence of online attendance among 122 undergraduate students and found a link between it and their performance at the end of the academic session. Unexpectedly, the data analysis shows that virtual involvement does not correlate with the performance of students who completed their courses online; on the contrary, students who did not perform well do not interact so much in class (Davies & Graff, 2005).

Several researchers at the Universidad Autónoma de Madrid investigated student success in higher education (Mseleku, 2020), examining how COVID-19 constraints affect student performance. They conducted a practical exercise with 458 students divided into two segments: the main class and the trial class. The results of the investigation were published in the journal *Psychological Science*. In addition, participants in the trial class were compelled to take online courses as a result of their detention. This led to the discovery by the investigators that the restriction had a tangible positive influence on students' grades, supporting students in transforming of their learning practices into a more regular habit and boosting their efficiency (Mseleku, 2020).

A study conducted by researchers in Pakistan during the COVID-19 pandemic examined the opinions of college students about online education. Students' views suggested that Pakistan is a developing nation and virtual classes will not give the expected results because the majority of students, particularly those who live in rural and marginalized communities in Pakistan, lack Internet access, which reduces their motivation and performance. These studies also discovered that kids have had other disadvantages during the COVID-19 crisis, including not having regular classroom socialization and having limited physical communication between students and the teachers (Adnan & Anwar, 2020).

Andrew et al. (2020) performed research that revealed that differences in learning styles widen achievement gaps between low-achieving and high-achieving students. Since they spend 30% fewer hours learning at home and have limited access to quality school materials, children from low-income families are less likely to participate fully in online courses. They also have less access to valuable school materials. Another study's findings corroborate the assumption that students with a slight academic advantage continue to succeed. Still, students with a small academic disadvantage continue to lag (Protopapas et al., 2011). Spitzer & Musslick (2021) looked into how school closures in 2020 would affect the performance of German children in a curriculum-based online learning program for mathematics. More than 2,500 K-12 pupils who computed over 124,000 mathematical problem sets before and during the closure were studied, and it was determined that kids' performance improved during the 2020 school shutdown when compared to the previous year's school shutdown.

Some studies have been performed to determine the relationships among attendance, online learning engagement, and online learning performance in higher education (Bekkering & Ward, 2020; Doggrell, 2020; Nieuwoudt, 2020). Doggrell (2020) investigated the relationships among lecture attendance, recording availability of the lectures, and the accomplishment in academic performance within the two sessions of medical laboratory science courses, recruiting a total of 117 medical students from them. Since the introduction of lecture recordings, they discovered that there is no longer a significant relationship between attendance at lectures and academic performance. They asserted that mixing a range of multimedia instructional technology will improve academic achievement in the classroom. Saleh et al. (2022) compared the efficacy of an e-learning technique with that of traditional learning for pediatric nursing student knowledge of, engagement with, and clinical performance related to neonatal endotracheal suction. A comparative quasi-experimental design was used in the study. A convenient sample of 120 pediatric nursing students was used as the study's subjects. During the first semester of the school year, students who chose the pediatric nursing course in the 2020–2021 academic year were divided into two equal groups at random. The finding was that extending the traditional technique through face-to-face interaction improved students' information retention. However, the e-learning group retained more skills than the traditional group.

While the COVID-19 pandemic was in full swing, Wang et al. (2022) concentrated on analyzing online learning readiness and emotional competence as essential characteristics to evaluate for their consequences on students' academic performance. These researchers looked at two groups of students: 1,316 high school students (mean age = 16.32 years, standard deviation = 0.63) representing adolescents and 668 college students (mean age = 20.20 years, standard deviation = 1.43) representing young adults. The analysis was conducted using a structural model after correcting for pre–COVID-19 academic performance. When it came to high school students, the findings revealed that online learning readiness and emotional competence were positively associated with online academic performance during COVID-19. However, when it came to college students, only online learning readiness was significantly associated with online academic achievement.

