The impact of AI usage on student performance in higher education institutions in B&H and Portugal

Teaching Assistant Jasna Imamović
International Burch University, Sarajevo
Bosnia and Herzegovina
jasna.imamovic@ibu.edu.ba

Teaching Assistant Lejla Šehanović
International Burch University, Sarajevo
Bosnia and Herzegovina
lejla.sehanovic@ibu.edu.ba

Prof. Dr. Irma Imamović
IPAM - Marketing School for Business, Porto
Portugal
irmaimamovic206@gmail.com

Abstract: *This study investigates the impact of AI usage on students' performance in HEIs in Bosnia and Herzegovina (B&H) and Portugal. The research integrates constructs such as performance expectancy, facilitating conditions, students' engagement, assessment effectiveness, students' interaction, information accuracy, personal innovations, pedagogical fit, AI tools use and students' academic performance. Using quantitative analysis, the study's aim is to determine the factors influencing AI adoption and its impact on student learning outcomes in the context of B&H and Portugal HEIs. The primary objective is to gain the understanding of AI tool adoption in diverse educational settings, providing insights for educational institutions and policymakers to inform AI adoption strategies. Expected results anticipate significant insights into the adoption and impact of AI-based academic support systems in B&H and Portugal HEIs. These findings could inform the development of effective strategies for integrating AI tools into educational settings, ultimately enhancing student engagement, satisfaction, and academic performance. The study's implications extend to educational institutions, policymakers, and stakeholders involved in higher education, guiding the design and implementation of AI-based academic support systems for personalized learning experiences, improved student outcomes, and enhanced institutional effectiveness in B&H and Portugal HEIs.*

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Introduction

In today's modern world, the growing use of AI is significantly impacting individuals and their daily tasks, and students are becoming increasingly familiar with its applications. AI has had a significant impact on a number of higher education-related issues, and the most well-known of these AI tools is ChatGPT, which is used in academic settings for a number of purposes like text or code generation, research support, and finishing assignments, essays, and projects (Bahroun et al., 2023; Stojanov, 2023; Strzeleck, 2023). HEIs are essential for producing the upcoming professionals, leaders, and innovators because they offer an atmosphere that encourages learning, skill development, and personal development. But the road to academic achievement is frequently filled with obstacles, such as challenging course offerings, restricted access to academic support, and issues in finding the tools and direction you need. It is anticipated that by 2025, there will be eight million international students worldwide, indicating a shift in the higher education environment. HEIs face new opportunities, and as a response, they are using more technology to improve the quality of education for students, with AI being one such technology that has a lot of potential uses in education (Wang et al., 2023). AI applications in education have the potential to completely transform the way that students study (Seldon & Abidoye, 2018).

The majority of respectable universities have realized that AI and machine learning (ML) are the trends of the future for both education and global advancement (Kuleto et al., 2021). In the United States of America, 65% of universities promote learning with AI and ML assistance, and forecasts show that between 2017 and 2021, the use of AI in US education grew by 47.5% (Chang, 2017). In this study, different variables are analyzed, such as performance expectancy, facilitating conditions, students' engagement, assessment effectiveness, students' interaction, information accuracy, personal innovations, pedagogical fit, AI tool use, and their impact on students' academic performance.

The data is primary data because it is collected directly from the source (the survey respondents) specifically for the purpose of the study or research being conducted. Using quantitative analysis, the study's aim is to examine the impact of the aforementioned independent variables on the dependent variable, students' academic performance. Gaining knowledge about the adoption of AI tools in various educational contexts is the main goal, as this will help policymakers and educational institutions develop AI adoption strategies. Anticipated outcomes are expected to provide important insights into how AI-based academic assistance systems are adopted and used in B&H and Portugal HEIs. The creation of successful plans for incorporating AI technologies into learning environments may be influenced by these findings, which would eventually improve student happiness, engagement, and academic achievement. The study has implications for higher education stakeholders, policymakers, and educational institutions. It will help design and implement AI-based academic support systems for personalized learning, better student outcomes, and increased institutional effectiveness in HEIs in Portugal and Bosnia and Herzegovina.

The main objectives of the study are:

1. To examine the relationship between the combined independent variables (performance expectancy, facilitating conditions, students’ engagement, assessment effectiveness, students’ interaction, information accuracy, personal innovations, pedagogical fit, and behavioral intention) and students' academic performance in higher education institutions (HEIs) in Bosnia and Herzegovina (B&H) and Portugal.
2. To analyze the specific impact of AI tools usage on students' academic performance in HEIs in B&H and Portugal.
3. To compare the findings with existing empirical studies and test if the selected variables (both combined and AI tools usage) affect students' academic performance in the same direction as hypothesized in other studies.
4. To provide a comprehensive empirical study on the adoption and impact of the combined variables and AI tools usage on students' academic performance in HEIs in B&H and Portugal.
5. To offer insights for policymakers and educational institutions on developing effective AI adoption strategies to enhance student engagement, satisfaction, and academic achievement in HEIs in B&H and Portugal.

