

ANALYSIS OF ACTIVE LEARNING IN MANAGEMENT ENGINEERING: A
STUDY AT EDEM BUSINESS SCHOOLVicente Asensio^{1*} , Irene Canals² , Claudia Silvestre² ¹Universitat Politècnica de València (Spain)²Escuela de Empresarios EDEM (Spain)**Corresponding author: viaslo@mat.upv.es
ircaes@edem.es, clsiga@edem.es*

Received November 2024

Accepted May 2025

Abstract

The educational paradigm is evolving towards competency-based learning rather than standardized testing. In this setting, Active Learning is to boost, among others, student engagement, critical thinking skills, and application of knowledge into real-world issues. This paper examines the overall performance of sophomore students in a new engineering and management bachelor's degree at a university in Valencia, Spain. The creation of this program relies on the absence of a versatile professional profile in Spain: an engineer with business insight. The study is carried out via simple and multiple linear regression models. Several variables that may affect performance have been considered to determine whether the implemented techniques are effective enough. The investigation is also divided into smaller subject groups as it comprises a wide variety of course topics, ranging from Fluid Mechanics or Thermodynamics to Business Law or Marketing. Therefore, by utilizing the same sample, it is possible to delve deeper into actual performance and the pivotal factors affecting results within each subject subset. As a result of the analysis, several models showing the relevance of these factors on student competences have been developed. The study offers recommendations to enhance student advice and elevate overall learning outcomes in this interdisciplinary educational context.

Keywords – Active learning, Linear regression models, STEM, Continuous assessment, Learning results.**To cite this article:**

Asensio, V., Canals, I., & Silvestre, C. (2025). Analysis of active learning in management engineering: A study at EDEM Business School. *Journal of Technology and Science Education*, 15(2), 437-455.
<https://doi.org/10.3926/jotse.3209>

1. Introduction

In the current academic landscape, learning has undergone significant transformations due to the widespread use of the Internet and new technologies such as Artificial Intelligence. Digitalization has brought tremendous changes in classroom practices (Li, Lund & Nordsteien, 2023). These technologies, while resourceful, are reducing student engagement and making it increasingly difficult for them to focus on traditional classroom settings.

This rapid shift has not allowed educational models to keep abreast of how students are learning. In this scenario, progressively declining levels of attendance to classes are becoming a concern for universities and threatening educational quality (Kelly, 2012; Moores, Birdi & Higson, 2019). Over the past years, numerous studies have examined the connection between class attendance and academic performance, leading to the conclusion that increased class attendance not only correlates with a decreased likelihood of students receiving failing grades (Guleker & Keci, 2014; Rodgers, 2002), but has also been proven to have a quantitatively significant effect on student learning (Stanca, 2006).

Implementing models that actively engage students in class is becoming a necessary action for higher education providers to keep up with the rapid changes occurring in this field (Alenezi, 2023). As a result, many educational institutions have opted to evolve from traditional models into Active Learning models. Active Learning classroom development is a part of the broader educational movement toward students that are involved and engaged in their learning (Brooks, 2011). It requires students to actively participate in engaging reflective tasks. These are activities in which students do things and think about what they are doing. Student engagement is a key element of effective learning and involves connecting students to the course, to their peers in the course, and to the instructor (Martin & Bolliger, 2018).

This model has been theoretically proven to be more effective in improving students' performance (Robinson, Robinson & Ogundimu, 2021). In a study comparing Active Learning versus lecture-centred course in STEM disciplines (Science, Technology, Engineering and Mathematics), it was found that students in traditional lectures were 1.5 times more likely to fail than those in courses with Active Learning (Freeman, Eddy, McDonough, Smith, Okoroafor, Jordt et al., 2014). Therefore, by promoting the development of self-efficacy, boosting learning motivation and attitudes of active learning, students are led to better learning outcomes (Huang & Wu, 2011).

However, despite frequent calls for more Active Learning approaches, its adoption in higher education remains limited. Research shows that teaching is still predominantly traditional and teacher centred (Børte, Nesje & Lillejord, 2020). This situation calls for a re-evaluation of traditional educational models, transitioning from a teaching-centred to a learning-centred environment (Aji & Khan, 2019). That is why in higher educational institutes, developing classrooms promoting Active Learning is becoming a part of an educational drive for students engaging in learning (Qureshi, Khaskheli, Qureshi, Raza & Yousufi, 2023). By implementing Active Learning models, students who are motivated to learn are more likely to exert the necessary effort to learn and engage with the course material (Bedi, 2023).

In this context, EDEM Business School emerges as a beacon of innovation and practical learning in Valencia, Spain. EDEM's learning approach is enhanced by its affiliations with two key academic institutions: the Universitat de València, linked to the BBA in Entrepreneurship; and the Universitat Politècnica de València, associated with the BSc in Engineering and Management.

The BSc in Engineering and Management (BEM) was launched in 2015 to bridge the industry's demand for professionals who blend technical and analytical skills with business acumen. It was developed in response to a growing need in the labour market for interdisciplinary profiles capable of understanding both technological challenges and business decision-making processes. At the time of its creation, the BEM was —and remains— distinctive in Spain as a single undergraduate degree that integrates both engineering and management disciplines. While similar educational offerings have since emerged, mostly as double degrees or postgraduate programs —such as the Double Degree in Industrial Technologies Engineering and Business Administration at URL and at UDG, or the Double Master's Degree in Industrial Engineering and Industrial Business Management at UPNa and at IQS-URL— these alternatives typically involve longer academic paths or require students to follow two separate programmes in order to acquire the same combined expertise.

During these nine editions, 432 students have enrolled in the program, with 40% of them having graduated as of today. BEM graduates enjoy high employability rates, with a 94% of its students not only employed but also venturing into entrepreneurship during the five editions already graduated:

Promotion	1st	2nd	3rd	4th	5th	Total
Works	93%	96%	85%	81%	71%	84%
Starts a business	7%	4%	11%	10%	17%	10%
Studies	0%	0%	0%	3%	13%	3%
Looking for employment	0%	0%	4%	6%	0%	3%

Table 1. BEM Program Graduates

BEM program embraces an interdisciplinary approach to cover what has been commonly seen as two different study areas: Engineering and Business. Interdisciplinary practice generally involves the integration of theories and/or methods from multiple disciplines (Szostak, 2008). The complementary nature of this relationship is that engineers need to learn communication and writing skills, and an integrated degree design gives them a chance to learn these skills that are more familiar to business students (Fleischmann & Huchison, 2012).

The curriculum is strategically divided into four main areas: Basic Sciences, Engineering and Technology, Business Management, and Advanced Operations Management, ensuring a solid education that prepares students to meet the challenges of the modern job market.

