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Student Performance In E-Education: How Far Do Leaning Style Differences Influence Student Grades?

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ABSTRACT

This study is a quantitative-based analysis of the end-of-year examination grades from a module delivered using a mixture of classroom lectures and computer-based sessions.

It is identified that e-learning engagement had a positive and statistically significant impact on performance. An additional hour of computer-based participation is found to increase a student's mark by approximately 0.75%.

The paper also finds evidence of personal-characteristic-related differences in teaching effectiveness. It is found that female students benefited significantly less from computer-based learning than did their male counterparts. Tentative evidence is also found that students from poorer economic backgrounds obtain a greater benefit from a computer based delivery medium.

It is concluded that this study has identified two potentially significant pedagogical issues in respect to computer-based teaching. The results indicate that to improve teaching effectiveness and academic achievement, teachers should consider developing delivery strategies that maximize engagement and also take into account learning-styles differences.

KEYWORDS
computer-based-education, student engagement, learning styles, teaching effectiveness

1. Introduction

The way in which computer-based-education develops as a delivery medium will be determined through the application of pedagogical principles and also through the examination of the success or otherwise of the teaching techniques applied. As part of this process, this study explores the extent to which the *effectiveness* of computer-based-learning depends on two factors; a student's engagement in the learning process and also personal-characteristic-related differences in their learning styles.

There are numerous studies that examine e-learning teaching methods from a pedagogic theory perspective (for example, Govindasamy [1]). There are also a considerable number of studies that examine what impact different teaching styles can have on academic success. For example, Emerson & Taylor [2] found that the use of an 'experimental' approach produced better academic results in the teaching of economics than did the use of what they characterised as 'traditional' methods. In relation to computer-based teaching, some studies indicate that this medium of delivery has a positive impact on performance, for example, Smith and Hardaker [3]. Other studies however, find that it has a negative impact on performance (Johnson [4]).

Although Emerson & Taylor found their 'experimental' approach produced better academic results they did not examine the reason for this out-performance. One explanation of the differences found is that this teaching method may have been more *effective* in terms of it more closely reflecting student learning styles. An alternative explanation is that the 'experimental' approach may have encouraged greater student engagement (effort). A third explanation is that it might have been a combination of both these effects.

Carini *et al* [5] found that engagement is positively correlated with student grades. Their conclusion is supported by a number of other empirical studies. For example, Rodgers and Ghosh [6] identified that 'effort' (or engagement) was highly significant in determining examination performance. However, a study made specifically in an e-learning context by Davies and Graff [7], found no statistically-significant engagement effects. Further studies have examined what factors determine the amount of time spent on e-learning. Arbaugh [8] argues that students who spend more time on computer-based courses tend to be those who take more ownership of the learning process, and as a consequence receive the greatest learning benefit.

Differences in student learning styles may result in variations in the *effectiveness* of e-learning delivery methods for different sub-groups within the student body. The idea that different learners have different cognitive styles has been extensively examined within the learning-styles literature (Messick [9], Klob [10]). Empirical studies have identified variations in the learning styles. For example, Cranfield [11] finds learning-styles differences between students enrolled on different courses within institutions, and Garland and Martin [12] find significant gender-related differences. It is interesting to note however, that a key learning-style factor in respect to e-learning may be the student's familiarity with the technology. Dyck & Smither [13] and Atkinson & Kydd [14] have shown that computing experience is a strong predictor of attitudes towards, and also use of, computers and the internet. This suggests that learning styles adapt as familiarity with the e-learning medium increases.

This study reported on in this paper is based on a regression analysis which examines data from an undergraduate module for engagement effects and learning-style effects. The module taught statistics and data analysis skills using a mixture of traditional-lecture and computer-based methods. Students were required to: find (or collect), examine and analyse statistical data on real-world economic and social issues. The computer-based based teaching materials included: practical exercises, use of web-based information sources and also statistical analysis. All of the computer-based materials were delivered online via WebCT.

The regression model presented below is in the form of an education production function. Academic performance is modelled as being a function of: the level of engagement in the e-leaning process (hours spent online), academic ability (measured in terms of qualifications on entering university and whether qualifications were "A" levels), personal characteristics (gender, ethnic origin, home or overseas student and if the individual was a mature student on entry) and economic background (if home address is in the most deprived 25% of UK postcode areas).

$$\text{Grade} = \int(\text{e-learning engagement, academic ability, personal characteristics, economic background})$$

2. Data Description

A total of 253 students enrolled on the module. Of these 218 completed the module, with 35 withdrawing.