Literature Review

Every aspect of life has benefited from the widespread use of technology and cutting-edge innovative diversities, and the educational sector stands to gain much from these innovations as well (Guilherme, 2019). The most well-known AI technologies are ChatGPT, Gradescope, fetch, Ivy Chatbot, and many more that give students access to a variety of knowledge and educational resources (McFarland, 2024). Similar to a tutor, AI chatbots can offer quick learning support and individualized services, enhancing students' academic performance (Xu et al., 2024). Several platforms, such scite.ai, Consensus, Scinapse, Research Rabbit, and ReadCube Papers, offer capabilities for academic research in addition to ChatGPT, such as context-aware citations and AI-driven research material organizing (Chatterjee & Bhattacharjee, 2020). The learning capacity, academic performance, and knowledge capability of students and teachers have all greatly benefited from the personalized, global, and simultaneous provision of learning on the internet through the use of AI tools and other specialized knowledge sources (Owoc et al.,2021). Study done by Fazil et al. (2024) has shown that there is a positive impact of AI tools on academic performance. However, the significance of engagement duration is marginal, highlighting the need for qualitative research to understand the depth of students' interactions with these tools. According to the analysis done by Fazil et al. (2024) , AI technologies are thought to have a good impact on students' engagement and most students think that using AI tools will improve their academic performance, although the degree of this benefit will depend on the type and complexity of AI engagement. According to the study done by Dahri et al. (2024), students in Pakistan and Malaysia view AI technologies favorably, and their behavioral intentions have a big impact on whether or not they embrace and employ AI tools. Adoption of AI tools and student satisfaction are positively correlated, suggesting that students who use AI technology are more satisfied with their educational experiences. This study has shown that adopting AI tools greatly improves students' academic experiences and performance. Study done by Jang et al. (2022) offered an AI-driven strategy for early student performance prediction.

To find out if early prediction was possible, several machine learning techniques were evaluated. The outcomes demonstrated that AI was capable of accurately identifying characteristics that affected students' performance and offering insights at both the individual and group levels. According to the study, students' academic performance can be greatly increased by combining suitable educational interventions with AI-powered early performance projections. According to the research, expanding the use of AI-driven early prediction approaches to include a wider range of courses and majors may help validate the findings and significantly raise student performance. Regarding the variables used, the "Performance Expectancy" evaluates the expected benefits that students believe AI tools will bring about in terms of improving academic performance and learning outcomes (Dahri et al., 2023; Venkatesh et al., 2016). The tools and help that people have access to in order to effectively use a particular technology are known as “Facilitating Conditions” (Venkatesh et al., 2016). Other conceptions are "Assessment Efectiveness," which assesses the function of tools in effective assessment procedures (Dodeen, 2013), and "Students' Engagement," which concentrates on interaction and involvement (Su et al., 2023). Peer engagement is examined in "Students' Interaction" (Wei et al., 2012), whilst content reliability is evaluated in "Information Accuracy" (Farooq et al., 2017; Filieri & McLeay, 2014). "Pedagogical Fit" assesses alignment with learning objectives and instructional strategies, whereas "Personal Innovations" investigates how AI technologies might stimulate creative thinking (Foroughi et al., 2023; Pittalis, 2021). What encourages students to use these tools is examined in "Behavioral Intention" (Dahri et al., 2021; Venkatesh et al., 2016). "AI Tools Use" gauges how actively students integrate AI tools into their coursework (Dahri et al., 2021; Venkatesh et al., 2016). "Enhancement of Students’ Academic Performance" assesses the tools’ demonstrable impact on grades and knowledge acquisition, while "Students’ Satisfaction" is essential for continued usage (Dahri et al., 2022; Alyoussef, 2021; Gopal et al., 2021).

Methodology

This chapter details the research design, methods, and data collection processes employed in the study investigating the impact of AI usage on students' performance in higher education institutions (HEIs) in B&H and Portugal.

To achieve the objectives of this study, several variables were identified and categorized into independent and dependent variables. The independent variables include:

1. Performance Expectancy: Students' expectations about the effectiveness and benefits of utilizing AI tools in their learning.
2. Facilitating Conditions: The availability of necessary tools and resources to support AI tool usage.
3. Students’ Engagement: The level of students' involvement and participation in academic activities facilitated by AI tools.
4. Assessment Effectiveness: The ability of AI tools to improve assessment procedures by providing timely feedback and insights.
5. Students’ Interaction: The extent of interaction and social inclusion promoted by AI tools.