The Table 2 summarizes the content per modules:

Basic Sciences Module 1	Engineering and Technology Module 2	Business Management Fundamentals Module 3	Advanced Strategy and Operations Module 4
<ul style="list-style-type: none"> • Calculus • Physics I • Chemistry • Biology • Physics II • Algebra • Differential Equations • Statistics I • Statistics II 	<ul style="list-style-type: none"> • Computer Science • Graphic Expression • Material Science • Fluid Mechanics • Electrical Technology • Operations research • Kinematics and Dynamics of Machines • Thermodynamics • Structures • Machine Technology • Energy Technology • Automation Technologies • Information Systems • Installations 	<ul style="list-style-type: none"> • Business • Economics • Business Law • Marketing • Financial Accounting • Finance 	<ul style="list-style-type: none"> • Human Resources • Supply Chain Design • Customer Needs • Managerial Control and Costs • Supply Chain Management • Project Management • Business Fiscalty • Creativity • Operational Excellence • Sales Management • Entrepreneurship Ethics and Values • Digital Business • Strategic Management • Innovation Management • Global Environment

Table 2. BEM modules

These modules can be organized into four main regions according to the disciplinary classification scheme of Biglan (1973). This scheme, together with Holland's hexagon of occupational interests and personality characteristics, are considered important frameworks when describing disciplines (Holland, 1997). Although originated in the twentieth century, these classification frameworks continue in use today (Donnay, Morris, Schaubhut & Thompson, 2005; Simpson, 2017). They are valuable for understanding collaborations between disciplines in multidisciplinary contexts such as characterizing disciplinary interrelationships in STEAM education (Williamson & Panigabutra-Roberts, 2021).

The disciplines in the BEM modules can be visually identified by using Biglan's classification as follows (Figure 1).

Biglan describes that attitudes and behaviours can be summarized along three dimensions. The hard(left)/soft(right) dimension refers to disciplines with high paradigmatic development such as chemistry, physics, and engineering, while disciplines with lower levels of paradigmatic development such as sociology,

history, and educational administration are soft disciplines (Jones, 2011). The applied(top)/pure(bottom) dimension depends on the level to which it is practical and used in real-world applications. The life/non-life dimension is based on the extent to which it involves the study of living organisms or systems.

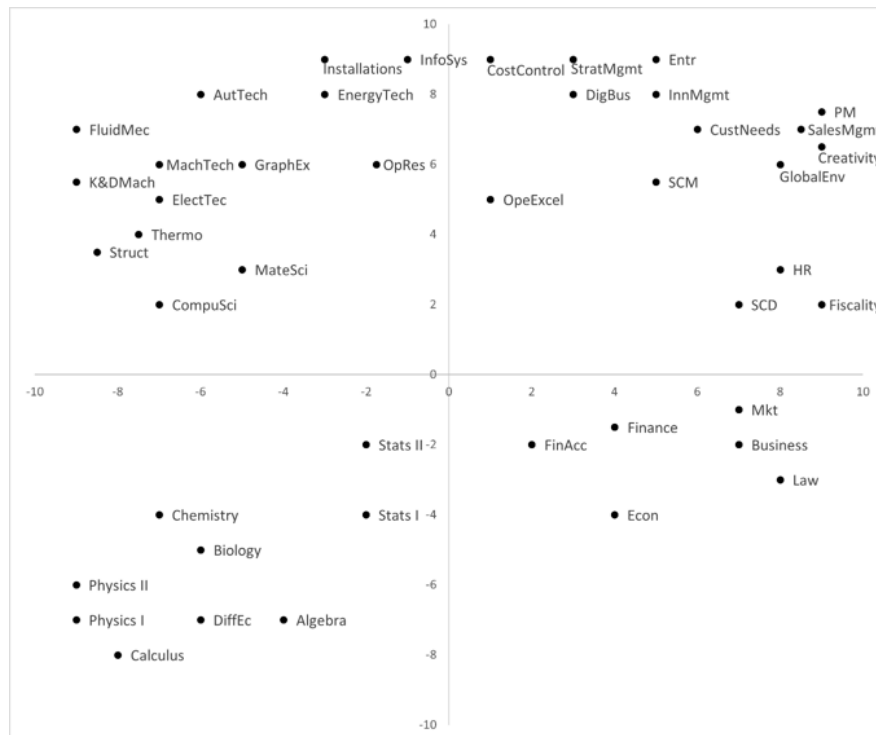


Figure 1. Horizontal axis from hard to soft, vertical axis from applied to pure

Figure 1 highlights the multidisciplinary approach of the subjects of BEM and its orientation towards applied areas. Engineering and business fields often work together in combined project classes, where engineering students address practical industry challenges. In line with the Holland classification system, engineers usually show investigative and realistic vocational interests, while business roles are known for their entrepreneurial interests. Engineers are often described as reserved and independent, while business students tend to be sociable and inclined towards leadership or persuasion. As a result, it is expected that these two disciplines would support each other (Fleischmann & Huchison, 2012).

2. Methodology

2.1. Hypotheses & Assumptions

The primary aim of this study is to identify key factors affecting students' performance. By analysing trends and patterns within the academic data, the study seeks to recommend specific strategies and suggest early interventions that students could implement during their course to enhance their results.

In order to achieve this goal, the following hypotheses are proposed:

H1. Doing well throughout the course is positively associated with achieving a higher final mark in the subject.

H2. Students who get involved in extra activities are more prone to be motivated.

H3. Women are more likely to get a higher final mark.

H4. Performance and engagement levels in business-related subjects (Modules 1&2) are similar to those in engineering subjects (Modules 3&4).

H5. Student engagement in the course is positively related with seat position.

The participation in extra activities (H2) and the seat position (H5) could affect the degree of performance and engagement achieved by students influencing the final mark (H1). Final mark could also be influenced by the gender of the student (H3). This relationship is represented in Figure 2 below.

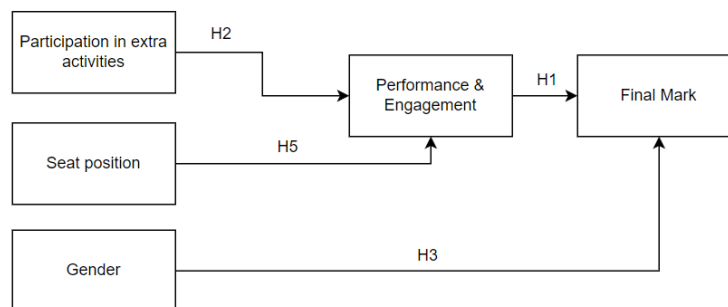


Figure 2. Hypotheses

2.2. Data Analysis

The methodology of the study for the analysis of the results has been done using the mathematical framework provided by linear regression models, utilizing the capabilities of R software version 4.2.3 for its execution.

2.3. Sample Description

Initially launched with small classes of about 15 students, the BEM degree has experienced a continuous increase in enrolment, reaching 80 new enrollees in the latest edition. Despite this growth, as of today, fewer than 500 students have coursed the program, of whom just 240 have successfully completed at least two years.

For the study, all 67 second-year students from the 7th cohort of the BEM program were selected. This group is of special interest as it is the first that has been split into two subgroups with no bias between them while maintaining the same professors. This targeted selection was to avoid external variables such as instructor influences, reducing possible teaching variances to ensure reliability of the data. In selecting this group, there has been no discrimination based on gender, race, or wage. The majority of the group coursed all the second-year subjects, while the rest of the sample (15 students) enrolled in a significant number of subjects to be considered. There is yet no data available of the forthcoming promotions coursing the second year.

Regarding academic course selection, sophomore year was chosen since it represents a critical point where the curriculum perfectly blends management and engineering subjects, offering a rich perspective on the multidisciplinary capabilities of the students.

