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RESEARCH ARTICLE

Exploring Key Determinants of Students' Performance Using PLS-SEM Model

Sihem BEN ZAKOUR [a], Nadia SELMI [a*]

[a] Department of Basic Science, Deanship of Preparatory Year and Supporting Studies, Imam Abdulrahman Bin Faisal University, SAUDI ARABIA

[a] Department of Basic Science, Deanship of Preparatory Year and Supporting Studies, Imam Abdulrahman Bin Faisal University, SAUDI ARABIA

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***Corresponding Author:**

nySELMI@iau.edu.sa

ABSTRACT

To improve students' performance, students, teachers, and institutions must have a thorough awareness of the important factors affecting the performance. Numerous elements, such as personal habits, educational background, and socioeconomic status, affect academic achievement. The factors affecting academic performance and partial least-square structural equation modeling were investigated. The findings showed that five factors are statistically significant with the students' scores. The use of PLS-SEM to study the path model hypotheses demonstrates its benefits in analyzing factors affecting student performance.

INTRODUCTION

Research on the factors influencing student performance is of great importance to educators, educational managers, and policymakers, among whom a high consensus is reached on the significance of and desire for improving educational outcomes. There is an ongoing and urgent need for research to investigate such influences. Academic success among university students may be fundamentally influenced by several factors. (Beasley – 2020) These students are faced with a number of educational and non-educational demands pertaining to academic and non-academic spheres, with educational success being multifaceted. Learning dispositions, personality, mind, learning methods, preferences, background characteristics, as well as environment, instructions, teaching methods, learning materials, curriculum content and management, and course impact are all encompassed here (Lynam 2024).

Educational achievement is, thus, complex because it involves a host of multifactorial unions. The relevance of investigating this area stems from our willing to contribute toward the existing body of knowledge and add empirical evidence regarding this important issue.

The paper is structured as follows: Section 2 provides a comprehensive review of the relevant literature, while Section 3 outlines the research methodology and concludes with a discussion of the findings.

2. LITERATURE REVIEW

In the last decade, the issue of student and learner performance has become a central area of research and policy making in various countries around the world. There are many factors driving students' achievement both within the control of educators or students and outside of their control. A multitude of studies have investigated the effect of socio-economic status (SES) since it is considered among the most significant factors as it affects access to resources, learning environments, and overall academic opportunities. Understanding the impact of SES provides insight into disparities in educational outcomes and highlights areas for support and intervention.

Using Covariance analysis through data from two million students over a 10 year period in Turkey, Suna et al 2022 assessed how socioeconomic status (SES) and school type impact academic achievement. They found that students in private schools, who were socioeconomically stronger, had significantly higher academic achievement levels in language, mathematics, and science tests. Liu et al 2022 employed two meta-analyses study to investigate relations between socioeconomic status (SES) and academic achievement, with a focus on macro-level, micro-level, and methodological moderating variables in primary and secondary education. They concluded that expanding educational opportunities does not appear to lessen disparities in academic outcomes between high- and low-SES school children in educational systems on the national level. Earlier, Zhang et al 2020 conducted a survey over 966 fourth- to sixth-grade students and their findings suggest that there is a pathway from family SES to children's academic achievement through parental academic involvement and that this pathway is dependent on the level of parental subjective social mobility. Through structural equation modeling (SEM), (Qureshia et al 2021) highlighted the importance of social factors in enhancing active collaborative learning and student involvement, thus affecting their learning performance. The authors also reported the double mediation used in this study. With the increasing prevalence of online learning in education, evidence has been provided that collaborative learning and student engagement, influenced by social factors, significantly enhance learning activities.

While socioeconomic status shapes the resources and opportunities available to students, another determinant seems to directly influence academic engagement and motivation. Indeed, a growing body of studies have considered parental involvement as a key factor supporting or challenging student performance in meaningful ways.