Information Accuracy: The perceived accuracy and reliability of information provided by AI tools.

6. Personal Innovations: Students' openness to experimenting with new learning

strategies using AI technologies.

7. Pedagogical Fit: The alignment of AI tools with educators' teaching techniques.
8. Behavioral Intention: Students' willingness and intention to use AI technologies for learning.
9. The dependent variable is Students' Academic Performance, which measures the total academic outcomes and success of students utilizing AI tools.

Data Analysis

The primary data for this study was collected through a structured survey distributed to students enrolled in higher education institutions in B&H and Portugal. The survey was designed to capture responses on various constructs related to AI tool usage, engagement, assessment, and academic performance. The study targeted a sample of 160 students from HEIs in B&H and Portugal. The respondents were selected using a stratified sampling method to ensure representation from different academic disciplines and institutions. The survey instrument consisted of several sections, each focusing on a different set of variables. The questions were designed using a Likert scale (1 being strongly disagree and 5 being strongly agree) to measure the extent of agreement or disagreement with various statements related to AI tool usage, engagement, assessment effectiveness, and academic performance.

Table 1: Construct, Item and Source of adoption

Construct	Item	Source of adoption
Performance Expectancy	4	(Venkatesh et al.,2016)
Facilitating Conditions	4	(Venkatesh et al.,2016)
Students’ Engagement	4	(Su et al., 2023)
Aassessment Effectiveness	4	(Dodeen, 2013)
Student’s Interaction	4	(Wei et al., 2012)
Information Accuracy	4	(Farooq et al.,2017; Filieri & McLeay, 2014)
Personal Innovations	4	(Foroughi et al.,2023)
Pedagogical Fit	4	(Pittalis, 2021)
AI Tools Use	4	(Venkatesh et al.,2016)
Students’ Academic Performance	4	(Alyoussef, 2021; Gopal et al., 2021; Tawafak et al., 2023)

The data collected from the surveys were analyzed using quantitative methods.

Descriptive statistics were used to summarize the demographic characteristics of the respondents and their responses to the survey items. Factor analysis was conducted to identify the underlying structure of the variables and to ensure the validity and reliability of the constructs (Harper et al., 1980). Multiple regression analysis was used to test the research hypotheses. This technique allowed for the examination of the relationship between the independent variables (e.g., performance expectancy, facilitating conditions) and the dependent variable (students' academic performance). The significance of each predictor was assessed using t-tests, and the overall model fit was evaluated using R-squared and adjusted R-squared values. The study adhered to ethical guidelines for research involving human participants. Informed consent was obtained from all respondents, ensuring their voluntary participation and the confidentiality of their responses.

Research Hypotheses

In this research there are nine hypotheses that are educational guess about the impact on the dependent variable students' academic performance.
Performance expectancy is students' expectations about the effectiveness and benefits of utilizing AI tools in their learning. Students are more likely to have high expectations for their performance if they think AI tools would improve their comprehension and performance in the classroom (Dahri et al.,2024). The first hypothesis is as follows:

H1: The performance expectancy has a statistically significant impact on the students' academic performance.

According to Chatterjee and Bhattacharjee (2020), students' perceptions of AI-infused technologies' usability and intention to utilize them were positively impacted by their access to necessary tools and resources therefore variable facilitating conditions is implemented in this study and the hypothesis is:

H2: The facilitating conditions have a statistically significant impact on students' academic performance.

Schwarz & Zhu (2015), discovered a correlation between more engagement and improved academic performance as well as satisfaction highlighting the importance of incorporating the variable student's engagement.

H3: The students' engagement has a statistically significant impact on student's academic performance.

The assessment effectiveness construct evaluates how AI tools improve assessment procedures by giving students prompt feedback and insights.
H4: The assessment effectiveness has a statistically significant impact on a student's academic performance.

When teachers employ various tactics to promote student contact and social inclusion, it's referred to as "social interaction" or student-instructor involvement and that the students' engagement and use of AI were found to be influenced by positive student involvement and mentoring (Alenezi, 2022).

H5: The students' interaction has a statistically significant impact on a student's academic performance.

The accuracy and consistency of the information supplied by AI technologies are perceived as important by students, and this is referred to as the information accuracy variable. Students' readiness to use these tools is influenced by their level of trust in the authenticity of the information (Dahri e al., 2024).

H6: The information accuracy has a statistically significant impact on a student's academic performance.

The personal innovations is a variable that represents student's openness to experiment with new learning strategies using AI technologies. Study done by Strzelecki (2023) showed that students were more likely to use AI technologies effectively if they felt motivated to try out novel learning tactics.

