



An analysis of the determinants of students' performance in e-learning



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ABSTRACT

Previous studies show empirical evidence on the positive effect on students' performance from the adoption of innovations in the technology of teaching and learning. These innovations do not affect all teaching methods and learning styles equally. Rather, it depends on some variables, such as the strategy of a university towards adoption of Information and Communication Technologies (ICT), students' abilities, technology uses in the educational process by teachers and students, or the selection of a methodology that matches with digital uses. This paper provides answers to these questions with data from an experimental set-up performed within the eLene-EE project, and using an empirical model based on structural equations. Our results show that motivation is the main variable affecting performance of online students, confirming the importance of this factor as a source of educational efficiency. Motivation appears in our model as a latent variable receiving the influence of students' perception of efficiency, which is, in turn, a driver for the indirect positive and significant effect on students' performance from students' ability in ICT uses.

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1. Introduction

The diffusion of ICT infrastructure in higher education has induced important changes, not only in the pedagogic sphere, but it has also had an effect on administrative and organisational areas. The desired result of this changing process is the improvement of students' achievement and performance.

At this point, some reasonable questions that require attention in order to ensure quality in and efficient training from virtual mobility, including the right choice of tools available from existing technology, are: (1) does the use of ICT affect student performance?; and (2) does the use of ICT affect student performance differently depending on the most usual variables that explain efficiency in higher education: students' profile and background, students' learning style, students' attitude toward learning, teaching methods and institutional resources?

This paper will try to provide answers to these questions with data from ongoing training and data from an experimental set-up performed within the eLene-EE project.¹ The analysis is based on

data collected from online students at the Open University of Catalonia (UOC).

Hence, this paper is divided into five sections: after this introduction, in section two we explore the international literature focused on the study of the relationship between ICT uses in higher education and students' performance; in section three research hypotheses are stated and the methodology used is explained; section four is devoted to the specification of the empirical model and the overview of the data collected from students; and, lastly, in section five we outline the main results obtained and the most important conclusions of our analysis.

2. Theoretical framework: ICT and student performance

The education industry has shown an important development in recent years in part as a consequence of the growing empirical evidence about the effect of improving educational attainment on economic and productivity growth (Sun, Tsai, Finger, Chen, & Yeh, 2008). The growth of the education market has also been facilitated by the irruption and diffusion of digital technologies. The use of ICT in the production process leading to the provision of education and training is changing the way education suppliers are developing this activity; new opportunities have emerged to integrate pedagogical and technological resources, to increase flexibility across the learning process, to improve communication between teachers and students, and also to reinforce the interaction between different educational resources (Collis, 1996). In fact, the increasing use of ICT, and particularly internet, in the educational process of

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universities across OECD countries explains the growing adoption of e-learning systems and the development of online courses in universities (European Commission, 2004; University of Southern California, 1990–2006; OECD/CERI, 2010).

The digital-based change in the provision of education is not constrained to the teaching and learning process, but also affects the organisational structure and management practices of education suppliers. To this effect, starting in the second half of the nineties, we find a growing belief that the use of e-learning systems in universities may lead to improvements in efficiency in the production of education, in terms of scale (number of student enrolments), students' achievement and costs (OECD, 1998).

In this field, Vilaseca-Requena and Castillo-Merino (2008) studied six e-learning universities around the world during the period 1997–2002 in order to analyse which are the determinants of cost efficiency in e-learning course provision by universities. The results show that cost efficiency can be explained by three complementary effects: (1) the attainment of scale economies based on high fixed costs and low marginal costs; (2) the enablement of productive capacity expansion without a proportional increase in fixed costs; and (3) the trend to a rise in variable costs consistent with decreasing marginal costs.

Therefore, e-learning production by universities is accompanied by a relatively high investment in ICT infrastructure and digital applications, as well as in methodological issues (course design, didactic materials, etc.) and labour adjustments at the university level. This capital accumulation required for e-learning development may lead to a saving in costs especially if universities are able to exploit some economic benefits based on the use of digital technologies (González-González, Serradell-López, & Castillo-Merino, 2012).

There is already empirical evidence that e-learning policies in universities are important drivers for quality improvement and strategic planning promotion. Following this direction, universities must go ahead in the research of efficient institutional models for the provision of high-quality education based on the use of digital technologies (Ben Youssef & Dahmani, 2008).

The desired result of this adjustment process is the improvement of students' achievement and performance, which is a direct consequence of the abovementioned policy, i.e. the technology used and, what is more important, the teaching and learning methodology adopted, because these two factors may explain how students and teachers make efficient or inefficient use of digital devices.

Within this field, there has been an emergence of economic papers analysing the impact of instructional ICT-based innovations on student performance. These works can be divided into two different groups, depending on the methodology used in the analysis of digital effects and on the conclusions about the efficiency of online courses.

