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The Internet in face-to-face higher education: Can interactive learning improve academic achievement?

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Abstract

Recent research on e-learning shows that blended learning is more effective than face-to-face learning. However, a clear empirical response has not been given to the cause of such improvement. Using a data set of 9044 students at two Catalan universities and a quasi-experimental approach, two possible hypotheses identified in previous research are studied. The results show that the principal cause of the improvement is not, in itself, the increase in time spent online for educational purposes. Rather, increasing the time devoted to studying online is only useful when it takes place as some form of interactive learning. The educational implications of these results are discussed.

Introduction

Internet use in higher education has grown exponentially in recent years (Allen & Seaman, 2010; OECD, 2010; Smith Jaggars & Bailey, 2010). However, with regard to improving students' achievement, there is no agreement in the literature on what the benefits of Internet use are.

Empirical research on the effectiveness of e-learning has focused mainly on comparing the results of fully computer-mediated teaching with those of face-to-face teaching (comparison of means). In such research, the results are often inconclusive and occasionally contradictory. Indeed, more recent meta-analyses generally tend to show that there are no significant differences in the level of learning that students achieve (Bernard *et al*, 2004; Means, Toyama, Murphy, Bakia & Jones, 2009).

No significant differences between the effectiveness of online and face-to-face learning have been detected in recent research either. However, the incorporation of the Internet into face-to-face education has indeed been shown to have beneficial effects on academic achievement (Means *et al*, 2009; Tamim, Bernard, Borokhovski, Abrami & Schmid, 2011).

The incorporation of technology into education is not a homogenous intervention (Ross, Morrison & Lowther, 2010). Today, the Internet can be used to accomplish various types of learning (Means *et al*, 2009):

Practitioner Notes

What is already known about this topic

- The incorporation of technology into education is not a homogenous intervention.
- Blended learning is often more effective than face-to-face learning.

What this paper adds

- This paper explores what causes blended learning to be more effective than face-to-face learning.
- The principal cause of the improvement is not, in itself, the increase in the time spent studying that using the Internet for educational purposes may entail.
- Increasing the time spent studying online is only useful when it takes place as some form of interactive learning.

Implications for practice and/or policy

- To maximise the time spent studying online, it is beneficial to interact with other actors in the learning process.
- Incorporating the Internet as an interactive learning catalyst is an effective strategy to get the maximum benefit from the investment made in that technology.
- Online interaction is especially relevant to the study of academic achievement inequality that the incorporation of the Internet can introduce into higher education systems.

1. Expository, where content is transmitted unidirectionally via the technology.
2. Active, where students use the technology individually to explore information and solve problems.
3. Interactive, where the technology mediates human interaction and knowledge emerges from such interaction.

In addition, the different learning modalities are often linked to different learning conditions. In this respect, Means *et al* (2009) point out that Internet use in education cannot be compared with face-to-face education because Internet use was usually associated with different curricula, although nowadays the curricula are often the same. Furthermore, Internet use may lead to longer study times and greater interaction.

Therefore, the higher academic achievement of students on blended learning courses compared to those on fully face-to-face courses (for a detailed review of research on this issue, see Tamim *et al*, 2011) cannot be explained as something intrinsic to the incorporation of the Internet into education, but rather as a consequence of the different instructional conditions that may be associated with the technology. However, while the conclusions of such studies (Means *et al*, 2009; Ross *et al*, 2010) highlight the need for further research to elucidate what the conditions are that make blended learning improve achievement, the data analysed in the studies reviewed do not allow this question to be answered.

Aim

In this research paper, we shall go a stage further and answer the following questions in the context of higher education:

- With an equivalent curriculum, is increasing the time spent studying online always effective in terms of improving academic achievement?

- With an equivalent curriculum, does the greater capacity of online instruction to incorporate interaction have a beneficial effect on improving academic achievement?

For our analytical objectives, we divided the three types of learning that can be accomplished online into two: interactive learning and individual learning, the latter of which encompasses the categories of expository learning and active learning. On the basis of this division, we shall compare the effects of making an intensive use of the Internet to accomplish interactive learning with the effects of making an intensive use of the Internet for other, more individual types of learning activities.

