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Student engagement in the e-learning process and the impact on their grades

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ABSTRACT

This paper presents the results of a study that examines the impact on end-of-year examination grades of the level of student engagement in the e-learning process. The study relates to a level one undergraduate module delivered using a mixture of traditional lectures and e-learning based methods.

Greater online interaction is found to have a positive and statistically significant impact on performance. One extra hour of e-learning participation is found to increase the module mark by approximately one percent.

The paper also examines the data for the presence of interaction effects between e-learning engagement and personal characteristics. This is undertaken to identify whether or not personal-characteristic-related learning style differences influence the extent to which students benefit from e-learning. It is found that, after controlling for other factors, female students benefited less from e-leaning material than their male counterparts. Tentative evidence is also found of a negative interaction effect in relation to overseas students.

It is concluded that in order to improve teaching effectiveness and academic achievement, higher education should consider aiming to develop e-learning teaching strategies that encourage greater engagement and also take into consideration the different learning styles found within the student body.

Keywords: e-learning, student engagement, learning styles, interaction effects

Introduction

As the use of e-learning is becoming more and more widespread in higher education it has become increasingly important to examine the impact that this teaching style has on student performance. There is a considerable body of evidence to suggest that different teaching delivery styles can have different degrees of effectiveness; as measured in terms of academic results (Emerson & Taylor, 2004). Some studies suggest that *online* teaching methods have a positive impact on performance, for example, through the promotion of greater student-centred learning (Smith and Hardaker, 2000). Other studies however suggest that greater online teaching can also have a negative impact on performance, such as through peer alienation (Johnson, 2005).

This paper examines what impact *the level of engagement* in the e-learning process had on student academic performance in a level one undergraduate Data Analysis Skills and Statistics module. The module was taught using a mixture of traditional lecture and e-learning methods. In the context of the Emerson and Taylor study, the teaching style of the e-learning element of this module could be characterised as being ‘experimental’ and ‘hands-on’. Students were required to: find (or collect), examine and analyse statistical data on real-world economic and social issues. The online based teaching materials included: practical exercises, use of web based information sources and the access to lecture notes. All of the e-learning based materials were delivered via WebCT. Emerson and Taylor found that the ‘experimental’ method produced better academic results than what they characterised as being ‘traditional’ methods. Their study made no attempt however to examine whether these better results were due to the teaching methods being more efficient, in terms of developing students’ understanding of the material, or whether they were better because the ‘experimental’ approach encouraging greater student engagement or effort. Previous work by this author (Rodgers and Ghosh, 2001) identified that ‘effort’ (or engagement) levels were highly significant in determining student examination performance in a non e-learning context. However, another study made in an e-learning context by Davies and Graff (2005), found that the amount of time spent online had no statistically-significant impact on examination performance.

The second objective of this paper is to identify any differential impact in the *effectiveness* of e-learning on individual sub-groups within the student body. The notion that different learners have different cognitive styles has been extensively examined in the literature (Messick, 1976; Klob, 2000). In addition to be general evidence, there is a considerable support in the literatures for the suggestion that there are identifiable variations in the learning styles of sub-groups within the student population. For example, Cranfield (1998) finds specific learning-styles differences between students enrolled on different courses within institutions. In addition, Garland and Martin (2005), and also Blum (2005), find evidence of significant gender-related differences in learning styles. Findings such as these have led some commentators to conclude that it may be advantageous to take into consideration different learning styles when developing online courses (Cooze and Barbour, 2007).

The study that this paper reports on is based on a regression analysis that uses data from a mixed group of 113 Economics, Accounting and Finance students. The regression model developed is based on an education production function approach. Student performance, as measured in terms of the end-of-year final module mark, is modelled as being a function of: the level of engagement in the e-leaning process (hours spent online), academic ability (qualifications on entering university), personal characteristics (gender, ethnic origin, home or overseas student and if the individual was a mature student on entry) and the subject of study.

$$Module\ \ Mark\ = \int \begin{pmatrix} e-learning\ \ engagement\ , \ academic\ \ ability\ , gender\ \ ethnic\ \ origin\ , \\ \text{hom}\ \ e/oversea\ \ , if\ \ mature\ \ on\ entry\ , \ subject\ \ area \end{pmatrix} \quad [1]$$

Data Description

A total of 181 enrolled on the module. These were a mixture of Economics (48) and Accounting/Accounting-and-Finance (133) students. As 36 withdrew during the year 145 completed the module.

