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Comparative of Face-to-Face, Blended and On-line scenarios in Higher Education: Analysis of its effects on academic results considering the interaction with e-learning platforms

Comparativa de los escenarios presencial, mixto y on-line en Educación Universitaria: Análisis de sus efectos sobre los resultados académicos considerando la interacción con plataformas e-learning

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Resumen

El objetivo de este trabajo es analizar el efecto de los escenarios presencial, mixto y on-line en los resultados académicos de los estudiantes considerando la interacción con plataformas e-learning. Los resultados muestran que los resultados académicos no se ven afectados por el escenario de aprendizaje, mientras que el grado de interacción con las plataformas e-learning se ve afectado por el escenario de aprendizaje. Además, el modelo de Efectos de Tratamiento se ha utilizado para estudiar el escenario de aprendizaje y la interacción con las plataformas de aprendizaje de manera conjunta. En este caso, los resultados académicos se ven afectados por el escenario on-line frente al presencial, pero no se ven afectados por el escenario mixto frente al presencial. En concreto, sobre un valor medio de 4,14 puntos, obtenido de los resultados académicos de todos los alumnos, con un tratamiento on-line los resultados bajan 1,01 puntos (24,41%), mientras que con un tratamiento mixto los resultados bajan 0,38 puntos (9,13%). Finalmente, utilizando la Regresión Extendida Polinomial Fraccionaria, se proponen modelos de predicción para cada uno de los escenarios.

Palabras clave

Educación Universitaria, Plataformas E-Learning, Análisis de Datos Exploratorio y Confirmatorio, Regresión Extendida Polinomial Fraccionaria, Efectos de Tratamiento

Abstract

The aim of this work is to analyze the effect of face-to-face, blended and on-line scenarios on students' academic results considering the interaction with e-learning platforms. The results show that academic results are not affected by the learning scenario, while the degree of interaction with e-learning platforms is affected by the learning scenario. Furthermore, Treatment Effects model has been used to study the learning scenario and the interaction with e-learning platforms together. In this case, the academic results are affected by the on-line versus the face-to-face scenario but are not affected by the blended versus the face-to-face scenario. Specifically, on an average value of 4,14 points, obtained from the academic results of all students, with an on-line treatment, the results drop 1,01 points (24,41%), while with a blended treatment, the results drop 0,38 points (9,13%). Finally, utilizing Fractional Polynomial Extended Regress, prediction models are proposed for each of the scenarios.

Key Words

Higher Education, E-Learning Platforms, Exploratory and Confirmatory Data Analysis, Polynomial Extended Regress Model, Treatment Effects

1. INTRODUCTION

After the arrival and spread of coronavirus SARS-CoV-2 in Spain in March 2020, the Spanish Government decided to impose a lockdown, thus limiting the mobility and interaction of people, in order to contain the spread of the virus. This involved the closing of schools, universities and many other sectors considered “non-essential”, which forced both students and workers to carry on with their activities from home.

Consequently, a sudden change occurred in the learning model, which went from face-to-face learning to on-line learning, since this was the only way to guarantee the continuation of education during the lockdown. In this new situation, teachers had to adapt immediately and adjust the teaching strategies in order to continue teaching in the on-line modality (Hodges et al., 2020; Morgan, 2020). On-line learning requires an instructive and careful design and the contemplation of different policies (Branch & Dousay, 2015). However, in most cases, this design process may be absent due to this improvisation and suddenness. Likewise, the infrastructure around on-line learning must be sufficient to support student success (Aldhahi et al., 2022). Despite this, on-line learning has several frequently highlighted advantages. For example, its affordability; its flexibility to accommodate a larger number of students than is possible with traditional face-to-face learning; the fact that anyone with an Internet connection can access a university education (thus removing additional costs such as travel and accommodation); the increase of opportunities of global connections; the fact that it allow for both synchronous and asynchronous learning; the possibility of facilitating teamwork by students; teaching more attractive lectures (due to innovative digital technologies) compared to traditional learning and traditional classrooms; the possibility of rapid student-teacher interaction, etc. (Anthony et al., 2019; Castro & Tumibay, 2021; Christie, 2004; Fouche & Andrews, 2022; Nguyen, 2015; Van Gelderen & Guthadjaka, 2017). Aldhahi et al. (2022) analyzed student satisfaction with on-line learning during the pandemic. Satisfaction with learning is a key indicator of student learning performance that was also analyzed by Maki et al. (2000).

