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TRANSFORMATION OF EDUCATION THROUGH DIGITAL TECHNOLOGIES: ADVANCING STUDENT ACADEMIC PERFORMANCE ACROSS LEARNING STAGES

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Abstract. Academic performance is considered an indicator reflecting the quality of higher education and is associated with graduates' academic mobility and employment opportunities. This study examines differences in students' academic results across three levels of education – bachelor's, master's, and doctoral programs – within the context of the digitalization of the educational process, including the use of online platforms, electronic courses, and digital forms of assessment. The aim of the research is to determine whether differences in average grades are related to the level of study and the characteristics of the disciplines undertaken. For statistical comparison of the groups, analysis of variance (ANOVA) and Tukey's post hoc test were applied, which made it possible to identify differences between educational levels and specify which groups differed from one another.

The results indicate that students enrolled in specialized master's programs and doctoral studies demonstrate higher average grades compared to bachelor's students and those in academic-pedagogical master's programs. This distribution may be explained by differences in educational objectives and the structure of academic activities: at advanced levels, there are more research-oriented tasks, a greater proportion of independent work, and increased requirements for planning skills, source analysis, and academic writing. Additional analysis revealed the influence of course complexity on academic performance. Subjects with a strong analytical or technical component, requiring mathematical background and systematic thinking, are characterized by lower average grades. Applied digital disciplines focused on mastering tools and completing practical assignments show higher results. The findings can be used to adjust curricula, distribute academic workload, develop assessment criteria, and select support strategies for students at different levels of education.

Keywords: academic performance, educational level, digital education, higher education, ANOVA, curriculum design

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ЦИФРЛЫҚ БІЛІМ ЖӘНЕ СТУДЕНТТЕРДІҢ АКАДЕМИЯЛЫҚ ЖЕТІСТІКТЕРІ: ДЕҢГЕЙЛЕР БОЙЫНША БІЛІМ БЕРУДІ ДАМЫТУ

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Аннотация. Академиялық үлгерім жоғары білім сапасын көрсететін көрсеткіш ретінде қарастырылады және түлектердің академиялық мобильділігі мен жұмысқа орналасу мүмкіндіктерімен байланысты. Бұл зерттеуде білім берудің үш деңгейі – бакалавриат, магистратура және докторантура – бойынша студенттердің оқу нәтижелеріндегі айырмашылықтар білім беру процесін цифрландыру жағдайында талданады. Зерттеу онлайн-платформаларды, электрондық курстарды және цифрлық бағалау түрлерін қолдануды қамтиды. Зерттеудің мақсаты орташа бағалардағы айырмашылықтардың оқу деңгейіне және пәндердің сипаттамаларына байланысты екенін анықтау болып табылады. Топтарды статистикалық салыстыру үшін дисперсиялық талдау (ANOVA) және Тьюкидің апостериорлық тесті қолданылды, бұл білім деңгейлері арасындағы айырмашылықтарды анықтауға және нақты қай топтар арасында айырмашылық бар екенін көрсетуге мүмкіндік берді. Нәтижелер бейінді магистратура бағдарламалары мен докторантурада оқитын студенттердің орташа бағалары бакалаврлар мен академиялық-педагогикалық магистратура студенттеріне қарағанда жоғары екенін көрсетті. Мұндай бөлініс оқытудың мақсаттары мен оқу қызметінің құрылымындағы айырмашылықтармен түсіндіріледі: жоғары деңгейлерде зерттеу сипатындағы тапсырмалар көп, дербес жұмыс үлесі жоғары және жоспарлау, дереккөздермен жұмыс істеу, академиялық жазу дағдыларына қойылатын талаптар артады. Қосымша талдау пәндердің күрделілігінің академиялық үлгерімге әсерін анықтады. Аналитикалық немесе техникалық құрамдасы басым, математикалық дайындық пен жүйелі ойлауды талап ететін пәндер бойынша орташа балл төменірек болады. Қолданбалы цифрлық пәндер, құралдарды меңгеруге және практикалық тапсырмаларды орындауға бағытталған, жоғары нәтижелер көрсетеді. Алынған қорытындылар оқу жоспарларын түзетуге, оқу жүктемесін бөлуге, бағалау критерийлерін әзірлеуге және білім деңгейіне сәйкес студенттерді қолдау тәсілдерін таңдауға пайдаланылуы мүмкін.

Түйін сөздер: академиялық үлгерім, білім беру деңгейі, цифрлық білім беру, цифрлық білім беру, ANOVA, оқу бағдарламасын әзірлеу

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ЦИФРОВОЕ ОБРАЗОВАНИЕ И АКАДЕМИЧЕСКАЯ УСПЕВАЕМОСТЬ УЧАЩИХСЯ: РАЗВИТИЕ ОБРАЗОВАНИЯ МЕЖДУ УРОВНЯМИ

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Аннотация. Академическая успеваемость является важным индикатором качества подготовки в системе высшего образования и тесно связана с академической мобильностью и последующим трудоустройством выпускников. В работе анализируются различия в учебных результатах студентов на трёх уровнях высшего образования - бакалавриат, магистратура и докторантура - в условиях цифровизации образовательного процесса, включая использование онлайн-платформ, электронных курсов и цифровых форм контроля знаний. Цель исследования заключается в выявлении различий в академической успеваемости в зависимости от уровня обучения и характеристик изучаемых дисциплин. Для статистического анализа применены методы дисперсионного анализа (ANOVA) и апостериорный тест Тьюки, позволяющие определить наличие статистически значимых различий между группами и уточнить, между какими уровнями образования они проявляются. Результаты показали, что обучающиеся магистратуры (особенно профильной) и докторантуры демонстрируют более высокие средние академические показатели по сравнению со студентами бакалавриата и академико-педагогической магистратуры. Это объясняется различиями в целях обучения и структуре образовательного процесса: на старших уровнях увеличивается доля исследовательской деятельности, самостоятельной работы и требований к академическим навыкам, включая анализ, планирование и научное письмо. Дополнительный анализ выявил влияние сложности дисциплин на уровень успеваемости. Курсы с выраженной аналитической или технической направленностью, требующие развитых математических и системных компетенций, характеризуются более низкими средними баллами. В то же время прикладные цифровые дисциплины, ориентированные на освоение инструментов и выполнение практических заданий, демонстрируют более высокие результаты. Полученные результаты могут быть использованы при совершенствовании образовательных программ, перераспределении учебной нагрузки, разработке критериев оценивания и формировании механизмов академической поддержки студентов на различных уровнях обучения.

Ключевые слова: академическая успеваемость, уровень образования, цифровое образование, высшее образование, ANOVA, разработка учебной программы

Introduction. Students' academic performance is commonly regarded as one of the central indicators of educational effectiveness in higher education. It reflects not only how successfully students meet curriculum requirements, but also how well educational institutions support learning, adaptation, and intellectual development. Academic achievement is closely connected with later professional opportunities, access to advanced study, and long-term career development. For this reason, the factors that shape student performance remain an important area of research in education, psychology, and pedagogy. Among these factors, educational level deserves particular attention, since the conditions, expectations, and forms of learning differ substantially between undergraduate, master's, and doctoral study.