Batool 2020 applied Path analysis through structural equation modelling to assess the mediational path model. Evidence was given that positive parenting has a significant impact on the self-esteem of university students, and self-esteem significantly mediates between positive parenting, academic procrastination and academic achievement. Later Wilder et al 2023 employed nine meta-analyses to reveal a positive relationship between parental involvement and academic achievement, regardless of a definition of parental involvement or measure of achievement. Furthermore, the results indicated that this relationship was most pronounced when parental involvement was characterized by parents' expectations for their children's academic success. However, the impact of parental involvement on student academic achievement was weakest if parental involvement was defined as homework assistance. Finally, the relationship between parental involvement and academic achievement was found to be consistent across different grade levels and ethnic groups. However, the strength of that relationship varied depending on the assessment method employed to evaluate student achievement. In the same line, Affuso et al 2023 used structural equation model to test the hypothesized longitudinal relations between the study variables. They concluded that teacher support and parental monitoring had a direct and positive influence on motivation and self-efficacy over time, which subsequently led to improvements in academic performance. They also demonstrated that teacher support and parental monitoring indirectly affected academic performance over time through the mediation of motivation and self-efficacy and that the Parental involvement had the most significant effect on motivation, while teacher influence was strongest on self-efficacy. Consistently, (Yusof et al 2024) investigated the factors impacting university students' academic performance through Structural Equation Modelling approach. Upon running a factor analysis, five determinants were identified; lecturer's assistance and motivation, self-determination, student's habit, universities facilities and services, and parents and friends' support. Finally, structural model was developed revealing relationships between these five factors.

Overall, there is a consensus that the involvement of parents positively influences student performance. However, the growing impact of technology is also shaping academic outcomes in significant ways. Indeed, technology has greatly enhanced our society and has shown the potential to reform the education system by making learning more effective. Leading to an annual effect on influencing student achievement. Numerous researches have addressed this concern to achieve multiple objectives of detecting the different elements of technology and understanding how technology influences student achievement levels in different countries

Panigrahi et al 2021 conducted a survey to measure the factors affecting the perceived learning effectiveness (PLE) of students. A summative assessment was also carried out to evaluate students based on their grades, measuring their achievements (actual learning). They concluded that the information system has a positive effect on PLE. Internet self-efficacy impacts PLE indirectly through the mediating role of all dimensions of student engagement. Additionally, a positive correlation was found between PLE and students' grades. Similarly, Singh et al 2021 explored data from 324 students studying in HEI of Maharashtra state in India. Their findings spotlighted the significant relationship between the use of the digital collaborative platform in education and students' performance in urban as well as rural India. Wu et al 2022 adopted a novel research model combining two critical aspects, technology affordances and constructivist learning, aimed at encouraging learning to enhance academic performance. Additionally, e-learning use serves as an important mediator in achieving academic success.

Another set of studies focused on predicting the academic performance of students. Some of them focused on the two aspects outlined above. .Xu et al. (2019) focused on internet usage data as a significant tool for predicting students' academic performance. Later, Waheed et al. (2020) predicted the achievement of the students based on their demographic and geographic characteristics by 85% accuracy. They stipulated a significant influence on their performance. Costa-Mendes et al. (2020), Cruz-Jesus et al. (2020), Costa-Mendes et al. (2020) defined income, age, employment, cultural level indicators, place of residence, and socio-economic background as main elements for predicting the academic achievement of students. Other studies considered past academic performances of students. Hofait and Schyns (2017) proposed a model that leverages students' academic performance from previous years to predict their success in upcoming courses for the new semester. They found that 12.2% of the students had a very high risk of failure, with a 90% confidence rate. Similarly, with a new model based on machine learning algorithms Babić (2017) predicted students' performance with an accuracy of 65% to 100%. The final exam grades of undergraduate students were predicted based on their midterm exam grades.

In light of the preceding literature review, three key themes emerged, each with its own host of sub-themes: demographic and socio-economic characteristics, parental involvement and the use of technology. However, gaps remain that warrant further exploration to deepen our understanding

3- METHODOLOGY AND RESULTS:

a- Survey and data analysis

The data for this study was collected from students in Saudi Arabia (KSA) during the academic year 2024. The sample comprised students from diverse academic tracks across leading universities, with a proportionate allocation of participants from each department. A total of 100 students were selected using the Simple Random Sampling (SRS) technique to ensure unbiased representation. The research utilized a structured questionnaire to gather both quantitative and qualitative data, providing a comprehensive insight into the study variables

The following questionnaire was given as follows:

- How many sessions do you attend during the term?
- How much time do you spend in order to prepare for the exam?
- What is your previous score in the subject?
- **Do you think that the school provides you with adequate resources?** (Low, Average, High)?
- Do you have access to the internet? (Yes/No)?
- Do you use AI in the subject? (Yes/No)
- How many tutoring sessions do you take during the term? (From 1 to 5)?
- How many questions do you solve during your preparation for the exam?
- What is your parental income level (low, average, high)?
- What is your parental education level (higher school, bachelor degree, master, or/and PHD)?
- Do you study in a public or private institution?