Taking account of the fact that the indicators measuring both treatments are comparable with respect to the weekly number of hours that students spend on each one, if it is shown that Internet use for interactive learning is more effective than Internet use for individual learning, then it will be possible to support the hypothesis that the principal element that makes the incorporation of e-learning effective is its capacity to increase the potential for interaction in the learning process.

Data and methods

Data

We used an online questionnaire to obtain the necessary data for the research. In 2006, the questionnaire was sent out to all students attending two Catalan universities of different types. A generalist university (University of Barcelona) and a technical university (Universitat Politécnica de Catalunya. BarcelonaTech). These data were complemented with information from the Government of Catalonia's administrative registers of academic achievement.

The differences between the two universities studied allowed us to access a variety of students that made the results less dependent on the type of degree courses offered and on the curricula and teaching–learning strategies of each university.

The information gathering method (online questionnaire sent via institutional email services) allowed those students that had dropped out of their studies (the number of students with zero credits passed was 3.37% from the sample and 7.6% from all students of the three selected universities) and that were not Internet users to be excluded, since a lack of response to the questionnaire served as a filter to eliminate those students for whom the effect of the Internet on achievement would be zero, either because they did not use the Internet or because their achievement was equal to zero.

In total, information was available on 8046 students. The characteristics of the students were similar to the characteristics of all students of the three universities studied as a whole, other than the variables for academic achievement and Internet usage (time). Given the high number of individuals in the study, the results obtained have greater external validity than those obtained in the majority of experimental studies on the effect of Internet use in education.

Treatment measurement and output

In order to meet the proposed objectives, we divided the types of learning that can be accomplished online into two: interactive learning and individual learning, the latter of which encompasses the categories of expository learning and active learning.

The items used to measure the degree of Internet use for learning are dichotomous variables, which include the students' answers to a set of questions on whether they had used the Internet for different academic purposes. Five of such uses were defined as individual learning (searching for information, looking up teaching plans and bibliographical references, looking up course materials, work with bookmarks and subscription to mailing lists on the study area) and four as interactive learning (communicating with lecturers, communicating with fellow students, online

Table 1: Descriptions of indicators of Internet use in education

	%	n
Interactive learning		
Communicating with lecturers	67.51	5432
Communicating with fellow students	50.30	4047
Online discussions on the study area	23.50	1891
Cooperative work	63.86	5138
Individual learning		
Searching for information	93.57	7529
Looking up teaching plans and bibliographical references	87.12	7010
Looking up course materials	87.70	7056
Work with bookmarks	39.50	3178
Subscription to mailing lists on the study area	19.60	1577

Table 2: Descriptions of academic achievement measures

	Mean	*Standard deviation*
Credits enrolled	61.69	17.99
Credits passed	46.10	21.89
Achievement rate	74.57	28.55

discussions on the study area and cooperative work). Table 1 shows the percentage of students who claim to use the Internet for each of the proposed purposes.

In order to elaborate indices of use for each type of learning (individual and interactive), the number of uses from those described previously was totalled. The result of this operation is an ordinal variable reflecting the number of different uses that each student makes of the Internet in each of the proposed types of learning (individual and interactive). So the maximum is five uses for individual learning and four uses for interactive learning.

In the analyses performed, students with intensive Internet use for individual learning were considered to be those making four or five of the uses defined as such (36.73% higher), and students with intensive Internet use for interaction to be those making three or four of the uses in that category (39.01% higher).

In order to measure academic achievement in the 2005–2006 academic year, the official measure contained in the Government of Catalonia's databases was used: percentage of credits passed in the academic year over the number of credits enrolled (see Table 2), excluding credits for which official recognition (and therefore exemption) had been obtained. Credit data were aggregated by year and, therefore, include both semesters of that academic year.

Methods

The stated objective poses a common challenge in educational research: that of estimating the causal effects of two treatments on the basis of data from a non-experimental observational design (Schneider, Carnoy, Kilpatrick, Schmidt, & Shalvelson, 2007). In our case, we are interested in establishing what the impact on students' academic achievement is of both treatments: intensive Internet use for interactive learning and intensive Internet use for individual learning.