On one hand, there are those studies concluding that online students perform worse than their face-to-face counterparts (Brown & Liedholm, 2002; Coates, Humphreys, Kane, & Vachris, 2004). Works in this group compare online with on-campus courses and share a common trait: they define online courses as a homogeneous commodity, without a detailed specification of the methodology and technology used in teaching and learning processes; this constraint does not allow them to capture differences in performance for different complementarities of teaching method, ICT uses and student profile.

Within this group of empirical evidence about the poorer performance of students enrolled in online courses, we wish to comment on two papers. Firstly, the empirical work of Brown (2002), in which it can be observed that students who are enrolled in an online course have better characteristics than face-to-face students. It seems like a contradiction, but the authors defend that

these results reflect the benefits and the importance of the direct student–teacher interactions that occur in on-campus courses, concluding that the difference between performances of the two methods is significant.

And secondly, the work of Coates et al. (2004), whose results also show that students in on-campus courses scored better than their online counterparts; however, this difference is not significant here. It is due to the relation between achievement and students' profiles through the effects of self-selection on students' outcomes. The inaccurate selection leads to biased and inconsistent estimates in education production functions and may result in misleading inferences regarding “no significant difference” between online and face-to-face instruction.

On the other hand, some works defend the idea that the discussion about whether or not to use technology in higher education courses is no longer of concern because the real significant issue is in what manner technology is used at the university, teacher and student level (Deed & Edwards, 2010; Sosin, Blecha, Bartlett, & Daniel, 2004). In other words, the benefit for students' performance derived from the adoption of innovations in the technology of teaching and learning does not affect all teaching and learning methodologies equally, because this benefit is based on a necessary equilibrium between institutional policy towards ICT adoption, students' abilities, technology uses in the educational process by teachers and students, and the selection of a methodology that matches with digital uses.

In fact, Sosin et al. (2004) analysed an extensive database of 67 sections of introductory economics in which 3986 students were enrolled, taught by 30 instructors across 15 institutions during the spring and fall semesters of 2002. The results of this study show that the use of digital tools, combined with adjusted teaching methods, has a significant and positive effect on students' achievement. Moreover, their conclusions also refute the belief that teachers using technologies in their classes spend more time than those who do not use them. Rather, teachers who show intensive ICT use spend the same amount of time in their teaching activity as those who are more reticent to use technology tools in their classes. The analysis of time costs and technology usage indicates that the discussion of whether or not to use digital equipment is no longer of concern; the critical point is what technology to use and in what manner.

These two different approaches to the analysis of online students' performance explain the emergence of a fruitful and interesting discussion regarding the best research methodology to use, keeping in mind that the choice of one or another perspective can lead to less comparable results and different conclusions.

In defence of this second group of works, it must be pointed out that the new forms of instruction in higher education are consistent with the potential of digital device use. The new dominant forms of active learning in many fields of higher education are explained by the transition from a teacher-based to a student-based model (Becker, 1997), in which methodologies must be customised to students' needs and study style (Huet, Escribe, Dupeyrat, & Sakdavong, 2011). In this sense, the properties of costless reproduction and flexibility that characterise internet and, broadly, information and communication technologies, may allow departments and teachers to adapt teaching and learning methodologies to these new dominant forms of instruction, such as class discussion, work groups, networking, individual attention, feedback and other forms of active learning.

The dominant forms of active learning in many fields of higher education are explained by the transition from a teacher-based to a student-based model, in which methodologies must be customised to students' needs and study style. In a seminal paper, Campbell and Lamphear (1969) analysed different teaching methodologies (lecture and lectureless classes) in the major of *Principles of*

Economics at the University of Nebraska, and concluded that “pedagogical capital should be substituted in certain highly resource-absorbing elementary courses in the social sciences and the released labour reallocated to provide classes sufficiently small at the junior and senior levels to achieve a meaningful relationship and dialogue between student and professor in the more specialised and advanced courses. Because the lectureless course does have the advantage of putting the burden of responsibility on the student. He is no longer the passive recipient of professorial spoon feeding via the lecture system; rather the initiative is his and he must get actively involved in the pursuit of knowledge.” (Campbell & Lamphear, 1969, page 30).

The analysis of the effects of these methodological and technological innovations on students' attitude towards the learning process and on students' performance seems to be evolving towards a consensus that an appropriate use of digital technologies in higher education can have significant positive effects both on students' attitude and achievement (Serradell-López, Lara-Navarra, Castillo-Merino, & González-González, 2010; Talley, 2005).

Therefore, to analyse the ICT-based teaching and learning process and its effects on students' performance, it is required previously to theoretically identify some critical explanatory variables.

One important set of variables are related with the potential learning benefits that emerge from *teaching methodologies empowered by e-learning environments*. In fact, these environments are suitable for the development of active learning methods, based on multimedia learning resources (in which reading, watching and interacting substitute listening), working groups, or practice and simulation activities (Heckman and Smith, 1995).