At the undergraduate level, students are usually introduced to the foundations of disciplinary knowledge and are required to adapt to university learning practices, assessment systems, and increasing academic independence. In master's programs, learning often becomes more specialized, with greater emphasis on analytical work, critical interpretation of knowledge, and the application of research skills in academic or professional contexts. Doctoral education, in turn, is generally characterized by a strong focus on original research, independent inquiry, and sustained scholarly productivity. These structural differences suggest that academic performance may vary across levels of higher education not only because of differences in student ability, but also because of changing academic demands, learning environments, and forms of self-regulation.

Despite the relevance of this issue, the relationship between educational level and academic performance has not been fully clarified in the existing literature. Many studies in educational psychology examine factors such as motivation, self-regulated learning, personality, engagement, and digital learning behavior, yet fewer studies directly compare academic outcomes across distinct stages of higher education within one analytical framework (Dent et al., 2016). As a result, there remains a gap in understanding whether differences in performance are associated with the level of study itself or with related variables that become more visible at different educational stages.

Some findings suggest that students in advanced academic programs may achieve stronger results because they have already passed earlier stages of academic selection and typically possess more developed learning strategies. Research on self-regulation and personality supports the view that students who continue into master's and doctoral study often demonstrate stronger goal-setting, planning, persistence, and metacognitive awareness, all of which can contribute to academic success (Mammadov, 2022). In this sense, higher educational levels may be associated with improved performance because students become more capable of managing complex tasks, working independently, and integrating theoretical knowledge with research-oriented practice.

At the same time, this relationship is not necessarily linear. Graduate and doctoral students also face a number of pressures that may negatively affect performance. These include a heavier reading and writing load, the need to combine study with employment, higher expectations for originality and autonomy, and increased responsibility for research outcomes. In many cases, postgraduate students must balance academic tasks with professional or family obligations, which may limit the time and energy available for coursework and assessment preparation. As some studies indicate, the complexity of graduate education may create conditions in which stronger academic maturity is offset by greater workload and stress (Berlanga et al., 2025). Therefore, the assumption that students at more advanced levels always perform better should be examined carefully rather than accepted automatically.

Another important dimension of the problem concerns the changing organization of higher education in recent years. The growing use of digital platforms, learning management systems, blended instruction, and online learning formats has transformed the way students engage with course materials, instructors, and peers. These changes have affected students differently depending on their educational level, since undergraduate, master's, and doctoral students often use digital tools for different purposes and with different degrees of independence. For example, undergraduates may rely more heavily on structured guidance, while graduate students may use digital environments more flexibly for research, collaboration, and self-directed study. This makes it necessary to examine academic performance not in isolation, but in relation to the broader learning conditions that now shape higher education (Mulyaningsih et al., 2022).

Against this background, the present study aims to determine the extent to which educational level influences academic performance among students in higher education. More specifically, the research seeks to compare academic outcomes across bachelor's, master's, and doctoral programs using a systematic statistical approach. In addition to identifying whether differences exist, the study also aims to explore possible explanations for those differences in light of the literature on self-regulated learning, student adaptation, educational engagement, and academic workload. By focusing on educational level as a central explanatory variable, the study contributes to ongoing discussions about fairness in assessment, curriculum design, and the development of learning support systems for students at different stages of academic progression.

Objectives and Hypotheses

The objectives of the study are threefold. First, it seeks to provide a structured review of scholarly literature addressing academic performance, educational level, and the methodological approaches commonly used to analyze group differences in higher education research. Second, it aims to assemble and examine student grade data representing different stages of university education. Third, it applies one-way Analysis of Variance (ANOVA) together with Tukey's post-hoc test in order to identify whether statistically significant differences in academic performance exist among the selected groups and, if so, between which specific levels these differences occur. The statistical analysis is supported by visual representations of the data in order to improve interpretability and provide a clearer understanding of score distributions across groups.

The study is based on the following hypotheses:

H_0: Educational level does not exert a statistically significant influence on academic performance.

H_1: Educational level significantly affects academic performance, with master's and doctoral students expected to demonstrate higher academic results than undergraduate students.

These hypotheses are grounded in previous research showing that students at higher educational levels tend to possess stronger cognitive, metacognitive, and self-regulatory competencies, which are often associated with better academic outcomes (Dent et al., 2016). At the same time, the literature does not provide a fully consistent picture. While some authors emphasize the positive role of maturity, academic experience, and developed learning strategies, others point to the negative impact of workload, role conflict, and pressure in postgraduate education (Mammadov, 2022). This mixed evidence makes the present comparison both relevant and necessary.

The study also has practical significance. Understanding how academic performance differs across educational stages may help universities reconsider how they organize teaching, assessment, and academic support. If performance differences are observed, they may indicate the need for more adaptive learning strategies, differentiated instructional models, or targeted interventions for specific student groups. Such findings are especially relevant in the context of digitally mediated higher education, where student autonomy, engagement, and access to learning resources play an increasingly important role. In this sense, the research is expected to contribute not only to statistical description, but also to discussions about how higher education institutions can respond more effectively to the needs of students at different stages of study.

The novelty of the present study lies in its integrated comparison of academic performance across three educational levels within a single methodological framework. By combining ANOVA with Tukey's post-hoc procedure and visual analysis, the study offers a structured way to identify both general and pairwise differences in student outcomes. This approach allows for a more detailed interpretation of educational-level effects and may support future work on curriculum modernization, academic advising, and the design of personalized learning environments (Berlanga et al., 2025; Mulyaningsih et al., 2022).

Literature Review. The selection of statistical techniques for analyzing students' academic performance is shaped by a number of methodological considerations widely discussed in contemporary scholarly literature. In recent years, the demand for rigorous quantitative approaches aimed at ensuring the objectivity and reliability of educational data analysis has grown substantially. This tendency is connected with the broader development of evidence-based educational research, where conclusions are expected to rest on transparent analytical procedures and clearly interpretable results. Among the most widely recognized tools are Analysis of Variance (ANOVA) and post hoc procedures such as Tukey's Honest Significant Difference (HSD) test, both of which are regarded as appropriate and reliable methods for detecting statistically significant differences across multiple comparison groups. Their methodological characteristics make them particularly suitable for assessing the influence of educational level on academic achievement (Akpen et al., 2024).

ANOVA has become a standard analytical instrument in comparative educational research due to its ability to evaluate differences in mean values across more than two groups simultaneously. This is especially relevant in studies where student populations are divided into several categories, such as undergraduate, master's, and doctoral levels. For instance, Evans and Taylor (2025) employed ANOVA to examine variations in students' academic performance while considering numerous contextual factors, including level of study (Iglesias-Pradas et al., 2021). One of the notable advantages of ANOVA is its capacity to reduce the inflation of Type I errors by eliminating the need for repeated pairwise comparisons of means. In this respect, it offers a more methodologically consistent approach than conducting several separate tests across the same dataset.

Moreover, ANOVA incorporates both between-group and within-group variance, thereby offering a more comprehensive analytical framework compared to basic mean-difference tests such as the independent-samples t-test (Witteveen et al., 2020). This feature is important in educational research, where differences in student performance may reflect not only distinctions between academic levels but also substantial variation within each level. By accounting for these two sources of variance, ANOVA allows the researcher to determine whether the observed differences in average performance are likely to reflect a meaningful group effect rather than random fluctuation. In our research, ANOVA served as the principal statistical tool for verifying whether meaningful performance differences existed among undergraduate, master's, and doctoral students.

