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INNOVATION OF THE EDUCATION PROCESS TOWARDS IMPLEMENTING AI TOOLS

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Abstract: Artificial intelligence (AI) is transforming education by offering personalized learning experiences, breaking traditional barriers, and preparing students for the future workforce. It enhances adaptability to modern educational demands and business trends while empowering both students and educators through innovative tools and methods. Our paper examines students' perceptions of AI and maps how they utilize AI tools, highlighting their role in meeting the challenges of today's educational and professional life. By analysing data collected through a structured questionnaire, we identified key themes, including the usefulness, ease of use, attitudes, and concerns surrounding AI. These findings serve as a foundation for understanding the role of AI in education and its potential to enhance learning experiences and adaptability to future challenges. The Kruskal-Wallis tests revealed significant differences in students' perceptions and use of AI based on demographic factors such as gender, study level, socioeconomic status, and place of residence. Female students reported greater difficulty using AI, highlighting the influence of historical gender stereotypes surrounding technology. Master's students, likely due to their advanced academic exposure, demonstrated higher confidence and a stronger inclination to use AI for learning. Socioeconomic background and urban residency were linked to more supportive attitudes toward AI integration in education and privacy concerns. Additionally, students further along in their academic journey reported more frequent use of AI tools for language learning.

Keywords: Artificial intelligence (AI), students, attitudes, learning process, education

JEL Classification: O34; M21; I23

INTRODUCTION

Artificial intelligence (AI) is increasingly permeating various aspects of our lives. Its integration into educational processes is essential, as these innovations can enhance adaptability to emerging trends in the business world. AI is revolutionizing education by offering personalized learning experiences tailored to individual needs. It enables students to access resources and tools anytime, breaking the barriers of traditional classroom settings. AI-powered systems can adapt new teaching methods based on a student's progress, enhancing understanding and retention. Additionally, it streamlines administrative tasks for educators, allowing them to focus more on teaching and mentoring. By integrating AI, students gain access to advanced technologies, preparing them for the future workforce. AI fosters creativity by offering innovative solutions to complex problems, promoting critical thinking. It also facilitates collaboration and knowledge sharing through interactive platforms. Furthermore, AI tools can assist in identifying learning gaps, enabling targeted interventions for better outcomes. The use of AI in education supports lifelong learning by providing flexible and accessible learning opportunities. Ultimately, AI empowers both students and educators to achieve greater efficiency, adaptability, and success in the learning process. Therefore, our paper focuses on this very issue, examining students' perceptions of AI and mapping how they utilize AI tools in their educational and learning processes. By understanding student´s attitudes and integrations AI into their studies, we aim to highlight its role in enhancing adaptability to modern educational demands and emerging trends in the business world.

1. LITERATURE REVIEW

Artificial intelligence (AI) has become increasingly important in recent decades, impacting numerous fields, such as medicine, finance, law, industry, and entertainment. Education is no exception, as there is a growing body of research into AI applications for education, including intelligent tutoring systems, adaptive learning, assessment design, and learning analytics (Salas-Pilco & Yang, 2020). As educational institutions strive to meet the diverse needs of learners, AI technologies offer new ways to personalize and enhance the educational experience, making learning more engaging, accessible, and effective. The integration of technology in education has rapidly evolved over the past 30 years. Initially designed as assistive tools, technologies like text-to-speech, predictive text, and search engines have expanded beyond their original purpose. Today, these tools are essential features embedded in digital platforms, reflecting a broader trend of technological integration in daily life. These advancements now augment the learning interactions of students globally, opening new possibilities for teaching and designing educational experiences (Popenici & Kerr, 2017). AI's presence in education can be traced back to the introduction of computers in the 1990s. Since then, research has focused on developing AI-enhanced learning environments, including intelligent tutoring systems and adaptive learning platforms, which manifest significant improvements in automated approaches to education (Chen et al., 2020). These innovations have empowered educators to create more dynamic and adaptive curriculums, catering to individual learning speeds and preferences. AI's influence extends beyond learning and teaching, encompassing administrative processes within educational institutions. According to Zhang and Aslan (2021), AI in education is an interdisciplinary field that integrates computer science, learning sciences, psychology, neuroscience, and other disciplines. This multidisciplinary synergy is vital for understanding how students learn and how technology can best support their educational journey, driving the development of adaptive and effective learning environments to optimize traditional education. AI has the potential to achieve sustainable change at all levels, not only in pedagogy but also in the management of educational institutions.