There seems to be a certain consensus in the idea that the diffusion of ICT infrastructure in higher education has the potential to induce important changes, not only in the pedagogic sphere, but also affecting administrative and organisational issues. Diversity of online learning tools offer more choices to students in online environments, but these changes may occur when equipment is complemented with efficient uses. And the fact is that availability of these digital devices is not consistent with intensity of use (and, of course, less so with an efficient use) in economic majors. To this effect, Becker and Watts (2001), in a study where they surveyed academic members of the American Economic Association (AEA) and teachers of economics listed in the College Marketing Guide (CMG), conclude that, although it has been proven that active learning combined with rapid feedback and positive reinforcement encourage persistence and appear to be conducive to learning, teachers in economics are reluctant to adopt new methodologies and technologies in their classes. And they suggest that one of the possible causes of this reluctance is the fact that the introduction of ICT-based tools in teaching methods requires a sunk cost investment and that teachers are not willing to accept a greater investment of time for teaching than is required with traditional methods. The decision to teach using the same chalk-and-talk method that earlier generations of economists used may be the most cost-effective approach for teachers who want to cover a lot of concepts and topics in their classes, while also saving as much time as possible for their own research, leisure and other activities.

In this sense, Navarro (2000) had also previously identified teachers' motivation structure as the main constraint for the use of digital technologies in the education sector. His results show that most teachers indicate that it took significantly more time to develop an online course than a traditional course, reported more time teaching, and demand a revision of the compensation system in order to equilibrate the relationship between time invested and wage level.

In reference to the benefits of teaching methodology on students' outcomes, it must be underlined that Hoskins and van Hooff (2005), through the analysis of data from 110 undergraduates in

the second year of a psychology degree, found that the dialogue method, via an online learning environment, has a positive and significant influence on student achievement. However, it must be noted that when an opportunity for dialogue is offered, individual differences will determine the extent to which students utilise this. And the tendency for this resource is to engage only already highly motivated and academically able students. But, they also conclude that in addition to motivation and academic ability, gender and age play a role in the degree of participation in discussion activities.

Complementary results about the main characteristics of e-learning environments were obtained by Navarro (2000). He studied the instructor's point of view through interviews, formal discussions and questionnaires involving more than 100 instructors from different institutions. And his results show the large majority of the respondents believe that they performed as well or better in an online environment. The explanation to this finding can be found in an increase in professor-to-student contact, a higher degree of student participation in discussions, and in some of the individual traits of online students: they are on average older students and often seem more motivated and self-directed.

This conclusion links with another important set of variables related to students' profile. Within this area, the work of Dutton, Dutton, and Perry (2002) is noteworthy. Firstly, they try to prove that there is a statistically significant difference between online and on-campus students through the analysis of the course *Introduction to Programming*, delivered with both e-learning and lecture methodology; and, secondly, they endeavour to identify the main traits that characterise online students. Their results show that the characteristics of students taking an online course differ from those of students taking the same course in a lecture format in several important respects: as in the case of Navarro (2000), the analysed data confirm that online students are older; they are less likely to be enrolled in traditional undergraduate programs and more likely to be lifelong learning students; they are more likely to have job and/or childcare responsibilities and longer average commutes to campus. In addition, the authors show that for online students class attendance conflicts with work and online study reduces commuting time; therefore, flexibility in studying is more important to them in their choice of course format than to lecture students. Lecture students, on the other hand, rate contact with instructors and fellow students, motivation from class meetings, and the need to hear a lecture as more important to them. Lecture students also more frequently report advice from university advisors as being important in their choice of format.

In their work, Dutton et al. (2002) also examine differences in performance levels for the two class formats. Their results confirm the hypothesis that online students obtained significantly higher exam grades than lecture students. Course grades for online students are higher, but the effect is not significant. They also confirm that homework completion had a positive impact on grades and course completion for both online and lecture students. In addition, they demonstrated that prior computer experience improved students' grade performance and that when this variable is taken into account, there is a reduction of the importance of online status in affecting grades.

Further research conducted in this field has been able to prove that students' characteristics such as ability or prior experience affect their performance. Benefits of technology may not be uniform across students' characteristics (ability, gender, or prior experience). Brown and Liedholm (2002) use the concept of “cognitive styles” to explore the role of differences in student abilities, past learning in the subject, attitudes, and aptitudes in the explanation of learning achievements. These authors argue that “a student's having a cognitive style is analogous to the student's having a production function for learning, and indeed, the cognitive style determines the underlying shape of the learning curves or the student's production function for

learning” (Brown and Liedholm, 2002, page 49). In this connection, they evolve in the direction of choosing those learning tools that maximise the gains available to students with diverse learning styles. Suitable learning tools must be created that are complements rather than substitutes for each other so that they take advantage of the diversity of students’ cognitive strategies.

Brown and Liedholm (2002) assume that students tend to use those materials that better contribute to the achievement of course goals. However, among the diversity of materials available in a course students will more highly value those they consider concordant with their diverse cognitive styles. Likewise, different uses have different effects for students, depending on their cognitive styles and the course curriculum.

