e-ISSN 1135-9250
EDUTEC. Revista Electrónica de Tecnología Educativa
Issue 89 – September 2024
Section: Artificial intelligence in the evaluation and personalization of learning

AI Tutors vs. Human Instructors: Perceptions of Higher Education Students in Hungary and Spain

Tutores de IA frente a instructores humanos: Percepciones de los estudiantes de educación superior en Hungría y España

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Abstract

Integrating AI-powered tutoring systems in higher education represents a significant advancement in educational technology, offering personalized and adaptive learning experiences. This study investigates the perceptions and expectations of higher education students in Hungary and Spain regarding AI tutors. Despite extensive research on the technological efficacy of AI systems, there is limited understanding of student attitudes in these specific cultural contexts. This research aims to fill this gap by exploring student expectations, satisfaction levels, and perceived benefits of AI tutors compared to human instructors. To achieve this, a validated questionnaire was administered to 184 higher education students from Hungary and Spain, capturing data on various dimensions of their expectations. The study's findings indicate that students appreciate the adaptability and continuous guidance provided by AI tutors, with Hungarian students showing higher overall expectations compared to their Spanish counterparts. These insights suggest that AI tutoring systems can enhance the learning experience by addressing individual student needs more effectively. The implications of this study are significant for higher education institutions seeking to integrate AI technologies.

Keywords: *Higher education, AI tutoring systems, adaptive learning, educational technology, Student perceptions*

Resumen

La integración de sistemas de tutoría impulsados por IA en la educación superior representa un avance significativo en la tecnología educativa, ofreciendo experiencias de aprendizaje personalizadas y adaptativas. Este estudio investiga las percepciones y expectativas de los estudiantes de educación superior en Hungría y España respecto a los tutores de IA. A pesar de la extensa investigación sobre la eficacia tecnológica de los sistemas de IA, existe un entendimiento limitado sobre las actitudes de los estudiantes en estos contextos culturales específicos. Esta investigación pretende llenar este vacío explorando las expectativas de los estudiantes, sus niveles de satisfacción y los beneficios percibidos de los tutores de IA en comparación con los instructores humanos. Para lograr esto, se administró un cuestionario validado a 184 estudiantes de educación superior de Hungría y España, capturando datos sobre diversas dimensiones de sus expectativas. Los hallazgos del estudio indican que los estudiantes valoran la adaptabilidad y la orientación continúa proporcionada por los tutores de IA, con los estudiantes húngaros mostrando expectativas más altas en comparación con sus homólogos españoles. Estos conocimientos sugieren que los sistemas de tutoría de IA pueden mejorar la experiencia de aprendizaje al abordar las necesidades individuales de los estudiantes de manera más efectiva.

Palabras clave: Educación superior, *sistemas de tutoría con IA, aprendizaje adaptativo, tecnología educativa, percepciones de los estudiantes.*

DOI: https://doi.org/10.21556/edutec.2024.89.3523

Received: 02-09-2024
Accepted: 21-09-2024

1. INTRODUCTION

Higher education institutions are encountering significant challenges as they strive to meet the varied needs of learners in the world (Hajeer et al., 2023). Traditional pedagogical approaches often fall short in delivering personalized instruction and accommodating individual learning preferences (Hajeer, 2024). The integration of Artificial Intelligence (AI) in higher education has emerged as a transformative force impacting education. AI-powered tutoring systems, in particular, have received attention for their potential to revolutionize teaching and learning processes by providing personalized learning experiences (Dede, 2014). The importance of this topic in higher education is undeniable, as these systems promise to address key challenges such as improving student engagement, personalizing education, and optimizing learning outcomes (Kim, 2020; Basri, 2024). In the context of higher education management and marketing, AI tutoring systems offer several advantages. These systems can enhance the learning experience, making institutions more attractive to prospective students by showcasing their commitment to innovative educational practices. Moreover, AI tutoring systems can provide valuable data insights, enabling better resource allocation and more effective marketing strategies aimed at prospective students and their parents (Nguyen et al., 2024). This technological advancement is particularly relevant as higher education institutions strive to differentiate themselves in a competitive market (Chan, 2023).

Studies have shown that these systems can adapt to individual student needs, provide immediate feedback, and support skill development in various subjects (Chounta et al., 2022; Nguyen et al., 2024). However, despite the promising results, there is a notable gap in research concerning the perceptions of students in specific cultural contexts, such as Hungary and Spain. Existing studies have primarily focused on the technological efficacy of AI systems, with limited exploration of student attitudes and expectations in these regions (Basri, 2024). To address this gap, the current study aims to investigate the perceptions of higher education students in Hungary and Spain regarding AI tutoring systems. Utilizing a validated questionnaire, this research seeks to capture student expectations, regarding AI tutors compared to human instructors. The primary research question guiding this study is: "What are the perceptions and expectations of higher education students in Hungary and Spain towards AI-powered tutoring systems?"