Baker and Smith (2019) identified three main educational processes impacted by AI applications: learning, teaching, and administration. AI supports students' learning through adaptive systems, assists teachers by automating tasks like grading and feedback, and aids administrators by providing data-driven insights for decision-making. These capabilities streamline educational processes, reduce costs, and improve the quality of education, allowing educators to focus more on student engagement and instruction. The benefits of AI in education are diverse. Owoc et al. (2021) highlighted advantages such as automating repetitive tasks, supporting teachers through AI facilitators, and providing adaptive learning experiences that cater to individual students' needs. AI-powered systems can offer personalized feedback, improve spaced repetition for better knowledge retention, and even detect academic misconduct. These examples show how AI simplifies educational logistics while introducing data-driven methods to enhance learning. Furthermore, AI has been integrated into higher education campuses worldwide. Universities use data to analyze trends and patterns in student behavior, enabling educators to gain a holistic understanding of their students' needs. This data-driven approach allows for the development of personalized learning platforms that adapt to each student's pace and progress (Popenici & Kerr, 2017). As AI continues to advance, it is expected to provide even more sophisticated tools for enhancing student learning.

A recent advancement in AI that holds promise for education is generative AI. Lv (2023) describes generative AI as a subfield capable of producing new and original content, such as text, audio, video, and code. This ability to produce diverse content autonomously has made generative AI a versatile tool across multiple industries, including entertainment, marketing, and education, where it can create engaging learning materials or provide instant feedback. Unlike traditional AI systems, which are explicitly programmed, generative AI can creatively adapt to different contexts, leading to more dynamic and personalized interactions with users (Feuerriegel et al., 2023). One notable example of generative AI in education is ChatGPT, which can revolutionize teaching and learning in higher education by serving as an AI-powered tool for various tasks (Lim et al., 2023). ChatGPT can function as an independent tool or integrate into existing educational platforms, providing personalized feedback, facilitating collaborative problem-solving, and even assisting with curriculum design. According to Hwang and Chen (2023) the use of ChatGPT can facilitate students learning experiences, generate alternative ways of expressing ideas, and based on data supplied by students or teachers, immediately give each student personalized feedback. Such capabilities make ChatGPT a valuable resource for enhancing student engagement and supporting differentiated instruction, allowing educators to address individual learning needs more effectively. Moreover, ChatGPT can be used as a collaboration coach to assist groups in researching and solving problems together, as a guide on the side to navigate physical and conceptual spaces, and as a codesigner to help in the designing or updating of curricula. Additionally, ChatGPT can be employed as an exploratorium to provide tools for exploring and interpreting data, as a study buddy to help students reflect on learning material and as a motivator that offers games and challenges to extend learning. These varied roles demonstrate the potential of ChatGPT to act not just as a passive tool but as an active partner in the learning journey, adapting to the evolving needs of students and educators alike. It can act also as a dynamic assessor for students' assignments and other evaluation tasks (Ivanov & Soliman, 2023).

However, the adoption of AI, including ChatGPT, is not without challenges. According to Lund et al. (2023), ethical considerations and concerns about plagiarism, privacy, and regulation are significant. The potential for misuse, coupled with the need for robust AI-detection mechanisms, has raised apprehensions among educators and institutions. A primary concern expressed by numerous universities and educators revolves around the potential escalation of plagiarism and cheating among students. Furthermore, there exist apprehensions regarding the efficacy of current plagiarism detection tools when faced with written content generated by ChatGPT (Cotton et al., 2023). This raises the need for developing more robust AI-detection mechanisms and establishing clear guidelines for ethical use of AI-generated content within academic settings. Moreover, the absence of regulation surrounding ChatGPT is also a concern, as it facilitates rapid development without adequate exploration of potential risks and shared protocols. Additionally, the tool's inability to discern between veracity and falsehood, right and wrong, raises concerns pertaining to cognitive bias (Kasneci et al., 2023). These biases, if not properly addressed, could lead to misinformation and misrepresentation, negatively impacting students' learning outcomes and perpetuating harmful stereotypes. Other concerns encompass privacy, accessibility and commercialization, necessitating meticulous deliberation and regulation to ensure fairness and equity in the application of AI tools in higher education (Rudolph et al., 2023). Ensuring that these tools are designed with privacy safeguards and equitable access is essential for their responsible deployment, making it crucial for policymakers and institutions to collaborate on standardized frameworks. Recent study found that providing teachers with AI knowledge and practical experience can reduce their concerns and improve their trust in AI tools. Sessions on AI-powered assessment and the use of an AI tool positively impacted teachers' knowledge, perceptions, attitudes, trust and willingness to adopt AI tools (Nazaretsky et al., 2022). This suggests that proper training and support can play a significant role in overcoming resistance to new technologies, ensuring that educators are well-prepared to integrate AI in a way that complements their teaching. Despite the benefits and challenges, there is still a gap in research specifically focusing on the use of ChatGPT by students

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in higher education. More empirical studies are needed to understand how students interact with AI tools, the perceived benefits, and potential issues that may arise with widespread usage. Such research is essential for developing strategies that encourage effective adoption and integration of AI technologies in academic settings.

