Effect of Homework on Student Learning in a University Level Mathematical Modeling Course

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Abstract

In the paper effects of homework and the number of absences on student learning are investigated using multivariate regression method. As the measure of the acquisition of students we consider the comprehensive final exam score while percentage of absences, homework scores and Midterm 1 and Midterm 2 scores are used as predictors. Our regression analysis results showed that student homework scores comes second after a second exam in explaining the variance of the comprehensive final exam scores of the course. Surprisingly, homework scores outperform the first exam as far as contribution in explaining the variance of the model. Additionally, the contribution of total homework scores is uniquely substantial.

Keywords

Homework, Mathematical Modeling, Absence, Regression

Introduction

A natural target of every effective teaching endeavor is effective student learning. Teaching an introductory level mathematical modeling course is no exception. As such, it is vital to continually check how certain methods used in the classroom work to foster student learning.

Student work in- and out-of class have been purported to consolidate student learning. Some researchers have shown that more student work foster learning while others have shown that too much of such activities may hinder the learning process.

In this study, we investigate how the components of a mathematical modeling course predict the comprehensive final exam scores.

Literature Review

Students who effectively acquire all concepts in a course have positively committed these concepts into their long-term memory. However, their success in using these concepts relies partly on their memory system reconsolidation (Sara, 2000). As described by Snow and Lohman (1989), incoming auditorial and visual stimuli such as in classroom discourses must be received and stored long enough in a sensory system, segmented or combined, and recognized, encoded, or otherwise represented in a memory system so that attention can be directed and further cognitive work can be done. Students who do not acquire concepts may store their understanding of concepts in short-term memory only, may not consolidate their memory, and thus may forget or lose retention as pointed out by many researchers (Dudai, 2004; Maren, 1999; Lee, Everitt, & Thomas, 2004). Wixted and Carpenter (2007) argued that the time-to-forgetting can best be modelled by a decaying power function. That is, without reinforcement effort to consolidate knowledge, memory of learning units may decay quite rapidly.

In the industrial setting, Jaber and Bonney (1997) discussed several learning curves to produce product that incorporate forgetting. These learning curves were investigated as function of time from initial production and from momentary stoppages of production lives. Globberson, Levin, and Shtub (1989) studied the effects of breaks on forgetting when subjects were performing repetitive tasks of data-entering 16 forms. The break length between two data entry sessions varied from 1 to 82 days. It appeared from the study that the longer the production times to create a product, the more the productivity. However, when the stoppage from production is longer, the forgetting phenomena becomes greater.

As acquisition of mathematical modelling concepts also require repetitive tasks to consolidate understanding and consolidate memory systems of concepts, work by Globberson et, al (1989) and Jaber and Bonney (1997) appear to be quite pivotal in shedding light on learning of mathematical modelling. Snow and Lohmann (1989) also stressed that an important assumption in accumulating information to build a novel train of thought has been the characteristics of the initial perception-memory-attention system, and the skills involved in working it which are fundamentally important in conditioning the success of further cognitive processing. Groen and Parkman (1972) observed that as computational skills are over-learned, response becomes quite fast. They observed that older children and adults for whom computation has become automatic rapidly respond to most types of computational problems.

One such learning instrument that involves the students at a personal level is homework. The value of such device has found some work in research literature. In recent years, the effects of homework on student performance have received some attention. On one hand, some researchers have doubted the value of homework on student success while in the other, others have reported positive effects. Some researchers focusing on the early schooling ages have reported that compulsory homework does not sufficiently improve academic accomplishment (Otto, 1950). Wildman (1968), for example, purported that when homework becomes too involved such as to deprive students of sleep social, experience, and creative activities, it works counter to the basic developmental needs of children and adolescents. Cooper (1989), however, suggested that homework, if used for instructional purposes, would be beneficial to both the instructor and the students. He further referred to homework as a cost-effective instructional device. Paschal, Weinstein, and Walberg (1984) conducted a synthesis of empirical studies on homework and found medium and significant effect sizes for homework. They moreover added that graded homework or those with teachers' comments produced stronger effects than ungraded homework.

