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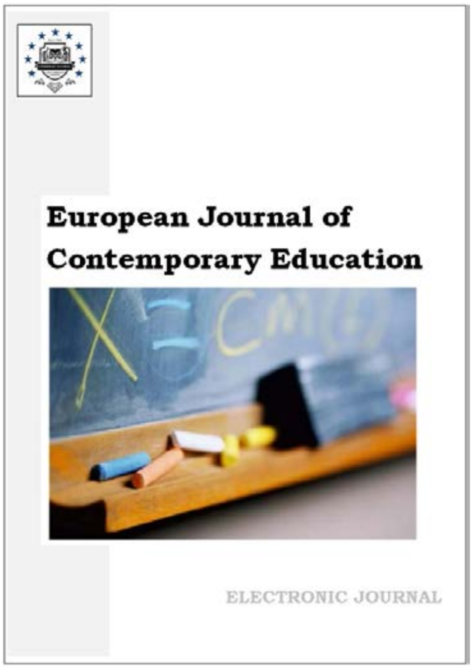

Identifying Key Predictors of Academic Performance in the Context of Higher Education Digitalization: A Regression Analysis with Regularized Models

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Abstract

This paper presents the results of a statistical analysis of educational disciplines based on data regarding various types of student activities, utilizing regression models with L1 regularization under the condition that coefficients remain positive. With the digital transformation of higher education and the integration of electronic educational technologies into traditional teaching methods, there is a growing need for an objective performance assessment of various educational components. A statistical analysis can be used to identify key factors influencing student performance, including activity in the electronic educational environment, attendance in classroom sessions, and results of interim assessments. The study was conducted using data from two academic disciplines that differ in their level of electronic support. The results confirmed two main hypotheses: 1) In disciplines with richer electronic content, student activity in the digital environment becomes a significant predictor of academic performance. 2) Disciplines where educational activity significantly influences learning outcomes receive higher ratings in student surveys. The proposed statistical analysis toolkit has dual practical value. On one hand, it provides educational institutions with a mechanism to monitor pedagogical activities. This mechanism serves as an empirical basis for developing intelligent decision-support systems within the educational process. On the other hand, based on the constructed models, personalized recommendations can be generated for students regarding optimal strategies for mastering a specific course.

Keywords: regression models, statistical analysis, performance predictors, electronic educational environment

1. Introduction

Contemporary higher education is undergoing a significant transformation due to the rapid digitalization of every aspect of the educational process. The adoption of hybrid learning

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approaches that combine conventional teaching practices with modern electronic tools has been expedited by recent worldwide disruptions. Today, most universities are embracing technological platforms that offer educational stability and flexibility, allowing educators to monitor, assess, and improve student engagement and academic performance.

Modern electronic educational environments collect substantial amounts of data on various aspects of student activity, including attendance at virtual and physical classes, assignment completion, discussion participation, and interim and final assessment results. These data represent a valuable informational resource for identifying key academic performance indicators. It enables timely adjustments to the educational process based on the collected information.

Traditional face-to-face learning also generates substantial volumes of both structured and unstructured information, including attendance logs, seminar work grades, lecturer observations, and written assignments resuts. However, without the aid of modern analytical tools, these data are often underutilized for making management decisions in the educational process. In this context, mathematical methods that can identify the most significant predictors of academic success are particularly valuable.

Regression (Bastos et al., 2024; Olsen et al., 2020) is a widely used machine learning method that approximates a set of labeled training data with a specific function. Although more advanced methods, such as neural networks, can handle complex dependencies, regression remains relevant due to its ability to provide interpretable solutions, foster trust in the results, and offer a range of statistically sound tools for assessing feature and coefficient significance. Additionally, regression can be used with smaller datasets, making it particularly suitable for analyzing educational data that may be limited by class sizes.

Determining the optimal set of independent variables is a critical challenge in developing an effective regression model. This is particularly important in educational analytics, where selecting the right features can not only improve prediction accuracy but also help identify the most significant factors that influence student outcomes.

This study presents a statistical analysis of educational disciplines using student activity data. The analysis employs regression models with L1 regularization with the constraint that the coefficients must remain positive. This approach can be used to identify crucial factors influencing academic performance and assess the effectiveness of various components of the educational process, such as online courses and traditional teaching methods.