The successful adoption of AI technologies like ChatGPT depends on several critical factors, which can be analyzed through the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003). This model emphasizes performance expectancy, effort expectancy, social influence, and facilitating conditions as key determinants influencing students' attitudes towards adopting new technologies. Addressing these factors can ensure that AI tools are perceived as beneficial, easy to use, and well-supported, ultimately shaping the future of learning in higher education (Strzelecki & ElArabawy, 2023). Performance expectancy refers to the degree to which a person believes that using a system will enhance their job performance. In the context of using ChatGPT, this translates to students' perceptions that the tool will improve their study practices. Specifically, it reflects their belief in the usefulness of ChatGPT for academic tasks, such as drafting essays, clarifying complex topics, or providing quick answers to queries. For instance, students might find that ChatGPT helps them improve productivity and comprehension, making it an essential aid in their learning process. Similarly, effort expectancy is characterized by the ease of use of the system and the level of comfort associated with it. In the study of ChatGPT, this pertains to how user-friendly and accessible the tool is, along with its ability to minimize distractions and streamline tasks. A user-friendly interface, intuitive commands, and seamless integration with existing educational platforms can significantly enhance students' willingness to engage with ChatGPT, as they can focus on learning rather than struggling with the technology itself. The simpler the system is to use, the more likely students will be to incorporate it into their study habits. Moreover, social influence plays a crucial role in technology adoption. It is defined as the extent to which a person perceives that significant others—such as peers, educators, or even broader societal groups—believe they should use a particular system (Strzelecki & ElArabawy, 2023). In the case of ChatGPT, peer recommendations, instructor encouragement, and the general acceptance of AI tools within the academic community can all shape students' attitudes towards integrating the tool into their educational practices. The more positive the social reinforcement, the greater the likelihood that students will feel encouraged to adopt ChatGPT as a part of their learning environment. Facilitating conditions represent the perception that a supportive administrative and technological framework is in place to assist in using the system. Within the study examining ChatGPT adoption among college students, these conditions can be especially significant because they directly impact how easily students can access and utilize the tool. Ensuring reliable internet access, availability of technical support, and effective integration with learning management systems are critical factors that can either encourage or hinder the effective use of ChatGPT. When these conditions are well-established, students are more likely to engage with the technology confidently, without facing barriers to access. These four determinants—performance expectancy, effort expectancy, social influence, and facilitating conditions—interact to influence students' behavioral intentions to use ChatGPT. According to Venkatesh et al. (2003), technology use behavior is positively impacted by behavioral intention. Therefore, if students perceive ChatGPT as beneficial, easy to use, and well-supported by their educational environment, their intention to use the tool is likely to translate into actual usage, further integrating AI into the academic ecosystem. This alignment of user expectations and system capabilities is essential for the sustained adoption of AI technologies, ultimately shaping the future of learning in higher education (Strzelecki & ElArabawy, 2023).