There was no clear pattern in respect to the types of students that withdrew. This suggests that bias is unlikely be an issue in relation to this aspect of sample selection. The withdrawal rates for the different student-characteristic-types identified in Table 1 corresponded approximately to the proportions found in the total enrolment. There was an exception in respect to gender however, where the proportion of withdrawals was relatively lower amongst female students (26% of withdrawals were female, compared to 35% of initially enrolled students). The ethnicity data exclude a number of cases from 'other' races. The household economic background measure (Deprived Bkg) relates to the student's home address and is derived from *The Indices of deprivation 2004* [15]. These indices are based on 'super output areas' (SOA). The measure used in this study is obtained by mapping the SOA against the UK postcode file. The measure itself is a dummy variable estimated using the income domain of deprivation; where one represents an observation from the lowest 25% of income SOAs. The 39 cases excluded from the sample are made up of overseas students with no UK permanent address and also a number of UK home students where the data was missing.

Table 1: Student characteristics: total enrolment

Characteristic	Total	Percentage
Female	90	35
Male	163	64
Home	220	87
Overseas	33	13
Non Mature	197	78
Mature	56	22
White	67	26
Asian	105	42
Black	41	16
Deprived Bkg	91	36
Non Deprived Bkg	123	49
Completed	218	86
Pass	195	89
Non Completed	35	14
A levels	159	63
Other Tariff	30	12

Incomplete data in respect to a number of the variables meant that only 151 of the 218 students completing the module could be used in the regression model. Table 2 presents the mean values of the dependent variable (Grade), the hours spent in computer-based engagement (Hours) and student entry qualifications (Tariff). The data shown distinguishes between the student cases who completed the module and the student cases used in the regression model (M). It can be seen in that the differences between the completion and regression model data-sets are fairly small. This is indicative of the omitted cases being broadly representative of the data-set as a whole. The module grades ranged from 17% to 84%. The fact that the full potential range of marks was not used indicates the possibility of an element of censoring in marking procedures. This issue will therefore need to be examined in the modelling process.

Table 2 shows that computer-based engagement, which is defined in terms of the hours logged into WebCT, ranged from 0.22 to 23.63 hours, with a mean of 7.92 hours and a standard deviation of 5.19 hours. The spread within the data relative to the mean indicates that there was a wide variation in the extent to which individual students engaged in the e-learning process. The hours of computer-based engagement need to be seen in the context of a module where there were 17 hours of lectures and the number of total study hours theoretical 'expected' of students was 200.

Tariff points are used to measure the academic ability of students on entry to the module. These are used in the UK in order to make comparisons between different pre-higher education qualifications. For example, between "A" level and BTEC qualifications. Where entry qualifications could not be translated into equivalent tariff points the cases were omitted from the model sample. Of the 253 students who enrolled on the module, tariff point data was available for 189 of them. Of the omitted cases mature students were overrepresented; 52% (33) were mature students, compared with 22% of mature students in the total enrolment. Possibly rather surprisingly, overseas students were marginally under represented; 11% (7) were overseas students were omitted cases compared to 13% in the total enrolment. The implication of these differences is that there is a possibility that sample selection effects may be present within the data.

Table 2: Student characteristics: module completion sample and regression model sample

Variable	Mean	St Dev	Min	Max	Sample
Grade	57.67	14.27	17	84	218
Grade(M)	59.35	14.45	17	84	151
Hours	7.92	5.19	0.22	23.63	242
Hours (M)	7.83	5.07	0.53	23.63	151
Tariff	233.65	75.63	40	420	189
Tariff (M)	233.18	74.58	40	390	151

Table A1 (see Appendix) show the variables in Table 2 in more detail for the different student-types used in the regression model. It can be seen, for example, that female students spent on average1.65 hours longer on computer-based learning than did their male counterparts. It can also be seen that, on average, females performed significantly better, with their mean mark being 7.06% higher than that of male students. The differences in performance may possibly be explained partly in terms of differences in the quality of the student intake (females averaged 15.5 tariff points more) as well as by differences in the level of engagement in the e-learning process.