When ANOVA indicates statistically significant outcomes, an additional step is required to determine which specific groups differ from one another. For this purpose, Tukey's HSD test is considered one of the most effective post hoc procedures. It is widely used in educational and psychological research because it enables multiple pairwise comparisons while preserving an acceptable level of statistical control. Xu et al. (2023) demonstrate that Tukey's method provides reliable pairwise comparisons across multiple groups while maintaining a high degree of control over Type II errors and minimizing the likelihood of false-positive results. In the present study, this test enabled a more precise differentiation of academic performance among undergraduate students, master's students in both academic-pedagogical and professional programs, and doctoral candidates. This step was necessary because the identification of a general difference across groups does not, by itself, explain the structure of that difference.

Contemporary literature on educational statistics also underscores the role of graphical data visualization in improving interpretability. Statistical significance alone does not always provide a complete understanding of how the data are distributed or how strongly groups differ in practical terms. For this reason, researchers often complement formal tests with visual methods that make patterns in the data easier to observe. Mishra et al. (2025) and Juarros-Basterretxea et al. (2024) highlight the utility of boxplots, histograms, and related visual tools in illustrating data distribution patterns, including variability, skewness, and the presence of outliers. Such instruments help reveal whether group means are supported by relatively consistent observations or influenced by dispersion and extreme values. In this research, visual representations were employed not merely as supplementary illustrations but as integral components that reinforce and contextualize the results of statistical testing.

The use of visualization is particularly relevant in the analysis of academic performance, since grade distributions often vary across student groups and may contain features that are not immediately visible in summary statistics alone. For example, two groups may have similar mean values while differing substantially in terms of spread, concentration of scores, or the presence of unusually high or low results. Graphical presentation helps identify these features and supports a more careful interpretation of quantitative findings. In this way, visual analysis serves as a bridge between statistical output and substantive educational interpretation.

Overall, the synthesis of findings from recent academic publications allows us to conclude that the combined application of ANOVA, Tukey's HSD test, and complementary visualization techniques constitutes an appropriate methodological framework for analyzing differences in academic performance across educational levels. This integrated approach provides statistically reliable results, supports a clearer understanding of performance patterns, and offers useful implications for the ongoing refinement of higher education curricula and assessment practices. It also makes it possible to connect quantitative findings with broader discussions about student progression, academic demands, and the conditions that shape learning outcomes at different stages of higher education.

Materials and main methods. The empirical basis of the study consisted of a dataset containing detailed information on students' educational levels, the academic disciplines they completed, and their final grades. The sample encompassed four distinct groups of learners: undergraduate students, master's students enrolled in academic-pedagogical programs, master's students pursuing professional tracks, and doctoral candidates (PhD programs). This group structure made it possible to compare academic performance across several stages of higher education within a single analytical framework. The primary objective of the statistical analysis was to identify systematic differences in academic performance across these educational categories and to determine whether such differences were statistically meaningful.

The dataset was organized in a way that allowed the examination of both general and subject-specific patterns of performance. Educational level was treated as the main independent grouping variable, while the final academic grade served as the dependent variable. In addition, the academic discipline completed by the student was used as an auxiliary analytical factor in order to explore whether differences in performance were related not only to the level of study, but also to the characteristics of particular courses. This made it possible to consider academic achievement from two perspectives: first, as a function of educational level, and second, as a function of subject-related complexity.

Only completed course records with available final grades were included in the analysis. Observations with missing or incomplete grade information were excluded in order to preserve the comparability of the groups and avoid distortion in the statistical calculations. This procedure helped ensure that all analyzed records reflected completed academic performance and could be interpreted within the same grading framework. The use of cleaned and comparable data was especially important because the study involved several educational levels and a wide range of subjects with different instructional formats.

As an initial step, descriptive statistics were computed, including the calculation of mean final grades for each category of students. This provided a preliminary indication of performance variation across educational levels and made it possible to identify broad patterns before applying inferential procedures. Descriptive analysis was also used to summarize average grades across individual disciplines, which later served as the basis for identifying relatively more difficult and less difficult subjects. In this way, the first stage of analysis established the empirical background for subsequent statistical testing.

Following this, Analysis of Variance (ANOVA) was employed to test for the presence of overall group differences. ANOVA was selected due to its suitability for comparing more than two independent groups and its ability to partition variance into between-group and within-group components. This feature is particularly relevant for educational research, where differences in performance may exist not only between educational levels but also within each student group. By comparing these two sources of variation, ANOVA makes it possible to assess whether the observed differences in mean academic performance are likely to reflect a real group effect rather than random fluctuation.

Before conducting the ANOVA, the main assumptions underlying this procedure were taken into account. These included the independence of observations, approximate normality of grade distributions within groups, and the relative homogeneity of variances. Although ANOVA is generally considered robust to moderate deviations from normality, attention to these assumptions was necessary in order to support the validity of the analysis and strengthen confidence in the interpretation of results. The level of statistical significance was set at $p < 0.05$.

Upon detection of statistically significant differences, Tukey's post hoc test was applied to conduct pairwise comparisons among the educational levels. This procedure enabled the identification of specific group pairs in which performance disparities were statistically significant, thereby offering a more granular understanding of the academic differences observed among undergraduates, master's students of different orientations, and doctoral students. While ANOVA determines whether at least one significant difference exists among the means, Tukey's test clarifies where exactly these differences are located. This was necessary for the present study, since the comparison involved more than two categories and required a detailed interpretation of intergroup relationships.

To enhance interpretability and ensure clarity of findings, graphical visualization techniques were incorporated. Histograms and boxplots were used to display the distribution of final grades across all categories, illustrating central tendencies, variability, and potential outliers. These visual tools supported the statistical analysis by showing whether the mean values were accompanied by concentrated or dispersed score distributions. In the context of educational data, such visualizations are particularly useful because they make it easier to identify internal heterogeneity within student groups and to assess whether some courses or educational levels are characterized by greater inconsistency in outcomes than others.

The integration of descriptive statistics, ANOVA, Tukey's post hoc test, and graphical visualization provided a comprehensive analytical framework for examining the relationship between educational level and academic performance. This approach allowed the study not only to determine whether performance differences existed, but also to interpret how these differences were distributed across student categories and subjects. As a result, the methodology supported both statistical rigor and educational interpretability.

Mean Grade by Educational Level

As part of this research, the final academic grades of students enrolled in different levels of higher education were examined. Table 1 presents the mean scores for undergraduate students, master's students from both academic-pedagogical and professional tracks, and doctoral (PhD) candidates.

Table 1 – Mean Final Grade of Students by Educational Level

Educational Level	Mean Grade
Undergraduate (Bachelor's program)	74.8
Master's (Scientific & Pedagogical)	75.1
Master's (Specialized / Professional)	84.7
Doctoral Studies (PhD program)	85.1

The descriptive results presented in Table 1 indicate that average academic performance differs across the four educational categories. The mean grades of bachelor's students and students enrolled in the scientific-pedagogical master's program are very close, suggesting that these two groups demonstrate broadly similar levels of academic achievement. In contrast, students in the specialized or professional master's track and doctoral candidates show visibly higher average scores. This pattern suggests that academic outcomes are associated not only with progression to a higher formal level of education, but also with the orientation and internal structure of the academic program.

The observed differences may reflect several educational factors. Students in specialized master's and doctoral programs often work in more focused academic environments, where narrower specialization, clearer professional or research goals, and stronger academic self-regulation contribute to better performance. At the same time, the similarity between bachelor's students and students in the scientific-pedagogical master's track may indicate that these two groups share certain structural features in terms of curriculum organization, instructional logic, or assessment format. Thus, even at the level of descriptive statistics, the results point to the need for a differentiated interpretation of graduate education rather than treating all master's programs as a single category. The distribution of these mean values is illustrated in Figure 1.