However, as AI continues to evolve, it also brings about anxieties and concerns regarding its impact on society. On the one hand, various AI events impact individual psychology. On the other hand, various studies and expert opinions have also incited anxiety (Li & Huang, 2020). The McKinsey Global Institute estimates that 400 to 800 million workers will be replaced by AI by 2030 (McKinsey Global Institute, 2017). This prediction has sparked a global debate about the implications of AI on the workforce, including concerns about job security, economic inequality, and the future of work. Recently, scholars have begun focusing on the existing problems and defects of AI. Therefore, anxiety has arisen concerning autonomous AI and personal privacy (Carsten & David, 2018). First, there are concerns that AI may produce artificial consciousness, which will give rise to a condition where AI exists independently and may not be controlled by humans. Second, there are worries concerning the opacity of AI operations and decision-making processes, which introduces unpredictable risks (Clarke, 2019). Third, AI makes decisions through calculations and pros-and-cons analysis, which results in concerns about discrimination and bias. These biases can manifest in unexpected ways, particularly when AI systems are trained on data that contains implicit biases, leading to unfair treatment of individuals based on gender, race, or other factors. Fourth, some worry that AI will not abide by human ethics, resulting in ethical violations such as murder by autonomous weapons. Fifth, future super AI applications may pose a threat to human survival (Leavy, 2018). These ethical and existential concerns have prompted calls for stricter regulation and oversight in the development of AI technologies. In addition to these particular anxieties, AI may generate a wider range of anxieties than computer anxiety, including job replacement anxiety, privacy violation anxiety, and safety and regulation anxiety. According to Erkin et al. (2009) privacy violation anxiety occurs when users experience direct violations of privacy by AI. This anxiety can arise because datasets used by AI may violate personal privacy, which is disturbing. For example, targeted advertising and face recognition can be performed automatically by unsupervised AI, leading to a risk of personal data leakage and hence the invasion of privacy. In particular, privacy anxiety concerning the widespread use of biometrics is rising. The misappropriation or modification of a user's privacy data when face recognition is used to verify identity has serious consequences. These concerns highlight the need for transparent AI systems that prioritize user privacy and data security. AI also generates learning anxiety that resembles anxiety related to other technologies. When AI is applied in various fields, various forms of anxiety arise spontaneously. In the future, new anxieties and safety issues will arise as AI technologies such as face recognition and autonomous driving enter the mainstream (Zhou et al., 2020).

Kemp et al. (2019) identified seven primary factor groups that were relevant to student attitudes towards educational technologies: attitude, affect and motivation, social factors, usefulness and visibility, instructional attributes, perceived behavioral control, cognitive engagement and system attributes. According to Kemp et al. (2024) many technology acceptance models used in education were originally designed for general technologies and later adopted by education researchers. This previous research suggested that an effective extended educational technology acceptance model should include perceived usefulness, perceived ease of use, cognitive engagement, class interaction and communication, feedback, instructor practice, access and convenience, system attributes, self-efficacy and comfort and well-being. These factors represent all of the primary factor classes suggested by the taxonomy, except attitude, in addition to the factors suggested by Kemp's (2023) qualitative study. COVID-19 had a significant impact on education globally causing disruptions in learning delivery. It was therefore important to explore how student attitudes towards educational technologies may have evolved during this period. The pandemic accelerated the adoption of digital tools, and many students who previously had little exposure to online learning had to quickly adapt, leading to new insights into how these technologies could be improved. In a separate qualitative study (Kemp, 2023), student attitudes to using Zoom for learning were investigated, revealing that social comfort and well-being, cognitive engagement, instructor practice, class interaction and feedback, access and convenience and system attributes were important considerations. These findings underscore the importance of designing educational technologies that are user-friendly, engaging, and supportive of both students and educators in diverse learning environments.

In conclusion, artificial intelligence (AI) represents a transformative opportunity for the education sector, offering the potential to enhance learning experiences, streamline administrative tasks, and provide personalized educational support. However, for AI to be successfully integrated into educational settings, a balanced and strategic approach is necessary. This approach must prioritize not only the technical reliability and performance of AI systems but also the ethical considerations that come with the use of such advanced technologies. Issues such as data privacy, security, bias, and the potential misuse of AI-generated content must be carefully addressed to ensure that these tools benefit students and educators without compromising their rights and well-being.

2. DATA AND METHODOLOGY

In this paper, we explored students' perceptions and use of AI in their educational and learning processes. To identify significant differences between student groups, we analyzed primary data collected through an online questionnaire. The questionnaire was divided into two sections. The first section included demographic and background questions, where respondents provided information about their gender, place of residence, level and year of study, field of study, and socioeconomic status. The second section focused on students' use of AI and was structured into several thematic parts: (1 - PU) questions about the perceived usefulness of generative AI; (2 - PE) questions on the perceived ease of use of AI; (3 - SE) scenarios involving AI usage; (4 - BI) questions about plans and ideas for integrating AI into learning; (5 - ATT) questions on students' attitudes toward AI; (6 - ANX) questions addressing privacy concerns related to AI use; and (7 - FRQ) questions about the frequency of AI use in specific activities. All responses in this section were recorded using a Likert scale. The survey participants were exclusively students specializing in business studies. Data collection took place between September and November 2024 as part of a pilot study.