There was no clear pattern in relation to the types of students that withdrew. This indicates that bias is unlikely be an issue in respect to this aspect of sample selection. The rates of withdrawal in the different student-characteristic-type sub-groups identified in Table 1 corresponded approximately to the proportions found in the total enrolment. The only exception was gender, where the proportion of withdrawals was relatively higher amongst female students (41.7% of withdrawals were female, compared to the 35.9% of initially enrolled students that were female).

Table 1: Student characteristics: total enrolment

VARIABLE		SAMPLE	PERCENTAGE
Gender-	Female	65	35.9
Gender-	Male	116	64.1
Origin-	Home	156	86.2
	Overseas	25	13.8
Age-	Non Mature	137	75.7
	Mature[1]	44	24.3
Ethnic origin[2] –	White	45	24.9
	Other	136	75.1
Degree type -	Economics	48	26.5
	Accounting/Finance	133	73.5
Completion status-	Completed	145	80.1
	Non Completed	36	19.9
	Pass rate	132	91.0

Incomplete data in respect to student entry qualifications meant that only 113 of the 145 students completing the module could be used in the regression model. Table 2 presents the mean values of the dependent variable (Module Mark), the hours spent in e-learning engagement (Hours) and student entry qualifications (Tariff Points). The module mark and e-learning

[1] Mature students are those aged 21 or over on entry.
[2] Within the data 14 different ethnic categories were identified. However, data constraints mean that only 2 categories were used.

engagement data in this table distinguishes between the student cases who completed the module (Completing Sample) and the student cases used in the regression model (Model Sample). The entry qualifications data distinguishes between the total enrolment cases (Enrolment Sample) and the cases used in the regression model. It can be seen in Table 2 that the overall 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. For example, the mean mark of 59.42% for the 113 observations in the Model Sample is only marginally higher than the mean mark of 58.26% in the Completing Sample.

The module mark ranged from 9.7% to 84.8%. The fact that the full potential range of marks was not used indicates the possibility of an element of censoring in the marking process at both ends of the distribution. If the data has been censored then biased results will be produced by OLS regression. The possibly of censoring will therefore need to be examined in the modelling process.

Table 2 shows that e-learning engagement, as defined in terms of the hours logged into WebCT, ranged from 1.4 to 29.4 hours, with a mean of 9.2309 hours and a standard deviation of 5.63 hours[3]. 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. These differences may possibly be partly due to e-learning based teaching methods better reflecting the learning styles of certain types of student[4]. The hours of e-learning 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 181 students who enrolled on the module, tariff point data was available for 142 of them. Of the 39 omitted cases three student-type categories were overrepresented; 53.8% (21) were mature students, compared with 24.3% of mature students in the total enrolment, 94.9% (37) were from a non-white ethnic origin compared to 75.7% in the total enrolment and 41% (16) were overseas students compared to 13.8% in the total enrolment. These differences are not unexpected. Mature students often enter university with non-standard qualifications that cannot be converted into tariff points. It is also not possible to make direct comparisons between tariff points and most overseas qualifications. The implication of these differences is that there is a possibility that sample selection effects will be present in the data.

[3] All hours are shown as decimals.
[4] There is no way of testing whether or not this is the case from the data and therefore this can only be conjecture.