3. Results

As mentioned above, the purpose of this study is to inspect the overall performance obtained by BEM students by carrying out a statistical analysis with which we can evaluate the different aspects that influence the student's learning outcomes. Furthermore, the study seeks to discuss the influence of a subject individually or as part of a cluster, in order to find connections between them that could be affecting the hypothesis stated above. To that aim, we consider the following variables:

- **Continuous Assessment (CA):** The EDEM Methodology focuses on continuous assignments designed to ensure students' consistent involvement and to measure their progress throughout their studies. These deliverables range from case studies and multiple-choice tests to oral presentations, peer reviews and group assignments. This approach demands active participation in classes, with specific attendance requirements tied to the continuous evaluation component, which accounts for 40% of a student's final grade in any given subject. Missing more than the

allowed number of classes (15%) triggers a higher threshold for passing the subject via the final exam, setting a minimum grade requirement that emphasizes the importance of regular attendance and continuous learning. CA ranges from 0 to 10.

- **Weighted mean (WM):** It is the variable consisting of the weighted mean of each subject. WM is calculated by 40% of CA and 60% of the synthesis part. This latter part, which consists of either two mid-term exams or one mid-term and one final exam, requires at least 5 out of 10 points to pass the subject. If this is not achieved, WM is calculated by the minimum mark between 4.5 and the 40-60% rule mark. This variable varies from 0 to 10, being 5 the minimum score to pass the subject.
- **Extracurricular activities (EA):** Students are not only encouraged to attend all classes but also to immerse themselves in the day-to-day academic and extracurricular activities. EDEM offers additional training courses with a corresponding diploma at the end of the degree in: Digital transformation, Sustainability, Leadership skills, and Total Quality Management. Further activities where students might participate include EDEM Emprende, Investment Team, Transversal Group Work, Talks, Hackathons, and more.
- **English (EN):** English is progressively incorporated in the degree, having 50% of subjects taught in English. This bilingual approach enhances students' language skills and broadens their perspectives, enabling them to operate effectively in international markets. This variable is recorded according to their certificates or fluency in English, rating it from 0 to 10.
- **Row (RO):** EDEM has small classrooms, consisting of four hemicyclic rows that surround the professor, and which bring the students sitting in the extremes closer to the front rows. The organization of the classrooms, in turn, tries to avoid the so-called last-row effect. RO equals 1 when the student sits in the front row, and subsequently.
- **Grant (GR):** EDEM offers high-school students the chance to join their first academic year at no cost. If the student maintains high standards of quality in their studies yearly and actively participates in extracurricular activities, this deal is extended for the following year. On the other hand, EDEM also promotes those students with less resources. Grants are offered to them as well, with similar conditions for the renewal. This dummy variable is recorded by 1 if the student is granted and zero otherwise.
- **Repeater (RE).** It stands as 1 for those who have at least one pending subject from the first academic year, and 0 otherwise.
- **Gender (GE):** In the 7th Edition, 22.8% of the sample are female students, which mirrors the broader challenge in STEM fields of attracting female participants. The reasons why female students opt not to enrol in this kind of degrees in Spain have been analysed in recent studies (Gómez, Tayebi & Delgado, 2021; López-Iñesta, Botella, Rueda, Forte & Marzal, 2020). Despite the increase in the number of women enrolling in STEM degrees, there is still significant work to be done to achieve gender parity. To tackle this problem, several prior initiatives have been made (Sinkele & Mupinga, 2011), although their effectiveness remains uncertain. It is worth noting that two of the three authors of the present article are women. GE equals 1 for male students and 0 for female students.

For our study, we are interested in the interdependence of any of the variables explained above. A suitable statistic to find whether a relationship between them exists is to proceed with a correlation analysis.

In Table 3, the correlation coefficient between each pair of the variables considered is computed.

	WM	CA	EA	EN	RO	GR	RE	GE
WM		0.945	0.31	0.41	-0.605	0.77	-0.33	-0.014
CA			0.386	0.375	-0.666	0.675	-0.212	-0.06
EA				0.328	-0.384	0.394	-0.428	-0.05
EN					-0.128	0.333	-0.111	-0.42
RO						-0.347	0.29	0.043
GR							-0.467	-0.13
RE								0.074
GE								

Table 3. Correlation matrix for the variables

Within the correlation matrix above, those that have the greatest absolute value are the ones more linearly related. This will be used to select the most appropriate models for our study.

In this sense, it is remarkable the 94.5% positive relation between the weighted mean (WM) and the overall continuous assessment (CA).

Furthermore, the sitting effect (RO) seems to be strongly negatively related to the students' performance, meaning that those sitting in the front rows get better results. This is consistent with the analysis performed in three subjects of the BBA in Entrepreneurship at the same university by Maldonado, Sotomayor and Villagrasa (2020).

Regarding the correlation coefficients of the extracurricular activities (EA) and level of English (EN), these variables have a value of around 0.3 on the overall performance (WM). This indicates a moderate positive correlation, meaning it could explain some linear relationship between these variables but not in detail.

Being granted (GR) with a scholarship may imply a higher performance (WM, CA). These students appear to be more likely to participate in extracurricular activities (EA) and to sit on front rows (RO). Contrary to them, repeaters (RE) tend to achieve lower results (WM, CA), enrol less on extracurricular activities (EA) and sit on back rows (RO).

It is also relevant to point out the correlation coefficients of the variable gender (GE) and the others, all of which being small values, yielding the somewhat surprising weak relation between such variable and others, such as the overall performance (WM).

3.1. Regression Models

Once the correlation matrix has been obtained and the behaviour of the variables with respect to each other has been analysed, the simple linear regression models can be introduced.

In order to be more precise, these models will help us find the optimized linear relationship between two or more variables. This will be useful to predict a student overall performance (WM) based on their specific combination of the values for each variable.

To proceed, it is convenient to calculate the p-value of each model to determine its significance:

	WM	CA	EA	EN	RO	GR	RE	GE
WM		0.000	0.157	0.052	0.002	0.000	0.131	0.951
CA			0.070	0.078	0.001	0.000	0.105	0.796
EA				0.013	0.003	0.002	0.002	0.729
EN					0.348	0.011	0.452	0.001
RO						0.008	0.048	0.755
GR							0.001	0.337
RE								0.618
GE								

Table 4. Level of significance for the simple linear regression models

We are interested in those p-values that guarantee significant models, that is, those that are smaller than 0.05. These p-values will show which potential models are relevant for our research.

In terms of academic performance, WM has a strong relation especially with the continuous assessment (CA), the seat position (RO) and being granted (GR).

These linear regression models have been computed and are displayed below:

$$WM = -4.3867 + 1.4648CA \quad (1)$$

$$WM = 9.2036 - 0.9855RO \quad (2)$$

$$WM = 6.089 + 2.3344GR \quad (3)$$

The first model yields that the mark obtained in the continuous assessment explains around 90% of the variation of WM, as $R^2 = 0.8922$. This model predicts that, to pass the subject, it is necessary to obtain a minimum score of 6.4 in CA. However, it should be noted that WM is partially calculated based on CA, which implies the need to consider other regression models that exclude this independent variable.

According to the second model, the sitting row seems to be quite determining. To be more precise, per each row behind the student seats, WM decreases by almost one point.

The third model shows the relevance of being granted, as there is a significant gap in terms of performance. From these two latter models it is also deduced that apparently those granted students sit down in the front rows, and vice versa, as we have seen in Table 3.

