

Article

Students' Intention toward Artificial Intelligence in the Context of Digital Transformation

Nikola Milicevic ¹, Branimir Kalas ², Nenad Djokic ^{1,*}, Borka Malcic ³ and Ines Djokic ¹

¹ Department for Trade, Marketing and Logistics, Faculty of Economics in Subotica, University of Novi Sad, Segedinski put 9-11, 24000 Subotica, Serbia; nikola.milicevic@ef.uns.ac.rs (N.M.); ines.djokic@ef.uns.ac.rs (I.D.)

² Department for Financial and Banking Management, Faculty of Economics in Subotica, University of Novi Sad, Segedinski put 9-11, 24000 Subotica, Serbia; branimir.kalas@ef.uns.ac.rs

³ Department of Pedagogy, Faculty of Philosophy, University of Novi Sad, Zorana Djindjica 2, 21102 Novi Sad, Serbia; borka.malcic@ff.uns.ac.rs

* Correspondence: nenad.djokic@ef.uns.ac.rs

Abstract: The analysis of students' attitudes and perceptions represents a basis for enhancing different types of activities, including teaching, learning, assessment, etc. Emphasis might be placed on the implementation of modern procedures and technologies, which play an important role in the process of digital transformation. Among them is artificial intelligence—a technology that has already been found to be applicable in various sectors. When it comes to education, several AI-based tools and platforms can be used by students and teachers. Besides offering customized learning experiences, AI may play a significant part in establishing the concept of sustainability, especially when concerning the achievement of sustainable development goal 4. This paper investigates students' intention to use artificial intelligence in education, taking three predictors from the UTAUT model and AI awareness as the moderator. The analysis included students from the Autonomous Province of Vojvodina, Republic of Serbia. For the purpose of the research, the partial least squares structural equation modeling (PLS-SEM) method was applied. Hereby, two models (without and with a moderator) were tested to examine the main and moderating effects, respectively. Regarding the results, while interaction terms were non-significant, the impacts of performance expectancy, effort expectancy, and social influence on behavioral intention were significant and positive.

Keywords: behavioral intention; UTAUT; artificial intelligence; education; digital transformation; AI awareness



Citation: Milicevic, N.; Kalas, B.; Djokic, N.; Malcic, B.; Djokic, I. Students' Intention toward Artificial Intelligence in the Context of Digital Transformation. *Sustainability* **2024**, *16*, 3554. <https://doi.org/10.3390/su16093554>

Academic Editors: Muhammad Irfan, Naim Ahmad, Ayman Qahmash and Mohammad Mahtab Alam

Received: 11 March 2024

Revised: 18 April 2024

Accepted: 22 April 2024

Published: 24 April 2024



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1. Introduction

The emergence of online courses and education platforms and the increase in domestic and global competition put higher education institutions in a complex position with many challenges [1]. In such an environment, those institutions, like any other business entity, should pay attention to their clients, i.e., students [2]. Hence, the delivery of service quality can be considered an important task for higher education institutions [3]. To become more student-oriented and improve the learning process, a greater emphasis should be placed on students' perceptions of educational services and on the understanding of how they learn [2,4]. Bearing in mind that technology has an important role in the educational and learning process, several studies investigated students' intentions toward its use [5,6].

Different types of technologies can be applied in higher education, whereas in the past few years, there has been a growing interest in artificial intelligence (AI). AI can be defined as “systems that display intelligent behavior by analyzing their environment and taking action—with some degree of autonomy—to achieve specific goals” [7] (p. 1). It is being implemented in various organizations and sectors with the aim of optimizing their effectiveness and efficiency [8].

When it comes to education, artificial intelligence can have an important role in the process of digital transformation (DT) [9]. DT refers to changes in an organization stimulated by the integration of digital technologies in its various sectors, whereby it overcomes the simple implementation of new technologies, implying alignment between three factors—human, technological, and organizational [10]. In education, digital transformation considers new ways of connecting data, people, and processes in modern digital conditions, intending to create a better environment and prepare for future challenges [11]. Regarding higher education institutions, DT can bring several practical benefits reflected in the improvement of the training process related to the creation of a good workforce; the facilitation of universities' internal governance; the prediction and management of different organizational, educational, and scientific issues; and the personalization of learning and other benefits to students [12]. In this context, AI represents one of the factors impacting the establishment of the digital education infrastructure [12]. Chassignol et al. [13] singled out four main areas that could be influenced by artificial intelligence: content, teaching methods, assessment, and communication. Among these, they presented several tools and platforms designed for personalized learning. In addition, Holmes and Tuomi [14] distinguished three categories of AI tools that can be applied in education, depending on who the focus is on—whether it is on the student, teacher, or institution. Hereby, in the case of student-focused AI, it should be noted that besides technologies that have been repurposed for education—such as Google Docs and Sheets—and some social networking platforms (WhatsApp and WeChat) and content-sharing platforms (YouTube and TikTok), there are AI-assisted technologies especially developed for students: “intelligent tutoring systems, AI-assisted apps, AI-assisted simulations, AI to support learners with disabilities, automatic essay writing, chatbots, automatic formative assessment, learning network orchestrators, dialogue-based tutoring systems, exploratory learning environments, and AI-assisted lifelong learning assistants” [14] (p. 551). As mentioned in the research of Rahman and Kodikal [15], AI technologies offer students attractive and customized learning experiences, allowing them to understand complex theories and solutions more effectively.

The use of artificial intelligence in education can have an important role in establishing the concept of sustainable development. This is particularly related to achieving sustainable development goal 4 (SDG 4), which refers to “equal learning opportunities for all throughout life” [16] (p. 12). Artificial intelligence technologies can make education more equitable and accessible, especially for underserved or marginalized communities [16,17]. In addition, AI can contribute to green or environmental education, i.e., the type of education focused on providing individuals with knowledge and values associated with sustainability and environmental topics, such as climate change, the lack of resources, etc. [17]. Its technology can be applied to help people better comprehend the importance of the previously mentioned themes and behave following the sustainable use of resources [17].

Taking into account the unavoidable influence of artificial intelligence and the need for a better understanding of students' requirements, this research was focused on their behavioral intention to use AI in education. For this purpose, several technology acceptance theories can be applied, such as the unified theory of acceptance and use of technology (UTAUT), the technology acceptance model (TAM), the value-based adoption model (VAM), and the theory of planned behavior (TPB) [18]. Among them, the theory that has been widely used for analyzing individual behavior concerning new technologies and covering different contexts refers to the unified theory of acceptance and use of technology [19]. Regarding artificial intelligence, the UTAUT model (with certain modifications and/or in combination with other theories) was implemented to examine behavior from various aspects, including virtual reality tourism [19], hotel in-room voice assistants [20], chatbot-based services [21], Open AI's ChatGPT [22], AI-CRM systems [23], and AI-based medical devices [24], as well as the intention toward AI technology use among recruiters [25,26], librarians [27], managers [28], risk professionals [29], and truck drivers [30].