In order to calculate the impacts, we used the counterfactual framework proposed by the philosophy of science, operationalised in the classic Roy–Rubin model (Roy, 1951; Rubin, 1974). This framework defines the treatment effect as the difference between the output an individual has after receiving the treatment and the output she or he would have had if she or he had not received it. The fundamental problem associated with this approach lies in the fact that, in practice, it is impossible to know about the counterfactual event that has not actually taken place.

The statistical solution to this problem consists in calculating the average treatment effect by comparing the means of the respective outputs in two groups—a treatment group and a control group—having the same pretreatment characteristics.

Given that an experimental design was not used, where randomisation—when it comes to designating the individuals of the treatment group—ideally manages to achieve two similar groups with comparable means, a decision was taken to use the Propensity Score Matching technique (Rosenbaum, 2002; Rosenbaum & Rubin, 1983; Rubin, 1974). Through this technique, each treated individual (intensive Internet user for interactive learning in the first case, and intensive Internet user for individual learning in the second case) is compared with another individual having the nearest match to her or him in terms of the probability of using the Internet intensively for the purpose being studied. The final result is the formation of two comparable artificial groups with regard to the pretreatment variables observed. Specifically, the questionnaire design and the data obtained from the official administrative registers allowed us to form two homogenous groups with regard to the following variables:

1. *The student's ability*: To control for an even balance between both groups in terms of the ability (innate and acquired) of their members, the university entrance exam grade was used as a variable.
2. *Socio-demographic variables.* Both groups formed were equal with regard to the distribution of gender and mean age.
3. *Academic variables*: To better control for the effects of the different instructional methods and curricula on the estimated impacts, the fact that both groups had, on average, the same proportion of students from the different universities and from the different study areas (Psychology and Education, Computer Engineering, Other Engineering Disciplines, Humanities, Documentation and Information, Economics and Business, Law and Political Sciences, Health Sciences, Exact and Natural Sciences, and Social Sciences) was controlled for, as was the fact that they had the same number of students taking degree courses lasting for 2, 3 or 4 years. Also controlled for was the fact that, on average, the individuals in each group had passed the same number of academic years, in order to control for the moment they were at in their studies. Finally, in the case of face-to-face universities, also controlled for was the fact that the same percentage of students in both groups had taken an online course at some stage during their studies.
4. *Time available for study*: Besides the socio-demographic characteristics, which are undoubtedly related to the time available, also controlled for was the fact that the groups had the same percentage of students combining work and study, and that, on average, the students had enrolled on the same number of academic years. Thus, this controls for the fact that the time available does not distort the results presented.
5. *Relationship with technology*: Finally, another possible confounding variable could be a student's relationship with technology and, for that reason, it was considered necessary to control for the following variables in the study design:
   - Ability to use the Internet*:* The fact that both groups had the same level of ability to use the Internet was controlled for. This was done by controlling for the digital leadership variable, which is a dichotomous indicator that distinguishes between students on the basis of their self-stated ability, their weekly usage (time) and years of use. The technique used to separate the students was a non-hierarchical cluster analysis.

- Internet use for extra-academic purposes*:* On the basis of a set of questions asking about the intensity of use of 14 Internet uses, a principal components analysis was performed, which gave, as a result, six factors that distinguish intensity of use for the following purposes: content downloads, relations, Web 2.0, email and information searches, e-commerce and employment. In the study, the fact that the scores in these factors were equal between both groups was controlled for.
- Internet use for education*:* To separate the benefit of the two treatments, it was necessary to control for the fact that, when studying, the effect of Internet use for interactive learning did not include the effect of Internet use for individual learning, and vice versa.