Other simple models can be obtained from the data taking into account the p-values calculated in Table 4: The variables RO and GR are significantly related to CA and EA, whereas the variable RE is so to EA and GR. Here we deploy the models for the number of extracurricular activities:

$$EA = 2.3793 - 1.4846RE \quad (4)$$

$$EA = 1.0444 + 2.2056GR \quad (5)$$

It is deduced that repeaters tend to attend to only one extracurricular activity while granted students participate in more than three.

Moreover, we can note that the variable GE has a non-significant relation with each variable considered, except the level in English (EN), where females outperform males.

$$EN = 7.3077 - 1.7395GE \quad (6)$$

Indeed, the model above (6) shows that females tend to have a B2-C1 level of English while males tested have an overall level of English below B2.

3.2. Analysis per Clusters

As noted, this second-year course consists of a wide range of topics, varying from theoretical-engineering subjects to business-related ones, being this the main reason for our choice. To obtain a more accurate analysis, we divide them, according to Figure 1, into four clusters so that each of them can be dissected to extract precise conclusions.

The cluster selection has been obtained grouping subjects based on their similar dimension levels. By doing so, the groups above have been obtained sorting all second-year subjects from soft (Cluster 1) to

hard (Cluster 4). In addition, all the subjects in Clusters 1 & 2 are taught in English, whereas those in Clusters 3 & 4 are taught in Spanish.

Business and Management Cluster 1	Applied Mathematics Cluster 2	Theoretical Engineering Cluster 3	Practical Engineering Cluster 4
<ul style="list-style-type: none"> Financial Accounting Business Law Marketing 	<ul style="list-style-type: none"> Statistics I Statistics II Operations Research 	<ul style="list-style-type: none"> Material Science Thermodynamics Electrical Technology 	<ul style="list-style-type: none"> Fluid Mechanics Kinematics and Dynamics of Machines Structures

Table 5. Clusters

By WM_i and CA_i it is denoted, respectively, the weighted mean and the continuous assessment for the cluster $i=1,2,3,4$. It is aimed to provide multiple regression models for each weighted mean, without considering the influence of the continuous assessment per each cluster.

To determine each model, we select the most relevant variables and add an extra independent variable. We then determine whether that variable increases our coefficient of determination (and its adjusted formula) or decreases it. If the coefficient increases, we retain the variable in the model.

Here there are the results:

$$WM_1 = 6.6010 + 0.2020EN^{****} + 1.5972GR + 0.6059RO^{***} \quad (7)$$

$$WM_2 = 3.0423 + 0.2764EN^{**} + 1.4187GR^{**} + 0.584EA^* \quad (8)$$

$$WM_3 = 8.5262 - 0.7636RO^{****} + 1.711GR^{****} - 2.3097RE^{***} \quad (9)$$

$$WM_4 = 6.7675 + 0.1711EA^* - 0.7913RO^{**} + 1.9098GR^{***} \quad (10)$$

****: level of significance of the variable is < 0.001

***: level of significance of the variable is > 0.001 and < 0.01

**: level of significance of the variable is > 0.01 and < 0.05

*: level of significance of the variable is > 0.05 and < 0.1

The significance of each model overall is quite high, as the corresponding p-values for the models are of order 10^{-7} . Besides that, the coefficient of determination is equal, respectively, to 0.6074, 0.7408, 0.7511, and 0.717.

In our first model for the Business and Management cluster, the intercept (6.6010) suggests that little effort could result in a passing outcome within the cluster. It is important to remark that the level of English (EN) might imply a variation in the mark of up to two points and the sitting row (RO) of up to 1.8 points. The second model, devoted to the subjects in Applied Mathematics, shows a bigger gap in terms of level of English, which could imply a difference of up to 2.7 points in the weighted overall mark. In this model it appeared the variable EA as (slightly) significant, which, according to the intercept, could imply a distinction between a pass or not. In the third model, about theoretical-engineering subjects, it seems to be relevant to sit in front rows and the type of student you are, in the sense that a granted student who sits in front rows may pass the subject with flying colours while a repeater sitting at the back is highly likely to fail it. Finally, the fourth model, which analyses the subjects of practical engineering, shows that the sitting row and being granted are again significant to predict the overall performance of the student. The variable EA also appears in this model despite its significance (p-value in between 0.05 and 0.1) and its slope (0.1711).

According to the four multiple linear models above, it is deduced that the independent variable of foreign language only affects if the subjects are taught in English (Clusters 1 & 2). The variable GR, on the other

hand, appears in every model, and it has a significant positive slope, implying that if a student is granted, no matter the cluster, their performance increases by between 1.4 and 1.9 points. Nevertheless, the p-value associated to the variable GR in the first cluster is a bit greater than 0.05, meaning that its relevance is limited and, in turn, students, *grosso modo*, achieve good marks in this type of subjects. Finally, the variable gender was not relevant for our analysis of the weighted mean of any of the clusters considered.

As an application of the models above, a granted student who sits in the front row with an excellent English level and attending to 3 extracurricular activities, would achieve a weighted mark between 8.4 and 9.5 in all the clusters. On the other hand, a non-granted student, who sits at the back of the class with a medium English level and barely attending to extracurricular activities, would obtain marks between 4.5 and 6.2.

3.3. Analysis Among Clusters

While in Section 3.2 the subjects in different clusters have been analysed in terms of the other variables considered, the aim of this section is to discuss the relation between clusters. This would be useful to have a deeper understanding of how versatile a student is among different disciplines.

We begin computing the correlation coefficients between weighted means and the score in continuous assessments per clusters:

	WM	WM1	WM2	WM3	WM4	CA1	CA2	CA3	CA4
WM		0.939	0.951	0.933	0.951	0.794	0.92	0.913	0.919
WM1			0.836	0.855	0.812	0.8	0.87	0.905	0.832
WM2				0.828	0.909	0.662	0.834	0.811	0.859
WM3					0.861	0.71	0.854	0.881	0.859
WM4						0.748	0.862	0.893	0.93
CA1							0.793	0.851	0.751
CA2								0.891	0.867
CA3									0.92
CA4									

Table 6. Correlation matrix between WM and CA per clusters

This correlation matrix allows us to know if we should focus on the relationship between clusters. It indicates whether a student's performance is specific to a particular cluster or if it reflects their overall performance.

To do so, we check if the correlation coefficient between the WM and the CA of the same cluster is the highest: In Clusters 3 and 4, i.e. those related to engineering subjects, the highest correlation coefficient of each weighted mean is achieved for the CA that corresponds to that cluster (0.881, 0.93). This situation differs from that in Cluster 2 where the highest coefficient is 0.859 that corresponds to Cluster 4 and, especially, in Cluster 1 where the correlation coefficient with the CA of the same cluster is the lowest. This shows that the variable CA plays a more important role in the practical and theoretical engineering subjects.

By calculating the p-value of each of these models, we find that each one is significant enough (with the largest p-value being 0.0004 for the model WM₂ and CA₁).

The simple regression models between weighted means in clusters are as follows:

$$WM_1 = 2.478 + 0.732WM_2 \quad (11)$$

$$WM_1 = 1.543 + 0.794WM_3 \quad (12)$$

$$WM_1 = 3.027 + 0.707WM_4 \quad (13)$$

$$WM_2 = 0.287 + 0.873WM_3 \quad (14)$$

$$WM_2 = 1.394 + 0.864WM_4 \quad (15)$$

$$WM_3 = 2.627 + 0.784WM_4 \quad (16)$$

The significance of each of the models is again high since the p-values for the models are of order 10^{-8} , and the R^2 are, respectively, 0.699, 0.731, 0.659, 0.685, 0.826, and 0.741.