Similar research has been conducted in the sector of education, and some of these studies are presented in the literature review section. Following those studies, the concep-

tual model and hypotheses were set. To the authors' knowledge, this is the first research related to the behavioral intention toward AI that, besides the main UTAUT predictors, includes AI awareness as a moderator. In addition to the mentioned novelty concerning the previous UTAUT applications, it can be added that studies regarding AI usage in education are scarce in the domestic context. After explaining the methodological part of the research, the obtained results and the discussion are presented. The research ends with conclusions, which include certain managerial implications.

2. Literature Review and Hypotheses Development

2.1. Students' Intention toward AI

As in many other sectors, artificial intelligence has been the subject of analysis in education. It was examined from different perspectives, whereas the attention was often dedicated to students' intention to learn AI [8,31–34], as well as studies in which the emphasis was on teachers' intention to teach or prepare students for AI [35,36].

Several studies investigated the intention of students to use artificial intelligence in education. Many of them applied the unified theory of acceptance and use of technology, as does the research of Alzahrani [37]. This study included seven variables, whereby students' behavioral intention was examined concerning their attitude, awareness, and facilitating conditions. Among the others, Alzahrani [37] investigated the effects of perceived risk, performance expectancy, and effort expectancy on students' attitudes.

Chatterjee and Bhattacharjee [38] investigated the adoption of AI in higher education by relying on several theories and models, including the UTAUT. They analyzed the effects of attitude and facilitating conditions on behavioral intention, as well as the effect of behavioral intention on AI adoption. In addition, their analysis included three more variables—perceived risk, performance expectancy, and effort expectancy. Hereby, besides students, the research covered teachers and administrative staff.

The UTAUT model with certain changes was applied by Ragheb et al. [39]. Their focus was on students' behavioral intention toward the adoption of chatbot technology in higher education. They investigated its three determinants (performance expectancy, effort expectancy, and social influence), whereby certain demographic factors were used as moderators.

Wu et al. [40] combined the UTAUT and the theory of perceived risk, which resulted in a model with six factors influencing students' willingness to accept an AI-assisted learning environment. Hereby, three factors (performance expectancy, effort expectancy, and social influence) were taken from the UTAUT model, while three factors (functional risk, psychological risk, and social risk) were based on the theory of perceived risk.

To examine the acceptance of ChatGPT by university students, Romero-Rodríguez et al. [41] used the constructs from the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model. Regarding the students' behavioral intention, its main antecedents were effort expectancy, facilitating conditions, habit, hedonic motivation, performance expectancy, price value, and social influence. Moreover, Romero-Rodríguez et al. [41] analyzed the influence of experience on students' behavioral intention, as well as the effect of the behavioral intention on user behavior.

Besides the UTAUT, the Technology Acceptance Model (TAM) was also applied to examine students' intentions toward AI. Yu [42] investigated students' behavioral intention to use next-generation information technology (which includes AI) in intelligent foreign-language learning by proposing a research model mostly based on TAM. In addition to behavioral intention, it consisted of four more variables: construction of foreign language intelligence classroom, computer self-efficacy, perceived usefulness, and perceived ease of use. When analyzing college students' intention to use AI in their learning, Le Dang [43] relied on factors derived from the Technology Acceptance Model, the Technology Readiness Model (TR), and the Technology Readiness and Acceptance Model (TRAM). Behavioral intention was set as a dependent variable affected by perceived usefulness and perceived ease of use. On the other hand, the previously mentioned two independent variables

were influenced by optimism about AI technology, AI technology innovativeness, and discomfort with AI technology.

In addition to focusing on intention, there are studies that covered different behavioral aspects of students concerning AI technology. The research of Buabbas et al. [44] dedicated attention not only to the willingness to use AI in medical education but also to other students' perceptions regarding AI, such as those related to its impacts, limitations, terminologies, basic principles, teaching, etc. Almaraz-López et al. [45] also examined perceptions and attitudes regarding AI among students at the Faculty of Economics and Business Management and the Faculty of Education. The emphasis of their study was on the importance of artificial intelligence concerning their professional future; the level of understanding of AI technology, including its computational principles, nomenclature, and limitations; the ability to use AI tools for professional purposes; and the level of reception of AI teaching.

2.2. Conceptual Model and Hypotheses

As previously presented, the UTAUT model has been applied by many researchers when examining students' intentions to use AI technology. It was formulated by Venkatesh et al. [46] after they reviewed eight different models. The UTAUT model consists of three direct determinants (performance expectancy, effort expectancy, and social influence) of intention. Along with facilitating conditions, they represent the direct determinants of usage. In addition, the model includes four moderators.

Bearing in mind that the UTAUT can be considered a useful tool for assessing "the likelihood of success for new technology introductions" [46] (p. 426), this research was based on its application. Following similar studies [39,40], the focus was on core UTAUT determinants of behavioral intention [46]: performance expectancy (the level of an individual's perception that technology will have a positive effect on her or his work performance), effort expectancy (the level of ease related to the use of the technology), and social influence (the level of an individual's perception that others believe she or he should use the technology). Consequently, three hypotheses were tested:

H1. *Performance expectancy positively affects students' intention to use AI in education.*

H2. *Effort expectancy positively affects students' intention to use AI in education.*

H3. *Social influence positively affects students' intention to use AI in education.*

Besides the main UTAUT determinants of behavioral intention, this research included an additional variable—awareness. In this context, following Collins's [47] definition, awareness can be considered the extent to which students are likely to be familiar with artificial intelligence.

Abubakar and Ahmad [48] proposed the use of technology awareness as a moderator of relations between intention and its predictors. Hence, stronger relations between UTAUT independent variables and behavioral intention could be expected for those individuals who have high technology awareness than for those with a low level [49]. Some moderating effects of awareness were detected in UTAUT-based studies associated with students' intention to use 4.5G mobile phones [50] and employees' willingness to use mobile applications [51]. Taking into account the previously mentioned hypotheses, three more hypotheses were tested:

H4. *AI awareness moderates the effect of performance expectancy on students' intention to use AI in education.*

H5. *AI awareness moderates the effect of effort expectancy on students' intention to use AI in education.*

H6. *AI awareness moderates the effect of social influence on students' intention to use AI in education.*

All research variables, including relations between them, are presented in Figure 1. Hereby, solid lines represent direct relations, while dashed lines represent moderation.