The Table 1 provides a comprehensive summary of the descriptive characteristics of the research sample, encompassing various demographic and academic dimensions. The gender composition reveals that 67.1% of respondents are female, while 32.9% are male, indicating a notable gender imbalance. The entire sample (100%) is comprised of students specializing in Business and Management, demonstrating a homogeneous focus on a single field of study. Such specificity may enhance the relevance of findings for exploring trends, challenges, or patterns within business education. Additionally, all participants are enrolled in public universities and reside in Slovakia (SVK). While this ensures a high degree of regional specificity, it also limits the study’s applicability to other geographic or institutional contexts, particularly those outside the Slovak educational system. The urban-rural distribution reveals a relatively balanced composition, as 53.7% of respondents reside in urban areas, while 46.3% come from rural regions. This balance contributes to the diversity of geographic representation within the sample, enabling potential insights into socioeconomic or educational disparities based on place of residence. Regarding educational levels, the sample is predominantly comprised of bachelor’s students, who constitute 65.9% of respondents, while 34.1% are enrolled in master’s programs. The prevalence of undergraduate students suggests that the research largely reflects individuals in the earlier stages of higher education, which may influence results related to academic motivation, preparedness, or career planning. When examining the year of study, the majority of respondents (65.9%) are in their second or third year, indicating a strong concentration in the mid-stages of their undergraduate programs. A smaller proportion are in their first year (8.5%), while 23.2% are in their fourth or fifth year. Only 2.4% of respondents have exceeded the standard duration of study. This distribution highlights the predominance of students who are actively engaged in their academic programs and likely approaching critical phases of career preparation and decision-making. Socioeconomic status was assessed on a scale ranging from 1 (poorest) to 9 (richest). The findings indicate a limited presence of respondents from the lowest income brackets, with 1.2% representing the two lowest levels and 4.9% occupying level 3. The majority of participants fall within the middle and upper-middle wealth categories, particularly at level 5, which accounts for 32.9% of the sample. Furthermore, levels 6 and 7 comprise 13.4% and 22.0%, respectively, whereas the highest levels (8–9) are underrepresented. This distribution indicates that the sample largely reflects individuals from middle-income backgrounds, with minimal representation from economic extremes.

Tab. 1: Descriptive characteristics of the research sample

GENDER	%	FIELD_STUDY	%
Male	32.9	Business and Management	100.0
Female	67.1	UNI_TYPE	%
COUNTRY	%	Public	100.0
SVK	100.0	SOCIOECONOMIC STATUS*	%
PLACE_RES	%	1	1.2
Urban	53.7	2	1.2
Rural	46.3	3	4.9
STUDY_LEVEL	%	4	8.5
Bc	65.9	5	32.9
Master	34.1	6	13.4
YEAR_STUDY	%	7	22.0
First year	8.5	8	14.6
2-3 years	65.9	9	1.2
4-5 years	23.2		
Over 5 years	2.4		

**1=the poorest; 9=the richest*

Source: own processing

According to the questionnaire design, the following research hypotheses were established:
H1: Perceived usefulness of generative AI is influenced by the demographic and background characteristics of students (gender, place of residence, level of study, year of study, and socioeconomic status).
H2: Perceived ease of use of AI is influenced by the demographic and background characteristics of students (gender, place of residence, level of study, year of study, and socioeconomic status).
H3: Using of AI in specific situations is influenced by the demographic and background attributes of characteristics (gender, place of residence, level of study, year of study, and socioeconomic status).
H4: Plans for using AI in learning are influenced by the demographic and background attributes of characteristics (gender, place of residence, level of study, year of study, and socioeconomic status).
H5: Attitudes towards AI are influenced by the demographic and background attributes of characteristics (gender, place of residence, level of study, year of study, and socioeconomic status).
H6: Concerns about the use of AI in the context of privacy are influenced by the demographic and background attributes of characteristics (gender, place of residence, level of study, year of study, and socioeconomic status).
H7: Frequency of using AI in specific activities is influenced by the demographic and background attributes of characteristics (gender, place of residence, level of study, year of study, and socioeconomic status). To determine whether statistically significant differences existed between groups of respondents (based on specific classification factors), the Kruskal-Wallis test was employed. The Kruskal-Wallis test serves as a non-parametric equivalent to one-way analysis of variance (ANOVA) for a single factor.