Although homework effects have been well researched, researchers still do not agree on its relationship to student achievement. Trautwein and Koller (2003) cited much research controversy in the effects of homework on achievement especially for school aged children. One problem raised by them is the analysis unit used in previous research since such research were typically done across classrooms and student grade levels whereas the data should have been treated as multilevel. Keith, Diamond-Hallam, and Fine (2004) further conducted a longitudinal study of homework on high school grades. They found that homework done by students at home had substantial effect on high school grades while homework done during school hours had no such effects. Dettmers, Trautwein, Ludtke, Goetz, Frenzel and Pekrun (2013) considered student's emotions while doing homework in mathematics as these emotions were found earlier to affect student learning. With a multi-level longitudinal analysis of 3483 9th and 10th graders, they found that unpleasant emotions during homework sessions was negatively related to homework efforts and thus negatively predicted later mathematics achievements. Kitsantas, Cheema, and Ware (2011) further studied, across gender and race, the role of homework and self-efficacy belief as they relate to mathematics achievement in a US program for International student assessment (PISA). They found achievement gaps are reduced when mathematics resources are available. However, increased time spent on mathematics homework tend to decrease mathematics achievement. They also found that educators should devote some time to enhance students' self-efficacy with regards to mathematics. Gustafsson (2013) showed with data from 22 countries on the TIMSS 2003 and 2008 study of eighth graders that there is a positive effect of homework time on student achievement.

All research presented so far have been done at the kindergarten to high school level. However, similar interest has been reported at the university level in the past decade (see Neilson, 2005). In the course of Principles of Economics, Trost & Salehi-Isfahani (2012) reported a positive correlation between homework and midterm exam scores but not on the final exam. They suggest that homework has a positive but decaying effect over the course of the semester. Grodner and Rupp (2013) further studied the effects of homework in a Principles of Microeconomics course where students were assigned to homework-required and not-required groups. They found that students in the homework-required group had higher retention rates, higher test scores, and better grades than the other group in the course.

For the current study which is done at the university level, we study the effects of student homework on their completion of a mathematical modelling with data course. In particular, we study the effect of student homework on their comprehensive final exam score.

Objectives of the study

There are three main objectives of our study:

1. To measure the effect of homework assignments in student learning measured by the final exam score

2. To measure the effect of the number of absences in acquisition of students
3. To provide a comparison between effects of these two provided above factors and midterm exams

Method

In this paper, we investigate components of a university level mathematical modeling course in explaining the comprehensive final exam score. In particular, we examine COL110, an undergraduate level course on mathematical modeling with data offered in Zayed University. We study which component or components is/are the most influential in determining student success in obtaining comprehensive understanding of the course. We then, respectively, explain the treatment we use in delivering mathematical modeling knowledge and skills to the students and how we analyze our results.

Data

The data for this study consist of the results of Zayed University students in the Fall 2013 who are roughly 18-19 years old, typically first year students. The students are required to take the course under the mandatory general education program of University College of Zayed Uinversity. The data include students' scores on homework, two mid-term exams and a final exam as well as the percentage of missed classes. There are 69 students who took three sections of COL 110 in the Fall 2013.

Treatment

COL110 is a course on mathematical modeling with data. The course has very applied nature where EXCEL is used to organize, present and analyze data. This course has been offered at Zayed University since 2007. It is given to first year students in the University College program with the objective of preparing them for subsequent math courses and laying the background for further courses on statistics and data analysis in their majors. The course is broken up into three main units, each consisting of 5 lessons, and assessed through two major exams and a comprehensive final exam. Some of the expected course learning outcomes include:

- Extracting both, qualitative and quantitative, facts from a given data set and evaluating their relevance;
- Utilizing investigative analytical thinking and logical deductions to examine alternatives, consider multiple perspectives, solve challenging problems;
- Transfer learning skills, modes of inquiry and information to new areas or real-world problems, using technology when appropriate.

Analyses Procedure

In this section, we attempt to quantify the effects of students' efforts on their comprehensive final exam for the mathematical modeling course. To do this, we employ the multiple regression analysis procedure with the following predictors:

- Percentage of absences
- Homework scores
- Exam 1 scores and

- Exam 2 scores.

The criterion variable for this regression analysis study is the comprehensive final exam scores for the course.

Student homework for each chapter provides a basis for measuring student effort in learning the concepts in this mathematical modeling course. Unlike exams in the course, students were eligible to seek help from the instructor on hints and directions to solve a particular problem. This quest for help is typically entertained during office hours. Also, such directional questions could be asked through other means such as phone conversations and email correspondence.