1.1. Evolution and applications of intelligent tutoring systems in higher education

AI tutoring refers to the use of artificial intelligence technologies to simulate human tutoring and provide personalized learning experiences for students. This involves using machine learning algorithms to analyze student data, identify knowledge gaps, and tailor instruction and feedback accordingly (Mitra et al., 2021). Natural language processing allows AI tutors to interact with students in a natural and engaging way, providing explanations and answering questions similarly to human tutors. Intelligent tutoring systems (ITS), as defined by Woolf (2009), are "computer systems that provide immediate and customized instruction or feedback to learners," serving as a prominent example of AI tutoring applications by providing customized instruction and feedback, thereby simulating a human tutor's role.

The concept of AI in education dates back several decades, with early systems focusing on simple programmed instruction and rule-based tutoring. For instance, the SCHOLAR system developed in the 1970s (Carbonell, 1970) was an early attempt to use AI for tutoring in geography. Over time, advancements in AI technologies have led to the development of more sophisticated and adaptive tutoring systems. Woolf (2009) discusses the evolution of intelligent tutors from simple feedback systems to complex, student-centered learning environments. The integration of AI in education has progressively moved from theoretical research to practical applications, marked by milestones in the development of adaptive learning platforms and AI-driven educational tools (Dede, 2014).

AI tutoring systems are employed to provide personalized learning experiences, adapting content and instructional methods to meet individual student needs. These systems are designed to identify students' strengths and weaknesses, offering tailored support to improve learning outcomes (Kim, 2020). For example, de Baker and Inventado (2014) discuss the use of AI-powered tutoring systems to address diverse learning needs and provide personalized feedback and guidance. Studies have shown that AI tutors can significantly enhance learning outcomes by providing adaptive learning experiences tailored to individual student needs (Chounta et al., 2022; Al-Shanfari et al., 2023). The use of AI in higher education also addresses the need for innovative solutions to enhance student engagement and motivation. For example, AI tutors can provide interactive and personalized learning experiences that are crucial in maintaining student interest and promoting active learning (Dede, 2014). Furthermore, AI technologies like chatbots and virtual assistants are increasingly used in student support services, aiding in administrative tasks and providing round-the-clock assistance to students, thereby enhancing the overall student experience (Chaudhry & Kazim, 2022). Despite the numerous advantages, the implementation of AI in higher education also raises important ethical considerations. Issues such as data privacy, potential biases in AI algorithms, and the need for transparency and fairness in AI-driven systems are critical areas that require careful attention. Ensuring that AI technologies are used responsibly and ethically is paramount to gaining the trust of educators and students alike (Nguyen et al., 2024).

1.1. Machine teachers: benefits, challenges, and student perceptions

Machine teachers, which include both embodied and disembodied agents, represent an innovative shift in educational technology. Embodied machine teachers necessitate a physical form, whether tangible, virtual, or a hybrid of both (Pfeifer & Scheier, 1999). Physical embodiments, such as robots made from materials like plastic, wood or metal could be used in face-to-face teaching scenarios to engage students directly (Li et al., 2015). Conversely, virtually embodied machine teachers are computer-generated and exist visually on screens (Li, 2015). Disembodied machine teachers. These include chatbots, software agents, and interface agents that communicate through text or voice. The rise in online education has amplified the necessity for machine teachers. Both disembodied and virtually embodied teachers are well-suited for online learning environments, providing continuous support without physical presence (Allen & Seaman, 2017). Despite their growing importance, there remains a paucity of research regarding student reactions to and acceptance of machine teachers (Kim, 2020).

Some studies suggest that while students may prefer human instructors, knowledge retention is notably better when instruction is provided by robots (Li et al., 2015). Conversely, concerns about the costs, the necessity for specialized teacher training, and the practical applicability of robots in diverse educational contexts persist (Edwards et al., 2016). Despite these concerns, a substantial body of literature highlights the beneficial impacts of social robots on educational outcomes. For example, researchers have found that social robots are perceived as credible and effective conveyors of educational content (Chaudhry & Kazim, 2022). Students have responded positively to robots that provide affirmative feedback, perceiving them as both attractive and acceptable in the learning environment. Moreover, social robots have facilitated the inclusion of homebound students, enabling them to participate in real-time classroom interactions with their peers and teachers (Double Robotics, 2017).

The positive effects of social robots in education are well-documented. For instance, Edwards et al. (2016) reported that students view social robots as reliable sources of information, capable of delivering educational content effectively. Additionally, research by Park and Whang et al. (2022) emphasizes the importance of empathy and engagement in human-robot interactions, noting that robots capable of exhibiting empathic behaviors and social cues can significantly enhance the learning experience. Li (2015) also discovered that physically present robots tend to be more persuasive and receive more attention compared to their virtual counterparts. Moreover, studies have shown varying impacts of robotic technologies on knowledge recall. For instance, Li et al. (2015) found that videos featuring human instructors and animated robots have similar effects on student knowledge recall, whereas videos of real robots resulted in weaker recall performances. These findings underscore the complex dynamics of robot-assisted learning and the necessity of tailoring robot design and deployment to specific educational contexts.