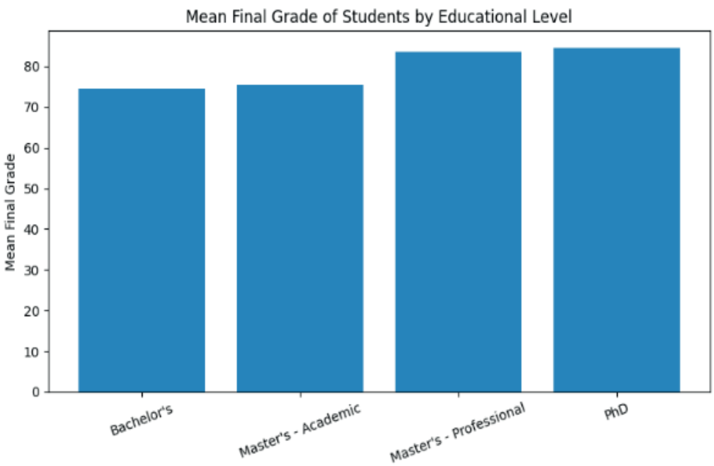

Figure 1 – Average final score of students by education level.

An analysis of variance (ANOVA) was then performed to determine whether the observed differences among the educational level groups were statistically meaningful. The resulting p-value ($p < 0.001$) indicates that academic performance varies significantly across the four educational categories. In other words, the differences in mean grades shown in the descriptive statistics are unlikely to be random and may be interpreted as reflecting a meaningful association between educational level and students' academic outcomes.

At the same time, the ANOVA result alone does not indicate which specific groups differ from one another. A statistically significant overall test only shows that at least one intergroup difference exists. For this reason, a post hoc comparison procedure was required in order to determine where the significant differences were located. Tukey's post hoc multiple comparison test was therefore applied as the next analytical step. The outcomes of this procedure are summarized in Table 2.

Table 2 – Tukey Post Hoc Multiple Comparison Test Results

Group Pair	Difference in Means	Adjusted p-value
Bachelor's vs PhD	10.25	< 0.001
Bachelor's vs Master's (Scientific–Pedagogical)	0.24	0.945
Bachelor's vs Master's (Specialized)	9.84	< 0.001
PhD vs Master's (Scientific–Pedagogical)	–10.00	< 0.001

The findings from Tukey's test confirm that educational level exerts a statistically significant influence on students' academic performance. The most substantial difference is observed between bachelor's students and doctoral candidates, with doctoral students achieving markedly higher final grades. This result may be associated with the selective nature of doctoral admissions, the narrower specialization of PhD study, and the research-centered character of doctoral education. These features typically require and reinforce a high degree of academic independence, sustained motivation, and analytical maturity, which may contribute to better academic outcomes.

The comparison between bachelor's students and students enrolled in the scientific-pedagogical master's track reveals no statistically significant difference. This finding is important because it suggests that the scientific-pedagogical master's program may remain relatively close to the undergraduate level in terms of curriculum demands, assessment logic, or general learning expectations. Such a result may indicate that the transition from bachelor's study to this particular master's track does not involve a strong enough shift toward advanced theoretical preparation or research-based learning. From a curriculum perspective, this may justify reconsidering the structure of the program in order to strengthen its academic distinctiveness.

A different pattern is observed in the case of the specialized master's program. Students in this category significantly outperform bachelor's students, which may be explained by the more applied and professionally oriented character of the program. It is also possible that this group includes students with stronger prior preparation, clearer career goals, or relevant practical experience. These factors may positively influence their engagement with course content and contribute to more stable and higher academic performance.

Moreover, the absence of a strong distinction between the specialized master's track and doctoral studies suggests that both groups occupy a relatively high-performance segment within the dataset. Although doctoral education differs from professional master's study in depth and research orientation, both groups may share common characteristics such as stronger self-regulation, clearer academic purpose, and greater capacity for independent work. This does not imply that the programs are equivalent in content, but it does indicate that their students reach similarly high levels of measured academic achievement.

Overall, the Tukey analysis shows that the most visible performance differences emerge between undergraduate education and the more advanced, specialized forms of graduate study. At the same time, the findings point to internal diversity within master's education itself. This suggests that educational level should not be treated as a purely formal category; the substantive orientation of a program also appears to matter for academic outcomes. These results support the need for a more differentiated view of graduate education and may be useful for improving program design, especially in tracks where performance remains close to the undergraduate level.

Analysis of Subject Complexity

The analysis of differences in students' academic performance across educational levels demonstrated that average grades are influenced not only by the level of education but also by the characteristics and complexity of the disciplines studied. To obtain a deeper understanding of how subject-specific factors affect academic outcomes, an additional examination of course difficulty was conducted based on students' average final grades.

For the purpose of analysis, all subjects were grouped according to their relative complexity. Two categories were identified:

(1) disciplines with the lowest average scores, interpreted as the most challenging (Table 3), and

(2) disciplines with the highest average scores, considered less difficult for students (Table 4).

It should be noted that, in the present study, subject complexity was not measured directly through an external rating scale or expert judgment. Instead, it was interpreted indirectly on the basis of students' average academic results. Courses with lower average grades were treated as relatively more difficult, while courses with higher average grades were considered comparatively easier for the student groups represented in the dataset. This operational approach does not claim to capture every dimension of course difficulty, but it provides a practical basis for comparing patterns of subject-specific performance within the available empirical material.

At the same time, average grade should not be interpreted as a perfect or exclusive indicator of objective course complexity. Academic results in a given subject may also be shaped by assessment design, teaching methods, students' prior preparation, grading practices, or the balance between theoretical and practical tasks. Therefore, the interpretation of low average grades as evidence of higher difficulty should be made with caution and in relation to the broader instructional context. This reservation is important because some courses may appear difficult not only because of their content, but also because of the way learning outcomes are assessed.

The findings show that courses related to programming, engineering technologies, and database management exhibit relatively high average grades in some cases, while other analytically demanding technical subjects demonstrate much lower averages. This pattern suggests that technical disciplines are not uniform in their effect on academic performance. Applied and practice-oriented courses may support stronger outcomes when students can rely on hands-on tasks, concrete problem-solving procedures, and clearer performance criteria. By contrast, highly theoretical, algorithmic, or systems-oriented subjects may create more difficulties because they require stronger abstract reasoning, deeper conceptual understanding, and more extensive independent preparation.

In contrast, subjects with low average grades warrant closer attention. Their complexity may arise from the inherent cognitive demands of the course content, insufficient foundational knowledge among students, or shortcomings in pedagogical approaches, instructional materials, or assessment design. In some cases, the low results may reflect the fact that students encounter these disciplines before they have fully mastered prerequisite concepts. In other cases, the difficulty may be associated with fragmented course structure or a mismatch between teaching methods and assessment requirements. For this reason, the interpretation of difficult subjects should take into account not only the nature of the content itself but also the broader educational conditions in which the course is delivered.

Future research will aim to examine the variance and distribution of grades for each discipline in order to pinpoint subjects with the largest performance disparities. Such analysis will make it possible to determine whether variability arises from structural curriculum issues, inconsistent assessment practices, or differences in instructional quality. These insights may serve as a basis for refining course design and improving support strategies for students encountering difficulties in specific subject areas.