In addition, it has also been demonstrated that better results on exams shown by students can be due, at least in part, to differences in student effort (Löfgren, 1998). Student effort, expressed in hours allocated to study, tends to be higher among on-site students than online students. The effort is related to the number of hours that a student works at a job. Therefore, the time that students allocate to work competes with their study time and, thus, working hours have a negative effect on student performance (Juster and Stafford, 1991). In consequence, it is important to consider this variable in the analysis of e-learning courses, according to the profile of online students.

3. Hypotheses and methodology

One of the main conclusions of the above explained theoretical framework is that the discussion about whether or not to use technology in higher education courses is no longer of concern because the real significant issue is in what manner technology is used at the university, teacher and student level.

Therefore, and according to this theoretical framework, it is feasible to identify some critical sets of variables in the explanation of online students’ achievement (Huet et al., 2011; Sun et al., 2008):

- (1) *Students’ profile*. Within this set of variables, some characteristics of students taking an online course must be remarked on: they are older than their on-campus counterparts, unlikely to be enrolled in traditional undergraduate programs and likely to be lifelong learning students, motivated and likely to have job and/or childcare responsibilities, longer average commutes to campus, and they need flexibility in study formats.
- (2) *Students’ ability and attitude*. Here, an important concept used to define students’ ability is “students’ cognitive styles”. In addition, an important concept used to define students’ attitude is “students’ effort”, a complex measure taking into account attendance, reading, study time, study effectiveness, group work and the allocation of study time over a course.
- (3) *Institutional resources*. This set of variables can in turn be divided into two subgroups of complementary variables:
 - (a) *Teaching and learning methodology*. There is empirical evidence on the significant and positive effects of the teaching methodologies empowered by e-learning environments on students’ performance. These methodologies are based on new dominant forms of instruction: work in groups, networking, feedback and dialogue methods, focused on a higher degree of student participation in discussions and an increase in professor-to-student contact; and
 - (b) *Use of ICT tools*. In this field, the main idea is that the use of multimedia-based materials, online networking software, asynchronous and synchronous devices for tea-

cher-to-student and student-to-student communication, wiki pages, learning objects, and other digital tools must be defined jointly with teaching and learning methodologies, and according to students’ profile and cognitive style.

Considering the abovementioned evidences on the relationship between educational inputs and students’ achievement, we are willing to verify the following hypotheses:

H1: Motivation is the main variable in the explanation of online students’ achievement, as it is a critical trait in the efficiency of net-based higher education.

H2: The ability to use ICT improves online students’ performance.

As in other production processes, for example manufacturing or farming production, the production of education implies the allocation and combination of different inputs in order to generate one or more outputs. This technical relation, within the framework of industrial economics, leads to the assumption of an objective of efficiency in production in terms of maximising the quantity of output and minimizing the consumption of inputs (Pritchett and Filmer, 1999).

The identification and measure of educational outputs have traditionally shown empirical constraints due to the multidimensional nature of these outputs, the lack of market value measures for some of the educational process results and the joint production of these different educational outputs (Maddala, 1983). There is a certain consensus that there exist two broad groups of outputs derived from education (Lassibille & Navarro-Gómez, 2004): cognitive skills and non-cognitive skills or abilities. Most economic works focused on education production functions use measures of student cognitive skills, such as achievement tests, as a proxy of educational output because they are easier to value than abilities and have a closer relation with the concept of human capital investment.

In economic literature there are four alternative methodologies that are used to specify the relation between educational inputs and outputs. These approaches are: production functions, frontier production functions, structural equations and minimization of investment costs.

Among these, production functions (Hanushek, 1979) and parametric (Levin, 1974) and non-parametric (Johnes, 2006) frontier analysis have been the most usual estimation methods to analyse students’ efficiency in higher education. Nevertheless, we have selected a structural equations model because this methodology allow us to go beyond the main constraints in defining a technical production relationship in education, multi-product and endogeneity problems, through an equations model useful to identify and estimate relations between explanatory variables and between these inputs and complex outputs.

Structural equation models (SEMs), also called simultaneous equation models, are multivariate regression models. They provide a methodology that can be viewed as a general methodology in the contexts of regression analysis and factor analysis. Unlike the more traditional multivariate linear model, however, the response variable in one regression equation in a SEM may appear as predictor in another equation; indeed, variables in a SEM may influence one another reciprocally, either directly or through other variables as intermediaries. These structural equations are meant to represent causal relationship among the variables in the model.

It is common to specify a structural equation model in the form of a graph called a path diagram. Some conventions are employed in drawing the path diagram:

- Directly observable variables are enclosed in rectangular boxes.
- Unobservable variables are enclosed in circles (more generally, in ellipses); in this model, the only unobservable variables are the disturbances.

- Bidirectional (double-headed) arrows represent non-causal, potentially nonzero, covariance between exogenous variables (and, more generally, also between disturbances).