3. Methodology and Results

The regression results presented in Table 3 are derived from an OLS model, with sample selection, based on a linear functional form. The results are conditional on participation in the Coventry University degree programme.

Sample selection effects were found not to be significant in respect to students dropping out of the module. However, there appeared to be possible selection effects in respect to tariff points and economic background. The model takes these into consideration using a logit selector equation following the Heckman [16] procedure. A tobit model was also tested, but as no censoring was found, these results are not presented.

There were found to be no significant instructor effects and these are therefore omitted from the model.

Interaction-effect dummy variables are used to identify any differences in the *effectiveness* of computer-based engagement for sub-groups within the student body. For example, they are used to identify if the impact on the module grade of the time spent in computer-based engagement is different for males and females.

Table 3: Regression results

Variable	Coefficient	Mean
Constant	44.9477***	
HOURS	.78600***	7.8392715
TARIFF	.06719***	233.17881
NONALEVEL	-2.84135	.8874172
GENDER	14.8051**	.3642384
MATURE	-2.3307	.0993377
ASIAN	-0.61607	.5033113
BLACK	-6.20864*	.1324503
HOME	-3.66123	.8741722
DEPRIVED BKG	-6.66394**	.3907285
ECON_ INT	1.72291	.7329082
GENDER_ INT	-5.18698*	.7260912
SELECTION TERM	-5.21783	0.119658
R^2 =0.343	Adj R^2 = 0.285	
Sample= 151	Mean X=59.35	
*** = significant at 1% ** = significant at 5% * = significant at 10%		

Table 3 shows that HOURS (computer-based engagement) has a positive, and statistically significant, impact on the module grade. An extra hour of engagement increases the module grade by 0.786%. This can be seen the context of a mean module grade of 59.35% (model sample) and of students spending on average 7.83 hours on computer-based learning. With a standard deviation of 5.07 hours, differences in computer-based engagement can be viewed as accounting for 3.99% of the variation in the grade of students within the model sample. These findings suggest that academic performance could be improved by encouraging more active engagement of students in the computer-based learning process.

These results can be contrasted with the findings of Davies and Graff [7] that e-leaning participation had no statistically-significant impact on performance. One possible explanation of this difference is pedagogical. It may well be that the types of materials covered in this statistics-based module (such as data analysis skills and statistical analysis skills) are more effectively delivered in a computer-based learning environment than are the types of materials delivered in less quantitative modules. It can also be noted that other cross-institution studies, for example Rodgers [17], have found that the general ‘effort’ level is an important explanatory variable in determining student performance. The results of these studies add credence to the view that the findings of a significant relationship made in this paper are not unexpected.

Student academic ability, as measured in terms of entry qualification tariff points, is also statistically significant. On average students were entering the module with 233 points. This average can be seen in the context of “A” levels which are the most common entry qualifications (students will normally take three “A” level subjects. The pass grades of these are A to E, where each grade represents 20 points). The regression coefficient (TARIFF) shows that an improvement of one grade, in a single subject, will increase the module grade by 1.34%. As the standard deviation for tariff points is 74.6, the model suggests that in terms of the ‘average’ student, differences in entry qualifications account for 5.1% of the variation in the module grade. The model developed also includes a dummy variable in respect to non "A" level tariff point entry qualifications (NONALEVEL). The negative sign suggests that students from other academic backgrounds under-perform. However, it should be noted that this variable is only significant at the 75% level.

Some of the student personal-characteristic variables also play a significant role in explaining module grade variation. The dummy variable GENDER indicates that female students, after controlling for other factors, out-performed their male peers by almost 15%. Gender differences are consistent with other studies in this area (For example, Smith and Naylor [18]). The omitted base-case in respect to ethnicity effects are students of white and 'other' ethnic origins; the BLACK ethnic origin group under-performed these by 6.2%. The ASIAN ethnic group however showed no statistically significant difference in performance.

The model indicates that economic background of a student is also a statistically significant factor. Students, whose home address was in the bottom 25% of income level neighbourhoods, under-performed by 6.6%.