On the basis of these variables, the steps listed as follows were followed to form the treatment and control groups:

1. We calculated two propensity scores for each individual, one to measure the probability of using the Internet intensively to interact in education, and another to find academic information. The method employed to do that was a probability calculation using a probit model.
2. Then, the individuals were matched on the basis of their estimated propensity score. To do that, there were various options available (Caliendo & Kopeinig, 2005; Dehejia & Wahba, 1998; Guo & Fraser, 2010). We implemented several matching algorithms to check the robustness of the results obtained. First, a decision was made to match each individual with the two nearest neighbours, with replacement and also limiting the calculation to the area of common support. In addition, matching was restricted to a probability range of 0.1%, thus ensuring that matching with the nearest individuals took place and, therefore, that the estimates were more accurate. Kernel matching was also done, which provides the weights for the individuals in line with the proximity of their propensity scores and does not eliminate any individual for reasons of rank. The advantage of this method is that, by not eliminating any individuals, it achieves a lower estimator variance, although the estimator is usually a little more biased.
3. We checked to ensure that the algorithms used actually managed to balance out the control group and the treatment group by using a mean comparison test between both groups (t-test) for each variable and considering those covariates balanced with less than a 5% probability of being different between both groups (see Table 3).

Results

By comparing the means for academic achievement of the control and treatment groups formed, it was possible to calculate the average treatment effect on the treated (ATT) for each of the two treatments. Thus, we come close to an experimental design (Dehejia & Wahba, 1998). Table 4 shows the estimated effects.

The estimated effects confirmed that using the Internet for interactive learning leads to a statistically significant improvement in academic achievement (with a probability level higher than 99%). This improvement is estimated between 3.6% and 3.7% compared to those that do not use it). However, the analyses performed did not bear out a statistically significant effect of Internet use for individual learning.

The results obtained are stable between the two matching methods and robust to hidden bias (Rosenbaum, 2002), with the highest Gamma value being 1.6 in the case of Internet use for interactive learning.

In order to be sure that the greater effect of interaction is due to the type of learning and not to the need to spend more time, it was necessary to check that both treatments were temporally equivalent in the way they had been measured. To that end, OLS regression was performed for the