H7: The personal innovations have a statistically significant impact on the students' academic performance.

The alignment of AI tools with educators' teaching techniques is known as pedagogical fit (Dahri et al.,2024). An et al.'s research from 2023 examined the educational potential of AI-driven content delivery systems and showed that students were more inclined to interact with these platforms if they thought they complemented the teaching methods of their teachers.

H8: The pedagogical fit has a statistically significant impact on the students' academic performance.

The willingness and intention of students to employ AI technologies for learning is referred by the variable behavioral intentions. Students that have positive behavioral goals are more likely to accept and incorporate AI tools into their teaching methods (Dahri et al.,2024).

H9: The behavioral intention has a statistically significant impact on the students' academic performance.

Results

Descriptive Statistics

The dataset has 160 valid responses across all variables, with no missing observations.

The analysis covers various descriptive components, such as gender, age, educational qualification, familiarity with AI tools, the AI tools used most frequently, the average daily usage of AI tools, and satisfaction with AI tools and if the person studies in Bosnia and Herzegovina or Portugal. The table for descriptive statistics can be found in the Appendices section.

Factor Analysis

A complex statistical technique called factor analysis (Table 3 in Appendices) is used to condense a large number of variables into a smaller set of factors. This method is useful for combining all of the variables into a single score for additional analysis by removing the largest common variation from each variable (Statistics Solutions, 2024). The results of the factor analysis indicate a high degree of internal consistency and adequacy of the dataset, shown by the high KMO value of 0.943 and significant Bartlett's test (Chi-Square = 1632.953, df = 36, $p < 0.001$). The communalities and component loadings suggest that a single factor accounts for 78.625% of the variance, showing an impact of AI tools on students' academic performance . High loadings of all variables on this single factor, ranging from 0.836 (“Students’ engagement”) to 0.939 (“Pedagogical fit”), indicate strong relationships, and displaying the potential impact of AI tools in education. Component score coefficients, such as 0.133 for the variable “Pedagogical fit” and 0.131 for “Academic performance”, are used for the calculation of factor scores for further analysis. The component analysis, which revealed that a single dominating factor accounts for a considerable proportion of the variance and suggests strong links among the variables, suggests a coherent construct related to the use and impact of AI tools on students' academic performance.

Discriminant validity

Different sets of definitions and the measurements that go along with them are distinguished from one another by discriminant validity (Harper et al., 1980). A statistical method used to evaluate discriminant validity in research is the Heterotrait-Monotrait ratio of correlations (HTMT) (Nawanir et al., 2019). The HTMT value should not exceed certain thresholds, such as 0.90 or 0.85 (Henseler et al., 2015). In this research, all HTMT values (Table 4 in Appendices) were not greater than the thresholds of 0.90 or 0.85. The discriminant validity of the constructs associated with the application and influence of AI tools on students' academic performance is supported by the HTMT ratio analysis. The robust and distinctive appearance of the structure contributes to a reliable assessment of the many educational outcomes that AI tools influence, as well as an analysis of potential differences in the effects of AI tools on students' academic performance across B&H and Portugal HEIs.

Hypotheses testing

Results indicate that the regression model (Table 5 in Appendices) may account for a substantial portion of the variance in students' academic performance. This research validates the use of predictors such as "Accomplishment Expectancy" and "AI Tools Use," in addition to identifying parts where other predictors, such as "Facilitating Conditions" and "Students' Engagement," do not substantially contribute to academic performance in this study. With an overall R Square of 0.832, the regression model's results (Table 6 in Appendices) show a high match for predicting students' academic performance. This indicates that the independent variables' combined effects account for 83.2% of the variation in academic performance.

According to the p-value ($B = 0.273$, $p < 0.001$), there is a statistically significant positive correlation between students' academic success and "Performance Expectancy." As a result, H1 is approved, showing that improved expectations about the advantages of utilizing AI tools have a beneficial impact on academic results.

There is no statistically significant effect of "Facilitating Conditions" on students' academic performance, according to the p-value ($B = -0.054$, $p = 0.394$). Therefore, H2 is not supported, indicating that in this situation, the presence of favorable factors has no direct impact on academic performance. H3 is not supported by the coefficient ($B = 0.063$, $p = 0.272$), which demonstrates that students' engagement has no statistically significant effect on their academic performance. This shows that although engagement matters, better academic results in this study could not always follow from it. Given that AI technologies are widely available in both regions under study, the lack of relevance for "Facilitating Conditions" may be explained by the fact that supporting situations have less of an impact. Furthermore, the survey's emphasis on direct AI usage rather than more in-depth qualitative measures of involvement may have contributed to the underrepresentation of "Students' Engagement" in this study.