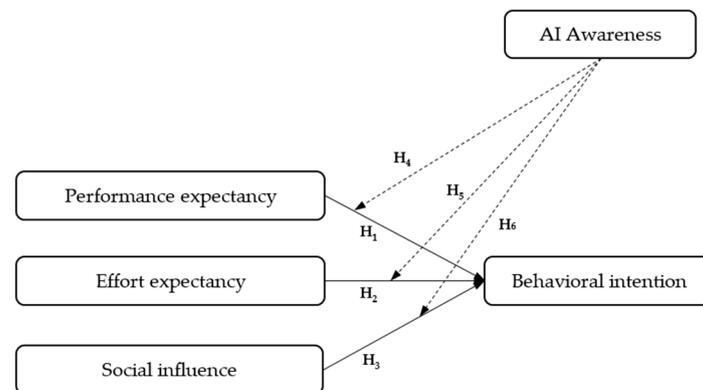


Figure 1. Conceptual model.

3. Research Methodology

The research was based on a convenience sample consisting of 356 undergraduate and master's students from the Autonomous Province of Vojvodina, Republic of Serbia. From the aspect of gender, more than 60% were female, with the mean age being around 22 years. A larger number of female respondents was expected, bearing in mind that, when it comes to the Vojvodina region, more female than male students enrolled in studies in each of the three consecutive years (2020/2021, 2021/2022, and 2022/2023) [52–54].

Regarding the sample size, the approach related to the minimum R^2 value was applied [55]. Hence, taking into account that there were three predictors of behavioral intention, the minimum sample size needed to detect an R^2 value of at least 0.25 (with a significance level of 5%) should be 37. Moreover, besides exceeding this threshold, the size of our sample met the criterion based on the “10 times rule”—it is greater than 30, i.e., 10 times the number of arrowheads (3) pointing at a dependent variable (behavioral intention) [55].

For collecting data, we used a questionnaire that did not include any sensitive issues that might be connected to respondents' integrity. The survey was anonymous, and respondents were also informed of that issue. The questionnaire was administered online, with professors from various faculties at the University of Novi Sad asking students to participate in a survey on a topic deemed important for the future of higher education. The research was conducted in 2024.

In addition to information related to the respondent's gender and age, the questionnaire included items for measuring model variables. Hereby, for measuring performance expectancy, we used five items (PE1, PE2, PE3, PE4, and PE5) adjusted from Venkatesh et al. [46], Chatterjee and Bhattacharjee [38], and Wu et al. [40]; for measuring effort expectancy, we used five items (EE1, EE2, EE3, EE4, and EE5) according to Venkatesh et al. [46] and Wu et al. [40]; for measuring social influence, we used five items (SI1, SI2, SI3, SI4, and SI5) according to Venkatesh et al. [46] and Wu et al. [40]; for measuring AI awareness, we used three items (AW1, AW2, and AW3) adjusted from Collins [47] and Raub and Blunschi [56]; and for measuring behavioral intention, we used three items adjusted from Venkatesh et al. [46]. It should be noted that all items were adapted to refer to artificial intelligence.

Each variable was modeled as a reflective construct (Figure 2). Due to their latent nature, for testing hypothesized relations, partial least squares structural equation modeling (PLS-SEM) was used. PLS-SEM is a type of SEM that refers to advanced statistical methods of a second generation, based on combining elements of regression and factor analysis; it is

particularly suitable for investigating latent variables (constructs) indirectly assessed by indicator variables [55].

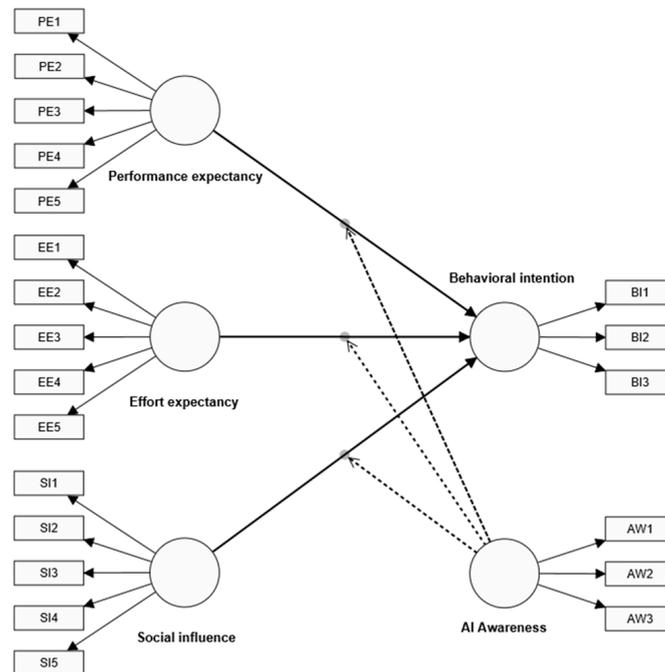


Figure 2. Statistical model.

When testing Hypotheses H1–H3, i.e., the direct-main effects of the three UTAUT predictors on behavioral intention, the moderator should be excluded from the model. “This is because the interpretation of the effect changes when a moderator is included in the model” [57] (p. 334). Hence, at first, we assessed the model without the moderator and estimated the reliability and validity of the reflective constructs by analyzing [55]:

- indicator reliability (by examining outer loadings),
- internal consistency reliability (by examining Cronbach’s α and composite reliability (CR)),
- convergent validity (by examining the average variance extracted (AVE)), and
- discriminant validity (by examining Fornell–Larcker and HTMT criterion).

Thereafter, we conducted a bootstrapping procedure and examined path coefficients, including the levels of their significance.

After that, the model was extended with the AI awareness construct, which was connected with the previously examined relations. The new model was also assessed relating to the constructs’ reliability and validity. Regarding moderating effects, i.e., Hypotheses H4–H6, we analyzed the level of significance and the f^2 effect size of the interaction terms, as well as the slope plots, by using graphical illustrations [55]. All analyses were conducted using SmartPLS4 software.

4. Results

Table 1 presents the quality criteria related to the base model consisting of four constructs (performance expectancy, effort expectancy, social influence, and behavioral intention) without the moderator (awareness). As can be seen, all obtained values are satisfactory—outer loadings for all items were higher than 0.70; values of AVE were higher than 0.50; and values of CR and Cronbach’s α for all four constructs were above 0.70.

Table 1. Indicator reliability, internal consistency reliability, and convergent validity.