Jacques et. al (2021) studied a group of engineering students in France (81 individuals). In the various knowledge examinations, the data revealed that e-learning did not affect the performance of engineering students in the same course. Instead, they obtained local outcomes equivalent to those expected from face-to-face training. In this research, the results of many satisfaction surveys revealed that the 81 engineering students who took part in it were generally happy, especially when the instructional formats did not need practical application. Kaczmarek et al. (2021) compared faculty assessments of student experiences to reported student perceptions to learn more about student and faculty distant learning experiences. There was a 100% response rate from 39 students, and a 74% response rate from 29 teachers. Over half of faculty (52%) believe that virtual learning has deteriorated, which is consistent with student perceptions (70%). According to students (54%) and faculty members (55%), distance learning has diminished student involvement and participation. Furthermore, most students (72%) and staff (52%) believed that student fatigue had worsened. Many faculty members (31%) also reported higher levels of exhaustion.

Using data from two successive semesters (autumn 2020 and spring 2021, all within COVID-19), Haldolaarachchige (2022) investigated student performance in a virtual synchronous calculus-based introductory physics class (Level I Mechanics). In the next section, the results were compared to those of a conventional (in-person) version of an identical class held in the autumn of 2019, prior to COVID-19. The performance of students on half-semester evaluations and final exams was compared and contrasted throughout three semesters of study. Student learning did not seem to be affected by the class type (virtual or in-person), according to the study's findings on academic integrity. When it comes to online live proctoring of exams utilizing video conferencing technology, the findings suggest that it works well.

Using online learning technologies (Zoom and Moodle), Adeyeye et al. (2022) explored the effectiveness of online learning technologies (Zoom and Moodle) and their influence on the academic accomplishment of Covenant University, located in Ota, Nigeria. Following the COVID-19 pandemic, an unforeseen shift from conventional in-class instruction to online instruction changed the course of the teaching process. Students who participated in practical courses outperformed their peers in academics while using online learning methods. Students enrolled in practical courses were enthusiastic about continuing to use online learning technologies such as Zoom and Moodle because of their efficacy (Zoom and Moodle) and the excellent communication that these platforms provide between instructors and students. Student satisfaction was high when Covenant University's e-learning resources were utilized during the outbreak of the flu pandemic.

In their study, Wilczewski et al. (2022) investigated the experiences that students had while learning through an online mode during the 2020 spring term, which coincided with the peak of the COVID-19 epidemic. The authors gathered data using an online survey, which received replies from 362 foreign and 488 local students at a big university in Poland. Correlation and path analyses were performed on the collected data. The results revealed that the experience explained adjustment as well as performance, satisfaction, and loyalty. It was also discovered that academic adjustment predicts performance, satisfaction, and loyalty, as well as that student loyalty can be predicted by academic performance and satisfaction. Additionally, it was shown that the time spent in quarantine or self-isolation had no influence on academic results.

Ramirez II et al. (2022) investigated whether new didactive tactics such as online learning and flipped classrooms may increase student performance while optimizing university resources and staff. They claimed that it is becoming more crucial to analyze how students perceive courses that have been constructed utilizing the aforementioned principles, as well as how they perform within such courses. For this study, the authors used proportional odds regression models and logged odds ratios to determine whether students' views and performance in the course were impacted by the teaching approach or their class status. Their findings revealed that class status had the greatest effect on students' responses to the questions related to perception and engagement. In contrast, the teaching approach had a negligible impact on students' answers to these same questions. It was also discovered that sophomores, who were the students who had the greatest likelihood of voicing possibly less favorable responses, were also the students who had the greatest likelihood of doing poorly in the course. According to the authors, the findings indicated that online learning and flipped classroom strategies are viable options that can help universities expand their resources, impact, and accessibility and that students' perceptions of college courses, which varied depending on their class standing in this study, can have an effect on their academic performance.

Despite the findings of numerous previous research, it should be recognized that none adopted the approach of this study, which is based solely on one course continuously taught by one instructor, thus eliminating possible spurious relationships as the basis for conclusions. Previous studies have also only compared between different courses, which is not a fair comparison, whereas the current study examines one course taught continuously by a single professor. In this article a study has been conducted, taking data from six years of a single course taught by a single professor, to identify the relationship between the number of participation hours of students in class and the score they achieved in order to identify the optimum number of hours. Because the data analyzed have come from a single course that has always been taught online, there is no longer a comparison between different courses (as is prevalent in the earlier studies), which eliminates any kind of bias from the analysis.