Table 2: Student characteristics: sample of students enrolling on/completing the module and regression model sample

VARIABLE		SAMPLE	MEAN	ST DEV	MIN	MAX
Module Mark	Completing Sample	145	58.26	14.77	9.7	84.8
	Model Sample	113	59.32	13.4	9.7	84.8
Hours	Completing Sample	145	9.29	5.63	1.4	29.4
	Model Sample	113	9.309	5.61	1.4	29.4
Tariff Points	Enrolment Sample	142[5]	228.08	66.21	120	420
	Model Sample	113	230	64.2	120	420

Tables A1 A2 and A3 (see Appendix) show the three variables in Table 2 in more detail for the different student-type groups used in the regression model. It can be seen, for example, that female students spent on average 4 hours longer on-line than their male counterparts and that on average females performed significantly better, with their mean mark being 5.56% higher than male students (63.32% compared to 57.74%). The differences in performance may possibly be explained partly in terms of differences in the quality of the student intake as well as by differences in the level of engagement in the e-learning process. For example, in Table A3 the tariff entry points of female students are shown to be on average 16.5 points higher than those of their male counterparts.

Methodology and Results

The results from the model developed are presented in Table 3. They are based on a linear functional form OLS regression model with sample selection. These results are conditional on participation in the Coventry University degree programme[6].

Sample selection effects were found not to be significant in respect to students dropping out of the module. However, there appear to be possible selection effects in respect to tariff points. The model takes these into consideration using a logit selector[7] equation. A tobit model was also tested[8], but as no censoring was found, these results are not presented.

There were also found to be no significant instructor effects and these are therefore omitted from the model. The lack of such effects is probably due to computer-workshop-based e-learning tutors following a fully proscribed set of teaching materials developed by the module leader. The role of the e-learning tutor was effectively one of being a facilitator.

The differential impact in the *effectiveness* of e-learning on various sub-groups within the student body is identified using a series of interaction effect dummy variables. These measure the interaction between hours of e-learning engagement and specific personal characteristics. The interaction effect variables presented in Table 3 are in

[5] This is the total number of enrolled students for whom tariff point data was available. It differs from the sample of those who completed the module because it includes a number of non-completing students and also excludes those who completed the module and for whom tariff point were not available.

[6] The academic 'quality' of the students following this programme at Coventry University cannot be taken as being representative of the 'average' student in UK higher education. See, for example, Coventry University student entry qualification points relative to other UK higher education institutions in the Times Newspaper 'Good University Guide'. (http://www.timesonline.co.uk/tol/life_and_style/education/good_university_guide/article671847.ece). Access date: 15/01/2008.

[7] Heckman (1979) showed that the expected error in the OLS equation can be controlled for by including a term based on the predicted probability of inclusion in the sample. This term was estimated using a logit model. This logit model correctly predicted 92% of the cases included in the model.

[8] Lower and upper limits were tested at 9% and 85% respectively

respect to: female gender (INTGEN), overseas student (INTHO), mature student (INTMAT), from a white ethnic origin (INTETH) and being an economics degree subject student (INTECO).

Table 3: Regression results

Variable	Coefficient	Mean
Constant	40.156***	
HOURS	1.035***	9.218
TARIFF	0.052***	230.177
HOVER	27.220**	0.062
GENDER	10.344**	0.327
ETHNIC	-6.240	0.301
MATURE	1.137	0.168
ECON	-3.818	0.301
INTGEN	-0.844**	3.618
INTHO	-1.380*	0.584
INTETH	0.422	3.027
INTMAT	0.012	1.472
INTECON	0.271	2.766
LAMBDA	-9.931	0.272
R^2 =0.31	Adj R^2 = 0.23	
Sample= 113	Mean X=59.32	
*** = significant at 1% ** = significant at 5% * = significant at 10%		

The coefficient on HOURS indicates that the level of engagement in e-learning has a positive, and statistically significant, impact on the module mark. An extra hour of engagement increases the module mark by 1.035%. This can be seen the context of a mean module mark of 59.32% and of students spending on average 9.218 hours of e-learning on this module. With a standard deviation of 5.61 hours, differences in e-learning engagement can be viewed as accounting for 5.81% of the variation in the mark of students within the sample. These findings suggest that academic performance could be improved by encouraging more active engagement of students in the e-learning process.

These results can be contrasted with the finding of Davies and Graff (2005) that the level of e-leaning participation had no statistically-significant impact on the module examination performances of level one business studies students. 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 an e-leaning 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 (2007), have found that the general ‘effort’ level (as opposed to the specific e-learning effort levels) is an important explanatory variable in determining student examination 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[9].

