The International Journal of Management Education 22 (2024) 100937

Contents lists available at ScienceDirect

The International Journal of Management Education

journal homepage: www.elsevier.com/locate/ijme

Pass or good grades: Direct and mediated effects of a teaching method

María J. Alonso-Nuez, Ana I. Gil-Lacruz, Jorge Rosell-Martínez *

Department of Management and Business Administration, University of Zaragoza, Spain

ARTICLE INFO

Keywords:
Academic performance
Active learning
Higher education
Student effort
Endogeneity
Mediator variable

ABSTRACT

This study analyses the impact of active learning methods on the academic performance of first year management students. It evaluates how the assessment system, whether focused on active methods or traditional exam-based approaches, affects students' academic performance. Academic data from more than 4000 students were collected and analysed using a bivariate probit model to determine the probability of passing the course and the probability of obtaining high grades. Our research shows that active teaching methods have a positive effect on academic performance. This relationship is influenced by factors such as student engagement and effort. The main contribution to the state of the art is the objective quantification of these mediators, which have traditionally posed methodological challenges to researchers. The research reveals subtle differences in how teaching methods affect pass rates and top grades. These findings provide valuable insights for educators and researchers seeking to understand the complex relationship between teaching approaches, academic achievement and student engagement.

1. Introduction

There is abundant empirical evidence showing that subject designs and assessment systems that are based on active methodologies provide a better learning experience, better academic results and higher quality learning. This is well known by teaching staff, and by university students, and particularly relevant in management subjects (Kłeczek et al., 2020). However, when students have the choice between an assessment system based on active methodologies and another based exclusively on an exam, not all of them opt for the former.

Although there is ample evidence of the positive impact of methodological innovations on student's performance (Burvill et al., 2022), there has been insufficient research into how much of these improved outcomes are due to better methodology and hence better learning. And how much of these methodological improvements are due to improved learner attitudes, motivation or effort, which in turn affect academic outcomes. In fact, the very measurement of determinants like effort, motivation or engagement are difficult and subject to errors. This article answers several research questions: How does a student's choice of assessment system determine their choices and academic performance? What other factors or student characteristics determine their performance? We know that active methodologies improve academic performance, but what part of that performance is due to the quality of learning and what part is due to its ability to stimulate effort or engagement?

Student effort is often considered to be a key element in the learning process and therefore a determinant of student achievement in

* Corresponding author.
E-mail address: jrosell@unizar.es (J. Rosell-Martínez).

https://doi.org/10.1016/j.ijme.2024.100937
Received 3 August 2023; Received in revised form 27 December 2023; Accepted 8 January 2024
Available online 13 January 2024

a subject. We could define effort as the effective time spent by the student on the subject. Or, more precisely, as the cognitive load experienced, which is the total amount of cognitive resources used during the execution of this dedication (Moissa et al., 2021). Students' performance is an increasing function of their learning effort.

Teachers and scholars often seek to increase students' motivation and engagement in the subject, as these are the drivers of their effort and, therefore, of good academic performance. Course design, and in particular assessment design, is a first-class tool with positive consequences for the affective aspects of learning, such as increased effort, motivation and engagement (Beck et al., 2013). Increasingly, studies advocate the value of adopting assessment practices that develop deep learning approaches in students at university (Boud & Molloy, 2013).

According to effort, neither observing is feasible nor asking is reliable. Our research methodology employs objective variables free of measurement error to identify the determinants of student choice and academic achievement. We run the estimates on a large dataset of 4103 students over five academic years in a first-year management course in engineering higher education.[1] Using microdata and objective variables, we estimated the probabilities of passing the course and obtaining a good grade, depending on the choice of coursework and controlling for students' personal characteristics and circumstances. Our first specification of the model shows a common estimation problem: endogeneity. We use biprobit estimation, which allows us to isolate the weight of endogeneity and thus obtain consistent estimations. We interpret the measurement of endogeneity of our model as the explanatory power of omitted variables, such as effort, as a determinant of students' academic performance.

Previous research analyses academic performance on the basis of subjective personal attributes of students. Debicki et al. (2016), study how self-esteem influences performance and that effect is at the same time mediated by the student's goal orientation. The main goal of this research is to explain the academic achievement through students' choice of a particular active and collaborative teaching method. We know that there is a mediating variable (effort or engagement) that is also important in explaining academic success. Our contribution is mainly methodological, being able to assess the effect of an implicit mediator variable (effort) that would otherwise not be objectively measurable. The design of our research relies exclusively on objectively measured variables and students' expressed choices. This allows us to separate the effect of the teaching method on academic outcomes from the effect of induced student effort on academic outcomes. We also observe that the impact of an active teaching approach as a motivator for student effort and commitment differs for high-performing students.

The paper is organized as follows. The next section reviews the state of the art regarding the effect of active methods and student effort on academic performance, as well as the pitfalls in empirical research on this topic. This is followed by a short section describing the case study and another describing the database and empirical methodology. This is followed by a section presenting the estimates of the models and the discussion of these results. The article ends with a section of conclusions.

2. Active methodologies: student's effort and academic performance

Changing the way students learn requires an evolution in the way teachers teach and assess. The aim is to adapt teaching methods to the characteristics of the new generations of students, with the main aim of increasing their attention, motivation and enjoyment of learning. As lecturing has been a common teaching method for management studies, an active teaching method greatly improves student outcomes in terms of learning and academic performance (Chan et al., 2019).