Methodology

An asynchronous online class at Eastern Michigan University called CNST 440-540–LEED for New Construction & Major Renovations (Leadership in Energy & Sustainable Built Environment) was studied over several successive semesters beginning in the winter semester of 2016 and continuing until the winter semester of 2021 to determine the relationship between student participation hours in an online class and the point scores they achieved overall. Students' online presence and activity were tracked by the Canvas learning management system, which was used to deliver this course to the students. It is acknowledged that some students may not always devote all or most of their online time to productive class activities. Still, their mere presence online provides many students with the opportunity to engage in class work rather than wasting all of their time on something else.

Python was used to conduct descriptive and inferential statistical analysis for the histogram and regression, respectively. In spite of the fact that there are many different types of regression analyses, including simple linear regression, polynomial regression, logistic regression, and others, for the purposes of this limited study, the first two methods have been chosen because they appear to provide a better explanation of the data. The specificity and control of this investigation, which focused exclusively on one particular asynchronous online class taught every semester by the same professor with a relatively similar student enrolment, appear to distinguish it from other studies in that it was conducted in a controlled environment.

SIMPLE LINEAR REGRESSION

Linear regression is a statistical technique for modeling the connection between dependent and independent variables used in many applications. According to the linear regression theory, the associations between two variables are represented using linear predictor functions which have unknown model parameters, and these are inferred from the data. Linear models are used to describe this type of regression (Seal, 1967). Among the various regression analyses, linear regression was the first to be thoroughly investigated. It was also the first type of regression analysis to be widely employed in practical applications (Yan & Su, 2009). For one thing, fitting models in a linear manner is substantially easier than fitting models in a non-linear fashion because it is much simpler to identify the statistical characteristics of the resultant estimators in a linear approach. Linear regression has numerous practical applications that can be broadly classified into two types: one is to predict, forecast, or reduce the error in fitted models, and the other is to explain the variation that may be observed in a response variable that can be further attributed to the variation in the explanatory variables. It is referred to as multiple linear regression when there is more than one independent variable, and it is referred to as simple linear regression when there is only one dependent variable (Freedman, 2009). Simple linear regression has been used in this research to analyze the data.

If x and y are the independent and dependent variables respectively, then the relationship between them can be expressed as a straight line given as follows:

$$y = \beta_0 + \beta_1 x + \varepsilon \tag{1}$$

where the intercept β_0 and the slope β_1 are the unknown regression coefficients and ε is the random error generated while fitting the scatter plot to a straight line for normality (Montgomery & Runger, 2010).

In matrix notation, for n points, equation (1) can be expressed as

$$\vec{y} = \boldsymbol{X}\vec{\beta} + \vec{\varepsilon} \tag{2}$$

where

$$\vec{y} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{bmatrix}, \quad \boldsymbol{X} = \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ 1 & x_3 \\ \vdots & \vdots \\ 1 & x_n \end{bmatrix}, \quad \vec{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} \quad \& \quad \vec{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \vdots \\ \varepsilon_n \end{bmatrix} \tag{3}$$

Now the objective of the problem is to estimate the unknown parameters β_0 and β_1 by minimizing the error ε utilizing the method of least squares, i.e., minimizing

$$L = \sum_{i=1}^{n} \varepsilon_i^2 = \sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_i)^2 \tag{4}$$

where n is the total number of data points.

The least square estimate of the slope is given as

$$\hat{\beta}_1 = \frac{\sum_{i=1}^{n} y_i x_i - \frac{\sum_{i=1}^{n} y_i \times \sum_{i=1}^{n} x_i}{n}}{\sum_{i=1}^{n} x_i^2 - \frac{\left(\sum_{i=1}^{n} x_i\right)^2}{n}} \tag{5}$$

and that of the intercept is given as

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} \tag{6}$$

where $\bar{y} = \frac{\sum_{i=1}^{n} y_i}{n}$ and $\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$.