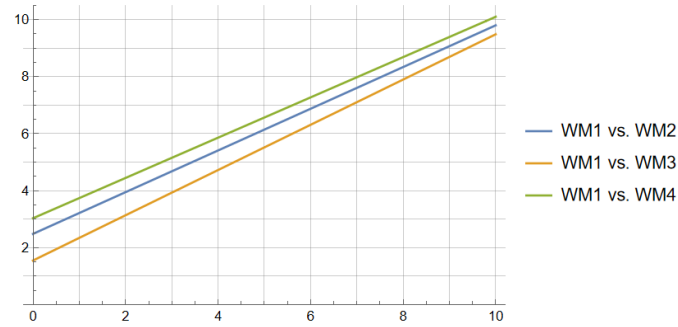


Figure 3. Analysis between WM_1 and the other clusters

From the first three models, WM_1 is normally the highest mark achieved. For example, if the mark obtained in WM_2 (resp. WM_3 and WM_4) is 7.5, then it is expected to obtain a mark in WM_1 of 8 (resp. 7.5 and 8.3). Here in Figure 3, it can be noted that that the different WM achieved for each cluster does not excessively vary. We provide below the graphic analysis comparing each of the remaining clusters individually with the other three clusters.

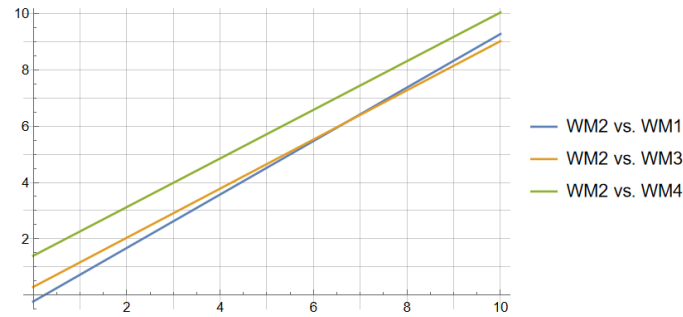


Figure 4. Analysis between WM_2 and the other clusters

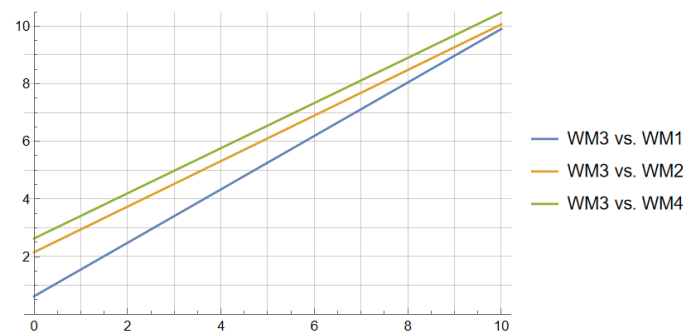


Figure 5. Analysis between WM_3 and the other clusters

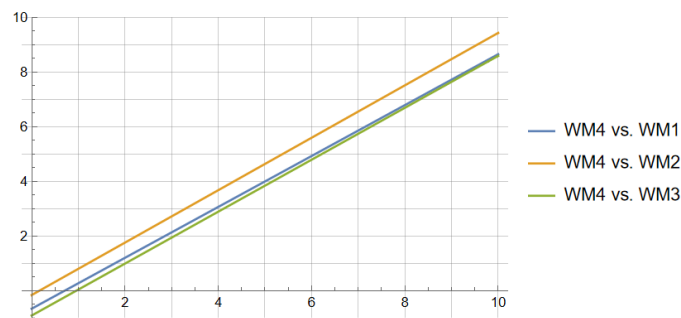


Figure 6. Analysis between WM₄ and the other clusters

From Figure 4, we see that the weighted mean for Cluster 2 may vary a bit depending upon the results in the other subjects. For instance, if a mark of 7 is obtained in Cluster 1 or 3 (resp. Cluster 4), then it is expected that a weighted mean of 6.5 (resp. 7.5) is obtained in Cluster 2. The consistency of the marks between Cluster 1 and 3 can be seen from Figures 4, 5 and 6, especially to determine the performance for Cluster 4 (Figure 6). In this case, better results in Cluster 2 are attributable to better ones for Cluster 4, despite being slightly lower than those observed initially in Figure 3.

4. Discussion and Conclusion

Pedagogical innovations are making it easier for teachers and educational institutions to implement strategies and act on activities that can be done to keep students motivated and engaged during the course. Educators who use active methodologies experience greater student engagement, improved academic outcomes, and greater satisfaction with their teaching (Aparicio, Ostos & García, 2024). That is why universities must have a more significant commitment to practical training (García & Cazaluade, 2022).

The teaching-learning processes that promote the development of competencies are linked to active, authentic, and situated methodologies (Reyes, Jiménez, Rojas, Lezama & Navarro, 2020). In the present study, through statistical analysis of student marks, a deeper understanding of the Active Learning factors influencing performance in the BEM degree has been achieved. As a result, precise models have been developed that incorporate how continuous assessment (CA), being granted (GR) and the row where the student sit (RO) impact the student weighted mean (WM). The correlation analysis suggests a moderate linear relationship (0.31) that directly relates the impact of extracurricular activities (EA) on performance, though it surprisingly shows minimal correlation between gender (GE) and performance (-0.014). The models for both EA and GE were not studied due to their p-values being greater than 0.05.

The analysis among clusters has shed light on which variables specifically impact on each module and on how different modules within the degree are interrelated. Findings confirm the multidisciplinary profile of the students, as the computed models show that the marks a student could achieve across different modules experience little variation. The highest influence of CA on engineering modules suggests that course activities are more beneficial to students, helping them better prepare for the final exam and, consequently, improving their overall marks (WM). This is in line with previous studies that show that a greater attendance is reflected in better marks obtained in the exercises carried out in class and in the exams, especially in subjects that require a mental functional gymnastics effort, which can only be developed progressively, week by week (Navarro-Jover & Martínez-Ramírez, 2018). The fact that the activities done during continuous assessment (CA) in business subjects have less influence on the final mark opens opportunities to improve the types of activities proposed in the classroom, shifting towards cases that better prepare students for the exam.

Regarding the first hypothesis (*H1*), the analysis in Section 3 has demonstrated that the efficiency in continuous assignments relates directly to the performance achieved in the overall mark, even more than the mere 40% of the calculus of WM. From the correlation matrix in Table 3, a 94.5% positive relation between the weighted mean (WM) and the continuous assessment (CA) was found, emphasizing the necessity of achieving a good performance throughout the year in order to successfully pass the subject.

In the regression analysis performed, the simple linear regression model between WM and CA explained around 90% of the variation of the weighted mean. From the analysis among clusters, the models for engineering-related subjects (Clusters 3 & 4) demonstrated a high relation between their corresponding CA and WM (0.881, 0.93), highlighting the relevance of the Active Learning activities displayed throughout the course. In Clusters 1 & 2 the relation is still high (0.8, 0.834), yet the weighted mean is better explained by the CA of other clusters. This circumstance may be attributable to the fact that engineering subjects require more consistency during the course. This is in line with studies in automatic control theory that note that active learning improves the understanding of abstract concepts (Chevalier, Dekemele, Juchem & Loccufier, 2021; Palacio, Zuluaga & Castro, 2024; Frenández-Samacá & Ramirez, 2011).