Table 3: Construction of the treatment and control groups: covariate balance

	Interactive learning								Individual							
	Pre-matching		NN			Kemel			Pre-matching		NN			Kemel		
	Treat.	Cont.	Treat.	Cont.	t-test	Treat.	Cont.	t-test	Treat.	Cont.	Treat.	Cont.	t-test	Treat.	Cont.	t-test
University entrance exam grade																
From 5 to 6	17.36	18.36	17.40	18.52	−1.09 (0.274)	17.32	17.88	−0.56 (0.572)	17.01	18.63	17.54	19.02	−1.48 (0.140)	17.03	18.14	−1.16 (0.247)
From 6 to 7	26.57	28.21	26.94	26.42	0.44 (0.662)	26.61	26.62	−0.01 (0.992)	25.42	29.00	26.14	25.37	0.68 (0.495)	25.50	25.47	0.03 (0.979)
From 7 to 8	22.03	22.04	21.81	22.61	−0.72 (0.470)	22.03	21.81	0.21 (0.836)	22.62	21.66	22.82	22.60	0.20 (0.841)	22.68	22.76	−0.07 (0.946)
From 8 to 9	14.52	14.08	14.41	14.02	0.42 (0.674)	14.54	14.85	−0.33 (0.739)	14.72	13.94	14.65	15.46	−0.87 (0.384)	14.76	14.39	0.42 (0.676)
From 9 to 10	2.54	3.28	2.60	2.01	1.47 (0.142)	2.54	2.32	0.56 (0.578)	3.00	3.02	2.96	2.39	1.37 (0.172)	3.00	2.91	0.22 (0.823)
Without exam	16.99	14.03	16.83	16.40	0.43 (0.667)	16.95	16.52	0.45 (0.656)	17.24	13.76	15.89	15.17	0.77 (0.442)	17.03	16.34	0.73 (0.465)
Age	22.66	22.49	22.65	22.64	0.07 (0.941)	22.66	22.66	0.01 (0.992)	22.81	22.39	22.73	22.62	0.87 (0.384)	22.80	22.67	1.05 (0.293)
Gender	58.04	58.48	58.51	57.72	0.59 (0.552)	58.00	57.84	0.12 (0.903)	53.33	61.50	54.20	53.95	0.20 (0.845)	53.39	53.23	0.51 (0.610)
Combining Job and Studies	62.71	55.79	62.03	61.71	0.25 (0.805)	62.68	62.97	−0.23 (0.817)	61.39	56.37	60.62	60.00	0.52 (0.606)	61.28	60.65	0.51 (0.610)
University																
UB	64.33	69.75	64.91	64.91	0.00 (1.00)	64.34	64.70	−0.29 (0.770)	63.59	70.43	64.01	64.52	−0.41 (0.685)	63.48	63.25	0.19 (0.848)
UPC	35.67	30.25	35.09	35.09	0.00 (1.00)	35.66	35.30	0.29 (0.770)	36.41	29.57	35.99	35.48	0.41 (0.685)	36.52	36.75	0.19 (0.848)
Length of Degree Courses																
2 years (2nd cycle)	9.98	5.52	9.54	8.65	1.16 (0.246)	9.99	9.55	0.50 (0.620)	10.04	5.32	8.57	7.98	0.82 (0.410)	9.81	9.52	0.39 (0.699)
3 years (1st cycle)	38.17	27.79	37.62	37.03	0.45 (0.649)	38.17	37.19	0.78 (0.437)	31.63	31.59	32.12	33.52	−1.15 (0.252)	31.69	32.36	−0.57 (0.570)
4 years (1st + 2nd cycle)	51.84	66.79	52.85	54.36	−1.14 (0.256)	51.90	53.35	−1.12 (0.265)	58.39	63.16	59.38	58.57	0.63 (0.527)	58.56	58.16	0.33 (0.745)
Study Areas																
Psychology and Education	19.97	8.62	19.00	19.13	−0.12 (0.905)	19.90	19.38	0.50 (0.619)	12.39	13.04	12.97	14.33	−1.53 (0.126)	12.43	12.66	−0.27 (0.786)
Computer Engineering	16.14	6.84	14.73	16.51	−1.84 (0.066)	16.10	16.46	−0.37 (0.713)	15.56	6.85	14.28	13.86	0.47 (0.641)	15.62	15.54	0.09 (0.929)
Other Engineering disciplines	19.93	23.28	20.71	19.08	1.54 (0.124)	19.97	19.30	0.64 (0.522)	21.22	22.58	21.98	22.08	−0.09 (0.925)	21.28	2 1.45	−0.16 (0.870)
Humanities	5.45	12.34	5.73	5.39	0.55 (0.580)	5.46	5.47	−0.02 (0.988)	8.25	10.80	8.64	8.03	0.84 (0.399)	8.28	8.08	0.28 (0.781)
Documentation and Information	5.31	2.16	4.98	4.66	0.56 (0.575)	5.32	5.23	0.16 (0.872)	6.21	1.47	4.37	4.18	0.35 (0.725)	5.94	5.66	0.48 (0.630)
Economics and Business	8.22	14.34	8.65	8.43	0.29 (0.775)	8.24	8.19	0.07 (0.945)	11.21	12.66	11.53	12.27	−0.88 (0.378)	11.25	11.56	0.48 (0.630)
Law and Political Sciences	3.38	4.52	3.56	3.77	−0.43 (0.670)	3.39	3.60	−0.44 (0.662)	3.41	4.55	3.60	3.83	−0.48 (0.631)	3.42	3.56	−0.29 (0.769)
Health Sciences	10.29	10.04	10.75	10.48	0.32 (0.745)	10.31	10.37	−0.08 (0.937)	9.37	10.62	9.68	9.22	0.60 (0.550)	9.39	9.36	0.05 (0.960)
Exact and Natural Sciences	7.68	14.18	8.08	8.31	−0.32 (0.752)	7.70	7.94	−0.35 (0.726)	9.24	13.43	9.68	8.65	1.37 (0.171)	9.27	9.17	0.13 (0.900)
Social Sciences	3.62	3.69	3.81	4.24	−0.81 (0.415)	3.63	4.07	−0.88 (0.378)	3.12	4.02	3.29	3.55	−0.53 (0.593)	3.13	2.97	0.36 (0.715)
Courses Passed (accumulated)	92.53	83.85	91.70	93.17	−0.61 (0.539)	92.55	91.88	0.29 (0.769)	94.15	82.49	93.36	91.35	0.88 (0.381)	94.28	91.85	1.08 (0.282)
Experience Online Courses	58.68	34.49	56.69	57.51	−0.62 (0.535)	58.61	58.75	−0.29 (0.770)	53.58	36.85	51.55	51.97	−0.32 (0.746)	53.45	53.36	0.08 (0.940)
Enrolled Courses	61.24	61.29	61.33	61.29	0.084 (0.937)	61.24	61.37	−0.28 (0.778)	60.80	62.26	61.21	61.30	−0.18 (0.859)	60.84	60.88	−0.09 (0.927)
Digital Leadership	44.91	28.84	43.03	42.37	0.50 (0.618)	44.81	44.77	0.03 (0.975)	49.54	25.27	47.18	47.01	0.13 (0.897)	49.39	49.47	−0.06 (0.949)
Internet for non-academic purposes																
Content downloads	0.19	0.07	0.17	0.17	0.12 (0.901)	0.19	0.19	−0.13 (0.895)	0.24	0.03	0.23	0.25	−0.90 (0.369)	0.24	0.27	−1.04 (0.297)
Relation	0.18	0.14	0.17	0.21	−1.18 (0.238)	0.19	0.18	−0.06 (0.956)	0.14	0.16	0.15	0.14	0.51 (0.607)	0.14	0.13	0.36 (0.716)
Web 2.0	0.18	−0.07	0.15	0.13	0.80 (0.427)	0.18	0.16	0.63 (0.528)	0.23	−0.11	0.18	0.16	0.73 (0.467)	0.23	0.21	0.73 (0.465)
Email and Information Searches	0.18	−0.04	0.18	0.18	−0.32 (0.753)	0.18	0.19	−0.07 (0.946)	0.15	−0.03	0.14	0.15	−0.34 (0.731)	0.15	0.15	0.15 (0.881)
E-commerce	−0.05	−0.17	−0.06	−0.07	0.35 (0.726)	−0.05	−0.06	0.41 (0.685)	0.01	−0.21	−0.01	−0.01	0.01 (0.991)	0.01	0.02	−0.25 (0.804)
Employment	0.02	−0.30	−0.01	−0.04	1.11 (0.265)	0.02	0.01	0.56 (0.577)	0.02	−0.31				0.02	0.02	−0.10 (0.920)
Internet use for education																
Individual learning	3.57	3.11	3.52	3.50	1.04 (0.300)	3.57	3.56	0.32 (0.748)								
Interactive learning									2.40	1.83	2.33	2.36	−0.78 (0.434)	2.39	2.36	1.24 (0.215)