The primary objective of this research is to determine the key factors that significantly impact student performance using regression analysis. Additionally, this study aims to evaluate the correlation between the importance of these factors and student satisfaction with the overall quality of the educational process.

The study tests two main hypotheses: (1) Activity in online courses will have a significant impact on performance in disciplines with a strong online component but minimal effect in those with little electronic support. (2) Disciplines where student activity significantly influences learning outcomes receive higher ratings in student surveys.

2. Literature Review

The development of objective assessments as a key indicator of competency acquisition and the identification of factors that influence academic performance are subjects of active study in the literature (Vasilev et al., 2024, Vlachopoulos, Makri, 2024).

One area of research focuses on the problem of qualitatively assessing student performance. For example, in (Eyad, 2021), the author emphasizes the importance of clear criteria, feedback, and adaptability in assessment methods. Study (Dinh, Nguyen, 2015) analyzes factors that influence the quality of educational assessment, including teacher preparation, methodologies, and assessment tools. The study found that subjectivity, inadequate teacher training, and inappropriate criteria reduce the reliability of assessments. Research (Hasanah, 2023) explores factors that influence the evaluation process in higher education from the perspective of lecturers, using qualitative methods such as interviews with lecturers. It was revealed that a lack of time and high academic workloads negatively affect assessment quality. Study (Day et al., 2018) discusses challenges in higher education assessment and potential solutions. The main issues identified include educational massification, student diversity, and pressure on faculty.

A separate group of studies evaluates factors influencing final grades based on statistical data. Authors (Kristiyandaru et al., 2023) investigate key factors affecting assessment systems within mandatory physical education courses at Indonesian universities. The dominant factors identified include infrastructure (87 %), teacher qualifications (79 %), and student motivation (72 %). The study outlines major issues in the assessment system, including subjectivity in evaluating practical skills and insufficient qualifications of faculty in modern assessment methods.

Study (Owuor et al., 2021) discusses factors influencing student performance, such as motivation, knowledge level, psychological state, and teaching methods. The research is based on a case analysis and reveals that both external conditions (e.g., stress) and internal factors (e.g., self-organization) play crucial roles. Recommendations include adapting assessment methods to meet the individual needs of students.

The authors (Tadesse, Gidey, 2015) explore various factors affecting students' academic outcomes, including socio-economic status, access to resources, and teaching quality. The analysis indicates that inequality in educational opportunities significantly impacts performance. Measures are proposed to reduce these barriers, including support programs and inclusive teaching methods.

The paper (Arbër et al., 2025) examines the use of machine learning techniques for predicting student performance based on socio-economic, demographic, and educational data such as age, marital status, initial qualifications, and average grades from a previous course.

While some studies use statistical methods to identify factors affecting performance, there is a notable lack of detailed analysis regarding student activity throughout the semester and its influence on final grades. Specifically, there is no analysis of students' digital footprints as a comprehensive data source for the learning process. Therefore, there is a need to develop tools based on modern data analysis and machine learning methods to objectively assess the factors affecting student performance, ultimately leading to personalized recommendations for all participants in the educational process.

3. Discussion and results

Lasso Method

To analyze the impact of various educational activities on student performance, the Lasso method (Least Absolute Shrinkage and Selection Operator) was chosen. This method effectively identifies the most significant predictors even with a small sample size (Yamasari et al., 2021; Bouihi et al., 2024; Yoon, Kim, 2023). Unlike traditional linear regression, Lasso employs L1 regularization, enabling sparse solutions by effectively selecting features and zeroing some coefficients. This study assumes that all regression parameters are positive since the features considered are different types of student activities, which cannot negatively affect their performance. The classical approach to solving this problem can be formulated as a linear Lagrangian form, which, considering the imposed constraint, takes the following shape:

$$\sum_{i=1}^{n}\left(y_i - \sum_{j=0}^{p} x_{ij}\beta_j\right)^2 + \lambda\|\beta\|_1 \to \min,$$
$$\beta \geq 0. \tag{1}$$

where λ is the regularization parameter;

x is the matrix of explanatory variables (features), with the first column consisting of ones;

y is the vector of dependent variable values;

β are the regression coefficients;

n is the number of observations;

p is the number of features.

To solve problem (1), the built-in Lasso method from the Python programming language was used with the parameter positive = True to ensure that the parameter estimates were positive. The regularization parameter was adjusted experimentally for each model.