As far as we are concerned, despite their potential benefits, structural equations have rarely been used in studies of economics of education (Löfgren, 1998).

A full structural model can be described by:

$$\eta = B\eta + \Gamma\zeta + \zeta$$

With

$\eta' = (\eta_1, \dots, \eta_m)$: m latent factors on the dependent variables side.

B : covariance matrix of the η factors.

$\zeta = (\zeta_1 \dots \zeta_n)$ n latent factors on the independent variables side.

Γ : matrix of the covariances of η and ζ factors.

$\zeta' = \zeta_1 \dots \zeta_m$ vector of residuals.

The full model incorporates both components of factor analysis and path analysis. The path analytic component of this model resides in the structural model part. This part describes relations of dependency. These relations connect latent variables, manifest variables (in path models), or both. Depending on the causality concept adopted by researchers, these relations are often interpreted as causal. The factor analytic component of the full model resides in the measurement models. These models specify the relations of the p observed, that is, manifest variables to the m latent variables, or factors on the dependent variables side, and the q manifest variables to their n latent variables on the independent variables side.

More specifically, the measurement model for the dependent variables is: $y = A_y\eta + \varepsilon$.

And the measurement for the independent variables is: $x = \Lambda\xi + \delta$.

With

$y' = (y_1, \dots, y_p)$: observed dependent variables.

$x' = (x_1, \dots, x_q)$: observed independent variables.

$\varepsilon' = (\varepsilon_1, \dots, \varepsilon_p)$: residuals on the dependent variable side.

$\delta' = (\delta_1, \dots, \delta_q)$: residuals on the independent variable side.

A : matrices of loadings of the x - or y -variables on their factors;

p : number of dependent variables; and

q : number of independent variables.

4. Empirical model and data

The structural equation model we defined is based on the identification and measure of some relevant explanatory variables under the different stated categories. With these variables and the grade obtained by students as the dependent variable, we have specified the original model. The variables and their measures are displayed in Table 1.

We assume that students' achievement on an exam (A) is a function of three main sets of observed dependent variables: students' ability and attitude (SA), teaching and learning methodology (TLM) and uses of ICT tools (ICT). And it is also influenced by a latent (unobserved) variable concerning students' actual motivation to follow a course and pass the exam (M):

$$A = a(SA, TLM, ICT; M)$$

We let that each of the sets of explanatory variables may be influenced by the others, as well as by the specified latent variable, arriving at the following equation system:

$$A = a(SA, TLM, ICT; M)$$

$$SA = s(TLM, ICT; M)$$

$$TLM = t(SA, ICT; M)$$

$$ICT = i(SA, TLM; M)$$

From this original model, and after adjusting for non-influencing explanatory variables (schooling and feedback intensity), we have developed our final operational model, in which all theoretical relationships are defined. Its graphical representation is shown in Fig. 1.

In order to achieve our objective, we collected information from students enrolled in three online introductory courses of the *Business Bachelor* at the Open University of Catalonia (UOC), an online university founded by the Catalan Government in 1994. The courses selected are *Introduction to Financial Accounting*, *Introduction to Mathematics* and *Principles of Microeconomics*. All three courses are subjects of the Degree in Business Sciences, and they are well-structured courses, meaning that learning resources (teaching, didactic materials, communication, etc.) are fully adapted to an online environment.

The data was obtained through a questionnaire sent in an electronic format² to a total number of 850 students enrolled in *Introduction to Financial Accounting*, 750 in *Introduction to Mathematics* and 675 in *Principles of Microeconomics*. The total number of respondents was 830, with 127 final valid answers after adjusting for missing and wrong values (Table 2).

For a better understanding of our results, it is important to outline some particular traits of UOC's students. These online students share the most relevant traits of lifelong learning students. These characteristics can be divided into five critical dimensions:

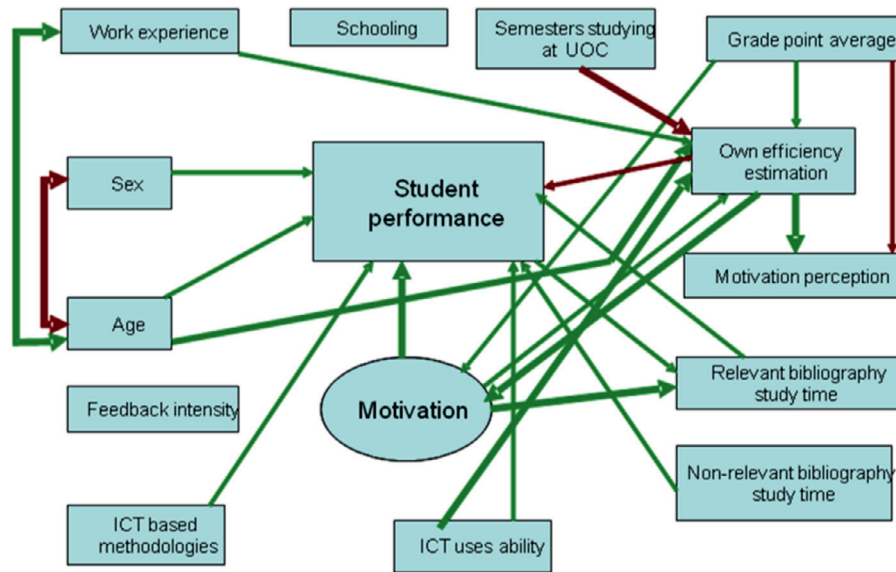
- First, *age profile*. UOC's students have an average age of 33 years old, higher than the rest of on-campus universities within the Catalan higher education system, and consistent with the profile of continuous learning students. From age groups approach, the distribution of frequencies is as follows: 0.2% of UOC's students are younger than 25 years old; 62.6% are between 25 and 40 years old, this age group being the one with the highest frequency; 34.5% of students are from 41 to 55; and the remaining 2.8% are older than 55.
- Second, *civil status*. The descriptive statistics of civil status in the case of UOC's students show that 56% of them are married. Furthermore, nearly 40% of all students have children, with the related duties that result in important time constraints and a considerable effort for carrying out study activities.
- *Educational attainment* is another particular trait of UOC's students. Here it worth commenting on the fact that, similar to the general profile of lifelong learning students, 85.7% of students enrolled in UOC's degrees have a graduate educational level.
- Fourth, the *economic role at home*. The economic importance of students' incomes at their homes is another critical issue for their characterisation. To this effect, it can be pointed out that more than half of UOC's students (51.5%) are the main economic sustainers at home. This situation is consistent with the high number of students holding a job, and it makes their learning process become more complex as they have to be continuously in charge of their working responsibilities.

² The selection of this format does not imply self-selection bias, as all students in all UOC's courses are online students; therefore, digital devices are the only channel of students' communication.

Table 1

Explanatory variables and measures in the original model. Source: own elaboration

Explanatory variables	Measures	Characteristics
<i>Student's profile</i>		
Sex	1 = Male 2 = Female	Binary
Age	Years old	Numerical
Schooling	Number of years studying before starting at UOC	Numerical
Work experience	Number of years holding a job	Numerical
<i>Student's ability and attitude (SA)</i>		
Experience at UOC	Number of semesters studying at UOC	Numerical
Grade average	Grade point average in previous education levels	Numerical
Ability	Own efficiency estimation	Numerical
Time spent studying relevant bibliography	Hours per week	Numerical
Time spent studying (non-relevant bibliography)	Hours per week	Numerical
Motivation perception	Extent to which students have been motivated during the course	Numerical
<i>Teaching and learning methodology (TLM)</i>		
Feedback intensity	Valuation of personal feedback during the course	Numerical
ICT-based methodology	Number of hours using UOC's platform	Numerical
<i>Uses of ICT tools (ICT)</i>		
ICT uses	Perception of ICT uses' ability	Numerical
<i>Latent variable (M)</i>	Motivation	



Source: own elaboration

Observable variables are represented in square shapes, while unobservable variables are displayed in circular shapes

Fig. 1. Final structural equations model.**Table 2**

Sample's distribution among subjects. Source: own elaboration

Subject	Number of students
Introduction to financial accounting	56
Introduction to mathematics	37
Principles of microeconomics	34
Total sample	127

– And, lastly, *job responsibility*. 95.7% of students hold a job when they are enrolled at the University. This figure increases the level of constraints in terms of time available to be devoted to study and confer students' motivation and asynchronous methodologies a critical significance in the learning process.

The aforementioned traits of UOC's students, jointly with the fact of being online students, make self-programming skills and motivation critical determinants for success in higher education.

Table 3

Squared multiple correlations. Source: own elaboration

Variable	Estimate
Own efficiency estimation	0.278
Motivation perception	0.998
Motivation	0.998
Time spent studying relevant bibliography	0.043
Student's performance	0.127

5. Results

The estimation of the original model (with all explanatory variables considered) has revealed a first relevant result: unexpectedly, schooling, measured as the number of years spent in previous education levels, and feedback intensity, measured as the valuation of personal feedback from the course teacher, have no influence in