3. RESULTS

The results presented in Table 2 summarize the outcomes of the Kruskal-Wallis Test, examining associations between several dependent variables and independent categorical factors, namely gender, place of residence, study level, year of study, and wealth. The table highlights statistically significant relationships where p-values fall below conventional thresholds of significance ($p < 0.05$, $p < 0.01$, $p < 0.001$). Regarding gender, significant results emerge for certain variables. Specifically, PE2 ($p = 0.046$), PE3 ($p = 0.003$), and

PE4 (p = 0.005) demonstrate meaningful associations, suggesting that gender differences exist in these measures. Conversely, most of the other variables across the table fail to show significant gender-based differences, indicating that gender generally does not play a substantial role in influencing outcomes for most of the measured constructs. For place of residence, a limited number of significant results are observed. Notably, ATT2 (p = 0.036) and ANX3 (p = 0.030) indicate differences between urban and rural participants. These findings imply that place of residence may impact specific attitudes and experiences, though its influence does not extend across most of the variables assessed. The variable study level produces a broader range of significant findings. For instance, differences are noted for PE3 (p = 0.006), PE4 (p = 0.027), SE1 (p = 0.028), SE4 (p = 0.031), BI1 (p = 0.034), BI3 (p = 0.046), and ATT4 (p = 0.005). These results suggest that the level of study (e.g., Bachelor vs. Master) significantly influences participants' perceptions and attitudes for several constructs, particularly those related to performance expectations, self-efficacy, and behavioural intention. In contrast, year of study reveals limited statistical significance, with only FRQ7 (p = 0.045) showing a notable association. While many of the variables do not exhibit significant differences, this isolated result suggests that progress through academic years might influence frequency-related outcomes to a small extent. Lastly, the wealth variable does not demonstrate significant associations across most measures. One exception is ATT5 (p = 0.048), where wealth shows a meaningful relationship. However, the absence of significance in other variables indicates that socioeconomic status, as measured here, has a minimal impact on the assessed constructs.

The analysis reveals that gender and study level exhibit the most consistent influence on the measured variables, with significant differences observed in multiple constructs. Place of residence and year of study show more limited effects, while wealth demonstrates minimal association overall. These findings suggest that demographic and academic factors play a variable role in shaping participants' perceptions, attitudes, and experiences, with specific constructs being more sensitive to certain factors than others. The results underscore the need to further explore these relationships to better understand the underlying dynamics influencing the measured outcomes.

Tab. 2: Kruskal-Wallis Test results

	PU1	PU2	PU3	PU4	PE1	PE2	PE3	PE4	SE1	SE2	SE3
GENDER	0.228	0.605	0.772	0.650	0.083	*0.046	**0.003	**0.005	0.432	0.746	0.453
PLACE_RES	0.166	0.210	0.108	0.245	0.134	0.158	0.233	0.921	0.251	0.642	0.953
STUDY_LEVEL	0.302	0.254	0.431	0.573	0.163	0.329	**0.006	*0.027	*0.028	0.387	0.447
YEAR_STUDY	0.074	0.117	0.074	0.204	0.574	0.730	0.098	0.227	0.055	0.564	0.505
WEALTH	0.512	0.230	0.429	0.126	0.084	0.651	0.378	0.361	0.441	0.363	0.918
	SE4	BI1	BI2	BI3	BI4	BI5	BI6	ATT1	ATT2	ATT3	ATT4
GENDER	0.476	0.701	0.527	0.597	0.768	0.132	0.206	0.413	0.509	0.862	0.961
PLACE_RES	0.630	0.587	0.686	0.314	0.950	0.761	0.568	0.270	*0.036	0.602	0.421
STUDY_LEVEL	*0.031	*0.034	0.132	*0.046	0.423	0.293	0.162	0.055	0.266	0.115	**0.005
YEAR_STUDY	0.219	0.148	0.167	0.119	0.756	0.556	0.572	0.420	0.638	0.389	0.099
WEALTH	0.660	0.773	0.324	0.621	0.579	0.668	0.933	0.491	0.705	0.405	0.629
	ATT5	ATT6	ATT7	ATT8	ANX1	ANX2	ANX3	FRQ1	FRQ2	FRQ3	FRQ4
GENDER	0.604	0.340	0.512	0.305	0.572	0.208	0.793	0.087	0.122	0.187	0.404
PLACE_RES	0.836	0.589	0.820	0.992	0.938	0.761	*0.030	0.913	0.893	0.144	0.289
STUDY_LEVEL	0.664	0.559	0.302	*0.038	0.565	0.340	0.802	0.884	0.887	0.214	0.532
YEAR_STUDY	0.510	0.760	0.637	0.180	0.275	0.373	0.581	0.997	0.246	0.489	0.380
WEALTH	*0.048	0.283	0.440	0.477	0.537	0.826	0.768	0.458	0.814	0.722	0.605
	FRQ5	FRQ6	FRQ7	FRQ8	FRQ9	FRQ10	FRQ11	FRQ12	FRQ13	FRQ14	FRQ15
GENDER	0.247	0.777	0.670	0.587	0.543	0.682	0.184	0.574	0.987	0.890	0.352
PLACE_RES	0.078	0.392	0.098	0.173	0.256	0.195	0.489	0.724	0.394	0.857	0.267
STUDY_LEVEL	0.553	0.823	0.876	0.410	0.907	0.347	0.401	0.151	0.917	0.258	0.321
YEAR_STUDY	0.544	0.572	*0.045	0.053	0.943	0.665	0.090	0.381	0.687	0.368	0.346
WEALTH	0.177	0.062	0.968	0.882	0.876	0.559	0.910	0.762	0.256	0.978	0.598