1.2. How are students' expectations affected?

The integration of AI-powered tutoring systems in higher education has generated significant interest and varying expectations among students. Several factors influence these expectations, including technological familiarity, perceived usefulness, and cultural context. Understanding these factors is essential for effectively implementing AI tutors in educational settings. One of the primary factors influencing student expectations of AI tutors is their familiarity with technology. Students who are more accustomed to using advanced technologies in their daily lives tend to have higher expectations of AI tutors. They anticipate that these systems will provide seamless, efficient, and personalized learning experiences (Dede, 2014). Additionally, the perceived usefulness of AI tutors plays a critical role. Students expect AI tutors to offer immediate feedback, personalized learning paths, and adaptive content that caters to their individual learning needs. This expectation is rooted in the potential of AI to address diverse learning styles and pace, thereby enhancing the overall learning experience (Chounta et al., 2022).

Empirical findings suggest that students generally perceive AI tutors positively, particularly in terms of their ability to provide personalized and adaptive learning experiences. Studies have shown that AI tutors can significantly improve student engagement and motivation by offering tailored support and feedback (Kim, 2020). For instance, Chounta et al. (2022) found that students appreciate the immediate feedback provided by AI tutors, which helps them identify and correct mistakes in real-time. This instant response mechanism is seen as a key advantage over traditional learning methods, where feedback may be delayed.

Moreover, AI tutors' ability to adapt to individual student needs is highly valued. Students perceive AI tutors as effective tools for personalized learning, as these systems can analyze student performance data and adjust the learning content accordingly (Al-Shanfari et al., 2023).

This adaptability not only helps in addressing specific knowledge gaps but also promotes a deeper understanding of the subject matter. Nguyen et al. (2024) highlight that such tailored learning experiences can lead to improved academic performance and higher satisfaction levels among students.

When comparing student perceptions of AI tutors with human tutors, several distinct differences and similarities emerge. One notable difference is the level of personalized attention. While human tutors provide personalized interaction, they are limited by time and availability. AI tutors, on the other hand, can offer continuous, individualized support without such constraints. This continuous availability is particularly appreciated by students who seek help outside of regular class hours (Nguyen et al., 2024). However, despite the benefits of AI tutors, students often express concerns about the lack of human empathy and emotional understanding in AI interactions. Human tutors are perceived as more capable of providing emotional support and understanding the nuances of student emotions, which AI systems currently struggle to replicate (Al-Shanfari et al., 2023). This human element is crucial for creating a supportive and motivating learning environment, which is often cited as a limitation of AI tutors. Furthermore, trust and reliability are critical factors in student perceptions. While many students trust AI tutors to deliver accurate and consistent information, there is still a degree of skepticism about the technology's reliability and potential biases (Nguyen et al., 2024). Ensuring transparency in AI algorithms and addressing ethical concerns are essential steps to build and maintain student trust in AI-powered educational tools.

Student Perceptions of AI tutors are influenced by factors such as technological familiarity, perceived usefulness, and the ability to deliver personalized learning. While students appreciate the adaptability and availability of AI tutors, concerns persist about the absence of human empathy. AI tutors excel in personalized learning but cannot replicate the emotional support human instructors provide. Overcoming these limitations with ethical and transparent AI implementation is essential for their successful integration in higher education.

2. METHODS

This study used a quantitative research design with a cross-sectional survey to examine higher education students' views on AI tutoring systems in Hungary and Spain. A questionnaire was designed and used to gather data on students' expectations, satisfaction, and perceived benefits of AI tutors compared to human instructors. Statistical tests were conducted to ensure that the questionnaire was both reliable and valid. First, Exploratory Factor Analysis (EFA) was conducted to identify the main factors and understand the structure of the questionnaire. Then, Confirmatory Factor Analysis (CFA) was used to confirm this structure and assess how well the model fits the data. To check the reliability of the questionnaire, Cronbach's Alpha and Omega coefficients were calculated.

2.1. Participants and data collection

This study aimed to explore higher education students' perceptions of AI tutoring systems in Hungary and Spain, two countries with distinct educational and cultural contexts. These countries were chosen because they offer a comparative look at how AI is perceived in educational settings where the adoption of new technologies is increasingly relevant. The participants were selected from institutions in both countries to represent diverse academic backgrounds in an attempt to ensure a comprehensive view of student attitudes.