Likewise, once the compulsory lockdown was over, universities had to plan the academic year 2020-2021 with proposals of different learning models or systems according to the possible scenarios that could appear. Thus, in addition to the face-to-face learning prior to the pandemic and the on-line learning due to the lockdown, blended learning was considered an adequate solution for the post-lockdown period. This blended scenario should also allow for a gradual transition to a traditional scenario based on the pre-pandemic face-to-face learning model (Bamoallem & Altarteer, 2022). According to Singh & Reed (2001), blended learning is defined as “a learning approach in which more than one delivery method is used to enhance the achievement of the learning outcomes and the cost of the programs". Blended learning has been widely explored by academics, and several empirical studies have demonstrated its efficacy (Halverson et al., 2014). A blended learning environment can improve the performance and achievements of the students (Dickfos et al., 2014), create an auspicious learning environment for them (Azizan, 2010; Wai and Seng, 2014) and allow experimenting a conceptual change compared to the teaching of traditional face-to-face or master lectures using more than one teaching method (Bazelais and Doleck, 2018). Likewise, this scenario can help students to be more responsible for their own learning and empower them in terms of how such learning will take place and the extent of it (Leidner & Jarvenpaa, 1995), as well as to develop self-reflection skills (Dickfos et al., 2014). Finally, in Bamoallem & Altarteer (2022) the perception and acceptance of students toward this blended learning model is also analyzed.

Faced with this situation, the impact of the COVID-19 pandemic on learning in higher education, focusing mainly on the adaptation of the learning model to the circumstances derived from the pandemic, as well as on the efficacy of the on-line learning model has been analyzed. So, Yang (2020) analyzed the difficulties of implementing the on-line learning model in higher education in China; such difficulties appear to be derived, among other causes, from the fragility of the infrastructure necessary for on-line learning and the lack of experience of teachers (including the differences in the learning outcomes caused by the varied experience of teachers). Yang (2020) also explains how, after great efforts by the Chinese Government, the use of on-line learning in Chinese universities, rapidly becoming the main learning modality implemented on a large scale. Similarly, Pham and Ho (2020) explored the impact of the pandemic on Vietnamese universities, focusing on the work performed to implement on-line learning and technology-based educational modalities. Thus, they provide some possible ways for the adoption of e-learning in higher education institutions of Vietnam in a post-pandemic environment. Once the pandemic ceases to be a threat, Vietnamese universities will be settled on a “new normality”, with flexible, updated, and reformed teaching and learning models, combining the traditional education models and the new on-line learning, thus giving rise to a blended learning model. Furthermore, Bolumole (2020) described his own experience as a postgraduate student in the United States during the coronavirus pandemic, reflecting on the main events: the hasty closing of university campuses, the clumsy transition to on-line learning, the controversial reopening of the campuses and, lastly, his hopes for higher education in the USA while it adapts to a new reality. Finally, Takayama (2020) reflected on the implications of coronavirus for teaching and learning in universities. Takayama recognizes the world health crisis as a catalyzing time to rethink the “habitual functioning” of university learning and develop a renewed appreciation of what is taken for granted in it.

In any case, in all these studies, a quantitative study that analyses and compares the academic results obtained by the students in the different learning scenarios (face-to-face, blended, and on-line) in university teaching, also taking into account, jointly, the use they make of e-learning platforms in these scenarios has not been presented. To solve this deficiency, the study presents the following objective: analyze the academic results or marks obtained by university students in function of the learning scenario together with the use they make of e-learning platforms.

2. METHODOLOGY

This section sets out the methodology followed in the development of the study and the way of obtaining and processing the data used. Thus, first the statistical sample is shown, then the variables and the procedure followed are detailed. Finally, the statistical analysis carried out is described.

2.1. Statistical sample

The data used in this study belongs to the subject of Analysis of Financial Operations of the second term of the first year of the Business Administration and Management Degree at the University of Burgos, Spain. Concretely, the data are gathered from the interactions of the students with the UBUVirtual (virtual teaching platform used by the University of Burgos, based on Moodle 3.0 technology). The data correspond to the interaction logs of the users with the platform. Data from several academic courses corresponding to the different types of learning scenarios are gathered. Second term of the 2018-2019 academic year for face-to-face learning, second term of 2019-2020 academic year for on-line learning and second term of 2020-2021 academic year for blended learning.