Thus, the fitted or estimated regression line can be written as

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x \tag{7}$$

Finally, the difference between actual and observed values $e_i = y_i - \hat{y}$ is called the residual (Montgomery & Runger, 2010).

POLYNOMIAL REGRESSION

Even if simple linear regression is an effective way of fitting data and evaluating the connection between them, it is not capable of providing a complete explanation for the same. As a result, Legendre and Gauss developed the polynomial regression technique in the early 1800s (Yan & Su, 2009), which has since been widely used. According to Gergonne (1974), the first design of an experiment for polynomial regression was published in an 1815 publication. Polynomial regression greatly influenced the development of regression analysis over the last century, with a particular focus on problems of design and inference (Smith, 1918).

For purposes of statistical analysis, polynomial regression may be defined as a kind of regression analysis in which a polynomial of m^{th} degree models the connection between an independent variable x and a dependent variable y. This is done in such a way that the non-linear relationship between x and y can be incorporated into the equation.

Similar to simple linear regression, the dependent variable can be expressed as

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \cdots + \beta_m x^m + \varepsilon \tag{8}$$

The same procedure discussed in simple linear regression is employed, i.e., minimization of the error ε using the method of least squares to estimate the unknown parameters β_i where $=0, \ldots, m$.

In matrix notation, for n points, equation (8) can be expressed as

$$\vec{y} = \boldsymbol{X}\vec{\beta} + \vec{\varepsilon} \tag{9}$$

where

$$\vec{y} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{bmatrix}, \quad \boldsymbol{X} = \begin{bmatrix} 1 & x_1 & x_1^2 & \cdots & x_1^m \\ 1 & x_2 & x_2^2 & \cdots & x_2^m \\ 1 & x_3 & x_3^2 & \cdots & x_3^m \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_n & x_n^2 & \cdots & x_n^m \end{bmatrix}, \quad \vec{\beta} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \vdots \\ \beta_m \end{bmatrix} \quad \& \quad \vec{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \vdots \\ \varepsilon_n \end{bmatrix} \tag{10}$$

To estimate $\overrightarrow{\beta}$ using least squares estimation, the following equation may be utilized.

$$\hat{\overrightarrow{\beta}} = (\boldsymbol{X}^{\mathrm{T}}\boldsymbol{X})^{-1}\boldsymbol{X}^{\boldsymbol{T}}\overrightarrow{y} \tag{11}$$

However, the aforementioned equation is valid if and only if $m < n$ and all values in $\boldsymbol{X}$ are distinct because only then will the matrix be invertible. Until and unless the matrix is invertible, it is not possible to get a unique least squares solution.

COEFFICIENT OF DETERMINATION

It is not enough to simply fit the data into a linear or polynomial curve to comprehend the relationship between the dependent and independent variables. As a result, it is important to do an appropriateness check on the regression model that was fitted. The coefficient of determination, often known as R^2, is one of the most reliable checks or measures.

The coefficient of determination in statistics refers to the percentage of variance in the dependent variable that can be predicted from the independent variable based on the independent variable. Based on other relevant information, it is a statistic employed in the context of statistical models, with the primary goal of either predicting future events or testing hypotheses. This metric measures how well-observed results are reproduced by the model, and it is based on the fraction of total variance in outcomes that can be explained by the model (Steel & Torrie, 1960; Draper & Smith, 1998; Glantz et al., 2001).

The coefficient of determination is expressed as

$$R^2 = 1 - \frac{SS_{\mathrm{res}}}{SS_{\mathrm{tot}}} \tag{12}$$

where $SS_{\mathrm{res}} = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} (y_i - \hat{y})^2$ is the residual sum of squares and $SS_{\mathrm{res}} = \sum_{i=1}^{n} (y_i - \bar{y})^2$ is the total sum of squares.

R^2 is a measure of the goodness of fit of a model (Casella, 2002). The closer R^2 is to 1 the better the fit of the regression model.