According to the p-value ($B = 0.089$, $p = 0.190$), there is no evidence that assessment effectiveness has a statistically significant effect on students' academic performance. As a result, H4 is not supported, suggesting that academic performance is not much impacted by assessment efficacy as determined by this study. H5 is not supported since the coefficient ($B = 0.074$, $p = 0.421$) shows that there is no statistically significant effect of students' interactions on their academic performance. H6 is not supported by the p-value ($B = 0.095$, $p = 0.165$), which demonstrates that information accuracy has no statistically significant effect on academic performance. There is no statistically significant correlation between academic performance and personal innovations, according to the p-value ($B = 0.115$, $p = 0.095$). Therefore, H7 is not supported, suggesting that students' innovative ideas may not have a direct impact on their academic performance.

According to the p-value ($B = 0.089$, $p = 0.190$), there is no evidence that assessment effectiveness has a statistically significant effect on students' academic performance. As a result, H4 is not supported, suggesting that academic performance is not much impacted by assessment efficacy as determined by this study. H5 is not supported since the coefficient ($B = 0.074$, $p = 0.421$) shows that there is no statistically significant effect of students' interactions on their academic performance. H6 is not supported by the p-value ($B = 0.095$, $p = 0.165$), which demonstrates that information accuracy has no statistically significant effect on academic performance. There is no statistically significant correlation between academic performance and personal innovations, according to the p-value ($B = 0.115$, $p = 0.095$).

Therefore, H7 is not supported, suggesting that students' innovative ideas may not have a direct impact on their academic performance. Pedagogical Fit has a slightly significant favorable influence on students' academic achievement, as indicated by the coefficient ($B = 0.164$, $p = 0.066$). As a result, even if the p-value for H8 is marginally over 0.05, it does not prove that the hypothesis that pedagogical fit has a beneficial impact on academic performance is unfounded. The use of AI tools has a statistically significant favorable influence on academic achievement, as indicated by the coefficient ($B = 0.197$, $p= 0.003$). Therefore, H9 is accepted, suggesting that students who utilize AI technologies more frequently perform better academically.

After accounting for the variation in the observations, the analysis indicates that Bosnian and Herzegovinian students perform 0.526 points more poorly academically on average than Portuguese students. The statistical significance of this discrepancy is demonstrated by the p-value of 0.000. Academic achievement and studying in B&H have a moderately unfavorable relationship, as indicated by the standardized coefficient of -0.274.The results of the investigation made it clearly obvious that academic achievement is statistically significantly impacted by the nation of study. Students enrolled in B&H specifically had, on average, 0.526 less points in their academic achievement than students enrolled in Portugal. This finding's credibility, which is reinforced by the coefficients and the ANOVA analysis, emphasizes how much the country of study affects students' academic performance.

Conclusion

The increasing adoption of artificial intelligence (AI) in higher education has had a profound impact on the academic achievements and learning experiences of students. This study has shed light on a number of variables influencing the adoption and utilization of AI technologies in Portugal and Bosnia and Herzegovina (B&H) higher education institutions.

1. Performance Expectancy: The study found that students' perceptions of the advantages

of AI technologies have a beneficial impact on their academic performance. This implies that students are more likely to perform well academically when they think AI will improve their learning.

2. Facilitating Conditions, Students' Engagement, Assessment Effectiveness, Students' Interaction, Information Accuracy, and Personal Innovations: There was no statistically significant correlation found between these variables and academic performance. This demonstrates that, even though these elements are significant, in the specific setting of this study, they might not always result in better academic performance.
3. Pedagogical Fit: The integration of AI technologies with teachers' instructional strategies has a little but beneficial impact on students' academic achievement. This suggests that for AI technologies to be effective, instructional practices must be adequately integrated with them.
4. Behavioral Intention and AI Tool Use: Higher academic achievement was highly correlated with both the willingness and actual usage of AI technologies. This emphasizes how crucial it is to motivate students to integrate AI technologies into their education.
5. Country of Study: The academic performance gap between students in B&H and Portugal, with students in Portugal generally scoring better, was a notable finding. This implies that a country's educational resources and environment may have a significant impact on students' academic performance.

Additionally, this research offers following contributions:

- Empirical Contribution: This study offers empirical evidence of the impact of AI technologies on academic performance through the analysis of primary data from students in Portugal and Bosnia and Herzegovina (B&H). The results offer important empirical insights into the uptake and effects of AI tools in various educational contexts, highlighting important elements that either support or undermine academic achievement.
- Theoretical Contribution: By incorporating concepts like performance expectancy, enabling environments, and pedagogical fit into the examination of AI adoption, the study enhances the body of current material. It supports and broadens theoretical frameworks about the adoption of technology and how it affects academic results.
- Methodological Contribution: The study uses quantitative techniques to assess the correlations between variables, such as factor and regression analysis. It helps to improve the methodological techniques used to research the adoption of technology and its effects on education.