Table 3 – The most difficult subjects by average final score

№	Discipline	Level	Avg. Score
1	Introduction to Distributed Systems	Bachelor	5.2
2	Machine Learning	Bachelor	7.8
3	Programming Languages 2	Bachelor	8.5

4	Fundamental Algorithms	PhD	12.4
5	System Software	Bachelor	34.7
6	Microcontroller Programming	Bachelor	36.1
7	Distributed Intelligent Systems	PhD	38.9
8	Fundamentals of Cybersecurity	Bachelor	40.3
9	Mobile Sensor Data Processing	Bachelor	42.6
10	IT Infrastructure	Bachelor	47.5

Table 4 – The easiest subjects by average final score

№	Discipline	Level	Avg. Score
1	Database	Bachelor	99.6
2	Database Management Tools	Bachelor	99.8
3	Internet of Things	Bachelor	100.0
4	Computer Engineering	Bachelor	98.9
5	Microprocessor & Embedded Systems	Bachelor	98.7
6	Artificial Intelligence	Master (prof.)	98.5
7	Higher Mathematics	Master (prof.)	97.2
8	Theoretical Mechanics	PhD	96.8
9	Numerical Methods	Master (sci.)	96.5
10	Data Analysis	Bachelor	95.9

The analysis of disciplines with the highest average final scores revealed a group of subjects in which students demonstrated consistently strong academic performance. The top-performing courses were predominantly concentrated within the bachelor's curriculum, including Database, Database Management Tools, and Internet of Things, each showing average scores close to or equal to 100. Such results suggest that these subjects are either well aligned with students' prior preparation or characterized by clearly structured content, practice-oriented learning tasks, and assessment methods that allow students to perform with a high degree of accuracy.

Additionally, subjects such as Computer Engineering and Microprocessor & Embedded Systems also showed high performance, with average scores above 98. These disciplines typically involve applied technical skills and hands-on laboratory activities, which may contribute to higher levels of student engagement and improved mastery of course material. Where learning tasks are concrete, iterative, and supported by practical feedback, students may find it easier to demonstrate competence in assessment settings.

Among graduate programs, the professional master's disciplines Artificial Intelligence (98.5) and Higher Mathematics (97.2) demonstrated strong results as well. This suggests that students in professional-oriented tracks possess sufficient prior knowledge and motivation, enabling them to perform successfully in advanced, specialized subjects. It may also indicate that these programs are more tightly aligned with students' academic interests and professional goals, which can positively affect learning persistence and final outcomes.

At the doctoral level, Theoretical Mechanics showed an average score of 96.8, indicating that even highly theoretical and conceptually complex subjects may result in high academic performance when taken by well-prepared and research-oriented students. Similarly, in the scientific master's program, the course Numerical Methods showed strong outcomes (96.5), reflecting students' ability to work with mathematical models and computational approaches. These findings suggest that high performance in difficult subjects is possible when students possess adequate background knowledge and when course expectations are clearly structured.

Overall, the analysis indicates that subjects with high average grades tend to share several characteristics: relatively well-organized curricula, applied or practice-intensive learning tasks, clear links between instruction and assessment, and student cohorts with strong initial preparation and sustained motivation. These findings draw attention to the role of course design and assessment clarity in shaping academic outcomes and suggest that successful performance often depends not only on the content of the subject, but also on how learning is organized and evaluated.

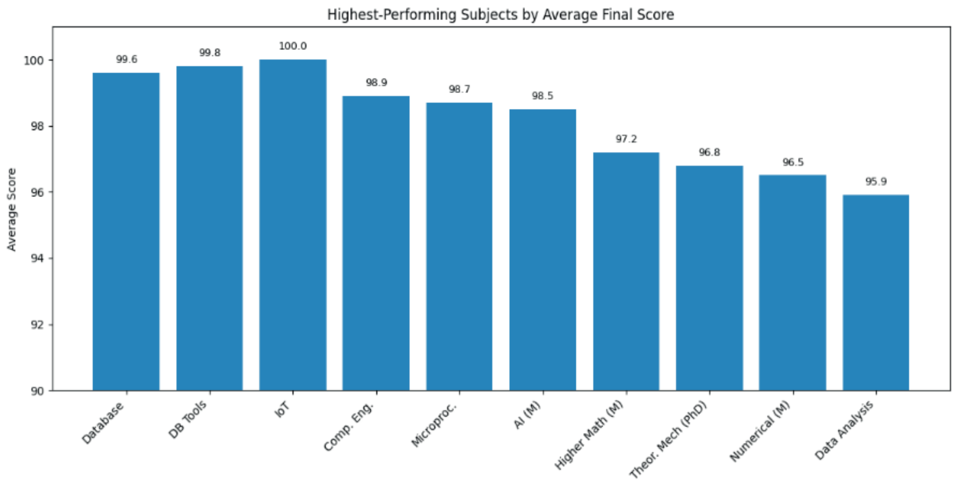

Figure 2 – Average final score of students by education level.

Figure 3 presents the distribution of average student scores across various subjects. The difficult subjects (highlighted in red), such as Machine Learning, Fundamental Algorithms, Microcontroller Programming, and Fundamentals of Cybersecurity, demonstrate comparatively low performance levels, with average scores ranging from 0 to 40 points. These results indicate that such disciplines involve a high degree of conceptual and cognitive complexity for the students represented in the dataset.

In contrast, the less difficult subjects (shown in green), including Database, Internet of Things, Artificial Intelligence, and Higher Mathematics, are characterized by very high student achievement, with average scores of approximately 98–100 points. This suggests that students perform more confidently in these courses, possibly because the material is delivered in a more structured way, because the assessment procedures are clearer, or because the learners have stronger prior preparation in these areas.

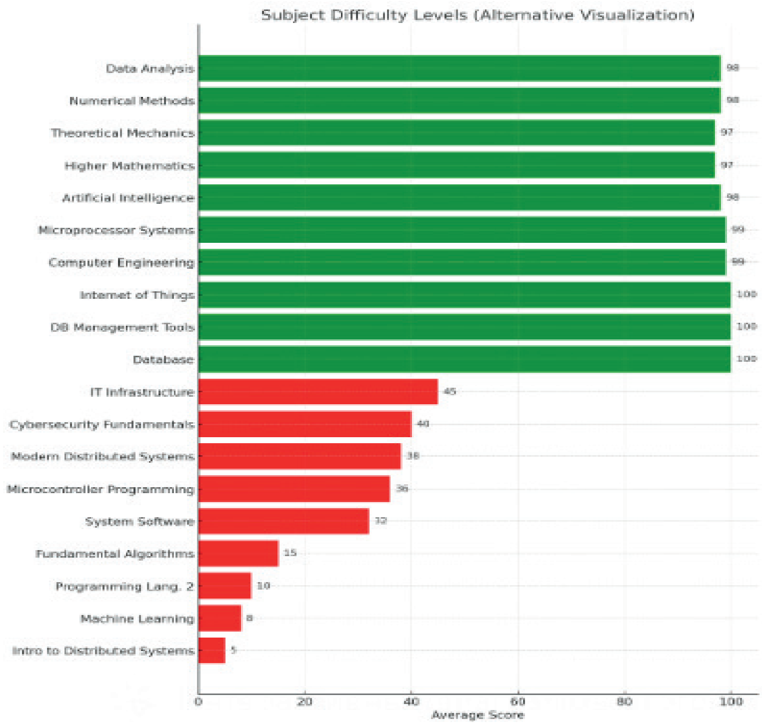

Figure 3 – Distribution of the most difficult and easiest subjects by mean score.