After data collection, a processing is necessary prior to their analysis. Specifically, the cleaning, filtering, arrangement, and anonymize steps are carried out. In the cleaning phase, we removed the logs of teacher access, guest profiles and system administrators. At this point, the data of the students who had cancelled their enrollment during the academic course and the data of the students who did not undertake the evaluation tests are also removed. Then, we discarded the logs of access to non-teaching materials, such as schedules, teaching guide and mark-related files. The filtering consisted of eliminating the logs with a date later than the date of the last evaluation test and, in addition, all duplicate logs are eliminated. In the arrangement phase, we calculated the number of times that each student accessed each teaching block into which the subject is divided, also calculating the total number of interactions of each student. At this phase, the student's final mark is added. Finally, the data is made anonymous, resulting in the final data matrix. Table 1 shows the descriptive numerical data of each academic course and learning scenario.

	Course/Scenario		
	2018-2019 Face-to-face	**2019-2020 On-line**	**2020-2021 Blended**
Total students	87	88	93
Nº logs (records)	12.244	35.538	21.872
Nº interactions after processing	3.494	11.719	5.805
Students who pass	51(59%)	63(71%)	47(51%)
Students who do not pass	21(24%)	13(15%)	26(28%)
Students nor presented	15(17%)	12(14%)	20(21%)

Table 1. Statistical sample numerical description

As can be observed in Table 1, the number of students increases each year. It is important to highlight that these data include the students who repeated the subject. Regarding the number of accesses to resources, as is reasonable, the on-line scenario obtained considerably more than the face-to-face and blended scenarios. The latter also had more accesses than the face-to-face scenario, although the number of students is slightly larger. The same relationship presents the number of accesses after data processing.

Regarding the performance rates, it can be observed that, in the on-line scenario, the number of students that passed the subject is considerably larger than in the other two scenarios, and the blended scenario is slightly worse than the face-to-face scenario; with respect to the rates of dropout and failure to undertake the evaluation test, these are lower in the on-line modality, and the face-to-face modality is slightly better than the blended modality. In the same way, the blended scenario shows the highest rate of students who do not pass the subject, while the face-to-face scenario shows a higher rate of students who do not pass the subject than the on-line scenario. Finally, with respect to the rates of dropout and failure to undertake the evaluation test, these are lower in the on-line scenario, and the face-to-face scenario is slightly better than the blended scenario.

2.2. Variables

The logs mentioned above contain the information about the activities of the students, specifically the date and time of access, student identifier, name of the resource accessed, type of resource accessed, name of the event and description. Along with these data, the academic results obtained by the students in the aforementioned subject are also considered. Thus, finally three variables are defined: the student's academic results or marks (Y), the number of accesses or number of clicks recorded by students in the e-learning platform (X) and the learning mode or learning scenario (A). Regarding this last variable, three scenarios are defined: face-to-face learning, before the lockdown period; on-line learning, during the lockdown period; and blended learning, after the lockdown period, which combines face-to-face learning with on-line learning.

2.3. Procedure

The procedure followed to complete the development of the work is based on the comparison of three learning scenarios (face-to-face, on-line, and blended). To contextualize these three scenarios, we lightly comment on the characteristics of each of them.

In the first place, in a scenario prior to the appearance of COVID-19, students carried out face-to-face learning. Face-to-face learning is understood as the classical methodology, in which students attend the classrooms and the teacher teaches orally, using the resources available both in the physical classroom and in the e-learning platform (UBUVirtual). The tutoring and evaluation tests are also carried out face-to-face. Second, in a situation of home lockdown caused by COVID-19, the students received a completely on-line learning. All teaching is performed in streaming, in real time, through the Microsoft Teams® tool. The contents of the subject are available in UBUVirtual. The tutoring and different enquiries, along with the evaluation tests, are also conducted virtually using the same tool or e-mail, facilitating both synchronous and asynchronous communication respectively. Finally, thirdly, in a scenario after the period of home lockdown, the students received blended learning. In this scenario, there are two determinants. The first is that part of the students received lectures in an identical way to face-to-face learning. The rest of the students attended a mirror classroom, attached to the face-to-face classroom, in order to maintain a safety distance between them, and following the teacher's explanations in streaming, requesting their presence if necessary. The second determining factor is the specific existence of students in a situation of home lockdown. In this case, these students followed the same streaming as the mirror classroom students, but from their homes. The contents of the subject are available in UBUVirtual. The evaluation tests are conducted face-to-face, postponing the dates for those students in a state of lockdown. The tutoring and other enquiries are carried out virtually, either through e-mail or Microsoft Teams®.