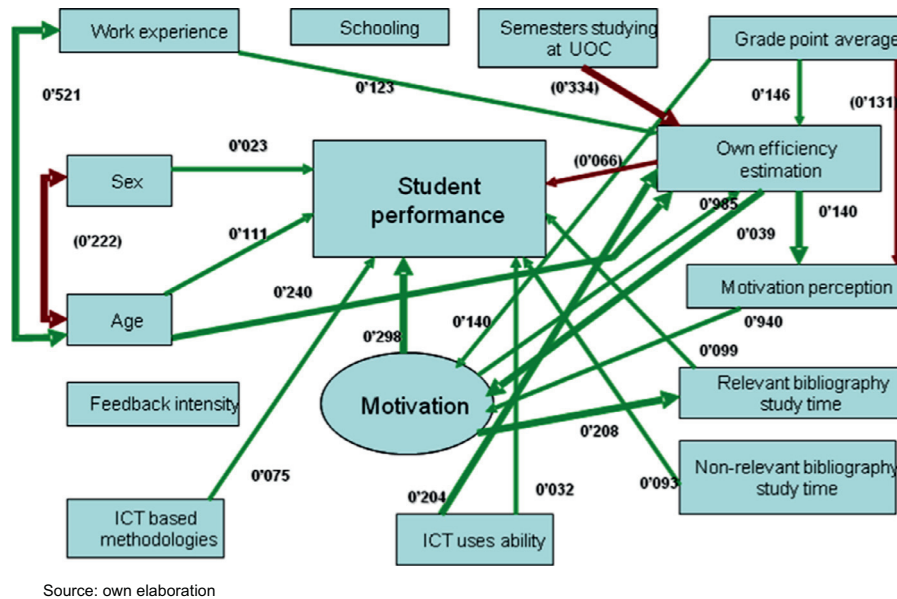


Fig. 2. Final model results (Green lines express a positive effect and red lines a negative one. Thick lines reflect a significant relationship, while thin lines show an insignificant incidence).

the structural equations model. The reasons may be the difference in teaching and learning methods between online courses at UOC and previous on-campus education for the schooling variable, as well as the lack of appropriate measures to capture the effect of feedback as a critical e-learning empowered methodology. Therefore, we have to go further in this field in order to identify new variables and/or measures that allow us to compute these two important parameters in the analysis.

The analysis made through our final model (excluding schooling and feedback intensity as explanatory variables) has allowed us to quantify the relationships between the different explanatory variables and between them and student achievement, using Generalized Least Squares estimation. It has a Chi-square value of 57.770, with 47° of freedom, showing a significant solution for the whole model.³ Squared multiple correlations are pointed out in Table 3.

The results obtained let us verify our hypothesis. The effect of motivation on students' performance has the largest standardized coefficient value (0.298), confirming the importance of this variable as a source of education's efficiency (Fig. 2). Moreover, this coefficient is the only one with a significant effect on the dependent variable ($p = 0.006$) at a 0.01 level (two tailed).

Here, an important question must be pointed out that requires our attention: how does motivation affects a student's performance? Or, in other words, what is the nature and what are the causes of the relationship between these two variables? To ask these questions, first we must keep in mind that motivation acts like a driver of different forces. As it can be observed in Fig. 2, motivation is a latent variable created from students' own efficiency estimation (with a positive and significant coefficient value of 0.039); what this means is that those students who believe they are well-prepared for online higher education are more motivated to follow a course. Own efficiency estimation, in turn, receives a positive and significant effect from age (0.240) and ICT uses ability (0.204); this result shows that older and higher ICT-skilled students are more likely to be confident about their capabilities to succeed in online higher education studies. In addition, it must be remarked that own efficiency estimations also have a negative

and significant effect from the number of semesters studying at UOC (0.334), maybe showing that experienced UOC students have evidence about the difficulties of reaching an equilibrium point between flexibility and time availability. And it also receives a positive influence from motivation (although without significance), possibly drawing a kind of virtuous loop between motivation and efficiency perception in the explanation of students' performance.

The use of a latent variable to capture motivation's effect allows us to avoid to some extent the measuring problems concerning this variable. It is well demonstrated that motivation is quite difficult to measure (Huet et al., 2011). It could be reflected by the number of hours spent studying, but this is not necessarily a good measure. For instance, some students could spend a large number of hours studying because they were raised to be a dutiful person. When studying, however, they do not pay attention to what they are working on. Another possibility is to ask students how motivated they are (as we have done and measured through the variable *motivation perception*). One problem with this method is, of course, that the measure will be highly subjective. With our estimations we have shown the weak relationship between the variable and its measure, as *motivation perception* receives a positive and significant influence from *own efficiency estimation*, as was expected, but it does not show any empirical relationship with students' achievement, which does not fit with theoretical assumptions. Romer (1993) uses the number of non-compulsory problem sets the student did during the course as a proxy for motivation. The more non-compulsory problem sets, the more motivated. Even though this is probably a reasonably good measure of motivation, it still suffers from the same drawbacks as the number of hours studying.

Finally, it is also interesting to remark that a higher level of motivation has a positive and significant effect on study effort, and, concretely, on the study of relevant bibliography (0.208, Fig. 2), which could have, in turn, some benefits in terms of achievement (in our model this relationship is not significant).