Student percentage of absences scores can be considered as the anti-effort factor in the course. This is because this score does not include genuine excuses for absences such as occasional health related issues.

The two summative major exam scores provide some semi-comprehensive measures of the students' performance over a subset of the total units covered in the mathematical modeling course while the final exam score covers all units taught in the course.

First, we analyze each of the predictors above by simple regression model to see what impact each component had on predicting the criterion variable.

Then, we employ the best subset regression procedure to identify the best model and use the following criteria for the identification of the best:

- Highest explained variation as indicated by the R2
- Highest explained variation with parameter penalization as indicated by the adjusted R2
- The smallest standard error of estimation as indicated by $s\varepsilon$ and
- The closest mallow statistics Cp to p + 1.

Finally, we employ the added-last regression procedure to identify the unique contribution of each predictor in our best regression model and use the following criteria for the identification of the best predictor:

- Highest increase in explained variation as indicated by the contribution to R2 and
- Highest decrease in the standard error of estimation as indicated by reduction in $s\varepsilon$
- The results of our analyses are given in the next section.

Results

Factors of success in the mathematical modeling course were analyzed. The effects of each factor individually and when they are together with others on the criterion variable, final exam scores, are presented in this section.

In Table 1 below, effects of each of the four predictors listed in the methods section above are presented. In particular, we present the predictors in descending order with regards to the R^2 criterion. From the R^2 criterion, it seems that Exam 2 score outperforms the other predictors in explaining the variance in the criterion variable, comprehensive final exam scores. Student homework scores come second. This rank order of the predictors is also preserved when considering the adjusted R^2 and the standard error of estimates. However, when considering the C_p mallow statistics, the predictor that ranks first is the student homework scores.

Table 1. . Summary of Linear Regression of Different components on the Comprehensive Final Exam

Model	Predictors	R^2	Adjusted R^2	C_p	s_ε
1	Exam 2	59.8	59.2	24.6	0.14189
2	Homework	34.5	33.5	1.7	0.18106
3	Exam 1	33.0	32.0	84.3	0.18317
4	Absences	12.3	11	24.3	0.20953

We now know how much effect each predictor variable individually has in predicting the criterion variable, final exam scores.

We now use the multiple linear regression analyses procedure to find out how the different components work together in predicting the comprehensive final exam scores. Table 2 below summarizes the results of the best subset regression for predicting the criterion.

Table 2. Summary of Best Subset Regression Analysis of Different Course Ccomponents

Model	Predictors	R^2	*adjusted* R^2	C_p	s_ε
1	Exam1, Exam2	62.8	61.7	19.8	0.13743
2	Exam2, homework	68.8	67.9	6.4	0.12582
3	Exam1, Exam2, homework	70.5	69.1	4.7	0.12335
4	Exam1, Exam2, homework, absence	71.3	69.5	5	0.12272

From the table, it seems that the first model with the two summative major exams as predictors explains about 63% of variable in the final exam could be explained. If we replaced exam 1 with homework in the model, thus having the previously best two individual predictors, the percentage explained increases to about 69%. The standard error of estimate also reduces. The C_p mallow statistics reduces to 6.4 which is closer to p+1 of 3 than the previous statistical value of 19.8. If the two summative major exams are included together with the homework scores, the R^2 increases to 70.5% of the variance of criterion variable explained, the standard error of estimates also decreases and the C_p mallow statistics moves closer to p+1 of 4. In the fourth model where all predictors including absences are present, the R^2 increases to 71.3% of the variance explained, the standard error of estimates reduces to the minimum of 0.12272 and the C_p mallow statistic is the closest to p+1 of 5.

However, when considering the penalty of increasing more parameters into the model, the adjusted R^2 points to model 3 as the best regression model with an adjusted R^2 statistic of 69.1%. The C_p mallow statistics also points to either model 3 or model 4, but considering parsimony, the best model is then model 3 with lesser parameters and 70.5% variance of final exam scores explained.

Now that we have found the best regression model, we want to see what unique contribution each component provides in explaining the variance of the comprehensive final exam scores. Table 3 below provides the results when each component was added last into the regression model.