[9] In should be noted that this study does not control for student ‘effort’ levels outside of the e-learning environment. The omission of such a variable in the model is possibly one on the reasons for the relatively low R^2. The possibility that the omitted term may be correlated with the independent variables mean that the regression results should to be treated with some degree of caution.

Student academic ability, as measured in terms of tariff points, is also statistically significant. On average students were entering the module with 230 points. This average can be seen in the context of “A” levels (which were the most common entry qualifications[10]), where each “A” level grade represents 20 points. The regression coefficient (TARIFF) indicates that an improvement of one grade will increase the module mark by 1.03%. As the standard deviation for tariff points is 64, the model suggests that in terms of the ‘average’ student, differences in entry qualifications account for 3.3% of the variation in the module mark.

Student personal characteristics also play a significant role in explaining the module mark variation. The dummy variables for gender and overseas students proved to be statistically significant. However, ethnic origin, subject of study and whether or not students were mature were all insignificant. The model indicates that female students, after controlling for other factors, out-performed their male peers by a significant margin. This is consistent with other studies in this area (For example, Smith and Naylor, 2001).

A negative value was found on the interaction term between female students and e-learning participation (INTGEN). The coefficient of -0.844 indicates that, after controlling for other factors, the beneficial effects of e-learning on the examination grades of female students was in the region of 1% less than the beneficial effects on the grades of their male counterparts (this is in spite of the overall performance of female students being considerably better than that of males). Although the size of this interaction effect is small it is statistically significant. This provides evidence to support the claims found in the academic literature that different student-types have different learning styles. For example, Gilbert *et al* (2007) identified that many students do not learn in the systematic way implicit in the structure of many e-learning packages. They found that students were using e-learning materials in different sequences and were often selective in their e-learning interactions and readings.

It is possible to tentatively infer from the results of this paper that there may very well be systematic differences in the ways that male and female students learn in an e-learning context. This would be consistent with the findings of Garland and Martin (2003) who use the Klob (2000) learning style inventory to examine gender based variations in e-leaning styles and e-learning engagement. They found clear gender-based differences in the way that male and female students interacted with online teaching resources. From this they concluded that the online instructors need to be aware of these differences when developing their teaching material. The e-learning package used in the study made in this paper was developed by a male academic. The negative interaction effect found for female students may therefore possibly be the result of the structure of the teaching material reflecting a male learning style.

This study also found some tentative evidence to suggest that there was an interaction effect between a student’s country of origin and e-learning participation. The coefficient of -1.38 (INTHO) suggests that, after controlling for other factors, overseas students benefit less from e-learning material than their home student counterparts. Although this coefficient is only statistically significant at the 10%

[10] Students will normally take three “A” level subjects. The pass grades of these are A to E.

level, similar conclusions to those made in respect to gender can be tentatively inferred. It may very well be that there are systematic differences in the ways that home and overseas students use e-learning materials[11] and it could also be the case that the e-learning teaching materials developed by a Western academic are more suited to the learning styles of Western students rather than those of overseas students.

The interaction effect term in relation to degree subject, which was in respect to students studying for an Economics degree (INTECON), was not significant. The lack of significance is not unexpected given that there were no major differences in the academic backgrounds of the students in the two subject areas. This finding does however runs counter to those of Bilerman and Buchanan (1986) who identified significant between-subject learning style differences in business related subject areas. Their results may possibly be explained in terms of the variation in learning styles between modules reflecting students adjusting to module-based variations in teaching styles rather than reflecting student-based differences in learning styles.

The study found no significant interaction term in respect to students being mature on entry (INTMAT) or being from a white ethnic group (INTETH). The lack of an age related effect is possibly a little surprising given that mature students are less likely to be familiar with e-learning methods from their secondary education. It may well be however that as information technology is now pervasive in most aspects of life they have gained experience of this technology from non-educational sources. The lack of a significant ethnic group related interaction effect is possibly to be expected. This is because, for home based students at least, the learning styles that students experience in secondary education are very similar for both the white and non-white ethnic groups.