There are certain situations in which R^2 may provide negative values. A situation like this might develop when the predictions that are being compared to the related outcomes have not been obtained by a model-fitting technique utilizing the data that are being compared to the predictions. It is possible for R^2 to be negative even when a model-fitting process has been performed. For example, if linear regression is undertaken without including an intercept (Barten, 1987), or if a non-linear function is used to fit the data (Cameron & Windmeijer, 1997), the result may be negative. According to this specific criterion, in circumstances when negative values are encountered, the mean of the data gives a better match to the outcomes than the values of the fitted function.

Results and Findings

Both simple linear regression and polynomial regression of order six were utilized in the current investigation. The correlation between participation hours and corresponding point scores of students in the asynchronous online class was investigated with data collected from one course taught by one professor every semester starting from the winter semester of 2016 to the winter semester of 2021.

The distribution of the participation hours (expressed as a percentage) in the form of a histogram is shown in Figure 1. The corresponding mean, median, and mode are 72.14%, 87%, and 100%, respectively.

Similarly, the histogram for point scores is shown below (Figure 2) with the corresponding mean and median as 487.72 and 518.61, respectively. The mode, however, does not exist, indicating that

Figure 1.
Histogram of Participation Hours

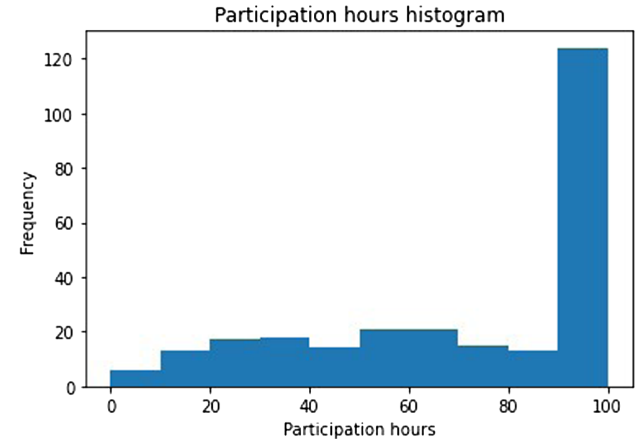
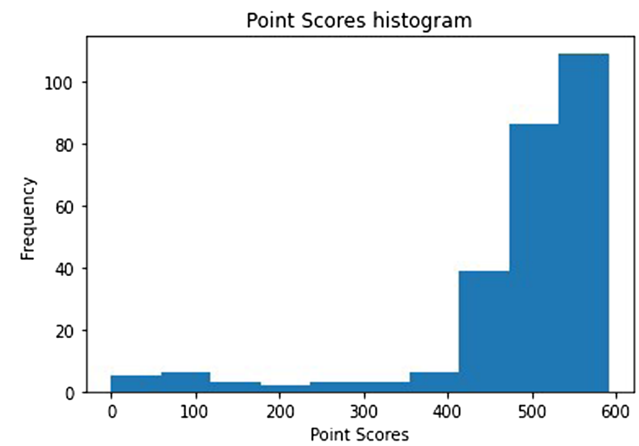


Figure 2.
Histogram of Point Scores



the variability in the point scores data set is extremely high; in other words, the data set is heteroscedastic.

Figure 3 shows a positive trend between participation hour point scores when a simple linear regression model was used to fit the data. However, the coefficient of determination for it is 0.43, which is below 50%. Thus, to improve on the fitted model and get a better coefficient of determination value, a polynomial regression of order 6 (i.e., $m = 6$) was explored.

As can be observed, Figure 4 also shows a positive trend with a coefficient of determination of 0.54, suggesting that polynomial regression better explains the data and that some conclusions can be drawn from it.