Constructs and Items	Loadings	AVE	CR	Cronbach's α
Performance expectancy		0.700	0.921	0.893
PE1	0.841			
PE2	0.856			
PE3	0.838			
PE4	0.866			
PE5	0.780			
Effort expectancy		0.668	0.909	0.875
EE1	0.783			
EE2	0.754			
EE3	0.851			
EE4	0.846			
EE5	0.846			
Social influence		0.641	0.899	0.859
SI1	0.801			
SI2	0.729			
SI3	0.821			
SI4	0.854			
SI5	0.792			
Behavioral intention		0.920	0.972	0.956
BI1	0.967			
BI2	0.971			
BI3	0.939			

Discriminant validity was also established, as shown in Tables 2 and 3. Regarding the Fornell–Larcker criterion, the square root of each construct's AVE (presented on the diagonal) was greater than the correlations between constructs (presented in the corresponding row and column). In addition, all HTMT values were below the threshold value of 0.85.

Table 2. Fornell–Larcker criterion.

	BI	EE	PE	SI
Behavioral intention (BI)	0.959			
Effort expectancy (EE)	0.569	0.817		
Performance expectancy (PE)	0.694	0.593	0.837	
Social influence (SI)	0.457	0.379	0.400	0.800

Table 3. HTMT criterion.

	HTMT
Effort expectancy <-> Behavioral intention	0.620
Performance expectancy <-> Behavioral intention	0.747
Performance expectancy <-> Effort expectancy	0.665
Social influence <-> Behavioral intention	0.504
Social influence <-> Effort expectancy	0.437
Social influence <-> Performance expectancy	0.457

Figure 3 presents the main effects and p -values obtained after the bootstrapping procedure. All three predictors (performance expectancy, effort expectancy, and social influence) had a positive and significant impact on behavioral intention, confirming the first three hypotheses.

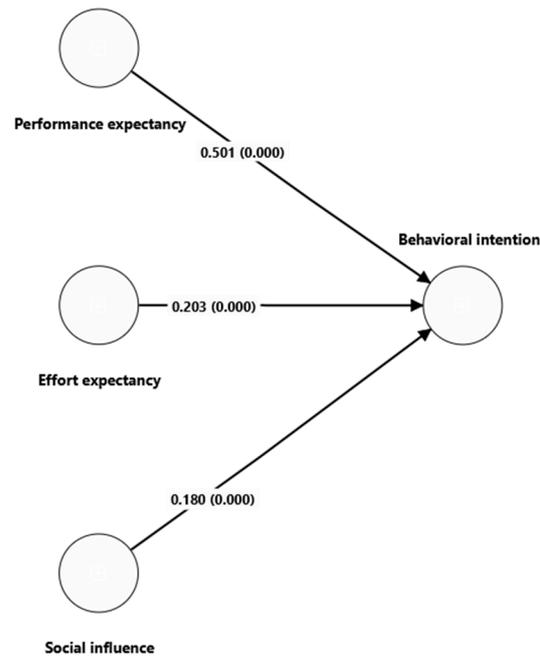


Figure 3. Model without moderator—main effects.

When it comes to multicollinearity, VIF values lower than 5 indicate no issues. Moreover, it should be noted that the R^2 value was 0.545, while the Q^2_{predict} value was above 0.

After assessing main-effect relations, we added AI awareness as a moderator. The extended model was then tested following previously used criteria. Since they were all satisfactory, the subject of the analysis was interaction terms. Their coefficients and significance levels are presented in Figure 4.

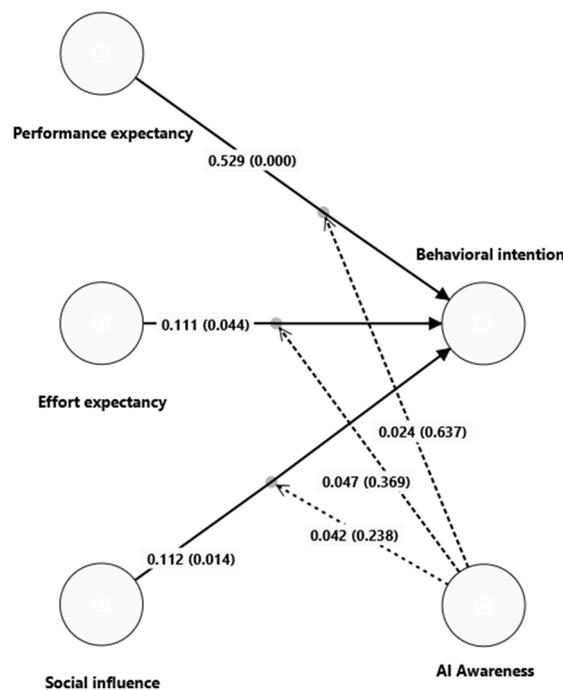


Figure 4. Model with the moderator—simple effects and interaction terms.

While coefficients presented in Figure 3 are named the main effects (when there is no moderator in the model), coefficients related to direct impacts of performance expectancy, effort expectancy, and social influence on behavioral intention, presented in Figure 4 (when a moderator is included in the model), are called simple effects [55]. They were positive, as were all three interaction effects. Thus, if the mean value of AI awareness increases by one standard deviation, relations between performance expectancy, effort expectancy, and social influence on one side and behavioral intention on the other would increase to values of 0.553 ($0.529 + 0.024$), 0.158 ($0.111 + 0.047$), and 0.154 ($0.112 + 0.042$), respectively.

However, opposite to simple effects, interaction effects had p -values higher than 0.05. In addition, none of them had an f^2 of 0.005 or higher, which is the lower bound for a weak effect size in moderation [57]. Slope plots presented in the following figures also confirm that there are no significant moderation effects regarding AI awareness—lines representing relations between performance expectancy and behavioral intention (Figure 5), effort expectancy and behavioral intention (Figure 6), and social influence and behavioral intention (Figure 7) at three levels of AI awareness (its mean, -1 standard deviation, $+1$ standard deviation) are almost parallel. Thus, Hypotheses H4–H6 were not supported.