A comparison between the lowest-performing and highest-performing disciplines reveals a visible contrast in the character of academic outcomes. The subjects classified as more difficult are largely associated with algorithmic thinking, abstract reasoning, systems-level understanding, and technically demanding problem-solving. These courses often require students to integrate several layers of knowledge at once, apply theoretical principles to unfamiliar situations, and work with complex computational or engineering concepts. Such demands may explain why average scores in these disciplines are substantially lower.

By contrast, the courses with the highest average scores appear to be more favorable in terms of assessment outcomes. In some cases, this may reflect the practical orientation of the subject, where students can demonstrate their knowledge through structured tasks, technical exercises, or hands-on projects. In other cases, the high average scores may indicate better alignment between teaching methods and expected learning outcomes. It is also possible that these courses attract or are taken by students who already possess a stronger academic foundation in the relevant field.

Another important aspect of subject-specific analysis concerns the internal variability of grades. A low mean score does not necessarily imply that all students performed poorly; rather, it may indicate that the subject produces a wider dispersion of outcomes, including both very weak and relatively strong results. Similarly, a high average score may conceal meaningful variation if a smaller subgroup of students performs below the majority. For this reason, the interpretation of subject difficulty should take into account not only average values but also the spread of grades, the concentration of scores around the mean, and the presence of outliers. This is why graphical tools such as boxplots are particularly useful in the present study.

The analysis of subject-specific performance demonstrates that students experience considerable challenges when studying complex technical disciplines, while applied and practice-oriented subjects are associated with notably higher academic outcomes. This contrast suggests that the cognitive load, theoretical depth, and algorithmic complexity inherent to certain technical courses significantly affect students' ability to achieve high scores. These findings indicate that some disciplines require a greater amount of independent study, stronger foundational knowledge, and more sustained academic effort than others.

From a practical perspective, the results are relevant for curriculum design and assessment policy. Subjects associated with lower average grades and wider dispersion may require additional instructional support, revised learning materials, or more transparent evaluation criteria. At the same time, the strong results observed in some applied disciplines suggest that well-structured courses with clearly communicated expectations can support consistently positive learning outcomes. A deeper analysis of these differences may help universities identify where academic difficulties are most concentrated and how teaching and assessment practices can be adjusted to support students more effectively.

In this regard, further examination of grade variability across disciplines will be particularly important. Identifying subjects with the widest dispersion of scores will make it possible to determine which courses are most challenging for learners in practice, not only in terms of average performance but also in terms of inequality of outcomes. High variability may indicate differences in students' initial preparation, methodological shortcomings, or instructional formats that require refinement. Such analysis can provide a basis for improving teaching methods, assessment strategies, and curriculum structure in order to make student achievement more stable and more comparable across disciplines.

Results. The analysis shows that educational level has a statistically significant effect on academic performance. Doctoral students and those enrolled in specialized (professional) master's programs demonstrate higher average grades than bachelor's students and students in scientific–pedagogical master's tracks. This pattern suggests that academic achievement is related not only to the formal stage of higher education, but also to the orientation of the program and the learning conditions associated with it. In many cases, students who continue into professional master's or doctoral study have already passed through a process of academic selection and may therefore represent groups with stronger subject preparation, clearer educational goals, and greater readiness for advanced study.

These differences may be linked to stricter selection procedures, narrower specialization, higher academic motivation, and stronger research skills. Students at more advanced stages of education are often expected to manage complex tasks independently, work with specialized literature, and engage in analytical or research-based activities with less external guidance. Such demands may gradually strengthen their ability to organize learning, maintain focus over longer periods, and apply knowledge in more structured and purposeful ways. As a result, higher average performance among doctoral students and students in specialized master's programs may reflect the cumulative effect of previous academic experience together with the more focused nature of their studies.

At the same time, the lack of significant differences between specialized master's and doctoral programs suggests that performance at these stages may be close to an upper limit within the given assessment system. This does not mean that the two groups are identical in terms of academic content or educational purpose. Rather, it indicates that both groups achieve similarly high measured outcomes, despite the fact that doctoral study usually involves a stronger research orientation and a higher level of academic independence. One possible explanation is that the grading system used in the analyzed context may not fully capture qualitative differences between these advanced groups, particularly when most students already perform at a consistently high level.

The similarity in results between bachelor's students and scientific–pedagogical master's students points to possible weaknesses in how the scientific–pedagogical track is designed and assessed. This finding is important because a master's program would generally be expected to demonstrate a clearer shift toward greater academic complexity, stronger theoretical grounding, and deeper engagement with research-related tasks. If students in this track perform at nearly the same level as undergraduates, it may indicate that the curriculum does not provide enough differentiation in rigor or research training compared to the bachelor's level. It may also suggest that learning outcomes, instructional methods, and assessment procedures are not yet sufficiently aligned with the expectations typically associated with graduate education.

Another possible interpretation is that the scientific–pedagogical master's track may function more as a continuation of previous study than as a qualitatively distinct academic stage. In this case, the transition from bachelor's to master's education may remain limited in practical terms, especially if students continue to work within familiar formats of coursework and evaluation. This would reduce the likelihood of substantial differences in average grades and may partly explain the statistical similarity between these groups. From the perspective of educational design, such a result points to the need for closer examination of curriculum content, progression logic, and the balance between pedagogical preparation and research-oriented learning.

Subject complexity also matters. Courses that require strong analytical and algorithmic thinking, such as Machine Learning, Fundamental Algorithms, and Microcontroller Programming, tend to have lower average scores, suggesting higher cognitive load and greater conceptual difficulty. These disciplines often require students to work with abstract models, sequential reasoning, and technically demanding problem-solving procedures. In addition, they may presuppose a level of prior preparation that not all students possess to the same degree. As a result, such subjects can produce lower average grades and greater variation in performance, especially when students differ in foundational knowledge or in their ability to adapt to mathematically or computationally complex material.

In contrast, database and internet-technology subjects show higher average grades, which may reflect clearer practical tasks, less abstract content, or more accessible assessment formats. In applied disciplines, students often benefit from direct links between theory and practice, more visible problem structures, and a stronger sense of how course tasks relate to real technical applications. This may make learning more manageable and allow students to demonstrate achievement more confidently during assessment. Higher grades in such subjects do not necessarily imply that they are simple, but they may indicate that the organization of instruction and evaluation is more transparent or better matched to student expectations.

Even in high-performing subjects, grade variation remains noticeable, indicating differences in prior preparation and/or limited standardization in assessment across groups. This point is important because high average performance alone does not guarantee consistency in student achievement. A course may have a strong overall average while still containing subgroups of students who perform substantially better or worse than others. This internal variation can reflect unequal entry-level competencies, different patterns of engagement, or differences in access to academic support. It may also indicate that some assessment formats allow stronger students to excel while leaving weaker students with fewer opportunities to recover or demonstrate partial understanding.

High dispersion is especially visible in programming and data-analysis disciplines, and outliers in the form of very low or very high scores may signal issues in course organization, uneven teaching quality, or gaps in assessment methods. In some cases, outliers may reflect genuinely exceptional performance or substantial learning difficulties. In other cases, they may point to inconsistencies in grading criteria, unequal instructional support across groups, or differences in how assignments and examinations are structured. For this reason, variability in grades should be treated as a meaningful analytical result rather than as a secondary feature of the data. A closer examination of dispersion can help identify courses where academic outcomes are less stable and where improvements in teaching or evaluation may be needed.