*Notes: *** p<0.001, ** p<0.01, * p<0.05*

Source: own processing

PE2: Perceived difficulty in learning how to use AI

The Kruskal-Wallis test yielded statistically significant differences in perceived difficulty in learning how to use AI (PE2) based on gender (p-value = 0.046). This finding may reflect the context of our research, conducted among university students, where gender disparities in learning how to use artificial intelligence are evident. Supporting studies indicate that gender significantly shapes how AI tools are perceived and utilized in educational settings, with male students generally rating their competencies higher compared to female students (Ofosu-Ampong, 2023; Armutat et al., 2024).

PE3: Perceived clarity and comprehensibility in using AI
A Kruskal-Wallis test yielded statistically significant differences in perceptions of clarity and comprehensibility in using artificial intelligence (PE3) based on gender (p-value = 0.003) and study level (p-value = 0.006). These results suggest that gender and level of study influence how individuals perceive the clarity and comprehensibility of AI tools. Research by Armutat et al. (2024) highlights that men generally have a more positive view of AI applications and demonstrate greater trust in the technology compared to women. Differences between bachelor and master students may stem from varying levels of exposure and experience with AI technologies.
PE4: Perceived ease of becoming skilled in using AI
A Kruskal-Wallis test yielded statistically significant differences in perceptions of ease of becoming skilled in using artificial intelligence (PE4) based on gender (p-value = 0.005) and study level (p-value = 0.027). These findings are supported by Nouraldeen (2022), who observed that male students tend to perceive becoming skilled in using artificial intelligence as easier than female students. Similarly, bachelor students are more likely to find it difficult to become skilled in AI compared to master students due to differences in prior experience and exposure to relevant technologies.
SE1: Concerns about technical skills in using AI
A Kruskal-Wallis test revealed a statistically significant difference in concerns about technical skills in using artificial intelligence (SE1) based on study level (p-value = 0.028). Chan & Hu (2023) explored university students' perceptions of generative AI technologies, noting that concerns about accuracy, privacy, and ethical issues influence their willingness to engage with AI. These concerns were linked to their technical skills and prior exposure to AI, aligning with our observation that study level influences apprehensions about using AI.
SE4: Confidence in using AI with only an online guide available
A Kruskal-Wallis test indicated statistically significant differences in confidence in using AI with only an online guide available (SE4) based on the level of study (p-value = 0.031). Biswas & Murray (2024) propose that master's students likely have greater exposure to AI concepts, contributing to their higher confidence in using online guides compared to bachelor's students.
BI1: Preference for using AI for learning
A Kruskal-Wallis test revealed statistically significant differences in students' confidence in using AI for learning activities (BI1) based on their level of study (p-value = 0.034). Both bachelor's and master's students commonly use AI tools, such as chatbots, but the extent and nature of AI usage differ between these groups, shaped by their academic level and specific needs. Supporting this, Parshutina & Kamaletdinova (2024) emphasize that the academic level influences how students engage with AI technologies for educational purposes.
BI3: Intention to use AI frequently for learning when given the choice
A Kruskal-Wallis test revealed statistically significant differences in students' intent to frequently use AI for learning when given the choice (BI3) based on their level of study (p-value = 0.046). According to Ferreira (2024), the disparity in AI adoption between bachelor's and master's students may stem from differences in exposure and familiarity with AI technologies. Master's students likely have more opportunities to engage with AI in specialized courses, which may explain their higher intent to utilize these tools.
ATT2: AI can improve access to educational resources and materials
A Kruskal-Wallis test revealed statistically significant differences in students' belief that artificial intelligence can improve access to educational resources and materials (ATT2) based on their place of residence (urban vs. rural), with a p-value of 0.036. This finding suggests that perceptions of AI's role in education differ notably between urban and rural settings. Yang & Zheng (2021) argue that these differences may arise from disparities in technology access and the quality of existing educational infrastructure, which influence how residents perceive AI's potential to enhance educational access.