2.4. Statistical analysis

The data were analyzed with the statistical software Stata vs. 12. The statistical analysis of the data matrix obtained in section 2.1 has been divided into two stages. First of all, to avoid serious objections to the validity, an Exploratory Data Analysis (EDA) was carried out through an analysis of variance (Levene's variance test), a normality analysis (Shapiro–Wilk test) and a mean test (Kruskal-Wallis test) for each of the study variables (Y and X) in the different learning scenarios (A). Secondly, a Confirmatory Data Analysis (CDA) has been carried out using a Treatment Effects (TE) model and a Fractional Polynomial Extended Regress model to try to confirm the research hypothesis. H: Student academic results depend on the learning scenario and the number of clicks on e-learning platforms (A is combined with X to explain Y). That is, we are going to analyze the relationship between the academic results and the number of clicks together with the learning scenario.

3. RESULTS

Table 2 shows a descriptive analysis of the variable academic results (Y) and the variable number of clicks (X), in the different learning scenarios (A).

	Scenario/Variable					
	Face-to-face		On-line		Blended	
	X	Y	X	Y	X	Y
Mean	40,16	3,80	133,07	4,63	62,42	3,90
Median	35	4	124	5.35	54	5
Std. Dev.	40,82	2,91	78,00	2,52	52,24	2,92
Iqr	42	5,80	101,50	3,05	54	4,90

Table 2. Descriptive analysis of X and Y in different learning scenarios (A)

As can be seen, with respect to measures of central tendency, the average of X is higher in the on-line scenario than in the other two scenarios and higher in the blended scenario than in the face-to-face scenario. In the same way, the mean of Y is also higher in the on-line scenario, obtaining the worst results in the face-to-face scenario. On the other hand, regarding the measures of dispersion, the variable X shows a higher standard deviation in the on-line scenario, followed by the blended scenario, while the variable Y shows a similar standard deviation in the face-to-face and blended scenarios, and a bit less on the on-line scenario.

3.1. Exploratory Data Analysis (EDA)

At first glance, it can be seen that the variances are different for variable Y with respect to learning scenario (Table 2). On-line learning presents a lower variance. This impression can be confirmed with a variance test (Sheard, 2018). The robust Levene's variance test allows rejecting, at 5% significance level, the null hypothesis of equality of variances (p-value = 0,03). For variable X, it can also see that the variance is different with respect to learning scenario (Table 2). There is greater variance in on-line learning than in the other two learning scenarios. The robust Levene’s variance test allows rejecting the null hypothesis of equal variances (p-value = 0,00). Therefore, there is heteroscedasticity in variable Y and X with respect to A.

Next, we verify whether variables Y and X follow a normal distribution for each of the three learning scenarios. When finding heteroscedasticity, it is convenient to use non-parametric tests (Weisberg, 2013). The Shapiro–Wilk test (Sijtsma & Emons, 2010) yields a value equal to 0,92 (p-value = 0,00)**,** 0,91 (p-value = 0,00), and 0,95 (p-value = 0,00) for variable Y, and a value equal to 0,80 (p-value = 0,00)**,** 0,97 (p-value = 0,03), and 0,86 (p-value = 0,00) for variable X in face-to-face, on-line, and blended learning respectively. Thus, the hypothesis of normality is rejected for all three scenarios in both variables.

By failing to pass the normality test, it is convenient to use non-parametric means test in order to compare the mean of variables Y and X in each of the learning scenario. The Kruskal-Wallis test (Sijtsma & Emons, 2010; Riffenburgh, 2012) throws a p-value of 0,10 for variable Y, therefore we cannot reject, at 5% significance level, the null hypothesis of equality of means in variable Y in the different levels of learning scenario. The academic results are not affected by the learning scenario. On the contrary, a p-value of 0,00 allows reject the null hypothesis of equality of means for variable X in the different levels of learning scenario. The average number of clicks is significantly affected by the learning scenario.

Last, the values for the p-values obtained in Kendall's (0,04**,** 0,00**,** 0,02) and Spearman's (0,04**,** 0,00**,** 0,01) rank correlation tests for the variables X and Y in the face-to-face, blended and online scenarios, respectively, allow to reject the independence between these variables. To deepen the relationship between these three variables, the results obtained in the Exploratory Data Analysis (EDA) and the Confirmatory Data Analysis (CDA) are detailed below.

