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Prediction of Students' Academic Performance: The Correlation between the Results of the Unified State Exam and Academic Success

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The purpose of the work is to study the impact of the USE results on the academic performance of university students. We analyzed the data accumulated during the operation of the university information system of a large regional university. We analized data on USE scores and diploma grades received during last 13 years of university education, applying linear regression and cohort analysis to identify correlations between USE scores and student performance in various specialties. The research results demonstrated a significant correlation between USE scores and the average academic performance of students in the university. It is noted that the USE scores should be included as additional explanatory variables when building models for evaluating the educational process. They can also be used to optimize the preparation process of students for university admission and subsequent education. This research is oriented on education professionals involved in assessing and improving the quality of the educational process.

Keywords: academic performance; educational process; linear regression; cohort analysis; education quality; performance modeling.

Additional materials: Rochev K.V., Kudelin A.G. (2024). The Analysis of the Correlation between Unified State Exam Results and Students' Academic Achievements. Dataset. RusPsyData: https://doi.org/10.48612/MSUPE/65u5-gf9t-45u3

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Проблемы прогнозирования успеваемости студентов: взаимосвязь результатов ЕГЭ и академических успехов

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Материалы статьи посвящены проблеме оценки влияния результатов единого государственного экзамена (ЕГЭ) на последующую академическую успеваемость студентов в высших учебных заведениях. Авторы ставили своей целью провести исследование, чтобы выявить, насколько суммарный балл ЕГЭ отражает способности студентов к обучению и коррелирует с их успехами в университете. Установлено, что существует значимая корреляция между результатами ЕГЭ и средним баллом студентов, а также их дипломными оценками. При этом чем больше разброс баллов ЕГЭ среди поступающих на одну специальность, тем сильнее влияние этих баллов на последующую успеваемость. Показано, что ЕГЭ, несмотря на критику, остается важным инструментом для оценки академических способностей абитуриентов и может быть использован в моделях прогнозирования успешности обучения в вузе. Делается вывод о том, что включение результатов ЕГЭ в оценку качества образования является целесообразным, так как они отражают ключевые способности и мотивацию студентов, которые влияют на их успеваемость.

Ключевые слова: ЕГЭ; успеваемость; образовательный процесс; линейная регрессия; когортный анализ; качество образования; моделирование успеваемости.

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Introduction

Since the introduction of the Unified State Exam (USE) into the Russian education system, debates about its impact on student performance and academic success in universities have remained at the center of attention of the educational community. Attitudes towards this standardized test are divided into opposing views: while some see it as an objective tool for assessing knowledge, others express concerns about its impact on the quality of education and the process of knowledge formation among students [6; 8; 13; 17; 23].

Most publications on the influence of the USE on university education can be divided into three groups:

1. Identifying regressors and the influence of factors on university preparation — on GPA or grades in individual subjects, primarily mathematics [3; 5; 7; 11; 15; 21].
2. Predicting university performance based on USE results, primarily using neural network models [2; 12; 18; 19].
3. Theoretical understanding and description of psychological factors influencing the USE on university education [1; 9; 10; 20].

Alternative approaches to predicting academic achievements include:

- Comparing predictions based on entrance exam results and psychological characteristics, as discussed in the works of A.L. Duckworth, V.G. Erofeeva, and S.K. Nartova-Bochaver [4; 25].
- Reviewing international experience in assessment tests, as conducted in the works of D. Opposs, J.A. Baird, and others [29].
- The growing popularity of using machine learning to identify hidden patterns [24; 26; 27; 30; 31].

Let us consider some studies closely related to ours in more detail.

In the study by N.A. Chernyshova [22], data from 6,000 students over 4 years were analyzed. It was noted that the correlation between total USE scores and students' GPA is quite strong, leading to the conclusion that the USE is valid for monitoring the quality of school graduates' education and assessing applicants' knowledge.

O.O. Zamkov and A.A. Peresetsky [5] provide a detailed analysis of international research on the impact of national school exams on university education. Based on data from 505 students, they note that USE results are an adequate indicator for selecting students for the MIEF program.

L.B. Pereyaslavskaya and V.I. Pereyaslavsky [11] examine correlations between USE scores in mathematics and academic performance in general education subjects among 394 students at two universities. The article reveals a significant change in performance compared to school results and shows that grades in mathematics at both universities correlate better with USE scores in Russian than with USE scores in mathematics, indicating problems with school mathematics education in the corresponding region.