The sample included 184 higher education students, with age distribution ranging from 18 to 25 years old. The largest age groups were 21 (35.33%) and 22 years old (32.61%), with smaller proportions aged 20 (10.87%), 23 (11.41%), and a minimal number aged 18, 19, 24, and 25. In terms of gender, the sample was nearly evenly split, with 52.17% male and 47.83% female participants. Students were drawn from different academic years, with first-year students making up 9.78% of the sample, second-year students 14.13%, third-year students 30.43%, and fourth-year students the largest group at 45.65%. Most participants were from Spain (72.28%), followed by Hungary (19.02%), with 8.70% international students from regions outside Europe, including Latin America and the Middle East. Regarding academic specialization, 29.35% of the students were from social sciences and humanities, 47.83% were from business and economics, and 22.83% were studying STEM subjects (Science, Technology, Engineering, Mathematics, and Medicine). The diverse demographics and academic representation of the sample is to ensure that various perspectives were captured in the study, making the findings possibly applicable to a broader student population.

The data were collected via an online survey created using the Google Forms platform, which was distributed through a learning management platform at the participating academic institutions. This platform served as the primary method for reaching students in Hungary and Spain. After the initial distribution via the learning platform, students were encouraged to share the survey link with their peers to increase participation. Informed consent was obtained from all participants, who were assured of the anonymity and confidentiality of their responses. While formal approval from an Ethics Committee was not sought for this study, the research followed ethical guidelines for data collection and participant consent. This includes ensuring voluntary participation, confidentiality, and transparency about the purpose of the study.

2.1. Instrument design and validation

The survey instrument was designed to assess students' perceptions and expectations regarding AI tutoring systems. It included 24 statements (see Appendix A) aimed at comparing the perceived benefits of AI tutors with those of human instructors. The key focus areas of the survey were skill development, information retention, adaptability to student needs, and personalized assessments. To ensure the validity and reliability of the questionnaire, Exploratory Factor Analysis (EFA) was conducted to uncover the underlying factor structure, followed by Confirmatory Factor Analysis (CFA) to confirm the structure and assess how well the model fit the data.

As for the Exploratory Factor Analysis, the scree plot, combined with parallel analysis as seen in Figure 1, indicates that there are three significant factors in the data. The first factor explains the most variance, followed by the second and third factors, each having eigenvalues slightly above 1. Factors beyond the third show eigenvalues less than or equal to 1, suggesting they do not significantly contribute to the explained variance and should not be retained. This conclusion is supported by the observed data points falling below the simulated data from the parallel analysis after the third factor.

Figure 1

Scree Plot of Eigenvalues from Exploratory Factor Analysis

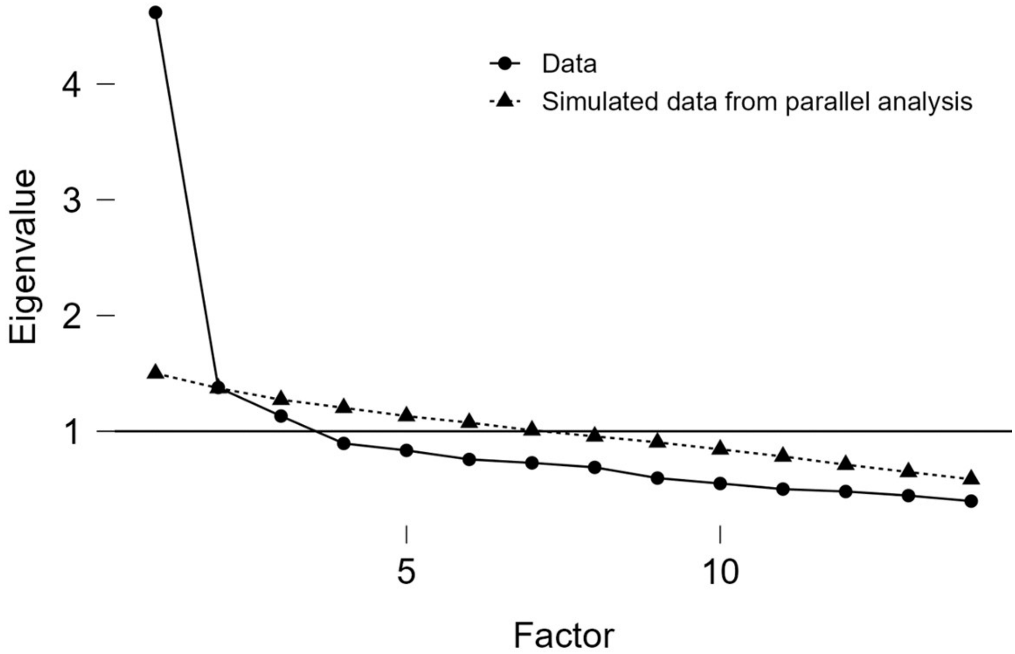


Table 1 presents the factor loadings for various items on three factors: Gains, Adaptability, and Guidance, with the "Uniqueness" column indicating the uniqueness scores of the items. Factor loadings indicate how strongly each item is associated with a particular factor. Here, the items (e.g., gains_2, gain_10) are listed in rows, and the factors are listed in columns. The values show the strength and direction of the association between each item and the factors. A cutoff of 0.4 is used, meaning only loadings of 0.4 or higher are considered significant.