3.2. Confirmatory Data Analysis (CDA)

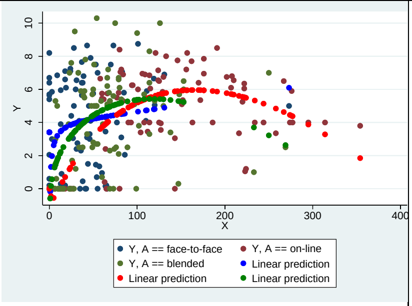
After the individual analysis of the variables Y and X, finally, we are going to analyze the relationship between variable Y on the one hand and variable X and factor A jointly on the other. In this way, we intend to analyze student academic results based on the number of clicks and the learning scenario.

The heteroscedasticity and the lack of normality in the distributions of the variables X and Y, together with the slight positive correlation (Pearson's correlation coefficient = 0,12) between the predictors (variable X and factor A), do not allow us to assume that the assumptions necessary to find a satisfactory function within linear regression models, from the most general to the most sophisticated, are met (Osborne & Waters, 2002). Furthermore, since the starting data are not experimental or designed, but rather observational data, neither orthogonality nor a structured variance can be expected in them. In this situation, it is convenient to use robust regression models, specific for observational data. One of these regressions is the Treatment Effects (TE) model. TE is a robust model in itself, allowing us to find out the effect caused by factor A. That is, the effect of X on Y is quantified in the different levels of a given treatment A (Abadie et al., 2004). Specifically, we compared the academic results obtained by students in the face-to-face learning scenario (which we took as a control level) with two treatments, on-line and blended learning.

The results reveal that the Average Treatment Effect (ATE) is -1,01 for the on-line treatment, which means 1,01 lower mark for each experimental unit treated with the on-line scenario, and -0,38 for the blended treatment, which means 0,38 lower mark for each experimental unit treated with the blended scenario. The results also show that the average mark of the experimental units both in the face-to-face scenario and in the on-line and blended scenario, i.e., both those experimental units who are treated and those who are not, is estimated at 4,14, which is the value of the Potential-Outcome MEAN (POmean). The treatment is the on-line and blended scenario, since these represent the change with respect to the common situation, that is, the control situation (face-to-face scenario). What TE does is precisely compare with equal click numbers. The marks decrease in on-line and blended scenario, since it considers blocks of equal number of clicks, in contrast with what was initially observed, i.e., although the difference of means is not significant, the on-line and blended marks are slightly higher to face-to-face scenario. Obtaining a better mark in on-line and blended learning is correlated with a larger number of clicks, thus X explains A and A explains Y. Regarding the first treatment (on-line), we can consider that it offers a clinical importance (Jacobson et al., 1999) (we consider clinical importance as a 10% variation), since losing 1,01 points out of a total of 4,14 points can be considered relevant (24,41%). On the contrary, with the second treatment (blended), we cannot consider a relevant clinical importance, since the variation of the mark for applying this treatment reached 9,13%, which is below the required 10%.

In this sense, we can reformulate the research hypothesis into two sub-hypotheses, H1: the academic results are affected by the on-line learning scenario with respect to the face-to-face learning scenario, also considering the number of clicks and H2: the academic results are affected by the blended learning scenario with respect to the face-to-face learning scenario, also considering the number of clicks. Therefore, taking into account the clinical importance, we cannot reject the sub-hypothesis H1 and, on the contrary, we can reject the sub-hypothesis H2.