This study also explored another approach for estimating regression parameters, based on solving a reformulated conditional optimization problem (Gribanova, 2022; Gribanova, 2020):

$$g(\beta) = \|\beta\|_1 \to \min,$$
$$\sum_{i=1}^{n}\left(y_i - \sum_{j=0}^{p} x_{ij}\beta_j\right)^2 = y^*,$$
$$\beta \geq 0. \tag{2}$$

where y^* is the target value.

To solve problem (2), an algorithm for solving the inverse single-point problem (Gribanova, 2022; Gribanova, 2020) was used, which was modified to account for the positivity constraint: after adjusting the values of the arguments, a check is performed; if the coefficient obtained in a particular iteration is negative, it is set to zero. The algorithm was implemented in Python.

One advantage of L1 regularization is that it enables parameter estimation even when there are more features than observations and in cases where highly correlated features are considered. Thus, methods (1) and (2) can be applied with a limited amount of input data while selecting significant features.

Experiments

To identify key factors influencing academic performance, two disciplines were examined: Economic Analysis and Computational Technologies.

Data were collected based on students' educational activities, which can be roughly categorized into five groups:

1. Student performance data from the previous period: Average grade at the time of studying the discipline (avgGrade).
2. Evaluation of student performance conducted by the lecturer during interim assessments regarding the discipline for the semester. Two interim assessments are conducted during the semester: First and second checkpoints, where the instructor evaluates students' current work, such as attendance at lectures and results from practical and laboratory work:
   – Score for the first checkpoint (scoreCP1)
   – Score for the second checkpoint (scoreCP2)
3. Information on student engagement with the electronic course in Moodle, expressed through their activity (total number of actions in the electronic course) and time spent in the course. Activity was categorized into three intervals relative to the interim assessment:
   – Activity before the first checkpoint (activityBeforeCP1);
   – Activity between the first and second checkpoints (activityCP1toCP2);
   – Activity after the second checkpoint (activityAfterCP2);
   – Time spent in the electronic course in minutes (timeInCourse).
4. Attendance rate for in-person lectures, expressed as a percentage of the total number (attendanceRate).
5. Final grade based on performance in the studied discipline (finalGrade).

The study focused on one group of students, resulting in a total of 22 observations. Figures 1 and 2 present the correlation matrices for two disciplines.

Furthermore, the content of the online course for each discipline was examined. The online course for Economic Analysis is actively used in the educational process and includes 13 different types of elements, totaling 163 items. In contrast, the online course for Computational Technologies consists of 4 types of elements, amounting to 12 items in total.

During the research, two hypotheses were tested.

Hypothesis 1: Activity in the online course will have a more significant impact on academic performance for the discipline with a richer content offering.

Hypothesis 2: The academic discipline in which student engagement has a more substantial effect on their final grades will receive higher ratings in student satisfaction surveys. This is because students tend to rate courses more positively when their active participation and involvement directly translate into better academic outcomes, creating a sense of fair evaluation of their efforts and predictability in the educational process.