E.A. Vlasova, N.M. Mezhennaya, and V.S. Popov [3] also note that the relationship between exam grades and USE results is statistically significant and more pronounced than the relationship with total test scores, despite the fact that applicants with high USE scores often demonstrate superficial subject knowledge, which hinders their ability to solve basic-level problems in entrance tests.

O.V. Poldin [12], based on data from 157 students, studies the dependence of student dropout rates on their USE scores and notes that mathematics scores are most strongly associated with the dropout of economics students.

A.V. Semerikov and M.A. Glazyrin [19] propose predicting student success based on USE scores using a neural network model, demonstrating its 65% effectiveness based on data from 36,830 students.

S.V. Rusakov, O.L. Rusakova, and K.A. Posokhina [18], after studying data from 274 students using a neural network, suggest creating a "profile" of students at risk of dropout and low academic performance.

The relationship between academic performance and various factors is shown in articles [7; 14; 15; 28].

In our study, we tested the extent to which the total USE score reflects individual students' learning abilities, which are later expressed in their performance in various university subjects. The main question requiring investigation is the extent to which USE results truly correlate with subsequent academic success in higher education institutions.

In this regard, the following research hypotheses were formulated:

- The total USE score correlates with subsequent academic success of students in higher education institutions.

• High USE scores indicate the presence of basic academic competencies and developed cognitive skills necessary for successful university education.

• USE results have predictive value for assessing future academic achievements of students.

• These assumptions are based on the following facts:

• The exam is standardized and objectively measures students' knowledge and skills, minimizing the influence of external factors.

• High USE scores indicate the presence of basic academic competencies and developed cognitive skills necessary for successful university education.

• Previous studies show a positive correlation between USE results and students' academic achievements, confirming its predictive value.

Research Organization and Methods

Since 2006, UGNTU has operated a system for recording the activities of students and teachers. Based on data collected in the UGNTU information system, our study examined the relationship between USE results and academic performance: GPA, grades in individual subjects, and diploma grades.

Key concepts necessary for justifying the research scheme are defined:

1. **Abilities**: General (affecting performance in all subjects) and special (needed for success in a specific subject).

2. **Competencies and learning outcomes**: Competencies (knowledge, skills, and abilities for performing activities) and learning outcomes (specific knowledge, skills, and abilities to be achieved).

3. **Learnability and training level**: Learnability (a person's ability to acquire new knowledge) and training level (the level of knowledge, skills, and abilities achieved as a result of training).

4. **Factors**: Academic performance (degree of achievement of learning goals), motivation (factors driving activity), level of preparation (possession of knowledge, skills, and abilities for learning), socio-economic factors (family living standards, parents' education, etc.), and USE specifications (determining the content, structure, and format of the exam).

USE results should reflect abilities, competencies, learnability, training level, and the influence of the motivational-volitional sphere, which affect students' subsequent academic performance.

5. **Research methods**:

• Correlation analysis: Relationship between two variables.

• Regression analysis: Predicting the value of one variable based on another.

• Experimental method: Cause-and-effect relationship between two variables.

6. **Research limitations**:

• Difficulty in establishing cause-and-effect relationships.

• Imperfection of research methods.

• Influence of other factors.

The analysis was based on a database containing information on student performance over 13 years [16]. Only data from students with both USE results and diploma grades were considered. Student grades were squared to enhance deviations.

The average score (quadratic) was calculated as:

$$O = \left(\frac{\sum_{i=0}^{n} \text{ОЭ}}{n}\right)^2 \quad (1)$$

Where:

O — average score (quadratic),

OE — exam grade (excluding credits),

n — number of student grades.

$$USE = \frac{\sum_{i=0}^{n} \text{E}}{\max\limits_{0 \le i \le n} \text{E}} * 100 \quad (2)$$

Where:

USE — normalized USE score,

E — USE exam score,

n — number of USE exams.

Based on diploma grades and calculated average scores, their dependence on the USE score was analyzed using a linear regression model:

$$y_i = b_0 + b_1 x_i \quad (3)$$

Where:
y — output parameters,
x — input parameters,
b — regression coefficients.

For a more detailed study, a cohort analysis was performed (4). For this purpose, the whole data set was divided into specialty groups (5).

$$y_{ij} = b_{0i} + b_{1i}x_{ij} \quad (4)$$

Where: *y — output parameters,*
x — input parameters,
b — coefficients of the regression equation.

For a more detailed study, cohort analysis was conducted. The entire dataset was divided into groups of specialties.

The study examined data from 45,743 students, but the final analysis included 9,520 students with USE results, full-time education, and successful diploma defense. Among them, 3,733 were female and 5,785 were male. Additional information is provided in Table 1.