- What is your motivation level for the subject (low, average, high)?
- Do your friends affect your performance in school? (negative, neutral, positive)?
- What is your understanding level of the subject from the teacher's explanation (low, medium, high)?
- How many other subjects do you study with your current subject?
- How do you classify your comprehension during the course session? (Low, Moderate, High)?
- What is your Gender?
- What is your current Exam score?

In the analysis, many explanatory variables were included, classified to factors related to the family and the institution; furthermore, the effect of the personal student motivation and friends; moreover, factors related to exam preparation; and the last one, the technology effect.

Table 1: Descriptive Statistics of scale variable

		Attendance	***Hours_Studied***	***Previous_Scores***	***Tutoring_Sessions***	***#treated questions***	***# studied subject***	***Exam_Score***
Mean		74.60	20.72	75.86	1.81	31.98	3.75	66.77
Std. Error of Mean		1.086	.548	1.505	.127	1.339	.093	.416
Median		73.50	21.00	78.00	2.00	26.00	3.00	66.00
Mode		69	21	51[a]	1	20	3	64[a]
Std. Deviation		10.860	5.476	15.051	1.269	13.388	.925	4.161
Variance		117.939	29.981	226.526	1.610	179.232	.856	17.310
Minimum		60	8	51	0	10	3	60
Maximum		100	33	100	5	68	6	89
Percentiles	25	65.00	17.00	63.25	1.00	20.00	3.00	64.00
	50	73.50	21.00	78.00	2.00	26.00	3.00	66.00
	75	83.00	24.75	89.75	3.00	40.00	4.00	69.00

a. Multiple modes exist. The smallest value is shown

Table 1 provides insights into students' attendance, study habits, previous performance, and exam scores. Attendance and hours studied show moderate consistency, while variables like previous scores and number of treated questions exhibit high variability, indicating a diverse range of study habits and academic preparation among students. Low variability in the number of studied subjects and exam scores suggests uniformity in focus areas and exam performance.

Table 2: Descriptive Statistics of scale variable according to gender

Variable	Gender	Mean	SE Mean	StDev	Q1	Median	Q3
Attendance	1	72.4390	1.56799	10.0400	64	69	80.5
	2	76.1017	1.46251	11.2337	67	76	84
Hours_Studied	1	21.2439	0.927743	5.94046	16.5	22	26
	2	20.3559	0.670303	5.14869	17	20	23
Previous_Scores	1	74.8049	2.36752	15.1595	60	75	88.5
	2	76.5932	1.96077	15.0609	64	79	90
Tutoring_Sessions	1	1.97561	0.195959	1.25475	1	2	3
	2	1.69492	0.166186	1.27650	1	1	3
Exam_Score	1	66.0976	0.441457	2.82670	64	66	68
	2	67.2373	0.631040	4.84711	64	66	70
Number of treated questions	1	28.5122	1.73772	11.1268	20	26	30
	2	34.3898	1.86919	14.3575	23	27	53
Number of studied subject	1	3.70732	0.140747	0.901219	3	3	4
	2	3.77966	0.123432	0.948098	3	3	5

According to table 2, Gender 2 generally has higher attendance, better previous scores, slightly higher exam scores, and more treated questions, possibly suggesting a more intensive preparation pattern. Gender 1 tends to attend more tutoring sessions and studies marginally more hours. Both groups are similar in the number of studied subjects. The analysis highlights small but consistent differences in academic behaviors and performance metrics across genders.

Table 3: Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Previous_Scores	.080	100	.118	.944	100	.000
Exam_Score	.113	100	.003	.889	100	.000
Hours_Studied	.088	100	.056	.986	100	.365
a. Lilliefors Significance Correction						

The normality of continuous variables (Studied hours, previous scores and Exam scores) were tested using Kolmogorov-Smirnov and Shapiro-Wilk.