Table 1

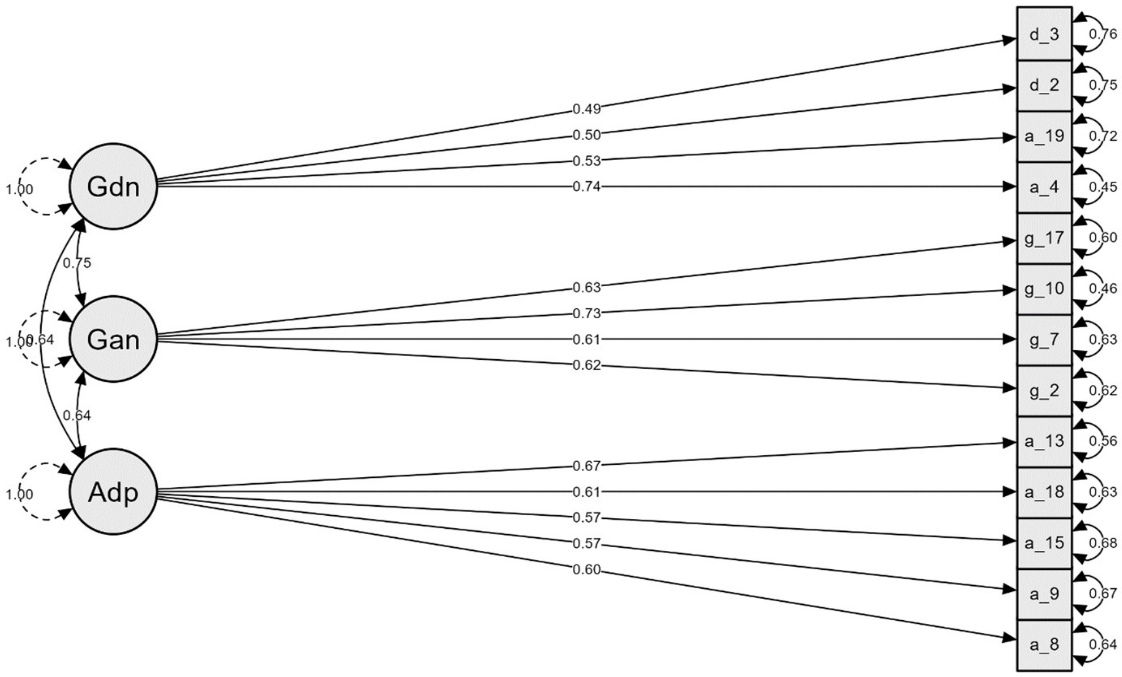
Factor loadings for the EFA

Items	Gains	Adaptability	Guidance	Uniqueness
gain_2	0.726			0.549
gain_10	0.602			0.526
gain_17	0.576			0.591
gain_7	0.576			0.562
adap_18		0.69		0.57
adap_15		0.584		0.654
adap_8		0.55		0.627
asse_9		0.537		0.673
asse_13		0.49		0.598
asse_19			0.741	0.584
asse_4			0.505	0.532
deve_24			0.465	0.729
deve_3			0.415	0.769

Regarding the Confirmatory Factor Analysis, the (CFA) path diagram (see Figure 2) illustrates the relationships between three latent factors—Guidance (Gdn), Gains (Gan), and Adaptability (Adp)—and their associated observed variables. Each latent factor is connected to several observed variables, with factor loadings indicating the strength of these relationships. For the Guidance factor, d_3 (0.74) and d_2 (0.75) show the strongest associations, followed by a_19 (0.50) and a_4 (0.49). The Gains factor is linked to g_17 (0.60), g_10 (0.46), g_7 (0.63), and g_2 (0.62), with notable strength in g_7 and g_2. Adaptability shows robust connections across all its observed variables: a_13 (0.61), a_18 (0.67), a_15 (0.68), a_9 (0.67), and a_8 (0.64). The model also indicates significant interrelationships among the latent factors, with correlations of 0.75 between Guidance and Gains, 0.64 between Gains and Adaptability, and 0.64 between Guidance and Adaptability. These correlations suggest a moderate to strong interconnectedness among the constructs. Measurement errors are depicted next to the observed variables, representing variance in the measurements. Overall, the CFA model demonstrates good convergent validity, with high factor loadings, and discriminant validity, supported by distinct correlations among different factors. This implies that the model represents the underlying constructs and their relationships with observed variables.