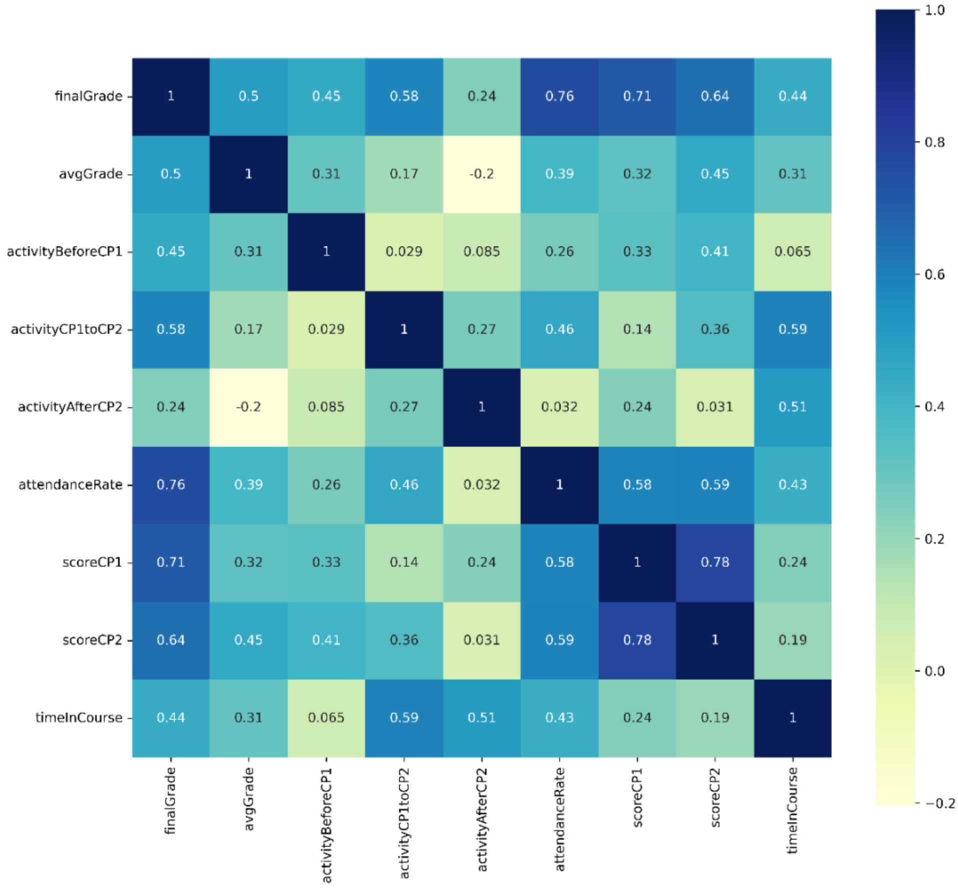

Fig. 1. Correlation Matrix for the Economic Analysis discipline

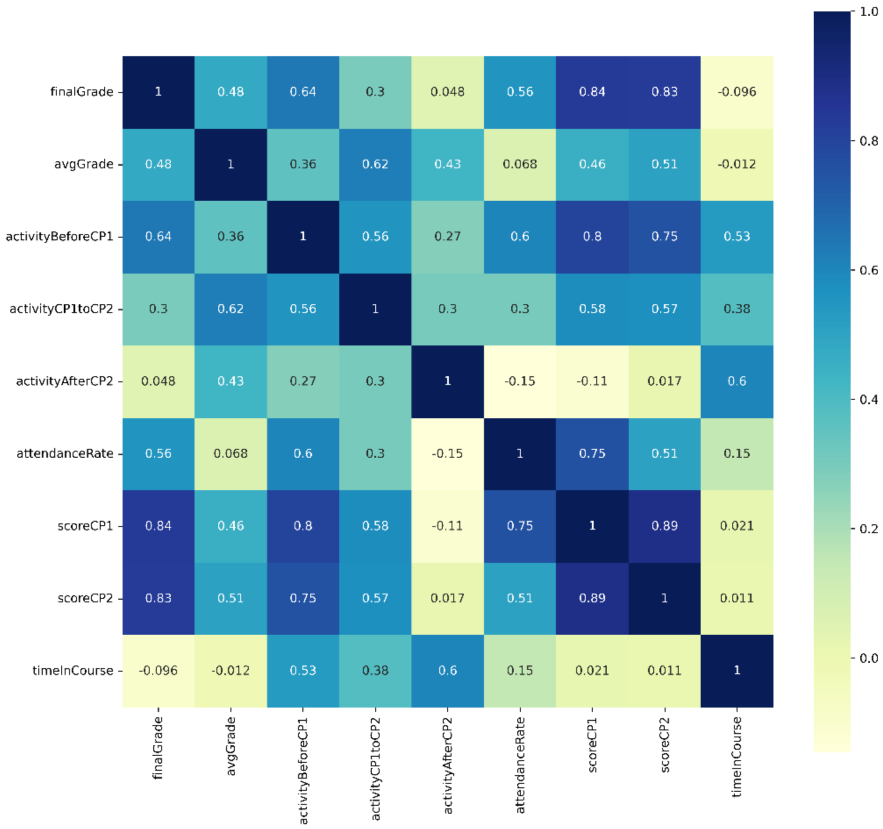

Fig. 2. Correlation Matrix for the Computational Technologies discipline

For modeling purposes, finalGrade serves as the dependent variable, while avgGrade, activityBeforeCP1, activityCP1toCP2, activityAfterCP2, attendanceRate, scoreCP1, scoreCP2, timeInCourse are independent variables.

Two types of regression models were considered: those with constant and decreasing marginal effects.