When students engage in active learning, they develop the ability to analyse, relate ideas to other concepts, explain and share meanings in relation to knowledge. In active learning, students are more actively involved in the assessment process and have the opportunity to see how it affects their learning process (Postareff et al., 2012). Active learning encourages students to be more open and engaged in the learning process (Aragón et al., 2016; Sharp et al., 2018). Research in undergraduate education supports the use of these active methods as a means of engaging students and improving learning outcomes across disciplines (Cavanagh et al., 2018; Matzembacher et al., 2019; Alonso-Nuez et al., 2021; Diaz-Perez et al., 2023).

On the other hand, differences between students in active learning are explained by the context of the learning environment and by the characteristics of the students themselves (Baeten et al., 2010; Furnham et al., 2009). In addition to student attitudes, explanatory variables of academic performance include pre-college education, college entrance, student maturity (age and professional activity), socio-cultural context or distance from home to college (Andrews, 2018; Sonnert & Fox, 2012; Yee, 2016). The variable of student effort must also be considered. Student effort is perhaps the most important determinant of students' academic success. However, it is difficult to objectively measure.

In terms of assessment, grading helps teachers to know the capacity and performance of their students and to promote positive changes in them (Espinosa-Vázquez et al., 2013). Grading involves a process of collecting, synthesising, analysing and interpreting data from students that teachers obtain in their subjects. The assessment system must be adapted to the teaching of competences (specific and generic skills), as it determines what and how students learn (Hamodi et al., 2015). However, several studies have shown that academic staff tend to be more concerned with course content and teaching methods than with assessment systems (Boud & Falchikov, 2006). Educational researchers are particularly interested in how assessment influences students' study strategies and learning processes (Gijbels et al., 2008).

Students are more aware of the content and methods of assessment as their main objective is to succeed in their studies. Learner-centred teaching methods such as coursework encourage students to focus more on learning and understanding, whereas more

[1] All records correspond to nine different engineering degrees at Zaragoza University, Spain.

traditional forms with written examinations lead students to focus more on memorisation and grades (Struyven et al., 2005). The written examination appears to have acceptable curricular, instructional and criterion validity. However, student learning outcomes as measured by the exam are lower than expected (Segers & Dochy, 2001).

Observing and compiling the effort item into a variable has its complexities for academics. Although it can be measured through student surveys, asking students about their effort may introduce bias. For example, insufficient interest responding may confound survey measures and inflate observed correlations (Huang & DeSimone, 2021). Self-report measures based on questionnaires have been widely used in educational research to study implicit and complex constructs such as effort, motivation and engagement. However, the presence of potential biases in such self-report instruments may cast doubt on the validity of the constructs being measured (Tempelaar et al., 2020). In the survey research literature, it is widely recognised that although questionnaires and psychometric instruments measuring constructs such as anxiety, motivation or self-regulation have strong internal and external validity, many respondents have a typical response style (Baumgartner & Steenkamp, 2001; Weijters et al., 2010). This type of bias is also documented in surveys of teacher performance (McNatt, 2022), where teacher's positive reputation interfered with students' decision-making process, leading to biased, inflated ratings of teacher performance. Similarly, in terms of confidence biases, some learners may underestimate their abilities, skills and knowledge, while others may overestimate their confidence (Schraw, 2009).

3. The study case

Fundamentals of Business Administration (FBA) is a basic course in the first year of most engineering courses in Spain. This course equips future engineers with some of the economic and management knowledge and skills they will need for their future professional performance. Students have the right to an overall assessment and an optional continuous assessment.

- Continuous assessment: supervised coursework together with laboratory (computer) classes and a final written examination (to complete the final grade). This should be the standard assessment scheme.
- Overall evaluation: only one final written examination. This evaluation scheme is intended for students with special personal or professional circumstances, but optional for everyone.

The coursework consists of project-based active learning. Groups of students will work in a coordinated way to produce a business plan. This methodology provides some specific learning outcomes that are particularly useful in this course because of their practical applicability. Students working on collaborative projects improve their ability to work in a team, encouraging assertive communication, task sharing, consensus on ideas presented and, consequently, reflection. They also feel more motivated to work hard and are more interested in the team's support, ideas and help in carrying out projects.

During the public defence of the projects, peers evaluate the work of other groups. Each student evaluates all the groups except his own according to a rubric. The teacher then prepares an overall evaluation of each team (unknown to the other teams). Each group is given a list of aspects rated positively or negatively by their classmates. The teacher also evaluates the coursework according to the same rubric.

In summary, students on this course have a choice of two assessments. The coursework assessment requires students to take a more active role throughout the semester and a sustained effort compared to the overall assessment. We have evidence that the results (passing the course) are better for students who choose the coursework assessment. However, some students choose the overall assessment even though they are advised against it.

4. Database and empirical design

For our empirical analysis, we combine data from all FBA faculty records with student's administrative records, for five academic years of this first-year subject in the School of Engineering and Architecture of Zaragoza (Spain). Eighteen different teachers (nine full-time and nine part-time) taught 19 FBA class groups along five years in two semesters (autumn or spring, depending on the curriculum of the programme, not on the student's choice). Part-time lecturers combine work at the College with their professional careers. In summary, our data comprise a pool of 4103 students in their first enrolment in the subject. The administrative office supplies information on students' gender, age, address, university admission type, semester of study, morning or afternoon session, teacher type (academic or professional), and the gender and age of the lecturer. Besides, the teachers have also indicated each student's chosen type of assessment (continuous or overall) and their academic achievement. Note that the data compiled is not a sample, but the total universe as information is collected from 100% of students in the subject over five academic years.