The research was conducted using several software tools: Microsoft Excel, Statistica, the university management system, and a custom data analysis program developed for student activity analytics.

Results

First, let us consider the general picture of the relationship between various factors and academic performance.

Table 1

Descriptive statistics

Statistics	USE	Average score	Age
Mean	53,4	15,6	20,8
Standard error	0,2	0,0	0,05
Median	53,0	15,0	19
Moda	49,0	9,0	18
Standard deviation	9,7	4,2	4,9
Sample variance	93,3	18,0	24,3
Excess	0,2	-0,7	101
Asymmetry	0,2	0,4	1,88
interval	66	16	157

Table 2

Correlation of various factors affecting students' academic performance and grade point average

Parameter	Part-time students	Full-time students	Dormitory	Local	FEMIT	TF	NGF
Date of birth	0,002	0,087	0,103	0,070	–0,027	0,097	0,109
Citizenship type	–0,007	–0,044	–0,103	0,011	–0,075	–0,003	–0,065
Dormitory (0-no, 1-yes)	–0,029	0,037			–0,035	0,030	0,070
Gender (0-f, 1-m)	–0,281	–0,251	–0,259	–0,254	–0,311	–0,259	–0,236
Job (0-no, 1-yes)	–0,055	0,018	0,008	0,024	0,011	0,038	0,006
Children (0-no, 1-yes)	0,012	0,022	0,027	0,021	0,033	0,043	0,001
Disability (0-no, 1-yes)	0,008	–0,013	–0,004	–0,016	–0,026	–0,002	–0,012
Age	–0,140	–0,039	–0,091	–0,035	–0,074	–0,087	0,000
USE score	0,368	0,481	0,482	0,479	0,525	0,451	0,466
Diploma grade	0,376	0,551	0,584	0,528	0,585	0,540	0,531

Note: FEMIT — Faculty of Economics, Management and IT; TF — Faculty of Technology; NGF — Faculty of Oil and Gas.

Table 2 presents the results of correlation analysis between various factors and students' GPA. For all cases except the "Correspondence students" column, data from full-time students were considered. Results for students from specific faculties are also shown: Faculty of Economics, Management, and IT (FEMIT), Technological Faculty (TF), and Oil and Gas Faculty (NGF), as they differ significantly in their specifics. As can be seen from the table, the strongest correlation with GPA among the considered factors is shown by the USE score.

Table 3 presents similar data on the correlation between USE scores and various factors.

As shown in Figures 1—3, there is a significant correlation between students' GPA and their USE scores upon admission. The correlation is 0.48, with 0.24 of the GPA explained by the USE score (significance above 0.001). Diploma grades also correlate with USE results, but to a lesser extent — 0.25, with only 0.07 of the variation in diploma grades explained by the USE score (significance above 0.001).

As is known, different specialties have different levels of competition and ranges of admission scores. It is logical to hypothesize that the greater the variation in USE scores among applicants, the greater the influence of this dif-

Table 3

Correlation of USE score and various factors affecting students' academic performance

Architecture	Part-time students	Full-time students	Dormitory	Local	FEMIT	TF	NGF
Safety of Technological Processes	0,276	0,236	0,249	0,221	0,131	0,226	0,272
Drilling of Oil and Gas Wells	0,011	–0,012	–0,056	0,015	0,012	–0,022	–0,044
Oil and Gas Geology	–0,070	–0,103	–0,109	–0,107	–0,108	–0,217	–0,026
Geophysical Methods of Prospecting and Exploration	–0,025	–0,031	–0,014	–0,042	–0,013	–0,043	–0,036
Documentation and Archival Studies	–0,015	–0,006	0,041	–0,016	–0,010	–0,046	0,010
Computer Science and Engineering	0,139	0,045	0,013	0,063	0,044	0,039	0,030
Information Systems and Technologies	0,368	0,481	0,482	0,479	0,525	0,451	0,466
Forest Engineering	0,184	0,254	0,233	0,273	0,355	0,199	0,201
Machinery and Equipment for Oil and Gas Complexes	0,328	0,433	0,453	0,421	0,492	0,418	0,408
Management	0,306	0,363	0,361	0,362	0,427	0,272	0,387
Oil and Gas Engineering	0,281	0,489	0,491	0,486	0,531	0,452	0,503
Applied Geology	0,096	0,269	0,262	0,274	0,345	0,227	0,250
Design, Construction, and Operation of Oil Pipelines	0,274	0,364	0,392	0,336	0,452	0,389	0,292
Development and Operation of Wells	0,149	0,362	0,390	0,339	0,447	0,361	0,361
Advertising and Public Relations	0,142	0,616	0,504	0,773	0,604	–0,213	0,801
Standardization and Metrology	0,282	0,333	0,341	0,327	0,368	0,289	0,325
Construction	0,228	0,361	0,330	0,386	0,458	0,331	0,324
Technological Machines and Equipment	0,305	0,455	0,461	0,449	0,503	0,415	0,437

Note: FEMIT — Faculty of Economics, Management and IT; TF — Faculty of Technology; NGF — Faculty of Oil and Gas.