Despite its contributions, the study has several limitations:

- Contextual Scope: The study's conclusions may not be as applicable to other nations with distinct educational systems and rates of technological use because it focuses on students in Portugal and Bosnia and Herzegovina. In order to investigate cross-cultural variations in AI adoption and impact, future research could broaden its geographic focus.
- Quantitative Approach: The study does not explore the qualitative aspects of students'

interactions with AI tools, despite using solid quantitative approaches. To fully capture the complexity of student experiences and perspectives, future study could use a combination of methodologies.

- Limited Variables: A more thorough understanding of AI adoption may be possible if additional elements like institutional support, cultural attitudes toward technology, or economic restraints are taken into account, even though the study takes a variety of characteristics into account. Future studies could examine these components.
- Student Segmentation: Because the study aggregates data from many student demographics, differences based on academic disciplines or study levels may be obscured. These subgroups could be studied in future studies to find specialized approaches to incorporating AI tools.

Overall, results have a number of implications for decision-makers in higher education, academic institutions, and stakeholders. Since their successful usage may have a major impact on academic achievement, educational institutions should focus on incorporating AI technologies that complement pedagogical aims and improve the learning experience. It is the responsibility of educators and legislators to raise students' understanding of the possible advantages of AI tools in order to improve their performance expectations and, in turn, their academic achievement. The notable disparity in academic achievement between students in Portugal and Bosnia and Herzegovina emphasizes the necessity of customized approaches that capitalize on possibilities and tackle particular obstacles within each nation's educational framework. Academic accomplishment, student engagement, and student happiness may all be improved at educational institutions by comprehending and addressing the several elements that affect AI adoption and efficacy.

Appendices

Table 2: Descriptive statistics

Variable	Category	Percentage (%)	Count
Gender	Female	67.70%	109
	Male	32.30%	52
Study Location	Bosnia and Herzegovina	65.40%	104
	Portugal	34.60%	55
Age	20–30 years	96.30%	155
	31–40 years	1.90%	3
	41–50 years	1.20%	2
	51–60 years	0.60%	1
Educational Qualification	Bachelor’s Degree	79.50%	128

Table 2: Descriptive statistics (cont'd)

	Master's Degree	11.80%	19
	PhD/Doctorate	5.60%	9
	Other	3.10%	5
Familiarity with AI Tools	Very familiar	32.30%	52
	Somewhat familiar	28.60%	46
	Moderately familiar	19.90%	32
	Not familiar	14.90%	24
	Extremely familiar	4.30%	7
AI Tools Usage Frequency	2–3 times a day	40.40%	65
	Once a day	31.10%	50
	More than 5 times	11.80%	19
	Do not use AI tools	9.90%	16
	5+ times	6.80%	11
Satisfaction with AI Tools	Quite satisfied	56.50%	91
	Moderately satisfied	23.00%	37
	Very satisfied	16.10%	26
	Slightly satisfied	3.10%	5
	Not satisfied at all	1.20%	2

Table 3: Factor Analysis

Analysis Metric	**Value/Result**
KMO Value	0.943 (high adequacy of the dataset)
Bartlett's Test of Sphericity	Chi-Square = 1632.953, df = 36, p < 0.001 (significant)
Variance Explained by Factor	78.63%
Communalities and Component Loadings	High loadings on the single factor (e.g., 0.836 for "Students' engagement" and 0.939 for "Pedagogical fit")
Component Score Coefficients	0.133 ("Pedagogical fit"), 0.131 ("Academic performance")
Factor Interpretation	Single dominant factor showing strong relationships among variables, reflecting the impact of AI tools on students' academic performance

Table 4: Discriminant validity

Construct Pair	HTMT Value	Threshold	Discriminant Validity
Performance Expectancy – Facilitating Conditions	0.76	≤ 0.85	Met
Students’ Engagement – Assessment Effectiveness	0.81	≤ 0.85	Met
Students’ Interaction – Information Accuracy	0.68	≤ 0.85	Met
Pedagogical Fit – Personal Innovations	0.82	≤ 0.85	Met
AI Tools Use – Academic Performance	0.71	≤ 0.85	Met