In our equations, the variables to be explained are categorical and represent passing or not passing the subject and obtaining, or not, a good grade. Thus, Passing is a dichotomic variable that takes the value 1 if the individual obtained at least 5 out of 10 and 0 otherwise. Similarly, *GoodGrade* is a dichotomic variable indicating whether the individual obtained at least 7 out of 10 and takes the value 0 if the student obtained a grade above or equal to 5 and below 7. Of the 4103 observations of students in their first enrolment, 2265 passed the course (about 55%) and of these, 795 received a good grade (about 35% of 2265).

The definitions and mean values (or percentages) of all variables (endogenous, explanatory and control) are shown in Table 1.

Table 1
Distribution of first-year students by explanatory and control variables (N = 4103 observations).

Variables	Description	Avg or %
Passing	1 if the student has passed the subject; 0 otherwise	55.20
GoodGrade	1 if the student scores at least 7 out of 10 on the evaluation; otherwise 0 (only for students who pass the final examination)	35.10
CourseworkEvaluation	1 if the student has chosen coursework evaluation; otherwise 0	43.87
OverallEvaluation	1 if the student has chosen overall evaluation; otherwise 0	56.13
Women	1 if the student is female; otherwise 0	39.06
Men	1 if the student is male; otherwise 0	60.94
Age	This variable informs us about the student's age	19.21
Zaragoza_Residence	1 if the student lives in Zaragoza during the academic year; otherwise 0	87.26
Huesca_Residence	1 if the student lives in Huesca during the academic year; otherwise 0	6.04
Other_Residence	1 if the student does not live in Zaragoza, neither Huesca during academic year; otherwise 0	6.70
Exam_Entry	1 if the student has accessed the University through the national exam; otherwise 0	79.97
TM_Entry	1 if the student has accessed the University after professional education; otherwise 0	6.24
Extinction_Entry	1 if the student has accessed the University through extinction programs; otherwise 0	13.06
Other_Entry	1 if the student has accessed the University through other ways such as older of 25 years old or after finishing a first degree; otherwise 0	0.73
FallSemester	1 if the student has attended the classes during autumn semester; otherwise 0	46.48
SpringSemester	1 if the student has attended the classes during spring semester; otherwise 0	53.52
MorningGroup	1 if the student has attended the classes in the morning; otherwise 0	57.49
EveningGroup	1 if the student has attended the classes in the evening; otherwise 0	42.51
FemaleTeacher	1 if the student's teacher is a woman; otherwise 0	24.01
MaleTeacher	1 if the student's teacher is a man; otherwise 0	75.99
TeacherAge	This variable informs us about the student's teacher's age	41.64
Academic	1 if the student's teacher follows academic career; otherwise 0	59.39
Professional	1 if the student's teacher follows professional career; otherwise 0	40.61
2010/11	1 if the student has enrolled for the first time the subject the academic year 2010/11; otherwise 0	26.44
2011/12	1 if the student has enrolled for the first time the subject the academic year 2011/12; otherwise 0	19.79
2012/13	1 if the student has enrolled for the first time the subject the academic year 2012/13; otherwise 0	17.91
2013/14	1 if the student has enrolled for the first time the subject the academic year 2013/14; otherwise 0	17.96
2014/15 [a]	1 if the student has enrolled for the first time the subject the academic year 2014/15; otherwise 0	17.90

Note 1: Exam_Entry (university access exam), TM_Entry (vocational modules), Extinction_Entry (transfer from discontinued degrees in the same university), Other_Entry (transfer from other colleges, second degree, access for older than 25 years old, and so on). Most students enter university after passing the entrance exam, so Exam_Entry has been omitted to avoid multicollinearity problems and has been taken as a reference when interpreting the results of TM_Entry, Extinction_Entry, Other_Entry. Huesca is the closest city to Zaragoza.

Approximately 39% of FBA students are female and 61% male. Most of the students live in Zaragoza (the same city as the university) during the academic year, and most of the students enter the undergraduate programme by taking a national exam. In terms of the gender[2] of the teaching staff, 76% of the students attend classes taught by a male teacher (compared to 24% taught by a female teacher), the average age of the teaching staff is 42 years and 59% of the students have a teacher with an academic career (compared to 41% with an external professional career).

The models for identifying the causal effects of students' choice of assessment type on academic performance (i indexes students enrolled in FBA and j indexes students enrolled in FBA who achieved at least 5 out of 10) are:

$$Passing_i = X_i\beta_1 + \delta_1 CourseworkEvaluation_i + u_{1i} \tag{1}$$

$$GoodGrade_j = X_j\beta_2 + \delta_2 CourseworkEvaluation_j + u_{2j} \tag{2}$$

$$CourseworkEvaluation_k = X_k\beta_3 + u_{3k} \tag{3}$$

Passing and *GoodGrade* are measures of academic performance, *CourseworkEvaluation* is the type of evaluation chosen by the student, *X* is a vector of explanatory variables related to the student (as listed in Table 1) and *u* is a zero-mean error term. Note that all available variables are measured objectively.

We propose to estimate equations (1) and (2) using a bivariate probit methodology.[3] A key parameter of interest is δ, as it provides information on the causal effect of the chosen assessment type on academic performance, controlling for differences in the observed (X) and unobserved (u) determinants of academic performance. The challenge in using observational data to estimate δ is the possibility that, even after conditioning on observed characteristics, the unobserved (u) determinants may vary with student behaviour. In our research, the potential challenge is that the unobserved determinants of academic performance vary with the choice of assessment

[2] Self-reported gender.