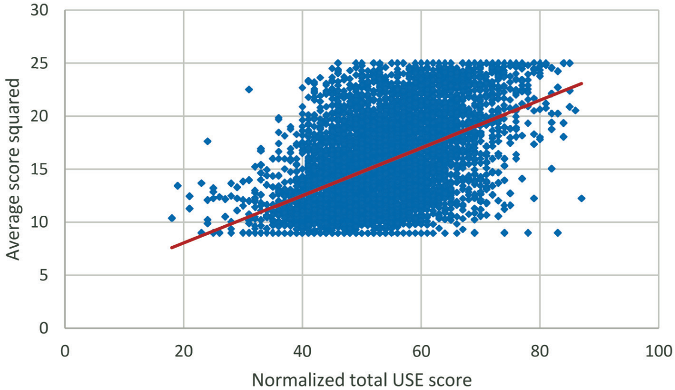

Fig. 1. Dependence of GPA on USE scores for all groups

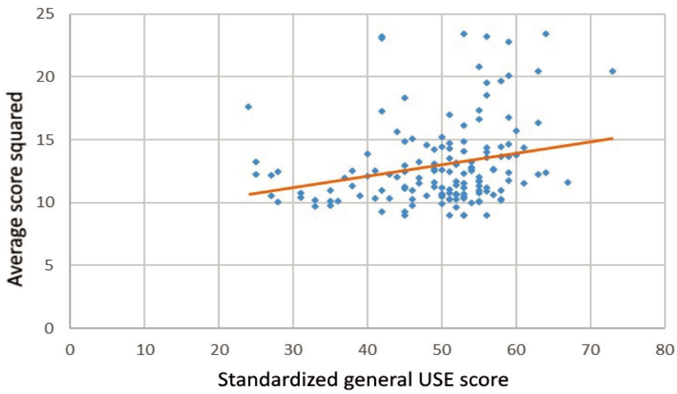

Fig. 2. Dependence of GPA on USE scores for MON (Machinery and Equipment for Oil and Gas Complex — minimum significance of explained variation)

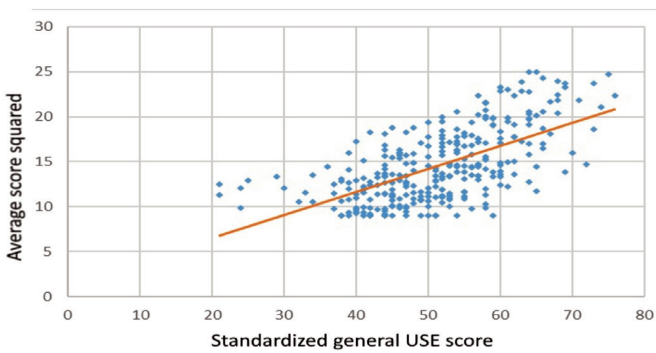

Fig. 3. Dependence of GPA on USE scores for FC
(Finance and Credit — maximum significance of explained variation)

Table 4

Summary statistics on USE results by specialty groups, percentage of GPA and diploma grade variation explained by the regression equation from USE scores