Figure 2

CFA Model Showing Four Factors of Intercultural Sensitivity



The adequacy of this CFA model was assessed using several fit indices, as summarized in Table 2. The chi-square to degrees of freedom ratio (χ2/df) was comfortably below the value of 3.0, indicating an acceptable fit with a calculated χ2/df of 1.039. This falls within the good-fit guidelines as recommended by Drasgow et al. (1995). The Comparative Fit Index (CFI) stood at .995, which, as suggested by Hu and Bentler (1999), suggests a model that fits the data well. The Tucker-Lewis Index (TLI) was at .994, above the recommended .95 indicating a good model fit. The Root Mean Square Error of Approximation (RMSEA) was well within acceptable limits at

.015, not exceeding the threshold of .06 set forth by Hu and Bentler (1999). Lastly, the Standardized Root Mean Square Residual (SRMR) was .04, which is below the .05 cutoff, as proposed by Byrne (2001), reflecting a good fit between the hypothesized model and the observed data. Overall, these fit indices suggest that the model is a good representation of the data.

Table 2

Fit indices

Index	Value
Comparative Fit Index (CFI)	0.995
Tucker-Lewis Index (TLI)	0.994
X^2/df	1.039
RMSEA	0.015
SRMR	0.04

2.2.1. Reliability measures for the three factors

Table 3 presents reliability measures for three factors—Adaptability, Gains, and Guidance—and the total reliability across all factors, using Omega (ω) and Cronbach's Alpha (α) coefficients. Adaptability shows good internal consistency with ω = 0.738 and α = 0.741. Gains also demonstrates strong reliability, indicated by ω = 0.745 and α = 0.744. Guidance, while slightly lower, still maintains acceptable internal consistency with ω = 0.660 and α = 0.655. The overall reliability across all factors is high, with an Omega coefficient of 0.858 and a Cronbach's Alpha of 0.835, indicating that the combined items reliably measure the overall construct. These results suggest that the items within each factor and the total scale have good to excellent internal consistency, ensuring reliable measurement of the underlying constructs.

Table 3

Reliability measures

Factor	ω	α
Adaptability	0.738	0.741
Gains	0.745	0.744
Guidance	0.66	0.655
Total	0.858	0.835

3. RESULTS AND DISCUSSIONS

3.1. Comparing the Scales

Given the background of the study, which aims to measure students' expectations about AI tutoring in higher education, the results of the paired samples t-test, as seen in Table 4, provide insight into how students perceive these different aspects of AI tutoring. Adaptability scores are significantly higher than Gains scores (t (183) = 6.256, p < .001, Cohen's d = 0.461), indicating that students believe AI tutors are better at adapting to their individual needs compared to human tutors. The moderate effect size suggests higher expectations for adaptability over gains. Additionally, there is no significant difference between Adaptability and Guidance scores (t (183) = 1.460, p = 0.146, Cohen's d = 0.108), suggesting that students view the adaptability of AI tutors and the guidance provided by them similarly.

Furthermore, Guidance scores are significantly higher than Gains scores (t (183) = -5.121, p < .001, Cohen's d = -0.378), indicating that students perceive the guidance provided by AI tutors to be significantly better than the overall gains they expect to achieve from AI tutoring. The moderate effect size indicates higher expectations for the guidance aspect over the gains one.

Table 4

Comparison among scales using paired samples t-test

Measure 1	Measure 2	t	df	p	Cohen's d	SE Cohen's d
Adaptability	Gains	6.256	183	< .001	0.461	0.08
Adaptability	Guidance	1.46	183	0.146	0.108	0.077
Gains	Guidance	-5.121	183	< .001	-0.378	0.075

The findings reveal that students highly value AI tutors for their adaptability and guidance, seeing them as crucial for personalized learning. However, the lower scores for expected gains suggest skepticism about AI’s ability to deliver tangible academic outcomes like skill development or knowledge retention. This could indicate that while students appreciate AI's ability to tailor learning and offer support, they remain unsure of its effectiveness in driving deeper learning or critical thinking. To meet student expectations, AI tutors must not only personalize learning but also clearly demonstrate their impact on measurable academic success, addressing these doubts.

3.1. Adaptability Across Groups

To compare the adaptability scores among different groups an ANOVA analysis was conducted. The results indicated a significant effect of the country of origin on adaptability scores, F (2, 181) = 6.438, p = 0.002, suggesting that the mean adaptability scores differ significantly between these groups. Post hoc comparisons using Tukey's HSD test revealed that Hungarian students have significantly higher adaptability scores than Spanish students, with a mean difference of 0.493 (p < .001). Descriptive statistics further showed that Hungarian students had the highest mean adaptability score (3.743) with relatively low variability (SD = 0.535), indicating more consistent perceptions. In contrast, Spanish students had the lowest mean adaptability score (3.271) with higher variability (SD = 0.737), suggesting more diverse opinions within this group. Additionally, the analysis found no significant differences in adaptability scores across students from different fields of study, genders, or years of study. This may indicate that perceptions of AI tutoring adaptability are not influenced by these demographic factors, highlighting the specific influence of regional differences. The results show that Hungarian students perceive AI tutors as significantly more adaptable to their needs compared to Spanish students, likely due to cultural or educational differences. The consistency in Hungarian students' scores suggests a more uniform perception, while the greater variability among Spanish students indicates a wider range of views. No significant differences were found across gender, academic field, or year of study, suggesting regional context plays a larger role in shaping perceptions of AI adaptability. These findings emphasize the importance of considering cultural differences when implementing AI tutoring systems to better meet the expectations of diverse student populations.