The interaction term between gender and hours of computer-based learning participation (GENDER_INT) has a coefficient of -5.187. This indicates that, after controlling for hours of e-learning engagement, the beneficial effects of e-learning on the examination grades of female students was in the region of 5% less than it was for their male counterparts (this is despite the overall performance of female students being considerably better). Although this interaction effect is only statistically significant at the 10% level, it provides evidence to support the claims found in the literature of differential learning-style effects in student performance. For example, Gilbert *et al* [19] identified that many students do not learn in the systematic way implicit in the structure of computer-based learning packages. They found that different students use material in different sequences and were often selective in their e-learning interactions and readings.

It can be tentatively inferred from the results of this study that there may very well be systematic learning-style differences in the ways in that male and female students approach computer-based learning. This would be consistent with the findings of Garland and Martin [12] of gender-based differences in the ways that male and female students interact with online teaching resources. They concluded that the online instructors need to be aware of these differences when developing their teaching material. It may possibly be that the negative interaction effect found for female students in this study may be the result of the structure of the teaching material reflecting the learning style of the male academic who developed it.

This study also found some tentative evidence to suggest that there was an interaction effect between economic background and hours of computer-based learning participation. The coefficient of 1.722 (ECON_INT) suggests that, after controlling for other factors, students from a poorer economic background benefit more from computer-based learning material than do their better-off background counterparts. It should be noted however that this coefficient is only statistically significant at the 75% level. It is possible that this result could reflect learning-style differences in students from different socio-economic backgrounds.

Finally, it can be noted that the SELECTION TERM is not significant. This term controls for differences between the students included in the sample and those omitted from the sample.

4. Conclusions

This study finds that greater computer-based learning engagement leads to better academic performance. The results are robust in respect to sample selection bias and also censoring in the dependent variable.

The paper also provides evidence of the impact on academic performance of mismatches between teaching styles and learning styles. It is found that, after controlling for other factors, female students benefited less from computer-based teaching than did males. Tentative evidence was also found of learning-style effects in relation to students' economic backgrounds.

The existence of personal-characteristic-related differences in the effectiveness of computer-based teaching is consistent with Klob's learning style inventory [10]. These effects could be interpreted as suggesting that computer-based teaching in higher education may be better suited to the learning styles of certain student-types. A more positive inference would be to follow Zapalska and Brozik [20] suggestion that the teaching strategies of online courses should reflect the learning methods of all types of learners.

The main recommendation of this paper for web-based education practitioners is that paying greater attention to different student learning styles is likely to lead to an improvement in academic achievement on computer-based courses. It may very well be possible to adjust teaching styles to cater for the needs of specific groups; for example, where there are large numbers of internationals students, or where there is a major gender imbalance. It may also be appropriate to give additional instruction on how to use of computer-based material to students with little previous experience of this medium. This is because the evidence suggests that experience is a good predictor of attitudes to, and use of, this type of material (Dyck & Smither [13]). An alternative possible approach might be to develop student learning groups with mixed levels of computer experience in order to encourage greater peer-to-peer learning. The experience of the current author is that both home and international students with a limited computing background tended to find e-learning based material difficult. It may very well be that in some cases we need to 'teach students how to learn' using this medium before we use it as a tool to teach them the subject itself.

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Appendix

Table A1: Hours of e-learning engagement, module grade and tariff points by: gender, country of origin, maturity status, ethnic origin, depravation status, "A" level entry (using regression model sample)

		Hours		Grade		Tariff points	
Characteristic	**Sample**	**Mean**	**StDev**	**Mean**	**StDev**	**Mean**	**StDev**
Female	55	8.89	5.25	63.84	12.89	243	66.77
Male	96	7.24	4.9	56.78	14.73	227.5	75.47
Home	132	7.91	5.09	58.97	14.16	233.5	76.9
Overseas	19	7.43	5.08	62.03	16.47	233.1	57.5
Non Mature	136	7.48	4.62	59.78	14.03	237.9	72.4
Mature	15	11.07	7.56	55.33	17.89	190.6	83.3
White	41	7.86	4.39	63.76	13.04	271.7	75.06
Asian	76	8.02	5.414	58.97	14.01	226.3	66.9
Black	20	7.23	5.20	52.3	17.7	193.5	76.6
Deprived Bkg	59	7.34	5.061	54.86	13.88	222.9	73.2
Non Deprived Bkg	92	8.16	5.09	62.23	14.15	239.8	75.1
A levels	133	7.66	4.76	58.8	14.34	58.7	14.39
Other Tariff	18	9.16	6.99	63.5	14.65	235.5	64.4