To enrich the model, we explore its predictive capacity. Therefore, the aim is to predict what happens in Y if there is a change in X for each of the modalities of A. To this end, we used a curvature model, specifically a Fractional Polynomial Extended Regress model (Figure 1), which is adequate for observational data and variables with non-linear relationships that, in addition, present heteroscedasticity (Royston & Sauerbrei, 2008).




```
(fitting 34 models)
(....10%....20%....30%....40%....50%....60%....70%....80%....90%....100%)

Fractional polynomial comparisons:
-------------------------------------------------------------------
           x |    df    Deviance   Dev. dif.   P(*)   Powers
-------------------------------------------------------------------
     omitted |     0   1308.028      77.621   0.000
      linear |     5   1285.375      54.967   0.000   1
       m = 1 |     6   1256.081      25.674   0.001   -.5
       m = 2 |    10   1235.121       4.713   0.318   1 1
       m = 3 |    14   1230.408       0.000      --   -.5 1 1
-------------------------------------------------------------------
(*) P = sig. level of model with m = 3 based on chi^2 of dev. dif.

Extended linear regression                      Number of obs     =        268
                                                Wald chi2(14)     =     879.71
Log likelihood = -615.20384                     Prob > chi2       =     0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval
-------------+----------------------------------------------------------------
    b#c.x_0  |
face-to-face |  -1.531175    1.85633    -0.82   0.409    -5.169515    2.10716
     blended |          0  (omitted)
     on-line |    2.95919   3.197603     0.93   0.355    -3.307996    9.22637
             |
    b#c.x_1  |
face-to-face |  -5.092673   2.691949    -1.89   0.059     -10.3688    .183450
     blended |  -1.989018   2.664536    -0.75   0.455    -7.211413    3.23337
     on-line |   2.752082   3.498467     0.79   0.431    -4.104788    9.60895
             |
    b#c.x_2  |
face-to-face |  -.0124149   .0932511    -0.13   0.894    -.1951837     .17035
     blended |   .2208677   .0762382     2.90   0.004     .0714436    .370291
     on-line |   .3175458   .0750895     4.23   0.000      .170373    .464718
             |
    b#c.x_3  |
face-to-face |   .0031703   .0165791     0.19   0.848    -.0293241    .035664
     blended |  -.0384308   .0133827    -2.87   0.004    -.0646605   -.012201
     on-line |  -.0518593   .0123399    -4.20   0.000     -.076045   -.027673
             |
          b  |
face-to-face |   4.939508   1.721882     2.87   0.004     1.564682    8.31433
     blended |   1.179942   1.560002     0.76   0.449    -1.877605    4.23748
     on-line |   -2.95919    2.10989    -1.40   0.161    -7.094499    1.17611
-------------+----------------------------------------------------------------
    var(e.y) |   5.773026   .4987135                      4.873836     6.8381
------------------------------------------------------------------------------
```

Figure 1. Fractional Polynomial Extended Regress

The blue curve represents the prediction when there is no treatment, that is, in face-to-face learning (control). The red and green curves represent the prediction when there is treatment, that is, in on-line and blended learning respectively.

Regarding the fit of the model, the p-value = 0,69 indicates that the model does not have a lack of fit; that is, there is no evidence against the adequate fit of the model to the data.

Then, we revise the predictive capacity of the model. To this end, the amplitude of the confidence intervals allowed us to assess the value/effectiveness of the model to predict. For the first treatment (on-line), we obtain an estimated ATE (average difference of the treatment vs control level in each value of X) of -0,99, whose 95% confidence interval contains 0. The margin of error in the estimation is so large that, actually, the ATE may have been null. For the second treatment (blended), we obtain an estimated ATE of -0,37, although, once again, the 95% confidence interval contains 0.

To complement this information, we determine the standard deviation of the residuals. We obtain a value of 2,41, which is a high value considering a range of 1 to 10 for the marks (variable Y). A high standard deviation involves high errors in the predictions. This value indicates the low explanatory power of this model. We confirm this low predictive power by calculating R^2. For scenario A = face-to-face, control level, R^2 = 0,10**,** thus 9,76% of variability explained by the model, whereas for scenario A = on-line, first treatment, R^2 = 0,41**,** thus 41,11% of variability explained. For the second treatment, scenario A = blended, R^2 = 0,27**,** thus 26,99% of variability explained.

After verifying the low proportion of the variance explained by the model, in Figure 2 (left part) it can be observed that, for the first treatment, in the range in which X is below 77 (value for Y = 4,46), the mark is higher for the face-to-face scenario. Between this point and a value of X equal to 217 (value for Y = 5,60), the mark is higher in the on-line scenario, and then the response is once again favorable to the face-to-face scenario. The black curve (in the right axis) shows the difference between the two predictions. As can be observed, in the range where the on-line scenario is superior, there is barely a difference point in the mark (0,89) for the point with the largest difference (X = 142), with a mean difference of 0,59; on the other hand, in the ranges in which the face-to-face scenario is superior, the mark decreases almost to 4 points in the left part of the axis of the number of accesses (3,40 points with X = 8) in their maximum difference, with a mean difference of 1,66 and up to more than 5 points in the right part of the axis of the number of accesses (5,01 points with X = 345) in their maximum difference, with a mean difference of 2,23.