6. Conclusions and discussion

This paper presents two main contributions to the analysis of students' performance in higher education: first, the focus on the determinants that may explain students' success in an online

³ The GFI measure is equal to 0.924, as values closer to 1 are preferable (Olobatuyi, 2006: 115).

learning environment, considering that neither student profile and attitude nor technology-based methodologies have a homogeneous behaviour; and second, the use of structural equations, a new and rarely applied research methodology in this field, which allows us to capture the empirical relationships between dependent variables in the explanation of students' achievement.

Thus, the analysis of determinants of students' performance in online courses has enabled us to reach to important and complementary findings:

Motivation is the most important driving force to explain online students' ability to pass exams (Chua & Don, 2013; Huet et al., 2011). In fact, it is the only variable that shows a direct, positive and significant effect on students' achievement. And motivation is positively influenced only by students' perception of their own efficiency, showing that the more confident an online student is about their learning skills the more motivated he is, which ultimately enables them to obtain a better grade.

Some variables under students' profile and attitude set appear to be important in the explanation of achievement, but in an indirect way. This point must be briefly discussed to be fully understood. In this connection, those variables showing a significant effect on students' performance (*age* and *number of semesters studying at the university*) explain variations in students' success through their influence on students' perception of their own efficiency.

Students' age shows a positive effect, meaning that the older students are the more confident they are about their learning capabilities, which translates into better performance in the courses they are enrolled in. But here we may also identify some hidden implications. If we consider that UOC's students are mature people (62.6% are between 25 and 40 years old, and 34.5% of students are from 41 to 55), we can assume that age variable is measuring students' practical experience of having a job (which is empirically demonstrated by the bidirectional correlation found between *age* and *working experience* variables) and student's pre-knowledge. It is reasonable to assume that a student's pre-knowledge will affect their ability to pass the final exam. Pre-knowledge is typically measured as previous college grades or previous experience in higher education. For instance, Park and Kerr (1990), Anderson and Benjamin (1994), and Durden and Ellis (1995) find high pre-university grades to have a positive effect on student performance. Romer (1993) and Coates et al. (2004) find the same positive effect of previous experience from university studies on student performance. Our results show, however, that pre-knowledge measures (*schooling* and *grade point average*) do not have a significant influence, neither direct nor indirect, on students' performance. This unexpected result can be explained because, as we mentioned above, pre-knowledge could be to some extent implicitly captured by the variable students' age, even if we keep in mind the homogeneous distribution of schooling data in our sample (85.7% of students enrolled in UOC's degrees have a graduate educational level).

Another unexpected result is related to students' effort on learning tasks. Here, we have not found any statistically significant relationship between the two variables measuring studying effort (hours per week spent studying relevant bibliography and hours per week spent studying non-relevant bibliography) and achievement. Literature covering the analysis of efficiency in face-to-face courses is indeed ambiguous on this point. For instance, also controlling for student motivation, an issue we will return to later on, Romer (1993) found that attendance did contribute to the academic performance of the students in a macroeconomics course he taught in the fall of 1990. Similar results have previously been found for courses in macroeconomics by Schmidt (1983) and also by Park and Kerr (1990) for a money and banking course. These results were later verified by, among others, Durden (1995). However, contrary to these results, Brown (2000) did not find

any evidence that students who attended typically structured lecture-based classes performed better on the Test of Understanding College Economics (TUCE) in comparison to students who attended a standard microeconomics principles course. What they did find was that students who attended the lectures performed better on essay questions than those who did not. A reasonable explanation for our result may be located again in the observable homogeneous distribution of study time of the students that comprise our sample.

Consistent with findings in literature on the analysis of students' performance determinants in face-to-face courses, in the case of online students we have not found a significant relationship between teaching methodologies (*feedback* and *ICT-based methodologies*) and students' performance. This result may be due to the fact that all three courses considered in our analysis present very similar methodologies, as courses at UOC have a very important common methodological basis, evidencing that we have not been able to capture significant differences between them.

Finally, it must also be pointed out that, as well as for the students' profile and attitude set of variables, students' perception about their ability to use digital technologies shows a positive and significant effect on students' achievement, but in an indirect way. The perception of ICT uses ability has a positive influence on students' perception about their learning skills, which ultimately improves their grades in online courses.

Therefore, with this paper we have found that structural equation modelling is a suitable research methodology to analyse the complex and multidirectional relationships between inputs and outputs in education. Following this methodology we have identified indirect significant effects on students' performance that usually remain hidden with production function or efficiency frontier methodology. Our finding is that motivation appears to be the main determinant of students' success in passing the exam in an online course. Students' motivation to learn is in turn positively influenced by students' perception of their own efficiency to learn, a perception that depends on student age, the number of semesters enrolled in the university, and on the perception of their ability to use digital technologies for learning.

Further research is needed in this field in order to verify these results in other kinds of online courses as well as in campus-based courses, to compare results between them, and to improve measures of students' effort and teaching methodologies based on digital uses. A step forward is also needed in the analysis of the relationship between organisational structure in universities, ICT uses for administrative and educational purposes, and students' performance (Ben Youssef & Dahmani, 2008; González-González et al., 2012).

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