[3] Bivariate probit model is a type of regression that estimates the probability of two binary outcomes simultaneously. It is a generalization of the logistic regression model, where it is assumed that the value of the dependent variable is always specified for any observation described by a set of independent explanatory attributes. The model involves an outcome equation and a treatment equation, where the treatment variable is an endogenous explanatory variable of the outcome equation.

type. Controlling for a wide range of explanatory variables reduces unobserved heterogeneity and improves our estimates of δ. Our research approach includes the main implicit hypothesis that the choice of an evaluation including coursework favours both the likelihood of passing the course and obtaining good grades (H0: $\delta = 0$ versus H1: $\delta > 0$). At this stage, there is no interpretation as to whether this causal relationship lies in the improvement in learning due to the active methodology, or that this methodology improves student engagement.

Nevertheless, in order to be as precise as possible when examining the relationship between academic performance and evaluation type, we use the Hausman endogeneity test to check whether evaluation type is statistically endogenous. The test rejects the null hypothesis of exogeneity for Equation (1) (H0: *CourseworkEvaluation* is exogenous for *Passing*, χ^2 (1 degree of freedom) = 7.24, with Prob. > $\chi^2 = 0.0071$) and failed to reject the null hypothesis of exogeneity for Equation (2) (H0: *CourseworkEvaluation* is exogenous for *GoodGrade*, χ^2 (1 degree of freedom) = 1.26, with Prob. > $\chi^2 = 0.2611$). Therefore, *CourseworkEvaluation* could imply endogeneity for *Passing* and an exogenous variable for *GoodGrade*.

To correct for the endogeneity problem, we estimated Passing considering CourseworkEvaluation as an endogenous variable. To proceed with this method, we would need to introduce variables, commonly referred to as instrumental variables, that affect the type of evaluation but not performance. The difficulty in finding the right instruments calls into question the validity of the estimation (Bound et al., 1995). To avoid the problems associated with weak instruments, our approach to developing an unbiased estimate of δ followed the approach of Altonji et al. (2005), where identification is achieved under the assumption of equal selection between observed and unobserved variables. The approach is based on the understanding that the determinants of the outcome can be divided into two parts: observed and unobserved determinants. The identification problem is that the endogenous variable is likely to be correlated with the unobserved determinants. To solve this problem, Altonji et al. (2005) argue that both the measured and unmeasured components are likely to be correlated with the endogenous variable. In fact, they assume that the correlation between the unobserved determinants and the endogenous variable is equal to the correlation between the observed determinants and the endogenous variable (equal selection rule, ESR).[4]

5. Estimation and discussion

The estimates of Equations (1) and (2) are shown in Tables 2 and 3, respectively. The first one explains the probability of passing the subject (success), among all the students. The second explains the probability of obtaining a good grade (excellence) among successful students. The estimates of Equation (3) which explains the choice of coursework are also included in both tables.

The first column of Table 2 shows that students who choose coursework assessment are more likely to pass the course than students who choose overall assessment (standard estimation). However, as discussed in the previous section, we have empirical evidence that the type of assessment is endogenously correlated with unobserved determinants of passing the course (χ^2 test). A consequence of endogeneity is that the estimated coefficient of the endogenous variable is overestimated, so the effect of evaluation type may not be as strong. The parameter ρ measures the correlation of the residuals from the two estimations (standard and equal selection rule), and both are positively associated ($\rho = 0.1942$). After controlling for this association of the estimations (third column of Table 2), we verified that the choice of coursework evaluation has a positive effect on academic performance, but not as strong as initially predicted (smaller coefficient). Regarding the remaining explanatory and control variables, the estimated parameters are very similar between the two estimations, which guarantees robustness.

The estimations of Equation (2) are shown in Table 3. The estimates correspond to successful students (those who passed the subject) and explain the determinants of obtaining a good academic grade (above 7 out of 10 points). The estimation method is, again, a biprobit with an equal selection rule to correct for potential endogeneity in the *CourseworkEvaluation* variable.

The determinants of the choice of coursework among students who pass the course are basically the same as those observed for the choice of coursework among all students, considering the sign and significance of each coefficient. These estimates also confirm that students who choose coursework assessment are more likely to get a good grade than students who choose overall assessment (standard estimate). In this case, there is no empirical evidence that the type of assessment is endogenously correlated with unobserved determinants of getting a good grade. In fact, the parameter ρ estimated under ESR shows no significant correlation between the residuals of both estimations. Consequently, the estimated coefficient for coursework evaluation among successful students to obtain a good grade is similar for both estimations of Equation (2).

If we compare the estimations in the third column of Table 2 (probability of passing without endogeneity) with the estimations in Table 3 (probability of getting good grades), the coefficient of the choice of coursework assessment has a similar value, i.e. a similar positive effect on achieving good grades and passing the course.

According to the statistical literature, endogeneity in a model can have several causes (Wooldridge, 2010): The most common explanation for endogeneity is that there is some simultaneity between the explanatory and endogenous variables. In this case, the endogenous variable (passing the subject) and the explanatory variable (choice of coursework) would be determined simultaneously. In our research, this possibility can be ruled out because there is a time lag of several months between the choice of assessment and the academic performance.

[4] The ESR is justified by the fact that the measured variables are randomly selected from a large set of possible determinants, which is a reasonable assumption given that most secondary data sets are not designed for the specific research question under investigation. Equality provides an estimate of the correlation between the errors in the bivariate probit model (a bivariate probit model imposing $\rho = 0$ is equivalent to estimating two independent probits for Passing/GoodGrade and CourseworkEvaluation).

Table 2
Biprobit estimation of the probability of passing the exam with at least 5 out of 10 and evaluation type among first-year students.