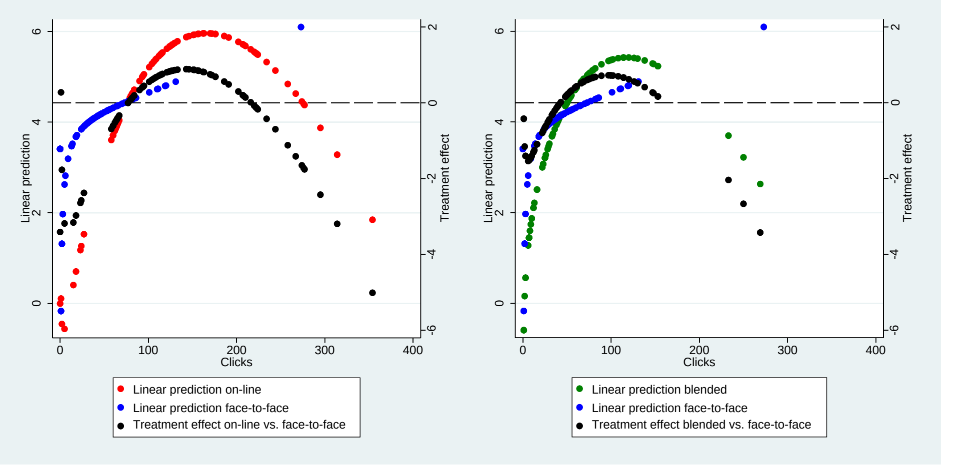


Figure 2. Comparison between treatments and control

With respect to the second treatment (right part of Figure 2), in the range in which X is below 42 (value for Y = 4,12), the mark is higher for the face-to-face scenario. Between this point and a value of X equal to 161 (value for Y = 5,14), the mark is higher in the blended scenario, and then the response is once again favorable to the face-to-face scenario. The black curve (in the right axis) shows the difference between the two predictions.

As can be observed, in the range in which the blended scenario is superior, there is barely a difference point in the mark (0,72) in the point with the largest difference (X = 96) with a mean difference of 0,48; on the other hand, in the ranges in which the face-to-face scenario is superior, the mark decreases 1,54 points in the left part of the axis of the number of accesses (X = 6) in their maximum difference, with a mean difference of 0,80**,** and up to over 3 points in the right part of the axis of the number of accesses (3,59 points with X = 273) in their maximum difference, with a mean difference of 1,61.

4. DISCUSSION

Different studies have analyzed the relationship between the academic results obtained by students and their interaction with on-line learning platforms. Thus Alajmi et al. (2012) point out that involvement in virtual classroom sessions has the most considerable impact on the student's final scoring or grade. Conversely, Cobo et al. (2014) highlight that their study does not permit to state that those students who adopt passive attitudes in on-line scenarios may necessarily produce low academic performance. In an intermediate position, Davies and Graff (2005) emphasize that greater on-line interaction did not lead to significantly higher performance for students achieving passing grades; however, students who failed in their courses tended to interact less frequently. Arbaugh et al.

(2009) conduct a literature review to examine and assess the state of research of on-line and blended learning in the business disciplines. Their results from the comparison studies suggest generally that on-line courses are at least comparable to classroom-based courses in achieving desired learning outcomes, while there is divergence in findings of comparisons of other course aspects. Finally, Asarta & Schmidt (2020) explore whether any significant gains accrue to students due to previous experience with online materials. They found that no effects on outcomes from having previous experience versus having none. However, when the transfer status of students and ranges of grade point averages were considered, they found that on-line and blended experience provided a positive marginal effect on outcomes for high-achieving transfer students.

In this work, the effect to face-to-face, blended, and on-line scenarios on students' academic results considering the interaction with e-learning platforms has been analyzed. In this sense, this work discovers that carrying out an exploratory analysis of the variables number of clicks and academic results, individually, against the learning scenario, slightly better values are obtained for the academic results in the on-line scenario, although the null hypothesis of equality of means between the three scenarios cannot be rejected, at 5% significance. On the contrary, the number of clicks is significantly affected by the learning scenario. In the on-line scenario there are more clicks than in the blended and face-to-face scenario, also confirming the hypothesis of the difference of means. Then we can consider similar marks in face-to-face, blended, and on-line scenarios, although with more clicks in the on-line scenario.