ATT4: AI can help identify areas where students may need additional support
A Kruskal-Wallis test revealed statistically significant differences in students' belief that artificial intelligence can help identify areas where they may need additional support (ATT4) based on their level of study (p-value = 0.005). Research by Gouveia et al. (2023) indicates that master's students, who may have greater exposure to AI tools in their academic activities, are more likely to believe in AI's capability to provide additional support.
ATT5: AI technologies should be integrated into curricula to prepare students for future job market applications
A Kruskal-Wallis test revealed statistically significant differences in students' belief that artificial intelligence technologies should be integrated into curricula to prepare students for future job market applications (ATT5) based on their socioeconomic status (p-value = 0.048). Supporting our result, Ma et al. (2024) note that wealth impacts attitudes toward AI in education through factors such as trust, digital competency, and interest in AI, shaping perceptions and acceptance of AI in educational settings.
ATT8: AI can help provide personalized feedback to students
A Kruskal-Wallis test revealed statistically significant differences in students' belief that artificial intelligence can help provide personalized feedback to students (ATT8) based on their level of study (p-value = 0.038). Supporting our result, Castro et al. (2024) suggest that this difference may stem from varying levels of exposure to AI technologies and differing educational needs.
ANX3: Predictions regarding preferences, such as well-recommended ads or websites, create a sense of privacy invasion
A Kruskal-Wallis test revealed statistically significant differences in students' belief that AI predictions regarding preferences, such as well-recommended ads or websites, create a sense of privacy invasion (ANX3) based on their place of residence (urban vs. rural), with a p-value of 0.030. Supporting our result, Carmody et al. (2021) note that the difference in privacy concerns between urban and rural residents may be influenced by varying levels of exposure to AI technologies and differing socio-economic factors. Residents of urban areas, which tend to be more technologically advanced, may be more aware of and concerned about privacy issues related to AI.
FRQ7: Frequency of using AI for activities such as language learning (e.g., Duolingo)
A Kruskal-Wallis test revealed statistically significant differences in the frequency of using AI for language learning activities (e.g., Duolingo) (FRQ7) based on year of study (first year, 2-3 years, 4-5 years, more than 5 years), with a p-value of 0.045. This finding suggests that students at different stages of their education may engage with AI tools for language learning at varying rates. Chen et al. (2021) note that students' intention to use AI for language learning is influenced by factors such as their knowledge of AI applications, attitudes towards AI, perceived ease of use, and social norms. These factors are likely to differ by year of study, as students become more familiar with AI technologies over time.

CONCLUSION

The findings from the Kruskal-Wallis tests reveal several significant differences in students' perceptions and use of artificial intelligence (AI) based on demographic factors such as gender, study level, socioeconomic status, and place of residence. These differences highlight the complex ways in which individuals' experiences and attitudes toward AI are shaped by their background and educational context.
Significant gender differences were found in students' perceived difficulty in learning how to use AI (p-value = 0.046), with female students reporting more difficulty than male students. This may be influenced by historical gender stereotypes surrounding technology and AI. Additionally, gender and study level were significant factors in perceptions of AI's clarity (p-value = 0.003; p-value = 0.006), ease of use (p-value = 0.005; p-value = 0.027), and skill acquisition (p-value = 0.028), with male students and master's students generally exhibiting more favorable views toward AI. Study level also played a crucial role in shaping students' confidence (p-value = 0.031), preference for using AI for learning (p-value = 0.034), intention to use AI for

learning (p-value = 0.046), perceptions of AI's potential to provide personalized support (p-value = 0.005), and perceptions of AI's potential to deliver personalized feedback (p-value = 0.038). Master's students, likely due to their greater exposure to AI technologies in their academic programs, were generally more confident in using AI independently and more inclined to adopt AI tools for educational purposes. Furthermore, socioeconomic status (p-value = 0.048) and place of residence (p-value = 0.036; p-value = 0.030) were found to influence students' perceptions of AI's role in education. Students from higher socioeconomic backgrounds and those living in urban areas were more likely to support the integration of AI into curricula and express concerns about privacy issues related to AI. Finally, students' use of AI for language learning also varied depending on their year of study (p-value = 0.045), with those further along in their academic journey showing more frequent engagement with AI tools for learning activities. These findings suggest that factors such as gender, study level, socioeconomic status, and place of residence significantly impact students' attitudes and engagement with AI in education. Understanding these factors can help educators and policymakers design more inclusive and effective AI-related interventions in educational settings.

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