Previous Scores: There's a discrepancy between the tests. While the Kolmogorov-Smirnov test suggests normality, the Shapiro-Wilk test indicates non-normality. Given that Shapiro-Wilk is often more sensitive to deviations from normality,

Exam Score: Non-normal according to both tests.

Hours Studied: Likely normally distributed according to both tests.

These results indicate that **Hours Studied** may meet the normality assumption, while **Exam Score** does not, and **Previous Scores** shows mixed indications, leaning towards non-normality.

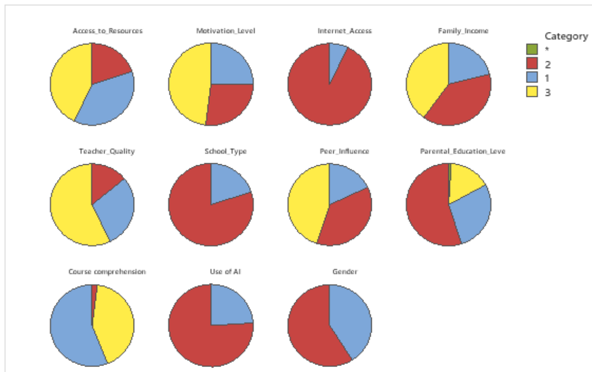

Figure 1: Pie graphs for categorical variables (Access to resources, Motivation level, Internet access, Family income, teacher Quality, school type, Peer Influence, Parental education level, Course comprehension, Use of AI and Gender).

Table 4: descriptive statistics of Likert scales

Variable	Gender	Mean	SE Mean	StDev	Q1	Median	Q3	Mode	N for Mode
Access_to_Resources	1	2.19512	0.116972	0.748983	2	2	3	2	17
	2	2.23729	0.0977209	0.750609	2	2	3	3	25
Motivation_Level	1	1.97561	0.118362	0.757885	1	2	3	2	18
	2	1.98305	0.0920306	0.706900	1	2	2	2	30
Internet_Access	1	1.95122	0.0340591	0.218085	2	2	2	2	39
	2	1.91525	0.0365692	0.280894	2	2	2	2	54
Family_Income	1	1.78049	0.128368	0.821955	1	2	2.5	1	19
	2	1.84746	0.0930475	0.714711	1	2	2	2	28
Teacher_Quality	1	2.24390	0.0909334	0.582258	2	2	3	2	25
	2	2.08475	0.0881266	0.676913	2	2	3	2	32
School_Type	1	1.14634	0.0558851	0.357839	1	1	1	1	35
	2	1.23729	0.0558604	0.429072	1	1	1	1	45
Peer_Influence	1	2.26829	0.126029	0.806982	2	2	3	3	20
	2	2.27119	0.0931007	0.715120	2	2	3	2, 3	25
Parental_Education_Level	1	1.60976	0.120355	0.770651	1	1	2	1	23
	2	1.61017	0.0967531	0.743175	1	1	2	1	32
Use of AI	1	1.78049	0.0654459	0.419058	2	2	2	2	32
	2	1.74576	0.0571750	0.439169	1	2	2	2	44
Course comprehension	1	1.51220	0.0931950	0.596739	1	1	2	1	22
	2	1.45763	0.0738126	0.566965	1	1	2	1	34

Table4, represent Likert scales studied in this survey, according to gender (1: Male & 2: Female). The Median Analysis is to identify the value that lies in the middle of an ordered data set. The mode analysis is to explore the most frequent data value in a dataset. Moreover, the distances between response alternatives are equal, researchers handle Likert scales as interval data. This method aims to make ordinal data be analyzed as if they were numerical (or interval) scale data. Each option is given a numerical score rather than the item values. This allows for arithmetic computations, such as mean and standard deviation, and the usage of tests that are commonly employed for quantitative variable analysis. The Mean according to gender are not significant different.

Across most variables, both genders report similar levels and distributions, indicating comparable experiences in areas like **Access to Resources**, **Motivation Level**, **Internet Access**, **Teacher Quality**, and **Peer Influence**. Differences are minor and suggest general consistency across these Likert scale measures, with slight variation in factors like **Teacher Quality** and **Family Income**.

b- PLS-SEM model

Structural Equation Modeling (SEM) has emerged as one of the most effective advanced multivariate statistical techniques for identifying the fundamental connections between exogenous and endogenous and latent variables in research challenges. It is a non-parametric approach that enables simultaneous estimation, and testing is the SEM technique.