Linear regression is characterized by a constant marginal effect and unlimited growth of the dependent variable, making it optimal for modeling processes with a steady rate of change. In contrast, nonlinear models with saturation, particularly logarithmic and power functions, feature decreasing marginal effects and asymptotic behavior at high values of the feature, allowing for the modeling of situations where the rate of change in the dependent variable decreases as it approaches a saturation limit.

For the linear model, methods (1) and (2) yielded the same selection of factors, whereas results differed for the nonlinear model. Therefore, based on data from the Economic Analysis discipline, the following models were examined:

1. Model 1 – Linear Model;
2. Model 2-1 – Logarithmic Model, with parameter estimation using method (1);
3. Model 2-2 – Logarithmic Model, with parameter estimation using method (2).

The results of these calculations are presented in Tables 1 and 2. For Model 2-2, the step size αused during parameter tuning is also provided. Model evaluation metrics included significance indicators (F-statistic value and p-value), Mean Squared Error (MSE), Mean Absolute Error (MAE), R-squared (R^2), and information criteria that characterize the balance between model accuracy and complexity: Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

Table 1. Regression results (dependent variable – finalGrade, standard errors are shown in parentheses)

Variables	**Model 1**	**Model 2-1**	**Model 2-2**
avgGrade	0.14	1.84	–
activityBeforeCP1	0.15^{λ}	–	–
activityCP1toCP2	0.29^{**}	–	–
activityAfterCP2	0.06	0.08	–
attendanceRate	0.23^{λ}	0.6^{λ}	0.43
scoreCP1	0.31^{*}	1.33^{*}	1.55^{**}
scoreCP2	–	–	–
timeInCourse	–	–	0.01

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; $^{\lambda}$ $p < 0.1$.

Table 2. Comparison of prediction measures of different models

Method	MSE	MAE	R^2	AIC	BIC	F-statistic	p-value
Model 1	0.1	0.27	0.86	26.46	34.41	15.6	$\mathbf{7.02 \cdot 10^{-6}}$
Model 2-1,	0.21	0.41	0.7	56.44	62.12	10.51	$1.4 \cdot 10^{-4}$
Model 2-2,	0.24	0.46	0.65	55.13	58.53	13.50	$1.8 \cdot 10^{-4}$

Comparing the three models suggests that the linear model is the best option in this case, as it is highly significant and has lower evaluation criteria values: MSE, MAE, R^2, AIC, BIC. Furthermore, this model has more significant coefficients with lower error values. Figure 3 presents the ranking of variables in this model according to their significance. All three types of variables related to online course activity, attendance at in-person lectures, and interim assessments are significant. Thus, it can be concluded that each type of student activity during the semester influences their final grade.