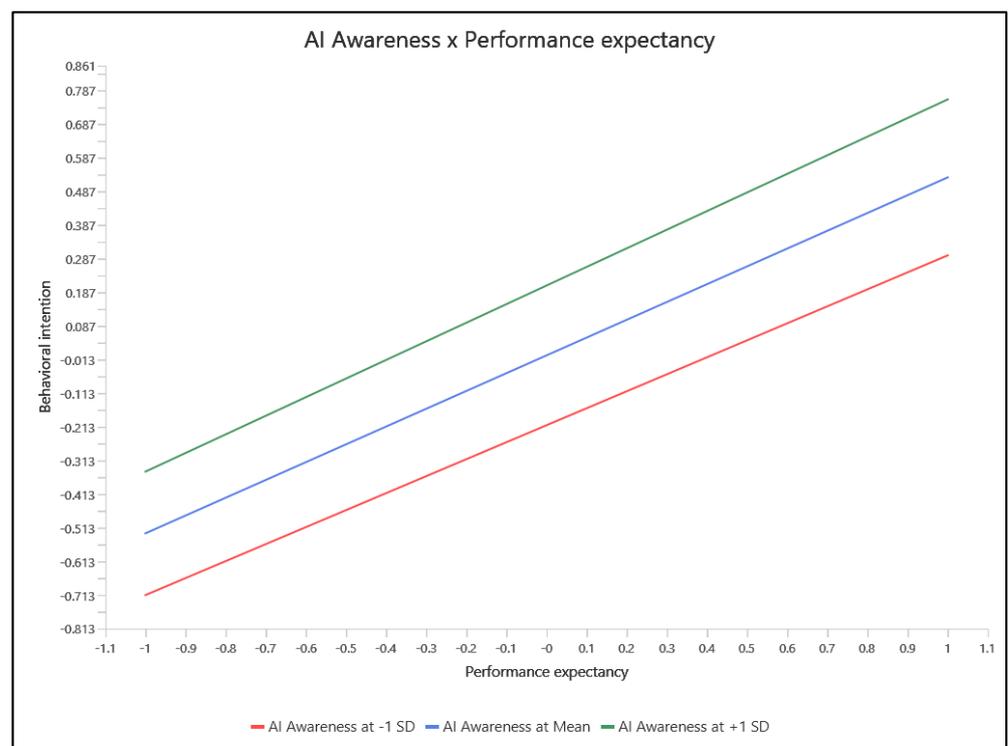


Figure 5. Slope plot—AI awareness \times performance expectancy.

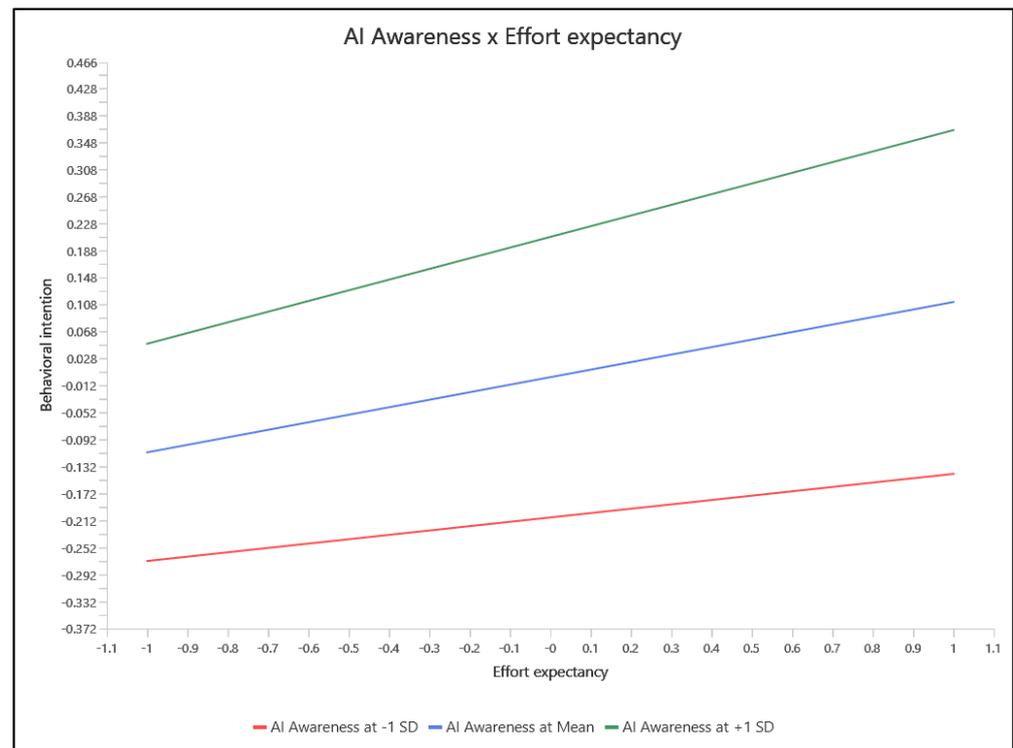


Figure 6. Slope plot—AI awareness \times effort expectancy.

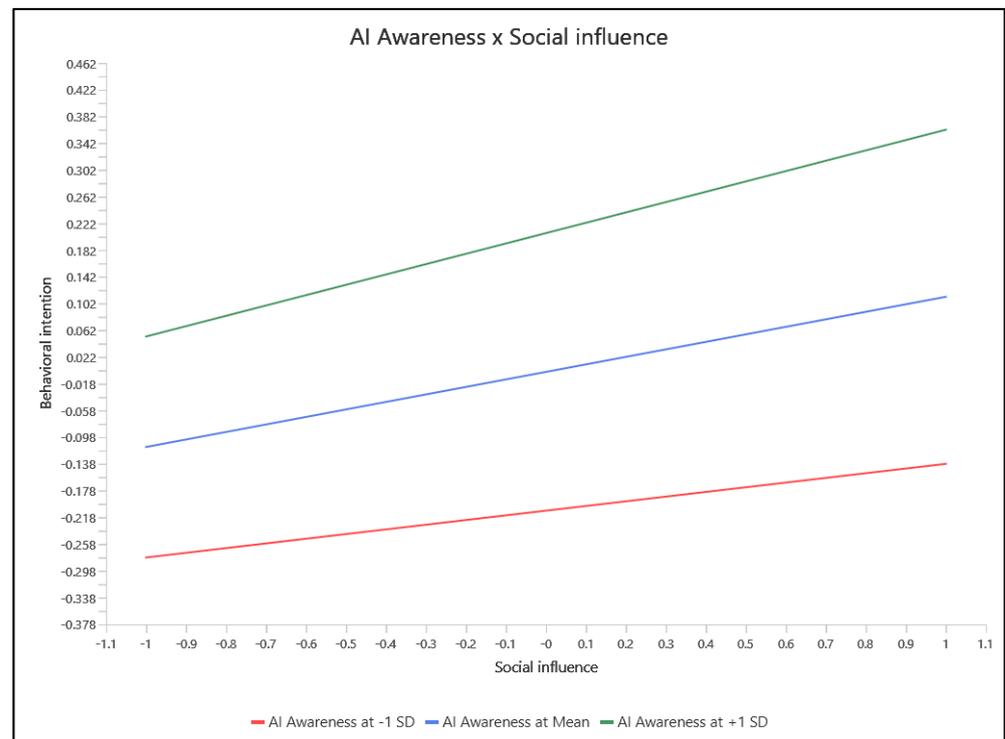


Figure 7. Slope plot—AI awareness \times social expectancy.