The student performance is measured here by the Exam score. The study posits that: (1) The use of technology could affect the student score; (2) the performance is affected by the family income and education level; and (3) Exam preparation has an effect on student performance (4) the educational institution affects the exam score (5) Personal and peers factors impact the student performance. The link between latent variables is studied by structural equation modeling using the partial least square technique structural equation model (PLS-SEM).

-<u>Research model and Hypothesis</u>

This research mainly explores the relationship between technology, family, exam preparation, institution, personal and peers with the variable exam score.
The structure of this research is shown in Figure 2:

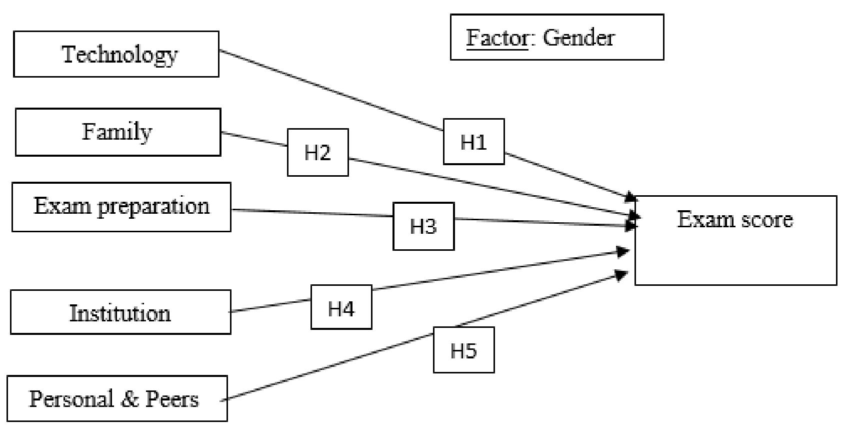

Figure 2: Graphical Model of factors affecting the student performance

Every aspect of this study makes use of pertinent literature to define and explain the variables. Each dimension contains more than one variable. Technology contains Access to internet and Use of Artificial intelligence (AI). Family contains the income of family and the educational level. The dimension of the variable Exam preparation contains several variables listed as attendance, the studied hours, number of treated questions, previous score and Tutoring sessions. For the institution dimension, it accommodates the number of studied subjects, access to the resources and the teacher quality. The last retained dimension is personal motivation and Peers effects.
Research requires a minimum sample size of 100 to get significant results. This study's sample size satisfies the minimal sample size criteria. Table 5, shows the distribution of each qualitative variable according to gender.

Table 5: frequency distribution of sample data according to background variable (gender)

Variable	Gender	Percent	CumPct
Access_to_Resources	1	41	41
	2	59	100
Motivation_Level	1	41	41
	2	59	100
Internet_Access	1	41	41
	2	59	100
Family_Income	1	41	41
	2	59	100
Teacher_Quality	1	41	41
	2	59	100
School_Type	1	41	41
	2	59	100
Peer_Influence	1	41	41
	2	59	100
Parental_Education_Level	1	41	41
	2	59	100
Use of AI	1	41	41
	2	59	100
Course comprehension	1	41	41
	2	59	100

The primary purpose of PLS-SEM is to determine if there is a statistically significant mutual linear relationship between the variables and to investigate the association between the research variables.

Scale tools' consistency is reflected in their reliability. Factor loading is used to examine each item's particular reliability. Cronbach's alpha and composition reliability (CR) are used to examine internal consistency. The suggested value is higher than 0.7. When examining convergent validity, the average variance extraction (AVE) is greater than 0.5. The majority of the variables that were kept in this analysis above the cutoff points of 0.7 and 0.5, respectively. The prerequisites are fulfilled.

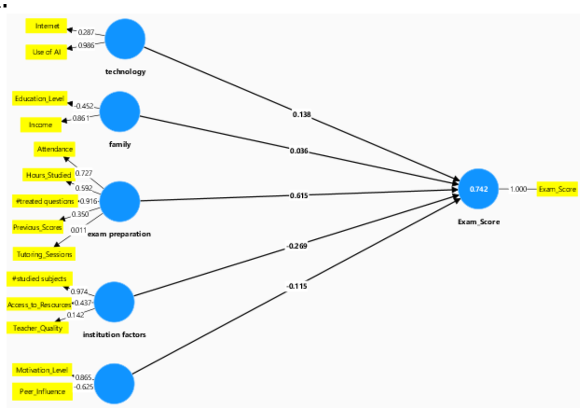

Figure 3: Model of PLS-SEM path analysis diagram.