	Standard		Equal Selection Rule (ESR)	
	$\rho = 0$		$\rho = 0.1942$	
	Passing (Equation (1))	Coursework Evaluation (Equation (3))	Passing (Equation (1))	Coursework Evaluation (Equation (3))
Women	0.062	0.154**	0.071	0.149**
Men [a]	–	–	–	–
Age	−0.408***	−0.120	−0.412***	−0.121
Age^2	0.007***	0.001	0.007***	0.001
Zaragoza_Residence [a]	–	–	–	–
Huesca_Residence	−0.210**	0.025	−0.206**	0.021
Other_Residence	−0.207**	−0.149	−0.219**	−0.154
Exam_Entry [a]	–	–	–	–
TM_Entry	−0.147	0.418**	−0.118	0.412**
Extinction_Entry	0.329***	−0.181*	0.310***	−0.191*
Other_Entry	0.989**	1.202**	1.072***	1.140**
FallSemester	−0.262***	0.140**	−0.248***	0.138**
SpringSemester [a]	–	–	–	–
MorningGroup	−0.161***	−0.278**	−0.182***	−0.278***
EveningGroup [a]	–	–	–	–
FemaleTeacher	0.079	−0.174***	0.061	−0.177***
MaleTeacher [a]	–	–	–	–
TeacherAge	0.224***	0.182***	0.241***	0.182***
TeacherAge^2	−0.003***	−0.002***	−0.003***	−0.002***
Academic	0.395**	−0.165**	0.384***	−0.171**
Professional [a]	–	–	–	–
2010/11	−0.107	0.426***	−0.065	0.425***
2011/12	0.069	0.341***	0.105	0.338***
2012/13	0.287***	0.537***	0.337***	0.537***
2013/14	0.139*	0.531***	0.188***	0.528***
2014/15 [a]	–	–	–	–
CourseworkEvaluation	0.520***	–	0.168***	–
OverallEvaluation [a]	–	–	–	–
Endogeneity test of Hausman	χ^2 (1) = 7.24 Prob> χ^2 = 0.007			

The model includes an intercept.
***, ** and * indicate significance levels of 1%, 5% and 10%.
[a] Variable of reference.

A second factor that contributes to endogeneity is the presence of measurement errors in the explanatory variables. This is deemed implausible because our selection of determinant variables is limited to objectively quantifiable measures and student-stated choices.

A third source of endogeneity is omitted variables. This explanation seems to be the most plausible in our case. The main determinant of passing the subject is the student's effort, which is not an objectively measurable variable and is not part of the explanatory variables in our equations. At the same time, this effort seems to be correlated with the student's choice of coursework, which would explain the endogeneity in the estimation of Equation (1) (Table 2). The use of biprobit estimation with an ESR would correct for any potential selection bias anyway.

It is noteworthy that the estimation of Equation (2) (Table 3) is not endogenous, and this provides some information. While we concluded (estimation of equation (1)) that students' effort to pass the subject is correlated with continuous effort during the course (choice of coursework), there is no such simultaneous correlation between the variable *CourseworkEvaluation* and students' effort to obtain good grades (estimation of Equation (2)).

In practical terms, our results demonstrate that the choice of coursework helps students to pass the subject. Teachers may also assume that students who choose coursework intend to put in more effort to pass (an anticipated signal of future effort). The results suggest that effort to pass the course is at least partially induced by the choice of coursework.

For successful students (those who pass the subject), the choice of coursework will also help them to achieve good grades, but it cannot be considered as an anticipatory signal of future effort, nor that the choice of coursework will motivate additional effort.

Fig. 1 summarizes the explanatory effect captured by the endogeneity correction as a mediation effect. According to the criteria of Baron and Kenny (1986), our case of endogeneity can be interpreted as a mediator variable because it meets certain conditions. This is due to the identification of a significant correlation between the independent variables and the residuals. After applying bi-probit estimation to correct for endogeneity, the implicit variable shows a significant correlation with the dependent variable. The introduction of this mediator variable leads to a significant reduction in the impact of an explanatory variable (the choice of coursework) on the dependent variable. For successful students, the choice of coursework improves their likelihood of achieving excelent results (better learning), but we do not find that it induces greater effort (mediating variable) (see Fig. 2).

Table 3
Biprobit estimation of the probability of passing the exam with at least 7 out of 10 among first-year students.

	Standard		Equal Selection Rule (ESR)	
	$\rho = 0$		$\rho = 0.0090$	
	Good Grade (Equation (2))	Coursework Evaluation (Equation (3))	Good Grade (Equation (2))	Coursework Evaluation (Equation (3))
Women	0.015	0.058	0.015	0.058
Men [a]	–	–	–	–
Age	−0.081	−0.135	−0.082	−0.134
Age^2	0.001	0.002	0.001	0.002
Zaragoza_Residence [a]	–	–	–	–
Huesca_Residence	−0.028	0.182	−0.027	0.182
Other_Residence	−0.233**	−0.087	−0.234**	−0.088
Exam_Entry [a]	–	–	–	–
TM_Entry	0.038	0.160	0.039	0.161
Extinction_Entry	−0.035	−0.446***	−0.036	−0.446***
Other_Entry	0.649	0.071	0.649	0.070
FallSemester	−0.060	0.220***	−0.060	0.220***
SpringSemester [a]	–	–	–	–
MorningGroup	0.065	−0.259***	0.064	−0.259***
EveningGroup [a]	–	–	–	–
FemaleTeacher	0.253***	−0.141	0.253***	−0.141
MaleTeacher [a]	–	–	–	–
TeacherAge	0.056	0.188***	0.057	0.188***
TeacherAge^2	−0.001	−0.003***	−0.001	−0.003***
Academic	0.157***	−0.525***	0.155**	−0.524***
Professional [a]	–	–	–	–
2010/11	0.130	0.488***	0.132	0.488***
2011/12	0.079	0.394***	0.080	0.394***
2012/13	0.281***	0.574***	0.283***	0.574***
2013/14	0.278***	0.542***	0.280***	0.542***
2014/15 [a]	–	–	–	–
CourseworkEvaluation	0.183**	–	0.165**	–
OverallEvaluation [a]	–	–	–	–
Endogeneity test of Hausman	$\chi^2(1) = 1.26$ Prob> $\chi^2 = 0.261$			

The model includes an intercept.
***, ** and * indicate significance levels of 1%, 5% and 10%.
[a] Variable of reference.