5. Discussion

The research results have shown that all three UTAUT predictors had positive and significant effects on students' behavioral intention to use AI in education. Among them, the largest coefficient was recorded in the case of performance expectancy. The positive effect of this variable on behavioral intention was also obtained in similar studies [39–41].

This relation implies that students perceived that their intention to use artificial intelligence mostly depends on its positive influence on their performance in education. In other words, students' intention is positively influenced by their perceptions that AI could increase their attention in class, improve their learning attitudes, and be useful for activities regarding the preparation of educational content, learning, and task accomplishment. These results can be understood as new insights into the previous research of Serbian students [58] (p. 18), according to which "AI and machine learning can help students develop customized learning skills and provide a collaborative learning environment".

The result related to the positive effect of effort expectancy on behavioral intention is consistent with the studies of Wu et al. [40] and Ragheb et al. [39]. Hence, students' intention toward AI is positively influenced by their level of ease in learning, understanding, and using artificial intelligence. So, it can be expected that students who are more skillful and find it easier to interact with AI technology will be more intent on using it in education. The results can also be treated as a confirmation of previous domestic students' research, according to which a learning environment being research-friendly is of great importance to them [59].

The positive impact of social influence on behavioral intention to use AI in education was in line with similar research [39,40]. This means that students' intention toward artificial intelligence significantly depends on the level of their perceptions that others believe they should use this type of technology. Influential groups may include fellow students, teachers, higher education institutions, and their management.

It can be added that previous research in Serbia also highlights that the positive potential outcomes of the use of AI in education are also perceived by the professors [60].

Although there were certain suggestions for using awareness as a moderator when it comes to relations between UTAUT predictors and behavioral intention [48,49], in this research, no moderating effect associated with AI awareness was significant.

6. Conclusions

Like in many other service sectors, education is also under the influence of various factors, including technological development. In the last few decades, the education sector has been affected by digital transformation, which can bring many improvements, not only management-related but also improvements associated with learning, teaching, assessment, and scientific activities [12]. Digitalization of education is based on the implementation of modern digital technologies, and it fosters the "development of knowledge" [9]. Among them, artificial intelligence has been particularly relevant in recent years. The application of its tools and platforms can influence different activities (such as learning, teaching, and assessment) by bringing benefits not only to students but to teachers as well. Some student-focused AI technologies are intelligent tutoring systems (ITS), automatic formative assessment, chatbots, etc. The application of artificial intelligence can be of great importance in achieving sustainable development goal 4, which is related to the provision of equal opportunities when it comes to learning. Also, it may induce green or environmental education and affect students' behavior in a way that they take care of the environment and use resources more efficiently.

Taking into account that the examination of students' perspectives represents an important step in implementing new procedures and solutions, their intention toward the use of artificial intelligence in education was analyzed by relying on the UTAUT model. Hereby, compared to similar AI studies based on the UTAUT approach, besides the main antecedents of behavioral intention, our model included AI awareness as a moderator. All three predictors (performance expectancy, effort expectancy, and social influence) positively and significantly influenced students' intention to use AI, whereby the largest coefficient was detected in the case of performance expectancy. Therefore, the acceptance of AI technology from the students' aspect greatly depends on their perceptions concerning the positive impact of AI on their performance and the level of ease of its use. Moreover, the influence of other people, including fellow students, teachers, and institution management,

was also relevant regarding behavioral intention toward AI. However, contrary to the main predictors, moderation concerning AI awareness was not confirmed.

Following the obtained results, i.e., students' perceptions, certain recommendations could be provided for educational institutions that plan to implement AI technology. Considering the positive effect of performance expectancy, the focus of those institutions should be on promoting the benefits of artificial intelligence and introducing its advantages to students in order to enhance their intention to use it. Additionally, to familiarize students with new AI tools and decrease the effort associated with their application, certain workshops and lectures can be held. Bearing in mind social influence, besides teachers, experts and students who already have significant experience in the field of AI could also participate in those events.

In addition to students' perspectives, other aspects related to the use of AI in education should be covered. Teachers, as important stakeholders, should also be introduced to the usage of AI technology. Hence, higher education institutions should motivate them to attend AI seminars and conferences, where they can learn about advantages, the way of use, and potential threats related to AI tools; nevertheless, educational institutions could organize their own events associated with the implementation of artificial intelligence in education. In this way, teachers would be prepared to use AI tools and to make it easier for students to apply this type of technology.

Adequate support for the process of digital transformation in education based on AI should be provided by policymakers. With their involvement on national, regional, and/or local levels, it would be much easier for educational institutions to develop and implement different AI projects, which may include connecting with other (domestic and/or foreign) institutions, the exchange of students and staff, etc. Moreover, policymakers may have an important role when it comes to the provision of financial support. This can come from different sources, including government grants, private donations, research funding, and partnerships with technology companies. Furthermore, it may involve funding research projects on AI applications in learning or providing grants for educational institutions to purchase AI software or tools, as well as offering training programs for educators to integrate AI technology into their teaching practices. In recent years, governments in countries such as the United States and the United Kingdom have been heavily investing in the development of technological instruments based on AI in classroom settings [61]. Also, there are various EU national strategies in terms of resource allocation, and most of them include packages of investment in AI initiatives through the National Fund [62]. These investments may be directed toward ongoing efforts (current investments) or plans (future investments). Likewise, with government support, policymakers could provide funding to local startups or research institutions that are focused on creating new AI tools or applications [63]. Therefore, it is essential to favor investments in AI technology in education to enable equitable access to high-quality learning opportunities and to have a competitive education system based on new technologies.

Hence, in future research, the emphasis could be put on the financial aspect of considering the application of AI in education. Moreover, other stakeholders (teachers, employees, and policymakers) could be included as well. From the aspect of the implemented model, moderation or mediation analysis could be added based on demographic factors, technological readiness, or institutional support.