Previous research has also shown the benefits of cooperative learning methodologies in engineering due to their effect on participation, the pace of learning, and, consequently, performance (García & Cazaluade, 2022). In regard to the importance of the CA in each cluster, the student council claims that for Cluster 1 (Business and Management) it is easier to obtain a high WM as it does not require to internalize and practice abstract concepts and problems during the course compared to the other clusters. This is in line with the results collected in Figures 4, 5 and 6, where from the first three models, WM₁ is normally the highest mark achieved. It is important to remark the consistency of the marks seen between Cluster 1 and 3, especially to determine the performance for Cluster 4. Furthermore, better results in Cluster 2 are attributable to better ones for Cluster 4.

EDEM promotes several activities out of the classroom, enhancing team building and learning soft skills, among others. For our second hypothesis (*H2*), in Table 3 the variable extracurricular activities (EA) has a correlation coefficient of 0.31 with respect to WM and 0.386 with respect to CA. Here we are looking at both WM and CA since motivation is explained by the performance throughout the year. Motivation offers not only a greater guarantee of learning success but also a significantly more consolidated learning experience (Reyes, Enfedaque & Gálvez, 2017). The student engagement, the knowledge construction approaches, and achievement motivation are meant to be related positively to the active learning of students at the university. Furthermore, previous research has shown that student engagement happened mostly always in aula in lecturing time (Xhomara, 2018). Moreover, from our research, granted students are three times more likely to engage in extracurricular activities compared to other students, whereas repeaters tend to participate 63% less than their peers. In the subjects of Applied Mathematics and Engineering (Clusters 2 & 4), there is enough significance to argue that participating in these initiatives is relevant to the overall performance, though with a p-value between 0.05 and 0.1. Therefore, there is no evidence enough to argue that *H2* holds for each cluster and further research should be carried out.

In this degree particularly, and contrary to what we expected, no model considered the variable Gender to be significant, as seen in the p-values calculated in Table 4, except for the level of English (0.001). In fact, its corresponding model states that women are one level above men in the Common European Framework of Reference for Languages (CEFR). This connects with the findings of Richardson, Abraham and Bond (2012), who highlighted the role of self-efficacy in academic performance, often higher in female students. Gender was not significant in any of the clusters considered either. In any case, there is no relation between gender and the mark achieved in the final exams, and *H3* cannot be proven to hold. These results contrast to those in Chen, Owusu-Ofori, Pai, Toca-McDowell, Wang and Waters (1996), which showed that females achieved better results overall. It is worth noting that this new engineering differs to a classical one, as that examined by Chen et al. (1996).

One of the distinctive characteristics of the degree analysed is its blend of engineering and business subjects. That is why for our fourth hypothesis (*H4*) we wanted to test whether students do perform similarly in both disciplines. From the linear regression models in Section 3.3, we have shown that when considering different clusters, there is consistency and correlation in the marks obtained by students with different interests. Indeed, the slopes of these models range between 0.707 and 0.873. This implies that despite the difference in difficulty among the clusters (for example, between Cluster 1 & 3), a student who

performs well in one cluster will do so in the rest of the subgroups, and accordingly for a student with a lower performance. This is in line with the examples seen in Section 3.2. By this, the interdisciplinary profile of the students is proven.

Finally, the fifth hypothesis (*H5*) is demonstrated as it has been determined in Table 3 that the sitting effect is negatively linearly related to the overall mark (-0.605) and even more to the performance in the continuous assessment (-0.666). This means that those that sit at the front during the course achieve better marks. Literature proves the influence of the seating place occupied by students on their attitude in the classroom, attention, participation, positive attitude, and commitment (See Navarro-Jover & Martínez-Ramírez, 2018, and the references therein). Furthermore, from the regression analysis we have found that per each row behind the student seats, the overall mark decreases by almost one point. This extends previous analysis performed for BSc in other fields such as in economics (Benedict & Hoag, 2004) or psychology (Holliman & Anderson, 1986). The reduced size of the group and of the room are factors also attributable to the positive results.

4.1. Applications in Education

As stated in Section 2, this study is aimed at optimizing students' performance. Our findings support existing theories that link student performance, engagement and effort as being fundamental for student success in college (Fredin, Fuchsteiner & Portz, 2015).

A key aspect of the findings and models created in this study is that they can serve not only as a resource for the existing coordinator role at EDEM, but also for coordinators at other institutions. This understanding can help them in implementing early interventions and regular feedback on their students. Being aware of which factors determine the final mark can help designing engaging classes and adjusting the percentages of teaching modules, posing greater emphasis on the value that CA has. By using the identified performance factors and regression models, the coordinator can oversee the implementation of tailored support programs and initiatives that address student needs in each module. These programs may include subject-specific tutoring sessions to advise each student about which variables are more relevant to them and recommendations on what can be improved to achieve better course results.

By integrating these tailored suggestions into the existing coordinator role and academic support programs at EDEM, the institution can effectively utilize the study's findings to optimize student success and improve overall learning outcomes. In this sense, an alignment between proposed activities at the CA and exams should be considered in modules where the CA is less relevant for the calculus of the WM. Moreover, this understanding can be used to forecast in advance the WM of a student based on its performance during the initial stages of the course.

Additionally, EDEM should prioritize training programs for professors, as many educational innovations have failed because they did not recognize the need for teacher learning (Bakkenes, Vermunt & Wubbels, 2010). This training should focus on enhancing teaching skills and pedagogical techniques to ensure high-quality instruction and support for students. The quality of these learning processes has been shown to determine the quality of the learning outcomes students achieve (Sudargini & Purwanto, 2020).

Since engagement levels do not differ significantly between modules, the factors affecting the students' performance might be more related to the instruction methods or student characteristics than the subject content itself. This leads us to believe, in line with Navarro-Jover and Martínez-Ramírez (2018), the importance of student motivation and the effect of participatory methodologies.

Moreover, the relationship found between seat position and engagement highlights the importance that a classroom layout has for students. Professors should consider this when arranging seats and institutions when designing new classroom spaces.

This paper has shown how student's performance is impacted by factors like extracurricular activity participation, class attendance, or continuous assessment. These findings emphasize the significance of

implementing an educational strategy that increases academic performance while also promoting greater student involvement and participation.

Additionally, the statistical analysis has highlighted the disciplinary profile of BEM students, offering new insights into how teaching modules could be structured. This suggests not only the multidisciplinary nature of the students but also the effectiveness of how concepts and knowledge are shared, regardless of the content. These findings open a new perception of the interdependence between engineering and business topic-oriented subjects, challenging traditional theories about the organization of academic programs and proposing new ways to understand the relationships between disciplines that have historically been viewed as separate. It supports the theory that academic programs could integrate more fields of study that complement each other. This opens the debate about the difficulty of the subject itself, and the importance of the personal traits of the students and their relationship with their professor. Gargallo-López, Pérez-Pérez, García-García, Giménez-Beut and Portillo-Poblador (2020) point out that the presence or absence of motivation by students in a subject can be attributed to the student's characteristics and that the student-teacher relationship is also essential in their motivation (García & Cazaluade, 2022).