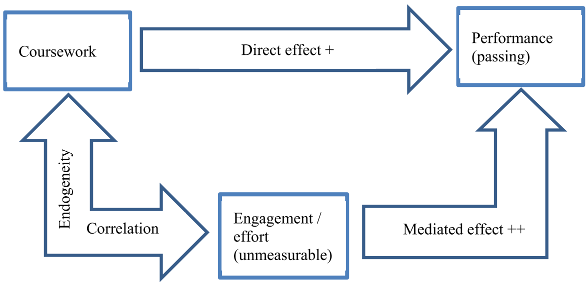

Fig. 1. All the students. Probability of passing.
Source: Own elaboration

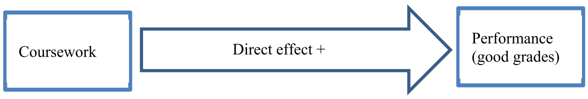

Fig. 2. Only successful students. Probability of achieving good grades.
Source: Own elaboration

In addition, a time course of the variables confirms the demonstrated causal effect: First the student chooses the assessment, then the student makes an effort in the subject, and then the student achieves academic results (academic performance). The intermediate variable acts as a conceptual bridge, linking cause and effect and providing a deeper understanding of the causal chain. In our study, it serves as a conduit through which the choice of methodology affects academic performance.

The coefficients of the remaining variables deserve some additional discussion. Particularly, the difference in the number of significant coefficients of control variables explaining the probability of passing the subject (Table 2) is higher than that explaining good grades (Table 3). However, there is no difference in the sign of the causality (sign of the coefficients) between both Tables. Several aspects influence the probability of passing the subject, such as age of the student, personal circumstances of the student (place of residence, academic background), circumstances of the course (semester, timetable) and characteristics of the teacher (age, academic or practitioner). Gender has no significant effect on the probability of passing, but female students are more likely to choose coursework. In other words, the probability of succeeding in the course depends on the student's choices about the coursework and on the student's effort. However, there are several significant factors that affect the likelihood of success, which are less controllable by the student.

When explaining outstanding performance (good grades), very few contextual factors stand out: having an academic and female teacher (both indicating positive impact) alongside the student's choices. Students' dedication and their choices in academic assessment are probable to lead to excellent grades, irrespective of contextual elements (Table 3).

In engineering studies in Spain, many students fail their subjects, and a minority of them drop out. A possible reason for this could be a lack of effort, which may be driven by uncertainty about the returns to study effort and (mis)perceptions of their own ability, according to Debicki et al. (2016) and Chevalier et al. (2018). A fundamental management course may not motivate first-year engineering students enough. If intrinsic motivation fails to promote enough effort, what measures could aid student efforts and improve their performance? Effort monitoring and teacher feedback imply increased motivation and effort, leading to a higher success rate in the subject. Our study shows that the selection of teaching methodology and assessment systems impact students' academic performance. First, the methodology contributes directly to the quality of learning; second, it promotes additional motivation and effort to pass the course.

Excellent students also benefit from choosing active methods that increase the likelihood of achieving good results. However, we did not find that the teaching method induced additional engagement in this group of students.

6. Conclusions

Teachers change training and assessment methods to enhance student learning and academic outcomes. Although it is recognised that the use of more active methods improves student outcomes, it is not easy to determine how much of this progress is due to improvements in the quality of learning and how much is due to improvements in student engagement and effort.

Using a large database of thousands of students in an introductory management course over five years, we estimate the probabilities of passing the course and obtaining a good grade. The determinants are a large set of variables related to the students themselves and their context, as well as their choice of an active learning and assessment system, which we call coursework here. We face an econometric problem: endogeneity. The solution to the problem itself provides us with additional explanations and the possibility of estimating (from objectively measured variables) aspects that are difficult to measure, such as the effort or commitment of the students induced by the teaching methodology and its impact on the probability of passing.

Estimating a bivariate probit model with an equal selection rule provides an estimation of the correlation of errors, which isolates the explanatory power of this omitted variable. After correcting for endogeneity, the estimated coefficient of coursework evaluation is reduced to one third of its previous value when explaining the probability of passing the subject. However, this endogeneity is not present when explaining good grades. We conclude that the choice of coursework is relevant to passing the subject and to achieving a good grade. That is, if a student chooses to do coursework, a hidden determinant emerges and explains part of the probability of passing the course. However, if we restrict the sample to successful students and explain the probability of getting good grades, endogeneity disappears. In other words, in the last case, there is no extra effort induced by the active methodology.

There is academic literature showing that learning by doing increases student engagement and ultimately student effort. Our estimates suggest that this is true for explaining the probability of passing, but not for explaining the excellent academic performance of successful students. What we can always expect from the implementation of an active methodology is an improvement in academic performance due to a better learning process. To enhance student engagement and effort through active learning, a variety of evidence-based strategies can be incorporated into the teaching approach, such as case studies and simulations (problem solving), group projects (active learning and collaboration, as in our case), class debates and discussions (critical thinking and articulation), etc.