3.2. Gains Scores Among Groups

The ANOVA results for the Gains scale indicate a significant interaction effect between gender and field of study, while the main effects of study and gender alone are not significant. Specifically, the significant interaction effect (F (2, 178) = 5.706, p = 0.004) suggests that the effect of field of study on Gains scores differs by gender. Post hoc comparisons reveal that female students in Social Sciences and Humanities have significantly higher Gains scores compared to male students in the same field (Mean Difference = 0.667, p = 0.017). Additionally, female students in Social Sciences and Humanities have significantly lower Gains scores compared to female students in Business and Economics (Mean Difference = -0.537, p = 0.047). These findings highlight the importance of considering both gender and field of study when assessing the perceived benefits of AI tutoring. Female students in Social Sciences and Humanities perceive greater gains compared to their male counterparts, while they perceive fewer gains compared to female students in Business and Economics. No significant main effects of study or gender alone were found, nor were there significant differences in Gains scores among students from different countries or years of study. This suggests that perceptions of gains from AI tutoring are specifically influenced by the interaction between gender and field of study rather than by these demographic factors individually.

3.3. Overall Expectations Scores

The ANOVA results for overall expectations scores, which combine the factors of Adaptability, Gains, and Guidance, show a significant effect of country, F (2, 181) = 6.137, p = 0.003. This indicates that the mean overall expectations scores differ significantly between the two country groups (Spain and Hungary). Post hoc comparisons using Tukey's HSD test reveal that Hungarian students have significantly higher overall expectations scores compared to Spanish students, with a mean difference of 0.370 (p = 0.002). The effect size (Cohen's d) of 0.643 suggests a substantial difference (Cohen, 1988), indicating that Hungarian students perceive AI tutoring more positively overall than their Spanish counterparts. Additionally, the analysis showed no significant differences in overall expectations scores across gender, year of study, or study specialization. This suggests that these demographic factors may not influence students' overall expectations of AI tutoring. The significant difference observed is specifically tied to the country of the students, emphasizing the need to consider regional differences when evaluating and implementing AI tutoring systems in higher education.

The significant difference in overall expectations between Hungarian and Spanish students highlights the influence of cultural and educational contexts on how AI tutoring is perceived. Hungarian students' higher expectations may reflect greater familiarity or a stronger focus on adaptability and guidance in their education, while lower expectations in Spain may indicate skepticism or less exposure to AI in learning. The large effect size emphasizes that these differences are driven by regional factors rather than individual demographics. This suggests that AI tutoring systems must be adapted to align with the specific educational and cultural contexts of each country to meet student expectations effectively.

4. CONCLUSIONS

This study sought to understand the perceptions and expectations of higher education students in Hungary and Spain towards AI-powered tutoring systems. The research problem addressed the gap in literature concerning student attitudes and expectations in these specific cultural contexts. Using a validated questionnaire, we captured data on student expectations, satisfaction levels, and perceived benefits of AI tutors compared to human instructors. The key findings indicate that students generally perceive AI tutors positively, particularly appreciating their adaptability and guidance. Hungarian students showed higher overall expectations and adaptability scores compared to Spanish students. The study achieved its objective of providing an understanding of student attitudes towards AI tutoring, contributing valuable insights to the discourse on educational technology adoption.

The implications of these findings are present both theoretically and practically. Theoretically, this study enriches the existing knowledge on AI in education by highlighting regional differences in student perceptions, which had not been extensively explored before. It confirms the adaptability and guidance provided by AI tutors as critical factors in student satisfaction, aligning with existing research on AI's potential to personalize learning experiences (Chounta et al., 2022; Nguyen et al., 2024). Practically, the findings suggest that higher education institutions can enhance their attractiveness by integrating AI tutoring systems, which are viewed positively by students for their ability to provide continuous, personalized support. This can inform marketing strategies and resource allocation, making institutions more competitive (Chan, 2023). Furthermore, the study contributes uniquely by focusing on Hungarian and Spanish students, offering insights into cultural and/or regional influences on the acceptance of AI technologies. This cultural specificity is crucial for tailoring AI implementations to better meet the needs of diverse student populations. By addressing the expectations and satisfaction of students in these countries, the research provides actionable data that can guide the development and deployment of AI tutoring systems in higher education.