Table 4: How interactive learning can improve academic achievement. Estimated Average Treatment Effects on the Treated (ATT). Interactive learning vs. Individual learning

	Unmatched	*Nearest neighbour*	*Kernel*
Internet for interactive learning			
Effect (1)	5.12%	3.59%***	3.69%***
Standard error	0.658	0.916	0.8
t-stat	7.78	3.92	4.13
n	8046	7901	8046
Gamma Rosenbaum bounds (2)		1.32	1.58
Internet for individual learning			
Effect (1)	0.59%	–0.46%	–0.14%
Standard error	0.653	0.877	0.777
t-stat	0.91	–0.53	–0.02
n	8046	7883	8037

***Statistically significant at 99%.
Notes:
1. Effects calculated using the STATA psmatch2 program (Leuven & Sianesi, 2003).
2. Gammas calculated using the STATA rbounds program (Gangl, 2004).

Table 5: Is it a time issue? Influence of different Internet uses on students' time online

	Coefficient.	*Standardised*
Downloads	1.98 (0.104)***	0.196
Relations	1.81 (0.102)***	0.182
Web 2.0	1.54 (0.103)***	0.157
Basic uses	0.83 (0.104)***	0.083
Commerce	0.93 (0.105)***	0.091
Work	1.15 (0.106)***	0.114
Communicative learning	1.39 (0.219)***	0.068
Individual learning	1.50 (0.220)***	0.074
Constant	10.66 (0.154)***	

***Significant at 99%.
Adjusted $R^2 = 0.155$.

students' Internet uses over weekly Internet usage (time) (Table 5), and tests of equality between the coefficients of both treatments were carried out.