Table 6: statistic hypotheses test

	test statistic	p value
exam preparation	0.599	0.000
family	0.311	0.000
institution factors	0.627	0.000
personal & peers	0.305	0.000
technology	4.010	0.000

All p-values <0.01, studied dimensions are significant in the model from table 6.

Exam results may be significantly influenced by a number of **exam preparation** elements ($p<0.01$), including regular attendance, which improves comprehension and memory of the subject matter. Additionally, students who have a track record of academic success typically do well on tests since they may have formed productive study habits related to the subject. Furthermore, the quantity of questions studied reflects the degree of practice and readiness, both of which are positively connected with improved exam results.

Scores are significantly influenced by the **family** especially parental education level and family wealth ($p<0.01$). Learning results can be improved by having better access to educational resources like books and private tutoring, which is frequently correlated with higher family income. Furthermore, parents who have more education are more inclined to respect and encourage their kids' education.
Student results are highly impacted by **institutional features** ($p<0.01$), including To provide excellent instruction and understandable explanations, qualified teachers are essential. In addition to allowing for greater focus and comprehension of each subject, the number of subjects can help students avoid fatigue. The availability of resources like labs, libraries, and technology enhances the educational setting and accommodates a range of learning requirements.
Peer relationships and personal motivation have an effect on exam grades ($p<0.001$). For example, students who are intrinsically motivated are more likely to create goals and stick with their studies. Additionally, supportive peers can promote group learning, knowledge exchange, and emotional support—all of which enhance academic achievement.
The statistically significant **technology** ($p<0.01$) highlights how the advance in technology such as AI tools and resources, facilitate more engaging and effective learning experience.

Table 7: Quality criteria

	R-square	R-square adjusted
Exam_Score	0.742	0.729

As R-Squared, or the coefficient of determination, gives the linear relationship between variables. It ranges from 0 to 1. The value **zero** indicates that the model does not explain any of the variability. The value **1** means that the model explains all the variability. When, R-Squared value closer to 1 suggests a better fit for the model. The Adjusted R-Squared is a modified version of R-Squared that align to the number of predictors in the model. In Table 7, the quality of the model, is 0.742 which is very satisfactory and also R-square adjusted is 0.729.

CONCLUSION:

The findings of this study reveal that the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach used to analyze the data is robust and well-fitted. The well-fitted nature of the PLS-SEM model indicates that the data aligns well with the proposed theoretical framework, providing a strong basis for interpreting the results. All hypotheses proposed in the study were supported by statistically significant results. This indicates that the relationships and effects hypothesized between the variables were confirmed

through the analysis. Hypotheses 1 through 4 are validated at p <0.01, while Hypothesis 5 is confirmed at p <0.001.
Empirical evidence has been provided that the student performance reflected by the variable exam score is strongly related and affected by the use of technology, the family dimension, the importance of exam preparation, the institution factors as well as personal motivation and Peers effects. Indeed, our analysis revealed the following key findings:
- **Technology Use**: The use of technology significantly impacts learning performance (p<0.01), emphasizing its indispensable role in the modern learning process.
- **Family Influence**: Family income and parental education level have a notable effect on evaluation scores (p<0.01). Adequate financial resources, a good quality of life, and family education contribute to improved student performance.
- **Exam Preparation**: Factors such as attendance, prior academic scores, and the number of reviewed questions significantly influence exam outcomes (p<0.01).
- **Institutional Factors**: Institutional characteristics, including teacher competency, the number of subjects studied simultaneously, and available resources, show a statistically significant effect on student results (p<0.01).
- **Personal Motivation and Peer Influence**: Personal motivation and peer interactions have a meaningful impact on exam scores (p<0.001).
This study was conducted in a specific context with a sample size meeting the minimum requirements. However, the results of this study may be limited in their applicability to broader populations. To enhance the generalizability of the findings, future research should consider incorporating a more diverse selection of universities, academic tracks, and subjects. This would allow for a more comprehensive understanding of the phenomena under investigation, as it would capture a wider array of environmental factors and varying educational contexts.

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