While this study offers valuable insights, it is essential to acknowledge its limitations. The sample was limited to students from Hungary and Spain, which may not represent the broader student population. Future research should consider expanding the study to include students from other countries and regions to provide a deeper understanding of global student perceptions. Additionally, the emotional and empathetic aspects of AI tutors were not deeply explored in this study. Furthermore, future research could investigate the cultural factors that contribute to differences in perceptions between Hungary and Spain. A deeper exploration of these cultural dimensions would provide a more comprehensive understanding of how local values and educational norms shape students' expectations of AI tutoring systems.

Moreover, exploring the potential applications of AI tutoring systems beyond academic support could be beneficial. For instance, AI tutors could be utilized for career guidance, mental health support, and administrative assistance, broadening their impact on the student experience. Implementers of AI in education, managers of higher education institutions, and marketers could perhaps utilize these insights to optimize the integration and promotion of AI technologies, ensuring they meet the evolving needs of students effectively.

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To cite this work:

Hajeer, A., Papp-Váry, Árpád, & Pólya, Éva. Tutores de IA frente a instructores humanos: Percepciones de los estudiantes de educación superior en Hungría y España. *Edutec, Revista Electrónica de Tecnología Educativa*, (89), XX-XX. https://doi.org/10.21556/edutec.2024.89.3523

Appendix A: Questionnaire

Survey: Attitudes towards AI tutoring

Please be assured that your participation in this survey is completely voluntary, and you can choose to withdraw at any time without any consequences. All responses will be kept strictly confidential and will be used for research purposes only. Your answers will be anonymized, ensuring that no personally identifiable information is collected. We do not share any data with third parties, and the results will be reported in aggregate form only.
By participating, you are contributing valuable insights that may help improve understanding AI tutoring higher education. The survey should take approximately 5-10 minutes to complete.

Thank you for your time and valuable contribution to this research!

Age :
Gender:
Country of origin:
Year of study:
Major field of study:

1. I expect an AI tutor to be able to adjust the difficulty level of the learning material based on my understanding of the topic. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

2. I believe explanations provided by AI tutors would be clearer and easier to understand than explanations from a human tutor. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

3.I believe an AI tutor could effectively guide me through the process of breaking down complex problems (problem-solving) into smaller, more manageable steps.

4. Compared to a human teacher, I believe an AI tutor could better explain the reasoning behind its assessments, such as why an answer is incorrect. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

5. I think using an AI tutor would encourage me to think more critically about the course material (analyze information, identify biases, etc.) than traditional tutoring methods. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

6. I believe AI tutors would be better at identifying my learning gaps compared to traditional tutoring methods. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

7. I expect using an AI tutor would help me understand complex topics better than a human tutor. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

8. I expect an AI tutor to be able to personalize the learning experience based on my preferred learning style. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

9. Compared to human teacher feedback, I expect AI tutors to offer more frequent feedback on my learning progress. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

10. I expect explanations provided by AI tutors would be clearer and easier to understand than explanations from a human tutor. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

11. Compared to traditional tutoring methods, I expect AI tutors would be more helpful in teaching me to evaluate the strengths and weaknesses of different approaches to solving problems. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

12. I believe an AI tutor could track my progress over time and provide personalized feedback better than a human teacher. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

13. Compared with human teachers, I expect feedback from an AI tutor to be more specific and actionable, helping me understand how to improve my learning.

14. I expect AI tutors could improve my long-term knowledge of a subject more effectively than traditional tutoring methods. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

15. I believe AI tutors would be better at focusing on areas where I need the most help compared to traditional tutoring methods. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

16. I expect AI tutors would be better at providing me with opportunities to practice critical thinking skills (e.g., analyzing evidence, forming arguments) compared to traditional tutoring methods. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

17. I believe I would learn and remember information faster if I used an AI tutor instead of traditional tutoring methods. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

18. I believe an AI tutor could adjust the pace of the tutoring session based on how quickly I grasp new information. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

19. Compared to human teacher, I believe an AI tutor could more effectively identify areas where I made mistakes in my work and suggest improvements. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

20. After working with an AI tutor (hypothetically), I would feel more confident in my ability to apply my knowledge to solve new and unfamiliar problems. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

21. I think using an AI tutor would provide me with various assessment methods (e.g., quizzes, exercises) to gauge my understanding. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

22. I expect AI tutors would be more effective in providing alternative explanations if I don't understand a concept the first time. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

23. Compared to traditional tutoring methods, I expect AI tutors would be more effective in helping me remember key facts and details. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

24. I think using an AI tutor would encourage me to be better at identifying different sources of information when approaching problems, compared to traditional tutoring methods. (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)

Scales: Adaptability(1, 6, 8, 15, 18, 22), Learning Gains (2, 7, 10, 14, 17, 23) Skills Development (3, 5, 11, 16, 20, 24), Assessment (4, 9, 12, 13, 19, 21).