Table 3. Summary of Regression Analysis of Different Course Components when Added in Last

Model	Last added Predictor	C_p *before*	R^2 *before*	*Contribution to* R^2	*Reduction in* s_ε
1	Exam1	6.4	68.8	1.7	0.00247
2	Exam2	48.7	50.2	20.3	0.03567
3	Homework	19.8	60.0	10.5	0.01508

Table 3 shows that in model 1, when Exam 1 was added last, it increases the model R^2 from 68.8 to 70.5, with a contribution of 1.7%. With the addition of Exam 1, the C_p index reduces from 6.4 to 4.7 and the standard error of estimates reduces by 0.00247. In model 2, when Exam 2 was added last, it increases the model R^2 from 50.2 to 70.5, with a largest contribution of 20.3% than in model 1 or model 3. The C_p index also reduces dramatically from 48.4 to 4.7 while the standard error of estimates reduces by 0.03567.

In model 3, when Homework score was added last, the model R^2 increases from 60 to 70.5, with a second largest contribution of 10.5%. Homework score also reduces the standard error of estimates by about 0.01508 and the C_p mallow statistics from 19.8 to 4.7. From this analysis, it seems that second major exam is the most contributing predictor in the best regression model, followed by homework which outperforms the first major exam scores.

Next, we consider the best model in detail by looking at the regression estimates from the regression analysis. Table 4 provides the results.

Table 4. Summary of Regression Coefficient of the Chosen Model

Predictor	Estimated coefficients	S_{coeff}	*t*-statistic	*P*-value
Intercept	-0.02648	0.07720	-0.34	0.733
Exam1	0.23243	0.05650	4.11	0.000
Exam2	0.23750	0.12390	1.92	0.060
Homework	0.52772	0.07894	6.69	0.000

From the table, apparently the intercept coefficient is not significant at any alpha level and can be removed from the regression model. With the intercept coefficient removed, all predictors are significant at the 0.05 significance level with the final regression model given as follows:

$$\text{Final\_Exam} = 0.208\text{Exam1} + 0.527\text{Exam2} + 0.228\text{HW}.$$

Conclusion and Limitations

This study shows the effects of components of a mathematical modeling course at the undergraduate university level. From our analyses, we found that in addition to our second exam, student homework scores appear to be important in predicting how well our students would score on the comprehensive final exam for this mathematical modeling course.

As the nature and the aim of the mathematical modeling with data course are to inculcate practical hands-on data analysis skills, it is not surprising that student homework is an important predictor of student success for the course. In addition, homework is a good opportunity for students to explore their understanding (and misunderstanding) of concepts outside of class and to practice their retrieval of important concepts from the course. What seems a little surprising from our results is that the homework seems to be a better predictor of success than the first exam for the course. We venture to guess that as the final exam is comprehensive, about less than a third of the material on the final exam corresponds to the material already tested by the first exam while homework is assigned more consistently throughout the course. But a critic may say this also appears to be true for the second exam. However upon examining the nature of such mathematical modeling with data course, although the emphasis would be on the current material, a typical second exam would also build more on the skills tested before (i.e. those tested in the first exam).

The results in this study appear to support results from other previous studies that purport the benefit of homework for university courses (Cooper, 1989; Grodner & Rupp, 2013). However to the best of our knowledge, our main contribution has been that we found similar importance of student homework on a university level mathematical modeling course where such course has not yet been studied. Homework turns out to be an essential predictor of success in this course on mathematical modeling with data where students' practical skills are important.

We would like to remark that in courses where student practical work may not be the main focus student homework may not appear to be a significantly important factor as reported by studies such as by Otto (1950) and Wildman (1968). Concerns on enhancing students' self-efficacy as brought up by Kitsantas, Cheema, and Ware (2011) are addressed when students in COL110 are guided thorough the mathematical modeling experience through hands-on use of EXCEL and can consult their instructors on homework hints during office hours, by email, or by phone. Thus, for our COL110 course, the practical skills aspect of the course highlights the importance of student homework in predicting the students' success in the comprehensive final exam. This is consistent with findings by Grodner and Rupp (2013) where students who do homework are found to have better grades than those who don't.

We also found that student absence does not affect much the success in this modeling course. Worth noting is that for this study, we are not considering excessive absences which are typically regulated policy-wise at middle-eastern universities. That is, for our data, the maximum observed absence is about 13% of the classes. Had excessive absences been included, our results might have been different.

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