As a result, beyond EDEM, educational institutions should reconsider their traditional teaching methods, as the implementation of active learning techniques appears to be effective regardless of the nature of the content. One effective method that could be considered for implementation is Flip Teaching. A form of Active Learning that has been used for more than a decade and that has demonstrated success in various academic disciplines, including those of Business Management (Pérez-Guillot & Jaime-Pastor, 2015), having obtained quite positive results. This approach involves students engaging with instructional content before class, allowing in-class time for discussions and activities. Although EDEM has not considered Flip Teaching to be incorporated yet, based on the regression models from Section 3, we recommend implementing Flip Teaching in Clusters 1 & 2, specifically targeting Modules 1 & 3 where performance in continuous assessments could be enhanced.

4.2. Limitations of the Study

One of the drawbacks of the study is the reduced sample. This may have implied a bias in some variables, such as the variable gender, where the number of women analysed is small. Additionally, individual outliers within the sample could have disproportionately affected the results. Several external factors may have conducted to the rejection of $H3$, such as the degree not being widely known or the absence of a robust female sample. To reinforce our findings, it is convenient to support them by a larger sample as the degree advances. We also acknowledge the potential risk of diversity in our sample as a limitation in our results and discussion. We can try to disaggregate the data by factors such as socioeconomic status, different academic backgrounds, etc. to see if any trends or differences emerge.

Finally, the relatively newness of the engineering program could limit the validity of our findings in the medium-long term since the curriculum, teaching methods, and the stability of the overall program structure might evolve as the degree matures, meaning that the experiences of these relative initial students might not reflect those of students in forthcoming years. Furthermore, as other established programs for engineering do not fully intersect with BEM, it makes difficult to benchmark the performance and outcomes of BEM students against those in other programs.

4.3. Future Lines of Work

The current project was conducted with students in their second year of the BEM program. To further validate the robustness of this research, it would be beneficial to extend this analysis to the entire degree program. This would permit the assessment of whether the patterns observed in the sophomore-year cohort hold true for students at different stages of their studies and under varying academic and experiential conditions. Additionally, tracking the same group to their graduation could provide more

insights into how early academic and extracurricular engagement influences long-term success and overall performance.

As a future line of action, the study could be replicated in other degree programs, and based on the results, adjustments to these models could be made to implement them in other universities. This provides educational institutions with a tool to better address students' learning needs and improve their overall performance. Additionally, external variables could be analysed, such as the social and economic environment or the available technology, in order to determine whether they influence the impact of active learning on academic performance. Other active learning methodologies could also be examined to understand which strategies yield better results regarding student engagement and performance.

Finally, while it is natural to use linear regression models to make predictions, quadratic models could be considered. Moreover, other non-linear regression models have been used since long (Walberg, 1971). This perspective is based upon slight modifications on the relevance of dependent variables. In our case, however, these adjustments did not significantly improve our models. Notwithstanding this, non-linear models should be considered for forthcoming projects.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and publication of this article.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

References

- Aji, C.A., & Khan, M.J. (2019). The impact of Active Learning on students' academic performance. *Open Journal of Social Sciences*, 7(03). <https://doi.org/10.4236/jss.2019.73017>
- Alenezi, M. (2023). Digital learning and digital institution in higher education. *Education Sciences*, 13(1), 88. <https://doi.org/10.3390/educsci13010088>
- Aparicio, O.M., Ostos, O.L., & García, C.A. (2024). Convergence between emerging technologies and active methodologies in the university. *Journal of Technology and Science Education*, 14(1), 31-44. <https://doi.org/10.3926/jotse.2508>
- Bakkenes, I., Vermunt, J.D., & Wubbels, T. (2010). Teacher learning in the context of educational innovation: Learning activities and learning outcomes of experienced teachers. *Learning and Instruction*, 20(6), 533-548. <https://doi.org/10.1016/j.learninstruc.2009.09.001>
- Bedi, A. (2023). Keep Learning: Student Engagement in an Online Environment. *Online Learning*, 27(2), 119-136. <https://doi.org/10.24059/olj.v27i2.3287>
- Benedict, H.E., & Hoag, J. (2004). Seating location in large lectures: Are seating preferences or location related to course performance? *The Journal of Economic Education*, 35(3), 215-231. <https://doi.org/10.3200/JECE.35.3.215-231>
- Biglan, A. (1973). The characteristics of subject matter in different academic areas. *Journal of Applied Psychology*, 57(3), 195. <https://doi.org/10.1037/h0034701>
- Børte, K., Nesje, K., & Lillejord, S. (2020). Barriers to student Active Learning in higher education. *Teaching in Higher Education*, 28(3), 597-615. <https://doi.org/10.1080/13562517.2020.1839746>
- Brooks, D.C. (2011). Space matters: The impact of formal learning environments on student learning. *British Journal of Educational Technology*, 42(5), 719-726. <https://doi.org/10.1111/j.1467-8535.2010.01098.x>

- Chen, J.C., Owusu-Ofori, S., Pai, D., Toca-McDowell, E., Wang, S.L., & Waters, C.K. (1996). A study of female academic performance in mechanical engineering. In *Technology-Based Re-Engineering Engineering Education Proceedings of Frontiers in Education FIE'96 26th Annual Conference* (2, 779-782). IEEE.
<https://doi.org/10.1109/FIE.1996.573067>
- Chevalier, A., Dekemele, K., Juchem, J., & Loccufier, M. (2021). Student feedback on educational innovation in control engineering: active learning in practice. *IEEE Transactions on Education*, 64(4), 432-437. <https://doi.org/10.1109/TE.2021.3077278>
- Donnay, D.A.C., Morris, M., Schaubhut, N., & Thompson, R. (2005). *Strong Interest Inventory Manual: Research, Development, and Strategies for Interpretation*. Mountain View, CA: CPP.
- Fleischmann, K., & Hutchison, C. (2012). Creative exchange: An evolving model of multidisciplinary collaboration. *Journal of Learning Design*, 5(1), 23-31. <https://doi.org/10.5204/jld.v5i1.92>
- Fredin, A., Fuchsteiner, P., & Portz, K. (2015). Working toward More Engaged and Successful Accounting Students: A Balanced Scorecard Approach. *American Journal of Business Education*, 8(1), 49-62.
<https://doi.org/10.19030/ajbe.v8i1.9016>
- Freeman, S., Eddy, S.L., McDonough, M., Smith, M.K., Okoroafor, N., Jordt, H. et al. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences*, 111(23), 8410-8415. <https://doi.org/10.1073/pnas.1319030111>
- Frenández-Samacá, L., & Ramírez, J.M. (2011). Learning control concepts in a fun way. *The International Journal of Engineering Education*, 27(1), 187-199.
- García, E.C., & Cazaluade, Ó.R. (2022). Increase in academic performance due to the application of cooperative learning strategies: A case in construction engineering. *Journal of Technology and Science Education*, 12(3), 578-595. <https://doi.org/10.3926/jotse.1694>
- Gargallo-López, B., Pérez-Pérez, C., García-García, F.J., Giménez-Beut, J.A., & Portillo-Poblador, N. (2020). La competencia aprender a aprender en la universidad: propuesta de modelo teórico. *Educación XXI*, 23(1), 19-44. <https://doi.org/10.5944/educxx1.23367>
- Gómez, J., Tayebi, A., & Delgado, C. (2021). Factors that influence career choice in engineering students in Spain: A gender perspective. *IEEE Transactions on Education*, 65(1), 81-92.
<https://doi.org/10.1109/TE.2021.3093655>
- Guleker, R., & Keci, J. (2014). The effect of attendance on academic performance. *Mediterranean Journal of Social Sciences*, 5(23). <https://doi.org/10.5901/mjss.2014.v5n23p961>
- Holland, J.L. (1997). *Making vocational choices: A theory of vocational personalities and work environments*. Psychological Assessment Resources.
- Holliman, W.B., & Anderson, H.N. (1986). Proximity and student density as ecological variables in a college classroom. *Teaching of Psychology*, 13(4), 200-203. https://doi.org/10.1207/s15328023top1304_7
- Huang, Y.M., & Wu, T.T. (2011). A systematic approach for learner group composition utilizing U-learning portfolio. *Educational Technology & Society*, 14(3), 102-111
- Jones, W.A. (2011). Variation among academic disciplines: An update on analytical frameworks and research. *Journal of the Professoriate*, 6(1), 9-27.
- Kelly, G.E. (2012). Lecture attendance rates at university and related factors. *Journal of Further and Higher Education*, 36(1), 17-40. <https://doi.org/10.1080/0309877X.2011.596196>
- Li, R., Lund, A., & Nordsteien, A. (2023). The link between flipped and Active Learning: A scoping review. *Teaching in Higher Education*, 28(8), 1993-2027. <https://doi.org/10.1080/13562517.2021.1943655>