A number of important control variables and student characteristics allow additional results to be obtained. For example, students attending the subject in the autumn semester are more likely to choose coursework assessment but less likely to pass the exam than students attending the FBA in the spring semester. We conclude that some students need to adapt to university life during their first semester at university. For example, to help first-year university students make the transition from secondary to tertiary education, institutions provide academic and emotional counselling, create an inclusive environment that fosters a sense of belonging, and offer resources and advice on effective study habits and time management to promote academic success.

The significance level of the explanatory variables for passing the course is higher than for obtaining a good grade. Most of the variables included in our model are strong predictors of the likelihood of overcoming the difficulties of the course. We should look at different determinants to explain good results. It is easier to find a solution to failure rates than to improve excellent results, simply because we have a better understanding of their causes. It is also possible that the commitment of the students that intend to get good grades allows them to overcome most of their contextual determinants. For example, improving students' understanding of their study plan and increasing their sense of belonging and participation will help them feel connected to their university and engage in academic and non-academic activities. These interventions could improve academic performance by addressing multiple aspects of students' engagement, well-being, and study habits.

This research uses ex-post information on academic performance and student characteristics. A direct estimation of students' effort through a questionnaire is therefore not available. This can be seen as a limitation of the study in demonstrating its mediating role between their choices and their outcomes. However, as has been argued, measuring this type of variable is subject to various types of error that affect the reliability of the results. For this reason, we consider that the implicit estimation of effort is not a limitation, but rather one of the outstanding contributions of this article. Another limitation is the scope of the study. While the large number of students from a management subject in this study ensures consistency of results, a future line of research could reach a larger number of subjects for the same degrees to compare whether the determinants of student engagement differ between social science and science subjects. And compare these results obtained with first-year students with those of more advanced courses, as their motivations may be different.

Statistical methodology in causal models can be tricky and problematic in interpreting estimates that may be biased or inconsistent. Proper model construction and a statistical methodology that provides consistent estimates of coefficients will ensure that conclusions are robust and realistic. Furthermore, the methodology allows conclusions to be drawn about relevant unobserved determinants and their interaction with the observed variables. In our case, by solving an econometric problem, we are able to obtain an implicit measure of student effort, which is interpreted as a mediator variable in our construct, and isolate the net positive contribution of a teaching methodology to academic performance.

CRediT authorship contribution statement

María J. Alonso-Nuez: Writing – original draft, Writing – review & editing, Validation, Supervision, Investigation, Data curation, Conceptualization. **Ana I. Gil-Lacruz:** Software, Methodology, Investigation, Formal analysis. **Jorge Rosell-Martínez:** Writing – original draft, Writing – review & editing, Methodology, Investigation, Formal analysis, Conceptualization.

Data availability

Data will be made available on request.

References

Alonso-Nuez, M. J., Gil-Lacruz, A. I., & Rosell-Martinez, J. (2021). Assessing evaluation: Why student engages or resists to active learning? *International Journal of Technology and Design Education, 31*, 1001–1017.

Altonji, J. G., Taber, C. R., & Elder, T. E. (2005). Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools. *Journal of Political Economy, 113*, 151–184. https://doi.org/10.1086/426036

Andrews, B. D. (2018). Delayed enrollment and student involvement: Linkages to college degree attainment. *Journal of Higher Education, 89*(3), 368–396. https://doi.org/10.1080/00221546.2017.1390972

Aragón, O. R., Dovidio, J. F., & Graham, M. J. (2016). Colorblind and multicultural ideologies are associated with faculty adoption of inclusive teaching practices. *Journal of Diversity in Higher Education, 10*(3), 201–215. https://doi.org/10.1037/dhe0000026

Baeten, M., Kyndt, E., Struyven, K., & Dochy, F. (2010). Using student-centred learning environments to stimulate deep approaches to learning: Factors encouraging or discouraging their effectiveness. *Educational Research Review, 5*, 243–260. https://doi.org/10.1016/j.edurev.2010.06.001

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*, 1173–1182.

Baumgartner, H., & Steenkamp, J. B. (2001). Response styles in marketing research: A cross-national investigation. *Journal of Marketing Research, 38*(2), 143–156. https://doi.org/10.1509/jmkr.38.2.143.18840

Beck, R. J., Skinner, W. F., & Schwabrow, L. A. (2013). A study of sustainable assessment theory in higher education tutorials. *Assessment & Evaluation in Higher Education, 38*(3), 326–348. https://doi.org/10.1080/02602938.2011.630978

Boud, D., & Falchikov, N. (2006). Aligning assessment with long-term learning. *Assessment & Evaluation in Higher Education, 31*(4), 399–413. https://doi.org/10.1080/02602930600679050

Boud, D., & Molloy, E. (2013). Rethinking models of feedback for learning: The challenge of design. *Assessment & Evaluation in Higher Education, 38*(6), 698–712. https://doi.org/10.1080/02602938.2012.691462

Bound, J., Jaeger, D., & Baker, R. (1995). Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. *Journal of the American Statistical Association, 90*, 443–450. https://doi.org/10.2307/2291055

Burvill, S., Owens, S., & Organ, K. (2022). The digital explosion: It's impact on international student achievement. *International Journal of Management in Education, 20*(1). https://doi.org/10.1016/j.ijme.2021.100585

Cavanagh, A. J., Chen, X., Bathgate, M., Frederick, J., Hanauer, D. I., & Graham, M. J. (2018). Trust, growth mindset, and student commitment to active learning in a college science course. *CBE-life Sciences Education, 17*(10), 1–8. https://doi.org/10.1187/cbe.17-06-0107

Chan, S. C. H., Wan, C. L. J., & Ko, S. (2019). Interactivity, active collaborative learning, and learning performance: The moderating role of perceived fun by using personal response systems. *International Journal of Management in Education, 17*(1), 94–102. https://doi.org/10.1016/j.ijme.2018.12.004

Chevalier, A., Dolton, P., & Lührmann, M. (2018). Making it count: Incentives, student effort and performance. *Journal of the Royal Statistical Society: Series A, 181*(2), 323–349.