Author Contributions: All of the authors formulated the goals of the research and interpreted available literature; conducting and analyzing research was performed by N.D., N.M. and B.K., while implications were developed by B.M., B.K. and I.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Provincial Secretariat for Higher Education and Scientific Research, AP Vojvodina, Republic of Serbia, in accordance with the project "Financial, marketing and management aspect of energy efficiency in the function of sustainable development of the AP Vojvodina"—a long-term project of special interest for sustainable development in AP Vojvodina 2021–2024. Project number: 142-451-3381/2023.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Prentice, G.; Brady, J.; McLaughlin, C. *Education Service Quality, Value and Satisfaction on Student Customer Intentions and Behaviour*; DBS Library Press: Dublin, Ireland, 2018.
2. Chawla, M. Customers' (students') perceptions about 7ps of higher education marketing mix. *Asian J. Multidiscip. Stud.* **2013**, *1*, 106–112. Available online: <https://core.ac.uk/download/pdf/229675328.pdf> (accessed on 13 January 2024).
3. Russell, M. Marketing education: A review of service quality perceptions among international students. *Int. J. Contemp. Hosp. Manag.* **2005**, *17*, 65–77. [[CrossRef](#)]
4. Faranda, W.T.; Clarke, T.B.; Clarke, I., III. Marketing student perceptions of academic program quality and relationships to surface, deep, and strategic learning approaches. *J. Mark. Educ.* **2021**, *43*, 9–24. [[CrossRef](#)]
5. Teo, T.; Zhou, M. Explaining the intention to use technology among university students: A structural equation modeling approach. *J. Comput. High. Educ.* **2014**, *26*, 124–142. [[CrossRef](#)]
6. Kaur, N.; Gopal, K. An assessment of students' intention of technology acceptance for online education. *J. Posit. Sch. Psychol.* **2022**, *6*, 4563–4577. Available online: <https://journalppw.com/index.php/jpsp/article/view/2127> (accessed on 15 January 2024.).
7. Boucher, P. Artificial Intelligence: How Does It Work, Why Does It Matter, and What Can We Do About It? In *European Parliamentary Research Service*; European Parliament: Brussels, Belgium, 2020; Available online: [https://www.europarl.europa.eu/RegData/etudes/STUD/2020/641547/EPRS_STU\(2020\)641547_EN.pdf](https://www.europarl.europa.eu/RegData/etudes/STUD/2020/641547/EPRS_STU(2020)641547_EN.pdf) (accessed on 18 January 2024.).
8. Sing, C.C.; Teo, T.; Huang, F.; Chiu, T.K.; Wei, W.X. Secondary school students' intentions to learn AI: Testing moderation effects of readiness, social good and optimism. *Educ. Technol. Res. Dev.* **2022**, *70*, 765–782. [[CrossRef](#)]
9. Klopov, I.; Shapurov, O.; Voronkova, V.; Nikitenko, V.; Oleksenko, R.; Khavina, I.; Chebakova, Y. Digital Transformation of Education Based on Artificial Intelligence. *TEM J.* **2023**, *12*, 2625–2634. [[CrossRef](#)]
10. Oliveira, K.K.S.; de Souza, R.A.C. Digital transformation towards education 4.0. *Inform. Educ.* **2022**, *21*, 283–309. [[CrossRef](#)]
11. McCarthy, A.M.; Maor, D.; McConney, A.; Cavanaugh, C. Digital transformation in education: Critical components for leaders of system change. *Soc. Sci. Humanit. Open* **2023**, *8*, 100479. [[CrossRef](#)]
12. Quy, V.K.; Thanh, B.T.; Chehri, A.; Linh, D.M.; Tuan, D.A. AI and digital transformation in higher education: Vision and approach of a specific university in Vietnam. *Sustainability* **2023**, *15*, 11093. [[CrossRef](#)]
13. Chassignol, M.; Khoroshavin, A.; Klimova, A.; Bilyatdinova, A. Artificial Intelligence trends in education: A narrative overview. *Procedia Comput. Sci.* **2018**, *136*, 16–24. [[CrossRef](#)]
14. Holmes, W.; Tuomi, I. State of the art and practice in AI in education. *Eur. J. Educ.* **2022**, *57*, 542–570. [[CrossRef](#)]
15. Rahiman, H.U.; Kodikal, R. Revolutionizing education: Artificial intelligence empowered learning in higher education. *Cogent Educ.* **2024**, *11*, 2293431. [[CrossRef](#)]
16. Pedró, F. *Artificial Intelligence in Education: Challenges and Opportunities for Sustainable Development*; UNESCO Education Sector: Paris, France, 2019.
17. Aggarwal, D. Green Education: A Sustainable Development Initiative with the Power of Artificial Intelligence (AI). *J. Image Process. Intell. Remote Sens.* **2023**, *3*, 39–44. [[CrossRef](#)]
18. Sohn, K.; Kwon, O. Technology acceptance theories and factors influencing artificial intelligence-based intelligent products. *Telemat. Inform.* **2020**, *47*, 101324. [[CrossRef](#)]
19. Huang, Y.-C. Integrated concepts of the UTAUT and TPB in virtual reality behavioral intention. *J. Retail. Consum. Serv.* **2023**, *70*, 103127. [[CrossRef](#)]
20. Kim, J.; Erdem, M.; Kim, B. Adoption of in-room voice assistants: A cross-cultural study. *J. Hosp. Tour. Insights* **2023**. ahead-of-print. [[CrossRef](#)]
21. Balakrishnan, J.; Abed, S.S.; Jones, P. The role of meta-UTAUT factors, perceived anthropomorphism, perceived intelligence, and social self-efficacy in chatbot-based services? *Technol. Forecast. Soc. Chang.* **2022**, *180*, 121629. [[CrossRef](#)]
22. Menon, D.; Shilpa, K. "Chatting with ChatGPT": Analyzing the factors influencing users' intention to Use the Open AI's ChatGPT using the UTAUT model. *Heliyon* **2023**, *9*, e20962. [[CrossRef](#)]
23. Chatterjee, S.; Rana, N.P.; Khorana, S.; Mikalef, P.; Sharma, A. Assessing Organizational Users' Intentions and Behavior to AI Integrated CRM Systems: A Meta-UTAUT Approach. *Inf. Syst. Front.* **2023**, *25*, 1299–1313. [[CrossRef](#)]
24. Kim, Y.J.; Choi, J.H.; Fotou, G.M.N. Medical professionals' adoption of AI-based medical devices: UTAUT model with trust mediation. *J. Open Innov. Technol. Mark. Complex.* **2024**, *10*, 100220. [[CrossRef](#)]
25. Horodyski, P. Recruiter's perception of artificial intelligence (AI)-based tools in recruitment. *Comput. Hum. Behav. Rep.* **2023**, *10*, 100298. [[CrossRef](#)]
26. Tanantong, T.; Wongras, P. A UTAUT-Based Framework for Analyzing Users' Intention to Adopt Artificial Intelligence in Human Resource Recruitment: A Case Study of Thailand. *Systems* **2024**, *12*, 28. [[CrossRef](#)]