However, in the analysis of the combined effect of the variable number of clicks and factor learning scenario, the marks obtained are lower in on-line and blended scenarios with respect to face-to-face scenario (1,01 and 0,38 points less, respectively), since we consider blocks of equal number of clicks and there is a correlation between clicks and learning scenarios. More concretely, we can consider a decrease of 24,41% in the marks when performing the first treatment (on-line) and of 9,13% in the marks when performing the second treatment (blended), with an average value of the marks for all students of 4,14 points, compared to those obtained in the exploratory analysis for the academic results in the three scenarios. More specifically still, the analysis indicates that marks are affected by the on-line scenario versus the face-to-face, also considering the number of clicks (H1), while they are not affected by the blended scenario versus the face-to-face, also considering the number of clicks (H2).

With the prediction models obtained (Figure 1), the face-to-face scenario offers better results with a small number of clicks (up to X = 42).

Then, the blended scenario offers the best results up to a value of 110 clicks. From this point, the best marks are obtained with an on-line scenario, until the number of clicks reaches a value of 217. Above this point, the best marks are once again obtained with the face-to-face scenario. With respect to the face-to-face scenario, the highest positive variation obtained with the on-line treatment is 0,89 points (mean 0,59) and 142 clicks, whereas with the blended treatment, the highest positive variation is 0,72 points (mean 0,48) with 96 clicks.

Individually (Figure 2), for the first treatment, up to 77 clicks, the face-to-face scenario offers better results, with an average difference of 1.66 points. Between 77 and 217 clicks, better marks are obtained in the on-line scenario, with an average difference of 0,59 points and a maximum difference of 0,89 points. After 217 clicks, the face-to-face scenario returns again better results with an average difference in the marks of 2,23 points. For the second treatment, up to 42 clicks, the face-to-face scenario offers better results, with an average difference of 0,80 points. Between 42 and 161 clicks, better marks are obtained in the blended scenario, with an average difference of 0,48 points and a maximum difference of 0,72 points. After 161 clicks, the face-to-face scenario returns again better results with an average difference in the marks of 1,61 points.

5. CONCLUSIONS

The aim of this work is to study the effect of face-to-face, blended and on-line scenarios on students' academic results considering the interaction with e-learning platforms. Firstly, individually, the results show that the academic results are not affected by the learning scenario, while the degree of interaction with e-learning platforms is affected by the learning scenario.

Then, Treatment Effects model has been used to study the learning scenario and the interaction with e-learning platforms and academic results together. From this study we can conclude that the academic results are affected by the on-line versus the face-to-face scenario but are not affected by the blended versus the face-to-face scenario. Specifically, on an average value of 4,14 points, obtained from the academic results of all students, with an on-line treatment, the results drop 1,01 points, while with a blended treatment, the results drop 0,38 points.

Finally, utilizing Fractional Polynomial Extended Regress, prediction models are proposed for each of the scenarios. With these models, the face-to-face scenario offers better results with a small number of clicks (up to 42), the blended scenario offers the best results up to a value of 110 clicks and from this point, the best marks are obtained with an on-line scenario (until 217). Above this point, the best marks are once again obtained with the face-to-face scenario.

We have already underlined the low explanatory power of the models, as well as their high margin of error in predictions. A clear reason for this is the lack of covariates (properties of the experimental units, such as age, gender, employment situation, family situation, study habits, reading habits, etc.), which has undoubtedly been the main limitation of this study. The predictive capacity of the models depends both on the variables captured for the right-hand side (RHS) and on the type of mathematical equation (curvature) used with the predictors (that is, the variables used as RHS). Therefore, the obtained results must be considered with relative caution.

As a possible future line of research, we can improve the predictive capacity of the model, proposing a generalized Structural Equation Model (SEM), in which the variable of interest is a function of several latent endogenous variables (hidden, non-observable), such as student profile, subject, study center, motivation, home environment, socio-economic level, etc. These variables, in turn, can be constructed from instrumental variables (exogenous, observable), latent classes, measurements, group variables and other elements of structural equations, such as the number of clicks in the e-learning platform, the duration of such on-line accesses, etc. In this way, we could have a lower margin of error when predicting student marks. With a rich RHS in the model, the estimation of the effect of the treatments would surely change, at least partially, since the rational logic states that, in the face-to-face scenario, a limited number of clicks can favor marks by complementing the learning time in the classroom, while exceeding a certain threshold will have penalizing effects (probably missing lectures, losing attention due to distraction, etc.).

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