Specialty Group	Observations	Average USE Score	Std. Dev. of USE Score	Min. USE Score	Max. USE Score	% of GPA Variation Explained by USE	% of Diploma Grade Variation Explained by USE
Architecture	154	56,75	10,27	30	85	0,263***	0,010
Safety of Technological Processes	104	51,85	9,32	26	82	0,239***	0,142*
Drilling of Oil and Gas Wells	114	50,38	9,00	19	69	0,184***	0,007
Oil and Gas Geology	171	48,99	7,43	24	70	0,165***	0,089*
Geophysical Methods of Prospecting and Exploration	106	48,55	8,07	31	74	0,277***	0,123*
Documentation and Archival Studies	78	55,86	7,12	41	72	0,120***	0,000
Computer Science and Engineering	190	55,14	8,69	39	83	0,139***	0,236***
Information Systems and Technologies	336	58,24	9,20	35	87	0,268***	0,033*
Forest Engineering	194	45,15	7,66	23	73	0,119**	0,000
Machinery and Equipment for Oil and Gas Complexes	146	49,71	9,11	24	73	0,062*	0,126**
Management	202	55,02	9,51	37	84	0,397***	0,330***
Oil and Gas Engineering	1 423	57,89	9,02	32	85	0,272***	0,094***
Applied Geology	217	48,10	6,82	36	72	0,196***	0,096***
Design, Construction, and Operation of Oil Pipelines	136	53,82	11,18	23	83	0,455***	0,446***
Development and Operation of Wells	130	54,88	9,98	18	80	0,269***	0,019
Advertising and Public Relations	187	56,46	9,16	39	82	0,197***	0,039
Standardization and Metrology	118	53,65	7,86	36	79	0,139***	0,121**
Construction	98	47,77	6,52	33	69	0,219***	0,000
Technological Machines and Equipment	436	49,46	6,50	32	79	0,077**	0,000
Technology of Geological Exploration	117	51,02	6,50	40	75	0,074**	0,022
Technology of Logging Operations	109	43,70	4,50	32	62	0,078**	0,004
Technosphere Safety	188	54,80	8,14	33	85	0,314***	0,109***
Physical Education	98	47,71	9,78	21	72	0,163***	0,056
Finance and Credit	203	53,31	9,13	29	76	0,509***	0,279***
Ecology and Environmental Management	205	53,95	8,19	36	81	0,266***	0,045*
Economics	93	56,53	8,97	36	72	0,220***	0,151
Electrical Power Engineering and Electrical Engineering	357	54,47	9,00	32	82	0,233***	0,022*

Note: * – significance at 95%, ** – significance at 99%, *** – significance at 99.9%.

ference on subsequent academic performance. Since with a small variation in USE scores, the difference in academic performance among former schoolchildren is also small, they differ less at the start of their studies, and this difference is determined by further university education and other factors. To test this hypothesis, let us examine the obtained data in more detail — we will evaluate the regression of the difference between the minimum and maximum USE scores of students admitted to different specialties on the R-squared correlation between USE scores and their GPA (see Table 4) (5). As can be seen in Fig. 4, this regression is quite noticeable and amounts to 0.34 for GPA and 0.23 for diploma grades.

$$R = \sum_{j=0}^{m} \sum_{i=0}^{n} r \quad (5)$$

Where:

R — average score (quadratic),

r — R-squared correlation between USE scores and GPA or diploma grades,

n — number of students in the specialty,

m — number of specialties in the specialty group.

Thus, it can be concluded that the range of USE scores upon admission affects average academic performance at a significance level of 0.001 and diploma defense results at a significance level of 0.011.

Conclusion

Based on the analysis of the presented data, we obtained significant dependencies of both GPA and diploma grades on USE results. Moreover, the greater the variation in USE scores among admitted students, the more accurately they determine subsequent academic performance. Undoubtedly, besides USE scores, there are many other factors that can significantly influence the quality of education. However, on average, most of the considered factors correlate with academic performance (as one of the main measurable parameters of education quality) significantly less than the abilities and motivational-volitional characteristics of students reflected in USE scores. Therefore, when building models for assessing education quality, it is advisable to include USE results as additional explanatory variables.

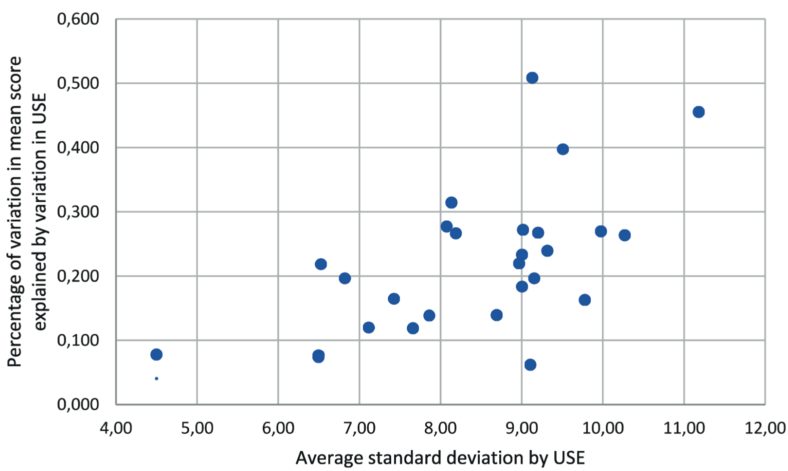

Fig. 4. Influence of the standard deviation of USE scores on the degree of correlation between USE scores and students' GPA

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