- López-Iñesta, E., Botella, C., Rueda, S., Forte, A., & Marzal, P. (2020). Towards breaking the gender gap in Science, Technology, Engineering and Mathematics. *IEEE Revista Iberoamericana de Tecnologías del Aprendizaje*, 15(3), 233-241. <https://doi.org/10.1109/RITA.2020.3008114>
- Maldonado, M., Sotomayor, V., & Villagrasa, J. (2020). Last row effect: ¿influye el sitting en los resultados del estudiante? In *IN-RED 2020: VI Congreso de Innovación Educativa y Docencia en Red*. <https://doi.org/10.4995/INRED2020.2020.11945>
- Martin, F., & Bolliger, D.U. (2018). Engagement matters: Student perceptions on the importance of engagement strategies in the online learning environment. *Online Learning*, 22(1), 205-222. <https://doi.org/10.24059/olj.v22i1.1092>
- Moore, E., Birdi, G.K., & Higson, H.E. (2019). Determinants of university students' attendance. *Educational Research*, 61(4), 371-387. <https://doi.org/10.1080/00131881.2019.1660587>
- Navarro-Jover, J.M., & Martínez-Ramírez, J.A. (2018). Academic Performance, Class Attendance and Seating Location of University Students in Practical Lecture. *Journal of Technology and Science Education*, 8(4), 337-345. <https://doi.org/10.3926/jotse.353>
- Palacio, C.V.R., Zuluaga, E.I.A., & Castro, H.A.B. (2024). Design and implementation of a novel didactic strategy using learning styles for teaching control theory. *Journal of Technology and Science Education*, 14(3), 1025-1040. <https://doi.org/10.3926/jotse.2564>
- Pérez-Guillot, M., & Jaime-Pastor, M. (2015). Flip-teaching aplicado al inglés para la Gestión Empresarial: una nueva experiencia. In *IN-RED 2015: Congreso Nacional de Innovación Educativa y de Docencia en Red*. <https://doi.org/10.4995/INRED2015.2015.1643>
- Qureshi, M.A., Khaskheli, A., Qureshi, J.A., Raza, S.A., & Yousufi, S.Q. (2023). Factors affecting students' learning performance through collaborative learning and engagement. *InterActive Learning Environments*, 31(4), 2371-2391. <https://doi.org/10.1080/10494820.2021.1884886>
- Reyes, E., Enfedaque, A., & Gálvez, J.C. (2017). Initiatives to foster engineering student motivation: A case study. *Journal of Technology and Science Education*, 7(3), 291-312. <https://doi.org/10.3926/jotse.265>
- Reyes, K.A.L., Jiménez, A.E.G., Rojas, C.D.P.V., Lezama, S.E.C., & Navarro, E.R. (2020). Aprendizaje colaborativo en línea y aprendizaje autónomo en la educación a distancia. *Revista Científica Cultura, Comunicación y Desarrollo*, 5(3), 95-100.
- Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: a systematic review and meta-analysis. *Psychological Bulletin*, 138(2), 353. <https://doi.org/10.1037/a0026838>
- Robinson, D.V., Robinson, T., & Ogundimu, A. (2021). Strategies for Creating Engaging Learning Communities to Inspire and Motivate Adult Learners. *Learning: Design, Engagement and Definition. Interdisciplinarity and learning* (261-268). https://doi.org/10.1007/978-3-030-85078-4_21
- Rodgers, J.R. (2002). Encouraging tutorial attendance at university did not improve performance. *Australian Economic Papers*, 41(3), 255-266. <https://doi.org/10.1111/1467-8454.00163>
- Simpson, A. (2017). The surprising persistence of Biglan's classification scheme. *Studies in Higher Education*, 42(8), 1520-1531. <https://doi.org/10.1080/03075079.2015.1111323>
- Sinkele, C.N., & Mupinga, D.M. (2011). The effectiveness of engineering workshops in attracting females into engineering fields: A review of the literature. *The Clearing House: A Journal of Educational Strategies, Issues and Ideas*, 84(1), 37-42. <https://doi.org/10.1080/00098655.2010.496812>
- Stanca, L. (2006). The effects of attendance on academic performance: Panel data evidence for introductory microeconomics. *The Journal of Economic Education*, 37(3), 251-266. <https://doi.org/10.3200/JECE.37.3.251-266>

- Sudargini, Y., & Purwanto, A. (2020). The effect of teachers pedagogic competency on the learning outcomes of students. *Journal of Industrial Engineering & Management Research*, 1(4), 1-8.
- Szostak, R. (2008). Classification, interdisciplinarity, and the study of science. *Journal of Documentation*, 64(3), 319-332. <https://doi.org/10.1108/00220410810867551>
- Walberg, H.J. (1971). Generalized regression models in educational research. *American Educational Research Journal*, 8(1), 71-91. <https://doi.org/10.3102/00028312008001071>
- Williamson, J.M. & Panigabutra-Roberts, A. (2021). An analysis of STEAM disciplinary interrelationships described in abstracts of higher education articles. *Impact: The Journal of the Center for Interdisciplinary Teaching & Learning*, 10(1).
- Xhomara, N. (2018). The role of students' engagement, knowledge construction approaches, and achievement motivation on increasing of active learning. *European Journal of Education Studies*, 5(5).

Published by OmniaScience (www.omniascience.com)

Journal of Technology and Science Education, 2025 (www.jotse.org)



Article's contents are provided on an Attribution-Non Commercial 4.0 Creative commons International License.

Readers are allowed to copy, distribute and communicate article's contents, provided the author's and JOTSE journal's names are included. It must not be used for commercial purposes. To see the complete licence contents, please visit <https://creativecommons.org/licenses/by-nc/4.0/>.