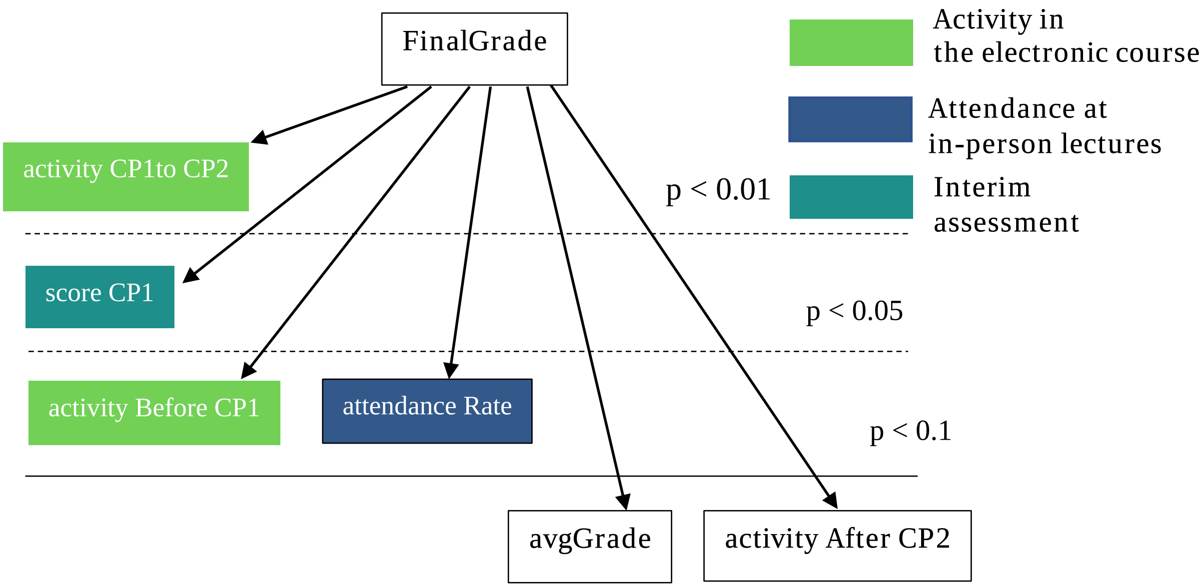

Fig. 3. Feature Importance Tree

Similar calculations were performed for the Computational Technologies discipline. The following models were considered:

1. Model 1 – Linear Model;
2. Model 3-1 – Power Model, with parameter estimation using method (1);
3. Model 3-2 – Power Model, with parameter estimation using method (2).

The results of the calculations are presented in Tables 3 and 4. According to the findings, the power model 3-2, obtained using method (2), showed the highest significance. However, none of the features were significant at the $p < 0.1$ level; in fact, some features had p-values close to 1. The insignificance of all coefficients generally indicates that the variables included in the model do not have a statistically significant impact on the dependent variable within the studied context. The significance level of the regression is also lower than that for the Economic Analysis discipline.

Table 4. Regression results (dependent variable – finalGrade, standard errors are shown in parentheses)

Variables	**Model 1**	**Model 3-1**	**Model 3-2**
avgGrade	0.012		0.05
activityBeforeCP1	–		
activityCP1toCP2	–		
activityAfterCP2	0.06	0.016	
attendanceRate	–	0.028	
scoreCP1	0.32	0.17	0.18
scoreCP2	0.23	0.17	0.17
timeInCourse	–	–	

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; $^{\lambda}$ $p < 0.1$.

Table 5. Comparison of prediction measures of different models

Model	MSE	MAE	R^2	AIC	BIC	F-statistic	p-value
Model 1	0.10	0.233	0.75	24	26.83	5.88	0.016
Model 3-1,	0.092	0.232	0.77	21.49	24.32	7.16	0.009
Model 3-2,	0.094	0.226	0.77	16.77	19.03	10.99	**0.002**

An analysis of the regression coefficients and their significance levels suggests that in a course rich in educational materials and interactive elements, the nature of the interaction between students and the electronic educational environment becomes a more substantial predictor of their academic performance.

To test the second hypothesis, an anonymous survey was conducted among students to evaluate the conditions, content, and quality of specific disciplines. The evaluation was based on nine criteria:

1. The instructor clearly articulates the goals and objectives of the class and presents the material in a clear and accessible manner while maintaining interest in the subject.
2. The quality and relevance of the knowledge gained in the specified discipline.
3. Organization of the course (learning process).
4. The instructor is objective in assessing students' knowledge.
5. The instructor conducts classes according to the schedule, starting and ending on time.
6. The instructor comments on the results of the tests, quizzes, assignments, term papers, etc.
7. The discipline includes various forms of learning: availability and content of the electronic course (including testing), group work, and project activities.
8. The instructor is friendly and tactful and is capable of building relationships with students.
9. The instructor clearly and consistently defines and adheres to a system of requirements.

Each criterion was assessed using a 5-point scale:

1 – Quality is absent
2 – Quality is rarely present
3 – Quality is partially present
4 – Quality is often present
5 – Quality is almost always present

Eighteen individuals participated in the survey. The results, as illustrated in Figure 4, show that the Economic Analysis discipline received the higher ratings across the various criteria. This outcome supports the second hypothesis, which proposes that the substantial impact of students' activities on their academic performance has a positive effect on their assessment of the quality of the educational process.