Table 5: Regression Coefficients Table

Predictor Variable	Unstandardized Coefficient (B)	Standardized Coefficient (Beta)	t-value	p-value	Support for Hypothesis
Performance Expectancy	0.273	0.321	5.432	< 0.001	Supported
Facilitating Conditions	-0.054	-0.062	-0.856	0.394	Not Supported
Students' Engagement	0.063	0.078	1.105	0.272	Not Supported
Assessment Effectiveness	0.089	0.102	1.317	0.19	Not Supported
Students' Interaction	0.074	0.089	0.806	0.421	Not Supported
Information Accuracy	0.095	0.112	1.391	0.165	Not Supported
Personal Innovations	0.115	0.134	1.673	0.095	Not Supported
Pedagogical Fit	0.164	0.184	1.849	0.066	Marginally Supported
AI Tools Use	0.197	0.211	2.977	0.003	Supported
Country of Study (B&H)	-0.526	-0.274	-6.521	< 0.001	Supported

Table 6: Model Summary

Statistic	Value
R-Square	0.832
Adjusted R-Square	0.827
F-Statistic	98.456

p-value (Model)	< 0.001

Table 7: ANOVA Table

Source	Sum of Squares	df	Mean Square	F-value	p-value
Regression	452.32	9	50.26	98.456	< 0.001
Residual	91.18	150	0.608		
Total	543.5	159			

References

Alyoussef, I. Y. (2021). E-Learning acceptance: The role of task–technology ft as sustainability in higher education. *Sustainability*, *13*(11), 6450.

An, X., Chai, C. S., Li, Y., Zhou, Y., Shen, X., Zheng, C., & Chen, M. (2023). Modeling English teachers' behavioral intention to use artificial intelligence in middle schools. *Education and Information Technologies*, *28*(5), 5187–5208.

Bahroun, Z., Anane, C., Ahmed, V., & Zacca, A. (2023). Transforming Education: A Comprehensive Review of Generative Artificial Intelligence in Educational Settings through Bibliometric and Content Analysis. *Sustainability*, *15*(17), 12983. https://doi.org/10.3390/su151712983

Chang, R. Report Artificial Intelligence to Grow 47.5% in Education over Next 4 Years. 2017. *The Journal: Technological Horizons in Education.* Retrieved from: https://thejournal.com/articles/2017/03/24/ai-market-to-grow-47.5-percent-over-next-four-years.aspx

Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: a quantitative analysis using structural equation modelling. *Education and Information Technologies*, *25*(5): 3443–3463. https://doi.org/10.1007/s10639-020-10159-7

Chatterjee, S., & Bhattacharjee, K. K. (2020b). Adoption of artificial intelligence in higher education: a quantitative analysis using structural equation modelling. *Education and Information Technologies*, *25*(5): 3443–3463. https://doi.org/10.1007/s10639-020-10159-7

Dahri, N. A., Al-Rahmi, W. M., Almogren, A. S., Yahaya, N., Vighio, M. S., & Al-Maatuok, Q. (2023a). Mobile-based training and certification framework for teachers' professional development. *Sustainability*, *15*(7): 5839.

Dahri, N. A., Vighio, M. S., Alismaiel, N. O. A., & Al-Rahmi, N. W. M. (2022). Assessing the Impact of Mobile-Based Training on Teachers' achievement and usage attitude. *International Journal of Interactive Mobile Technologies*, *16*(09): 107–129. https://doi.org/10.3991/ijim.v16i09.30519

Dodeen, H. (2013). College students' evaluation of efective teaching: Developing an instrument and assessing its psychometric properties. *Research in Higher Education Journal*, *21*.

Farooq, M. S., Salam, M., Jaafar, N., Fayolle, A., Ayupp, K., Radovic-Markovic, M., & Sajid, A. (2017). Acceptance and use of lecture capture system (LCS) in executive business studies: Extending UTAUT2. *Interactive Technology and Smart Education*, *14*(4): 329–348.

Fazil, A. W., Hakimi, M., Shahidzay, A. K., & Hasas, A. (2024). Exploring the broad impact of AI technologies on student engagement and academic performance in university settings in Afghanistan. *RIGGS Journal of Artificial Intelligence and Digital Business*, *2*(2): 56–63. https://doi.org/10.31004/riggs.v2i2.268

Filieri, R., & McLeay, F. (2014). E-WOM and accommodation: An analysis of the factors that infuence travelers' adoption of information from online reviews. *Journal of Travel Research*, *53*(1): 44–57.

Foroughi, B., Senali, M. G., Iranmanesh, M., Khanfar, A., Ghobakhloo, M., Annamalai, N., & Naghmeh-Abbaspour, B. (2023). Determinants of Intention to Use ChatGPT for Educational Purposes: Findings from PLS-SEM and fsQCA. *International Journal of Human-Computer Interaction*: 1–20. https://doi.org/10.1080/10447318.2023.2226495

Gopal, R., Singh, V., & Aggarwal, A. (2021). Impact of online classes on the satisfaction and performance of students during the pandemic period of COVID 19. *Education and Information Technologies*, *26*(6): 6923–6947.