Debicki, B. J., Kellermanns, F. W., Barnett, T., Pearson, A. W., & Pearson, R. A. (2016). Beyond the Big Five: The mediating role of goal orientation in the relationship between core self-evaluations and academic performance. *International Journal of Management in Education, 14*(3), 273–285. https://doi.org/10.1016/j.ijme.2016.05.002

Díaz-Pérez, L., Lopez-Pellicer, F. J., Brufau, P., Lacasta, J., Trillo-Lado, R., Yagüe-Fabra, J. A., & Zarazaga-Soria, F. J. (2023). Providing a common approach to designing dataset-based learning activities based on a literature review. *Applied Sciences, 13*(23), Article 12704.

Espinosa-Vázquez, O., Martínez-González, A., & Díaz-Barriga Arceo, F. (2013). Formas de enseñanza y evaluación utilizadas por los docentes de Odontología: Resultados y su clasificación psicopedagógica. *Investigación en Educación Médica, 2*, 183–192.

Furnham, A., Monsen, J., & Ahmetoglu, G. (2009). Typical intellectual engagement, Big Five personality traits, approaches to learning and cognitive ability predictors of academic performance. *British Journal of Educational Psychology, 79*, 769–782. https://doi.org/10.1348/978185409X412147

Gijbels, D., Segers, M., & Struyf, E. (2008). Constructivist learning environments and the (im) possibility to change students' perceptions of assessment demands and approaches to learning. *Instructional Science, 36*(5–6), 431–443. https://doi.org/10.1007/s11251-008-9064-7

Hamodi, C., López-Pastor, V. M., & López-Pastor, A. T. (2015). Medios, técnicas e instrumentos de evaluación formativa y compartida del aprendizaje en la educación superior. *Perfiles Educativos, 37*, 146–161.

Huang, J. L., & DeSimone, J. A. (2021). Insufficient effort responding as a potential confound between survey measures and objective tests. *Journal of Business and Psychology, 36*, 807–828.

Kłeczek, R., Hajdas, M., & Wrona, S. (2020). Wicked problems and project-based learning: Value-in-use approach. *International Journal of Management in Education, 18* (1). https://doi.org/10.1016/j.ijme.2019.100324

Matzembacher, D. E., Gonzales, R. L., & do Nascimento, L. F. M. (2019). From informing to practicing: Students' engagement through practice-based learning methodology and community services. *International Journal of Management in Education, 17*(2), 191–200. https://doi.org/10.1016/j.ijme.2019.03.002

McNatt, D. B. (2022). The biasing impact of positive instructor reputation on student evaluations of teaching. *International Journal of Management in Education, 20*(1). https://doi.org/10.1016/j.ijme.2022.100607

Moissa, B., Bonnin, G., & Boyer, A. (2021). Measuring and predicting students' effort: A study on the feasibility of cognitive load measures to real-life scenarios. In T. DeLaet, R. Klemke, C. AlarioHoyos, I. Hilliger, & A. OrtegaArranz (Eds.)*, Vol. 12884*. *Technology Enhanced learning for a free, safe and sustainable world, EC-TEL 2021* (pp. 363–367). Lecture Notes in Computer Science. https://doi.org/10.1007/978-3-030-86436-1_36, 2021.

Postareff, L., Virtanen, V., Katajavuori, N., & Lindblom-Ylänne, S. (2012). Academics' conceptions of assessment and their assessment practices. *Studies In Educational Evaluation, 38*, 84–92. https://doi.org/10.1016/j.stueduc.2012.06.003

Schraw, G. (2009). Measuring metacognitive judgments. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Handbook of metacognition in education* (p. 415). Routledge/Taylor & Francis Group. https://doi.org/10.4324/9780203876428. –429.

Segers, M., & Dochy, F. (2001). New assessment forms in problem-based learning: The value-added of the students' perspective. *Studies in Higher Education, 26*(3), 327–343. https://doi.org/10.1080/03075070120076291

Sharp, J. G., Sharp, J. C., & Young, E. (2018). Academic boredom, engagement and the achievement of undergraduate students at university: A review and synthesis of relevant literature. *Research Papers in Education*. https://doi.org/10.1080/02671522.2018.1536891

Sonnert, G., & Fox, M. F. (2012). Women, men, and academic performance in science and engineering: The gender difference in undergraduate grade point averages. *Journal of Higher Education, 83*(1), 73–90.

Struyven, K., Dochy, F., & Janssens, S. (2005). Students' perceptions about assessment in higher education: A review. *Assessment & Evaluation in Higher Education, 30* (4), 325–341.

Tempelaar, D., Rienties, B., & Nguyen, Q. (2020). Subjective data, objective data and the role of bias in predictive modelling: Lessons from a dispositional learning analytics application. *PLoS One, 15*(6). https://doi.org/10.1371/journal.pone.0233977

Weijters, B., Cabooter, E., & Schillewaert, N. (2010). The effect of rating scale format on response styles: The number of response categories and response category labels. *International Journal of Research in Marketing, 27*(3), 236–247. https://doi.org/10.1016/j.ijresmar.2010.02.004

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. Cambridge, Massachusetts: The MIT Press.

Yee, A. (2016). The unwritten rules of engagement: Social class differences in undergraduates' academic strategies. *Journal of Higher Education, 87*(6), 831–858. https://doi.org/10.1080/00221546.2016.11780889