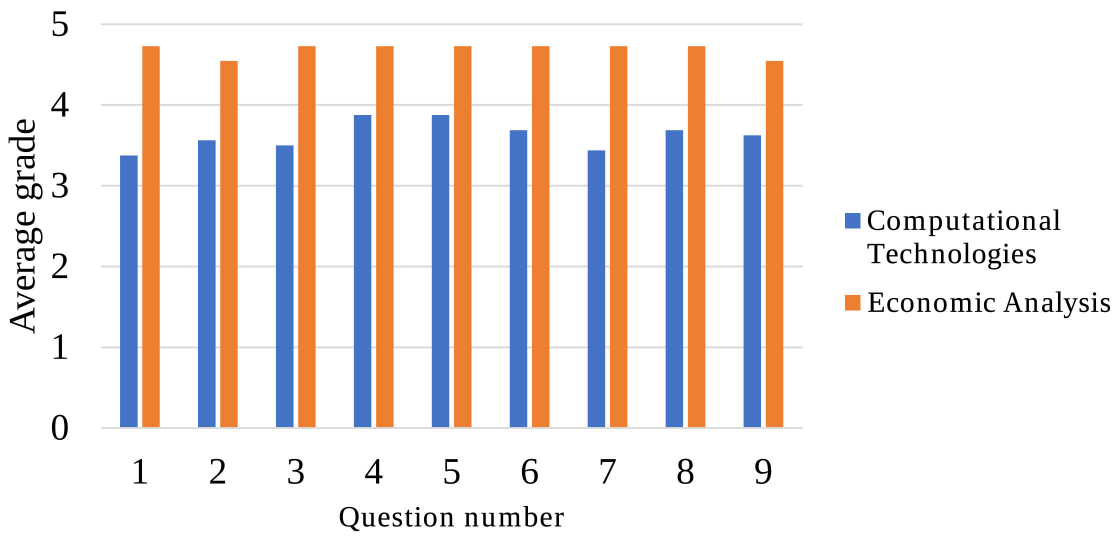

Fig. 4. Results of the Anonymous Survey

This study conducted a statistical analysis of the discipline based on data regarding various student activities throughout the semester to identify the key factors influencing academic performance. The statistical analysis procedure involved the following steps:

1. Gathering data on student activities during the semester.
2. Constructing a Lasso regression model with positive coefficients. For linear models, either method 1 or method 2 can be used. However, for nonlinear models, both methods can be

considered, resulting in different outcomes. Specifically, method 1 produced the best outcome for the logarithmic model, while method 2 was more effective for the power model.

3. Selecting the most significant model from the results. The analysis also included assessing the significance of the coefficients and the regression model. If the coefficients were not significant, it may indicate that students' efforts do not translate into outcomes. Significant coefficients help identify the effectiveness of various learning components, such as online education, in-person classes, and interim assessments.

It is crucial to consider that the level of significance is affected by the number of observations. If there are insufficient observations, the critical significance level may need to be adjusted upward. This study analyzed 22 observations, with a critical significance level set at 0.1. The level can be adjusted based on disciplines used as a sample during the research.

The statistical analysis of educational data presented here enables the creation of a multidimensional "portrait" of the course, reflecting key predictors of the educational process: The effectiveness of integrating digital tools into teaching practices, the relationship between class attendance and students' academic success, the determinism of final educational outcomes based on systematic study activities. The results obtained have dual practical value. On one hand, they provide administrators of educational institution with an objective tool for monitoring and evaluating teaching activities. On the other hand, they serve as an empirical foundation for developing intelligent decision-support systems in the educational process. Based on the constructed models, it is possible to create personalized digital assistants capable of generating adaptive recommendations for students regarding optimal strategies for mastering specific disciplines. For example, if the model identifies a statistically significant impact of activity in an online course on final performance, the intelligent system can generate personalized notifications about the need to intensify engagement with the online components of the course.

4. Conclusion

This study proposes a toolkit for identifying key factors influencing student performance, using regression analysis methods with L1 regularization under the constraint of positive coefficients. A comparative analysis of two regression parameter estimation methods – the classical Lasso and the algorithm for solving the inverse single-point problem – demonstrated their effectiveness when working with limited data samples and highly correlated features.

Experiments conducted on two disciplines (Economic Analysis and Computational Technologies) confirmed the proposed hypotheses. It was established that for the discipline with a more comprehensive online course (163 elements), student activity in the e-learning system is a significant predictor of final performance, while for the subject with minimal online support (12 elements), no such dependence was found.

Survey results from students supported the second hypothesis: the discipline where activity significantly influenced learning outcomes received higher ratings in terms of teaching quality and organization of the educational process. This indicates that creating an educational environment where students' efforts directly reflect on their results is positively perceived by learners and enhances their satisfaction with the educational process.

Statistical analysis of subjects based on student activity represents an effective tool for evaluating educational programs. This approach not only identifies significant factors affecting performance but also assesses the effectiveness of various learning elements, which can serve as a basis for making informed decisions to improve the educational process.

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