Guilherme, A. (2017). AI and education: the importance of teacher and student relations. *AI & Society*, *34*(1): 47–54. https://doi.org/10.1007/s00146-017-0693-8

Harper, D., Kim, J., & Mueller, C. W. (1980). Introduction to factor analysis: what it is and how to do it. *Contemporary Sociology a Journal of Reviews*, *9*(4): 562. https://doi.org/10.2307/2066279

Henseler, J., Ringle, C. M., & Sarstedt, M. (2014). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1): 115–135. https://doi.org/10.1007/s11747-014-0403-8

Jang, Y., Choi, S., Jung, H., & Kim, H. (2022). Practical early prediction of students' performance using machine learning and eXplainable AI. *Education and Information Technologies*, *27*(9): 12855–12889. https://doi.org/10.1007/s10639-022-11120-6

Kuleto, V., Ilić, M., Dumangiu, M., Ranković, M., Martins, O. M. D., Păun, D., & Mihoreanu, L. (2021). Exploring opportunities and challenges of artificial intelligence and machine learning in higher education institutions. *Sustainability*, *13*(18): 10424. https://doi.org/10.3390/su131810424

McFarland, A. (2024, July 13). *10 best AI tools for Education (July 2024)*. Retrieved from: https://www.unite.ai/10-best-ai-tools-for-education

Nawanir, G., Binalialhajj, M., Lim, K. T., & Ahmad, M. H. (2019). Becoming Lean: The Way towards Sustainability of Higher Educations Institutions. *KnE Social Sciences*. https://doi.org/10.18502/kss.v3i22.5078

Owoc, M. L., Sawicka, A., & Weichbroth, P. (2021). Artificial intelligence Technologies in Education: Benefits, challenges and Strategies of implementation. *IFIP advances in information and communication technology*: 37-58. https://doi.org/10.1007/978-3-030-85001-2_4

Pittalis, M. (2021). Extending the technology acceptance model to evaluate teachers' intention to use dynamic geometry software in geometry teaching. *International Journal of Mathematical Education in Science and Technology*, *52*(9): 1385–1404.

Schwarz, C., & Zhu, Z. (2015b). The impact of student expectations in using instructional tools on student engagement: A look through the Expectation Disconfirmation Theory lens. *Journal of Information and Systems in Education*, *26*(1): 47–58. https://jise.org/Volume26/n1/JISEv26n1p47.pdf

Seldon, A., & Abidoye, O. (2018). *The Fourth Education Revolution*. Legend Press Ltd.

Statistics Solutions. (2024, April 17). *An introduction to factor analysis: reducing variables*. Retrieved from: https://www.statisticssolutions.com/free-resources/directory-of-statistical-analyses/factor-analysis/

Stojanov, A. (2023). Learning with ChatGPT 3.5 as a more knowledgeable other: an autoethnographic study. *International Journal of Educational Technology in Higher Education*, *20*(1). https://doi.org/10.1186/s41239-023-00404-7

Strzelecki, A. (2023). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive Learning Environments*: 1–14. https://doi.org/10.1080/10494820.2023.2209881

Strzelecki, A. (2023b). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive Learning Environments*: 1–14. https://doi.org/10.1080/10494820.2023.2209881

Su, F., Zou, D., Wang, L., & Kohnke, L. (2023). Student engagement and teaching presence in blended learning and emergency remote teaching. *Journal of Computers in Education*, *11*(2): 445–470. https://doi.org/10.1007/s40692-023-00263-1

Venkatesh, N., Thong, N., & Xu, N. (2012). Consumer Acceptance and use of Information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1): 157. https://doi.org/10.2307/41410412

Wang, T., Lund, B. D., Marengo, A., Pagano, A., Mannuru, N. R., Teel, Z. A., & Pange, J. (2023). Exploring the potential impact of artificial intelligence (AI) on international students in higher education: generative AI, chatbots, analytics, and international student success. *Applied Sciences*, *13*(11): 6716. https://doi.org/10.3390/app13116716

Wei, C.-W., Chen, N.-S., & Kinshuk. (2012). A model for social presence in online classrooms. *Educational Technology Research and Development*, *60*: 529–545.

Xu, Y., Zhu, J., Wang, M., Qian, F., Yang, Y., & Zhang, J. (2024). The impact of a digital Game-Based AI chatbot on students' academic performance, Higher-Order thinking, and behavioral patterns in an information technology curriculum. *Applied Sciences*, *14*(15): 6418. https://doi.org/10.3390/app14156418