By comparing the coefficients, it is clear to see that there is no difference between the two in terms of usage (time). Consequently, it is possible to assert that the need to spend more time is not the explanatory cause of the greater effectiveness of Internet use for interactive learning:

$$\text{Interactive learning} - \text{Individual learning} = 0$$

$$F(1, 8037) = 0.12$$

$$\text{Prob} > \text{F} = 0.7315)$$

Conclusions and implications

In recent years, various authors have demonstrated that incorporating the Internet into face-to-face instruction improves students' academic achievement (Means *et al*, 2009; Tamim *et al*, 2011). However, a clear empirical response has not been given to the cause of such improvement.

In this research paper, we have demonstrated that the principal cause of the improvement is not, in itself, the increase in the time spent studying online that using the Internet for educational purposes may entail. Rather, increasing the time spent studying online is only useful when it takes place as some form of interactive learning.

The Internet can improve communication and interaction (including collaboration), thus overcoming the barriers of time and space and also involving a larger number of people. According to our analysis, this improvement in interaction capacity is the strength of incorporating such technology into education.

Our results reinforce the arguments of previous research on the benefits of face-to-face collaborative and cooperative learning (Johnson & Johnson, 1987; Slavin, 1996) and extend such arguments to computer-mediated learning. Likewise, the results concur with the positive perceptions that students have of online interaction (student-student and student-lecturer) in relation to learning objective attainment (Osorio & Duart, 2012).

The implications of these results can be analysed from a threefold perspective:

- From the point of view of students, it shows that, to maximise the time spent studying online, it is more beneficial to interact with other actors in the learning process than to search for information individually.
- From the point of view of universities and the instructional design of courses, it highlights that incorporating the Internet as an interactive learning catalyst is an effective strategy to get the maximum benefit from the investment made in that technology. However, using the Internet as a space where academic information can be posted or where students can actively search for complementary information is not shown to be an effective strategy for improving learning. This conclusion is consistent with international assessments of some e-learning implementation policies that focus on the incorporation of connection infrastructures rather than the promotion of interactive potential. The effects of such policies are minimally or not at all significant (Angrist & Lavy, 2002; Neuman & Celano, 2006; Rouse & Krueger, 2004).
- Finally, from the point of view of inequality and the digital divide, the fact that some students use the Internet for interaction in learning while others do not means that the latter are excluded from the benefits of e-learning. Therefore, online interaction is especially relevant to the study of academic achievement inequality that the incorporation of the Internet can introduce into higher education systems.

A potential limitation on the results of this research is the way in which Internet use was measured, since it was based on participants' responses to a questionnaire and not on direct data. Having direct data available about the students' actual Internet uses and intensity would have been the ideal situation. Nevertheless, studies on the topic show that self-declared measures are a good proxy for real measures when referring to Internet literacy and use (Hargittai, 2002, 2005).

A challenge to the validity of the results obtained in 2006 is the fact that more interactive e-learning environments have since been created. In light of our results, it could be posited that online interaction should have increased as the technological infrastructure has grown. If that is so, then it is possible to infer that the positive effects of online interaction have multiplied, and that the number of students who do not benefit from such interaction has decreased. However, more up-to-date empirical research on this topic is required because the simple fact that a technology exists does not necessarily mean that it will be used by lecturers and students.

It should also be noted that the new models of online interaction in learning tried out in recent years may actually change the meaning of such interaction. The spread of e-learning to more and more people is leading to pedagogical designs in which peer interaction gains ground over student-lecturer interaction (eg, MOOCs). If these models are transferred to blended learning, then attention will need to be paid to the various impacts they have on academic achievement, by comparison to the currently widespread online interaction models in which lecturers play a more important part in interaction processes.

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