Overall, the results indicate that academic performance in higher education is shaped by a combination of educational level, program orientation, and subject-specific demands. The findings suggest that higher achievement is more common in advanced and specialized programs, while lower and more variable performance is observed in courses with stronger analytical and technical complexity. At the same time, the results show that curriculum structure and assessment design remain important factors in understanding why some groups and disciplines produce more favorable outcomes than others.

Discussion. The overall pattern supports the idea that higher educational levels are associated with stronger learning regulation, deeper specialization, and more developed analytical competencies, which helps explain why PhD students and specialized master's students perform better (Dent & Koenka, 2016; Broadbent & Poon, 2015; Milkova et al., 2024). Prior research has repeatedly shown that academic success is connected with self-regulated learning, planning, monitoring of progress, and the ability to manage complex tasks over time. These qualities tend to become more visible as students move into advanced stages of education, where independent study and sustained academic effort are required more consistently. In this sense, the present findings are in line with the broader view that educational progression is often accompanied by the development of stronger academic habits and more effective learning strategies, especially under conditions of digital and technology-supported learning (Mena-Guacas et al., 2025).

Related work also connects academic progression with metacognitive and research-oriented skill development (Mammadov, 2022). Students who continue into specialized master's and doctoral programs are often better equipped to evaluate their own learning, identify gaps in understanding, and adjust their study strategies when working with difficult material. These forms of metacognitive control may contribute to more stable and higher performance, especially in programs where academic expectations are clearly defined and closely linked to professional or research goals. The results of the present study support this interpretation by showing that more advanced and specialized educational tracks are associated with stronger average outcomes.

The absence of significant differences between specialized master's and doctoral students can be interpreted as a sign that both groups already demonstrate stable high performance once key competencies are formed (Iglesias-Pradas et al., 2021). This pattern may suggest that, beyond a certain stage of academic development, differences in measurable performance become less pronounced because both groups function at a similarly high level within the grading system. It is also possible that the assessment format used in institutional practice is better suited to distinguishing between lower and middle levels of achievement than between already high-performing graduate groups. Therefore, the similarity between specialized master's and doctoral students should not necessarily be understood as evidence of equivalent academic depth, but rather as an indication of comparable performance within the available measurement framework.

At the same time, the fact that bachelor's and scientific–pedagogical master's students show similar outcomes suggests that the scientific–pedagogical master's curriculum may not sufficiently increase complexity, research depth, or academic rigor. This is one of the more important findings of the study because it raises questions about the internal differentiation of graduate education. If a master's track does not produce a clear shift in academic performance compared with undergraduate study, this may point to limits in curriculum progression, insufficient emphasis on independent inquiry, or a continued reliance on instructional and assessment formats that remain close to those used at the bachelor's level. In the context of current higher education transformation, this issue also relates to the broader need to align program design with emerging technological and pedagogical demands (Mena-Guacas et al., 2025; Zhang et al., 2025).

Studies on program competitiveness also emphasize curriculum redesign and stronger specialization as factors that improve outcomes (Berlanga & Corti, 2025). In this context, the present results may be interpreted as support for revising the scientific–pedagogical master's track in order to strengthen its academic identity. Such revision could involve deeper theoretical preparation, a larger research component, clearer connections between coursework and scholarly practice, and more explicit expectations regarding independent analytical work. These changes may help the program become more distinct from undergraduate education and may contribute to stronger academic results in future cohorts. Recent studies on digital transition in higher education also suggest that curriculum redesign should increasingly account for AI-assisted and technology-enhanced teaching models (Zhang et al., 2025).

Differences across subjects are consistent with research showing that algorithmic and abstract courses often create higher cognitive load and lead to lower averages and larger variability (Mulyaningsih et al., 2022). The present findings fit this pattern. Courses that depend heavily on formal reasoning, mathematical abstraction, or programming logic tend to require sustained concentration and a strong command of prerequisite knowledge. When these foundations are uneven, academic performance is likely to become more dispersed. This helps explain why certain technical subjects in the dataset combine lower average grades with wider variation in results. At the same time, recent work on AI-assisted engineering teaching suggests that the integration of digital instructional frameworks may help reduce some of these difficulties by improving the structure and support of technically complex learning environments (Zhang et al., 2025).

The observed grade dispersion in technical disciplines also fits discussions in STEM assessment research. Variability can reflect uneven starting skill levels, instructor differences, and inconsistent grading, especially in practical work (Xu et al., 2023; Witteveen & Attewell, 2020; Tempelaar et al., 2015; Conijn et al., 2017). In applied and technical courses, assessment often includes project-based tasks, laboratory assignments, coding activities, or open-ended problem solving. These formats can provide valuable evidence of student competence, but they may also introduce greater variation if grading criteria are interpreted differently across instructors or if students receive unequal levels of methodological support. As a result, dispersion in grades may reflect not only student ability but also differences in course implementation. This point is also consistent with recent findings that digital competence and ICT-supported instruction can influence academic outcomes by shaping how students engage with course requirements and learning tasks (Milkova et al., 2024).

Another point worth considering is that high variation in grades may indicate that some subjects are functioning as points of academic stratification within the curriculum. In such cases, technically demanding courses do not simply measure knowledge; they also separate students according to prior preparation, adaptability, and persistence. This may be educationally meaningful, but it also creates a need for more transparent support systems and more clearly structured assessment practices. Where very low and very high results coexist within the same discipline, the issue may lie partly in student heterogeneity, but it may also suggest that course design could be improved to make expectations more accessible and learning trajectories more consistent. Broader reviews of educational transformation through emerging technologies likewise underline the importance of redesigning learning environments so that they support different student groups more effectively (Mena-Guacas et al., 2025).

From a broader perspective, the discussion of educational level and subject complexity suggests that academic performance should not be interpreted as the product of one factor alone. It emerges through the interaction of student characteristics, curriculum structure, instructional methods, and assessment design. Higher educational levels may support stronger achievement because they attract and develop students with greater academic maturity, but this effect is also shaped by the kinds of courses students take and by the way institutions organize learning. In this sense, the present findings support a multidimensional understanding of academic performance in higher education, including the role of digital transition, technological support, and evolving teaching models (Milkova et al., 2024; Zhang et al., 2025).

Taken together, the discussion indicates that stronger performance among doctoral and specialized master's students is consistent with existing literature on self-regulation, specialization, and advanced academic skill development. At the same time, the similarity between bachelor's and scientific–pedagogical master's students points to a possible need for curriculum revision in order to strengthen the distinctiveness and rigor of that track. The subject-level findings further suggest that technical and analytically demanding courses require particular attention in terms of teaching support, grading transparency, and instructional design. These conclusions may be useful for universities seeking to improve both program structure and the comparability of academic outcomes across student groups, especially in the context of ongoing educational transformation driven by emerging technologies (Mena-Guacas et al., 2025; Zhang et al., 2025).

Limitations of the Study. Despite the analytical insights provided by the present study, several limitations should be acknowledged when interpreting the results.

First, the empirical data used in this research were derived from a single institutional context. As a result, the observed patterns in academic performance may reflect the specific characteristics of the university, its grading culture, curriculum structure, and student population. Consequently, the findings should not be generalized to all higher education institutions without caution. Future studies involving multiple universities or international datasets could provide a broader comparative perspective.