Finally, it can be noted that the selection term (LAMBDA) is only significant at the 70% level. This term controls for differences between the students included in the sample and those omitted from the sample.

Conclusion

This study of Economics, Accounting and Accounting/Finance students on a level one undergraduate module finds that greater e-learning engagement leads to better academic performance. The results are robust in respect to a number of potential sample selection bias issues and also in respect to the possibility of censoring in the dependent variable.

After controlling for student personal characteristics, it was found that one extra hour of e-learning engagement increase the module mark by 1.035%. Given a sample standard deviation of 5.61 hours, differences in e-learning engagement can be viewed as accounting for 5.81% of the variation in student marks. These findings suggest that academic performance could potentially be improved by developing teaching strategies that encourage greater student engagement in the e-learning process.

The paper also provides evidence of the impact on academic performance of mismatches between e-teaching styles and e-learning styles. Evidence is found of

[11] Zhenhui (2001), for example, found that traditional East Asian leaning styles differ significantly from the teaching styles of Western universities. East Asian learning styles were found to be largely teacher-centred and book-centred and it was suggested that this can result in a mismatch between the teaching and learning styles of non-Asian universities and their Asian students.

personal-characteristic related differences in the *effectiveness* of the online teaching process. It is found that, after controlling for other factors, female students benefited less from e-leaning than did their male counterparts. The study also found some tentative evidence to suggest that there was an interaction effect between a student's country of origin and e-learning effectiveness.

The existence of personal-characteristic-related interaction effects can be viewed as indicating that e-learning in higher education may be better suited to the learning styles of certain student-types. A more positive inference that could also be made is that when develop e-leaning based modules academics need to pay greater attention to the learning styles of the different sub-groups within the student body. Zapalska and Brozik (2006), for example, suggest that the teaching strategies of online courses should reflect the learning methods of all types of learners. Some of the proposed solutions to this problem may however prove difficult to implement. Blum (2005), for example, suggested the use of separate-gender teaching groups. Whether or not many higher education institutions would have the resources to implement such an approach is open to question.

If it is eventually possible to find e-teaching methods that can accommodate different e-learning styles then we are likely to see an improvement in overall student academic achievement on e-learning based courses.
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Appendix

Table A1: Hours of e-learning engagement by: gender, country of origin, maturity status, ethnic origin and subject of study (regression model sample)

VARIABLE		SAMPLE	HOURS	STDEV
Gender-	Female	37	11.328	6.25
Gender-	Male	76	8.326	5.02
Origin-	Home	104	9.208	5.6
	Overseas	9	10.638	5.91
Age-	Non Mature	93	9.316	5.69
	Mature	20	9.276	5.38
Ethnic origin –	White	34	10.059	6.73
	Others	79	8.987	5.07
Degree type -	Economics	34	9.193	5.59
	Accounting/Finance	78	9.359	5.65

Table A2: Average student marks by: gender, country of origin, maturity status, ethnic origin and subject of study (regression model sample)

VARIABLE		SAMPLE	MEAN MARK	ST DEV
Gender-	Female	37	62.32	11.25
Gender-	Male	76	57.74	14.08
Origin-	Home	104	58.61	13.61
	Overseas	9	67.53	3.43
Age-	Non Mature	93	59.61	13.24
	Mature	20	57.488	14.01
Ethnic origin –	White	34	60.47	15.93
	Others	79	58.712	12.14
Degree type -	Economics	34	58.48	14.72
	Accounting/Finance	79	59.56	12.73

Table A3: Student tariff points by: gender, country of origin, maturity status, ethnic origin and subject of study (regression model sample)

VARIABLE		SAMPLE	TARIFF	SD DEV
Gender-	Female	37	238.61	82.12
Gender-	Male	76	222.10	59.9
Origin-	Home	104	227.52	68.97
	Overseas	9	225.71	54.11
Age-	Non Mature	93	230.10	66.67
	Mature	20	214.21	74.48
Ethnic origin –	White	34	251.47	75.88
	Others	79	216.92	61.79
Degree type -	Economics	34	234.11	68.84
	Accounting/Finance	78	224.48	67.77