Furthermore, considering 75%, i.e., 450/600 as the passing point score, it can be found from the linear model that the optimum number of hours to achieve that is around 65%. Still, from the polynomial model the number of hours is identified to be around 45%. Hence, it can be claimed with some confidence that a student participating between 45% and 65% of the total participation hours will most likely be able to get at least a passing grade. The optimum participation hours of this class

Figure 3.
Linear Regression between Participation Hours and Point Scores

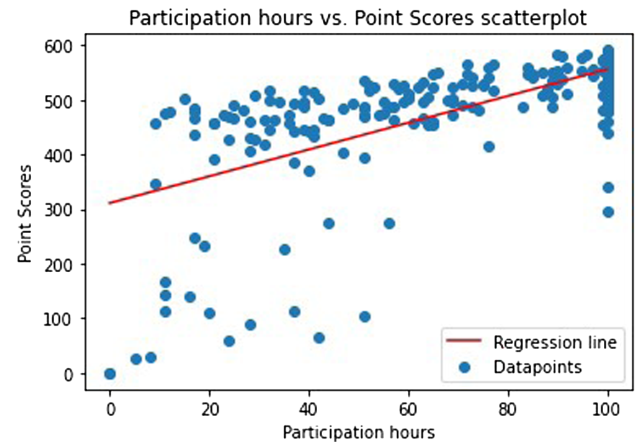
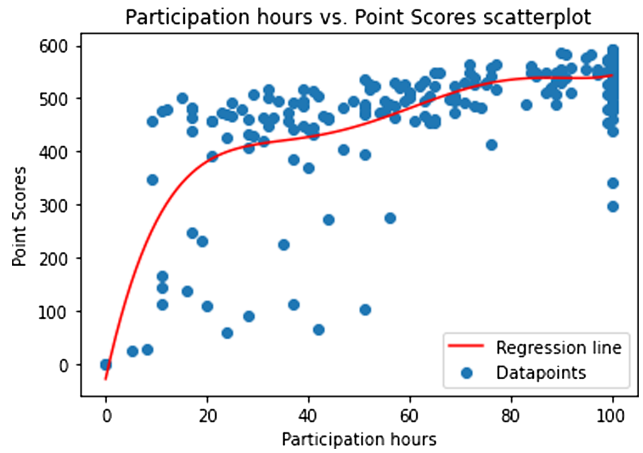


Figure 4.
Polynomial Regression of order 6 between Participation Hours and Point Scores



thus lies between 34 and 49 hours per semester as 100% participation hours is equivalent to 75 hours, or 4,500 minutes.

Conclusions and Further Studies

It can be seen from the results that there exists a positive correlation between participation hours and point scores the students achieved. Although the coefficient of determination is just a little above 50% with polynomial regression, it still indicates that more investment of participation hours by the students is associated with better point scores and grades achieved. This result somewhat differed from the cited previous studies, which found insignificant and little difference in student performance relative to the amount of time (hours) invested in the online course shell and materials. The difference may be in the structuring of the studies whereby previous investigations were on multiple and disparate classes taught by different instructors rather than the approach adopted in this study, which focused entirely on one course taught by the same professor through many succeeding semesters. Also, it was identified that to get a passing grade, i.e., 75% or 450/600 points, a student must participate somewhere between 45% and 65% of the total 75 semester participation hours.

Because, as discussed earlier, the data analyzed have been collected from a single online course taught always by a single professor and because the course content has remained mostly unchanged throughout the six years that the data have been collected, there should be little to no pre-existing bias within. However, one limitation does arise, and that is that there is no collected data with regard to the amount of self-study hours spent by the students. If such data are also incorporated in the study, then it might also be possible to identify a stronger positive correlation between hours spent and grade achieved.

The statistical analysis adopted here has given insight into associations from a targeted single asynchronous online class. A study to determine the optimum number of participation hours in tandem with the optimum number of self-study hours to achieve the highest grades may make an interesting additional or future investigation. The outcome of such a study would help students work smarter by knowing the optimum number of hours to invest for the highest performance. Beyond this, little additional improvement in scores can be expected with additional excess hours of exertion. Another investigation can be conducted to compare this asynchronous online course with other asynchronous online courses elsewhere that are individually taught by the same instructors for several semesters and that have greater student populations (in the thousands). It would be interesting to see whether the results and conclusions of this study can be revalidated or invalidated.

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