Second, the relatively high academic performance observed among doctoral students may partly reflect the effect of academic selection. Admission to doctoral programs typically involves rigorous evaluation of candidates' academic background, research potential, and prior achievements. Therefore, doctoral students may represent a group that has already undergone substantial academic filtering. This factor may contribute to higher average grades and should be considered when interpreting differences between educational levels.

Third, the study relies on final course grades as the primary indicator of academic performance. Although grades are widely used as a measurable outcome in educational research, they may not fully capture all aspects of learning. Differences in grading practices, instructor expectations, and assessment formats across courses may affect the comparability of scores. In addition, some disciplines rely more heavily on project-based or practical assignments, while others emphasize theoretical examinations, which may influence the distribution of grades.

Another limitation concerns the interpretation of subject complexity. In this study, course difficulty was inferred from average student performance rather than from an external evaluation of curriculum difficulty or instructional design. While this approach provides useful insights into patterns of student achievement, it does not necessarily reflect the intrinsic difficulty of the subject itself.

Future research may address these limitations by incorporating additional variables such as prior academic preparation, student engagement, learning analytics data from digital platforms, or qualitative analysis of course design and teaching methods.

Recommendations for Improving Educational Programs

Based on the findings of the statistical analysis, several recommendations can be proposed for improving curriculum design and instructional practices across different levels of higher education.

The results indicate that academic performance among students in scientific–pedagogical master's programs remains relatively close to the bachelor's level.

This suggests that the curriculum of this track may require stronger differentiation in terms of academic rigor and research orientation. One possible improvement is the earlier integration of research-oriented learning activities, including project-based research tasks, methodological training, and participation in supervised research projects.

Another important aspect concerns technically complex disciplines that demonstrate lower average academic performance. Courses such as Machine Learning, Distributed Systems, and Microcontroller Programming require strong analytical thinking and substantial prior preparation. To support student learning in these areas, instructors may consider incorporating additional learning support mechanisms, including step-by-step problem-solving sessions, interactive digital learning tools, and adaptive learning platforms that allow students to practice complex concepts at their own pace.

Improving transparency and consistency in assessment procedures is also essential. Greater standardization of grading criteria and clearer communication of learning expectations may reduce grade dispersion and improve comparability of academic outcomes across groups. This is particularly relevant for technical disciplines where project-based evaluation and programming assignments may introduce variability in grading practices.

Finally, curriculum planners may benefit from regularly analyzing academic performance data in order to identify subjects with unusually high variability or consistently low results. Such monitoring can help institutions detect potential weaknesses in course design and provide targeted academic support to students encountering difficulties.

Table 5 – Suggested Curriculum Improvement Measures

Educational Area	Identified Problem	Proposed Improvement Strategy	Expected Academic Outcome
Scientific–pedagogical master's programs	Academic performance close to bachelor's level, limited differentiation in curriculum rigor	Introduce research-based learning modules, expand methodological training, integrate supervised research projects and thesis preparation earlier in the curriculum	Stronger analytical skills, improved research competence, clearer distinction between undergraduate and graduate academic levels
Analytical and algorithmic technical disciplines (e.g., Machine Learning, Algorithms)	Lower average scores and higher grade dispersion due to cognitive complexity	Implement scaffolded instruction, increase problem-based learning sessions, provide additional digital learning resources and coding practice environments	Reduced learning difficulties, improved conceptual understanding, more stable academic performance
Assessment and grading practices	Grade variability across courses and instructors	Develop standardized grading rubrics, clarify evaluation criteria, and implement transparent assessment frameworks across departments	Greater comparability of grades and improved fairness of academic evaluation

Academic performance monitoring	Lack of systematic analysis of student performance across disciplines	Establish institutional learning analytics systems to track grade patterns, identify high-risk subjects, and monitor curriculum effectiveness	Data-driven curriculum improvement and earlier identification of learning difficulties
Student academic support	Uneven student preparation in technically complex courses	Provide preparatory modules, tutoring programs, and adaptive digital learning systems for foundational subjects	Increased student readiness and improved academic outcomes in complex disciplines

The recommendations presented in Table 5 summarize the main practical implications derived from the statistical analysis conducted in this study. The results indicate that differences in academic performance across educational levels are not determined solely by student ability, but are also influenced by curriculum structure, instructional approaches, and assessment practices. Therefore, improving educational programs requires a systematic approach that combines curriculum redesign, enhanced instructional support, and data-informed monitoring of academic outcomes.

In particular, the findings highlight the need to strengthen the scientific–pedagogical master's curriculum so that it more clearly differs from the bachelor's level in terms of research training and analytical depth. Introducing research-based learning activities and methodological courses may help students develop stronger academic competencies and better prepare them for advanced academic or professional work. At the same time, the results emphasize the importance of additional instructional support in technically demanding disciplines, where lower average scores and higher variability suggest that students face greater cognitive challenges.

The implementation of standardized assessment frameworks and learning analytics systems may also contribute to improving transparency and consistency in grading practices. By systematically analyzing academic performance data, universities can identify disciplines with persistent learning difficulties and implement targeted improvements in teaching methods and curriculum design. In this way, the integration of empirical evidence into educational planning can support more effective learning environments and promote sustainable improvement in student academic outcomes.

Conclusion. At the same time, the results also indicate that the scientific–pedagogical master's track remains relatively close to the bachelor's level in terms of performance. This finding deserves particular attention, since a master's program would normally be expected to reflect a higher level of academic complexity and a clearer transition toward advanced theoretical and research-oriented work. The observed similarity may suggest that the current curriculum of the scientific–pedagogical track does not provide enough differentiation from undergraduate study in terms of content, assessment logic, or academic demands. In this regard, the results support the idea that this program could benefit from revision. Such revision may include a stronger research component, more consistent theoretical preparation, clearer learning outcomes, and better alignment between course content, teaching methods, and assessment tasks.

The study also shows that academic performance is influenced by the nature of the subjects students take. Courses with a stronger analytical, mathematical, or algorithmic component tend to produce lower average scores and greater variation in results. This may reflect the higher cognitive demands of such disciplines, as well as differences in students' prior preparation and confidence when working with abstract or technically complex material. By contrast, more applied subjects, including courses related to databases and internet technologies, generally show higher average grades. However, even within these better-performing disciplines, noticeable variation remains, which suggests that strong average performance does not necessarily mean that outcomes are uniform across all students.

An important conclusion of the study is that differences in academic outcomes should be considered not only at the level of student groups, but also at the level of curriculum design and assessment practice. Where grade dispersion is high and outliers are frequent, the issue may lie partly in uneven preparation, but it may also be linked to differences in course organization, grading standards, or the clarity of performance criteria. For this reason, one of the practical implications of the study is the need for more standardized and transparent approaches to assessment, especially in technical and analytically demanding disciplines. Clearer criteria, more consistent grading procedures, and closer alignment between learning objectives and evaluation methods could help reduce unnecessary variability and make the comparison of results across groups more meaningful.

Overall, the study supports the conclusion that educational level remains a relevant predictor of academic performance, but this relationship is not isolated from program structure, subject difficulty, and assessment design. The results suggest that academic success in higher education should be understood as the outcome of several interacting factors, including the level of study, the type of curriculum, and the characteristics of the disciplines being taught. In practical terms, these findings may be useful for improving curriculum development, revising master's programs with weaker differentiation, and strengthening support for students in courses that are associated with lower performance and wider score dispersion.

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