27. Andrews, J.E.; Ward, H.; Yoon, J. UTAUT as a Model for Understanding Intention to Adopt AI and Related Technologies among Librarians. *J. Acad. Librariansh.* **2021**, *47*, 102437. [CrossRef]
28. Cao, G.; Duan, Y.; Edwards, J.S.; Dwivedi, Y.K. Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. *Technovation* **2021**, *106*, 102312. [CrossRef]
29. Ferri, L.; Maffei, M.; Spanó, R.; Zagaria, C. Uncovering risk professionals' intentions to use artificial intelligence: Empirical evidence from the Italian setting. *Manag. Decis.* **2023**. ahead-of-print. [CrossRef]
30. Loske, D.; Klumpp, M. Intelligent and efficient? An empirical analysis of human–AI collaboration for truck drivers in retail logistics. *Int. J. Logist. Manag.* **2021**, *32*, 1356–1383. [CrossRef]
31. Chai, C.S.; Wang, X.; Xu, C. An Extended Theory of Planned Behavior for the Modelling of Chinese Secondary School Students' Intention to Learn Artificial Intelligence. *Mathematics* **2020**, *8*, 2089. [CrossRef]
32. Chai, C.S.; Chiu, T.K.; Wang, X.; Jiang, F.; Lin, X.F. Modeling Chinese Secondary School Students' Behavioral Intentions to Learn Artificial Intelligence with the Theory of Planned Behavior and Self-Determination Theory. *Sustainability* **2023**, *15*, 605. [CrossRef]
33. Ayanwale, M.A. Evidence from Lesotho Secondary Schools on Students' Intention to Engage in Artificial Intelligence Learning. In Proceedings of the 2023 IEEE AFRICON, Nairobi, Kenya, 20–22 September 2023; pp. 1–6. [CrossRef]
34. Wang, F.; King, R.B.; Chai, C.S.; Zhou, Y. University students' intentions to learn artificial intelligence: The roles of supportive environments and expectancy–value beliefs. *Int. J. Educ. Technol. High. Educ.* **2023**, *20*, 51. [CrossRef]
35. Ayanwale, M.A.; Sanusi, I.T.; Adelana, O.P.; Aruleba, K.D.; Oyelere, S.S. Teachers' readiness and intention to teach artificial intelligence in schools. *Comput. Educ. Artif. Intell.* **2022**, *3*, 100099. [CrossRef]
36. Sanusi, I.T.; Ayanwale, M.A.; Chiu, T.K.F. Investigating the moderating effects of social good and confidence on teachers' intention to prepare school students for artificial intelligence education. *Educ. Inf. Technol.* **2024**, *29*, 273–295. [CrossRef]
37. Alzahrani, L. Analyzing Students' Attitudes and Behavior toward Artificial Intelligence Technologies in Higher Education. *Int. J. Recent Technol. Eng.* **2023**, *11*, 65–73. [CrossRef]
38. Chatterjee, S.; Bhattacharjee, K.K. Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. *Educ. Inf. Technol.* **2020**, *25*, 3443–3463. [CrossRef]
39. Ragheb, M.A.; Tantawi, P.; Farouk, N.; Hatata, A. Investigating the acceptance of applying chat-bot (Artificial intelligence) technology among higher education students in Egypt. *Int. J. High. Educ. Manag.* **2022**, *8*, 1–13. [CrossRef]
40. Wu, W.; Zhang, B.; Li, S.; Liu, H. Exploring Factors of the Willingness to Accept AI-Assisted Learning Environments: An Empirical Investigation Based on the UTAUT Model and Perceived Risk Theory. *Front. Psychol.* **2022**, *13*, 870777. [CrossRef] [PubMed]
41. Romero-Rodríguez, J.M.; Ramírez-Montoya, M.S.; Buenestado-Fernández, M.; Lara-Lara, F. Use of ChatGPT at university as a tool for complex thinking: Students' perceived usefulness. *J. New Approaches Educ. Res.* **2023**, *12*, 323–339. [CrossRef]
42. Yu, S. A Research on University Students' Behavioral Intention to use New-generation Information Technology in Intelligent Foreign Language Learning. *ACM Trans. Asian Low-Resour. Lang. Inf. Process.* **2022**, in press. [CrossRef]
43. Le Dang, H. An analysis of the factors affecting intention to use artificial intelligence technology in learning: A case study of Hanoi students. *AJMI-ASEAN J. Manag. Innov.* **2020**, *7*, 1–16. Available online: <https://ajmi.stamford.edu/index.php/ajmi/article/view/183> (accessed on 13 January 2024).
44. Buabbas, A.J.; Miskin, B.; Alnaqi, A.A.; Ayed, A.K.; Shehab, A.A.; Syed-Abdul, S.; Uddin, M. Investigating Students' Perceptions towards Artificial Intelligence in Medical Education. *Healthcare* **2023**, *11*, 1298. [CrossRef]
45. Almaraz-López, C.; Almaraz-Menéndez, F.; López-Esteban, C. Comparative Study of the Attitudes and Perceptions of University Students in Business Administration and Management and in Education toward Artificial Intelligence. *Educ. Sci.* **2023**, *13*, 609. [CrossRef]
46. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. User acceptance of information technology: Toward a unified view. *MIS Q.* **2003**, *27*, 425–478. [CrossRef]
47. Collins, C.J. The interactive effects of recruitment practices and product awareness on job seekers' employer knowledge and application behaviors. *J. Appl. Psychol.* **2007**, *92*, 180–190. [CrossRef]
48. Abubakar, F.M.; Ahmad, H.B. The moderating effect of technology awareness on the relationship between UTAUT constructs and behavioural intention to use technology: A conceptual paper. *Aust. J. Bus. Manag. Res.* **2013**, *3*, 14–23. [CrossRef]
49. Abubakar, F.M.; Ahmad, H.B. Empirical Investigation of Moderating Effect of Technology Awareness in UTAUT. *Niger. J. Manag. Technol. Dev.* **2015**, *1*, 109–134.
50. Daniali, S.M.; Barykin, S.E.; Zendehdel, M.; Kalinina, O.V.; Kulibanova, V.V.; Teor, T.R.; Ilyina, I.A.; Alekseeva, N.S.; Lisin, A.; Moiseev, N.; et al. Exploring UTAUT Model in Mobile 4.5 G Service: Moderating Social–Economic Effects of Gender and Awareness. *Soc. Sci.* **2022**, *11*, 187. [CrossRef]
51. Al-Azizi, L.; Al-Badi, A.H.; Al-Zrafi, T. Exploring the factors influencing employees' willingness to use mobile applications in Oman: Using UTAUT model. *J. E-Gov. Stud. Best Pract.* **2018**, *2018*, 553293. Available online: <https://ibimapublishing.com/articles/JEGSBP/2018/553293/553293.pdf> (accessed on 19 January 2024). [CrossRef]
52. Statistical Office of the Republic of Serbia. *Statistical Yearbook of the Republic of Serbia*; Statistical Office of the Republic of Serbia: Belgrade, Serbia, 2021. Available online: <https://publikacije.stat.gov.rs/G2021/Pdfe/G20212054.pdf> (accessed on 19 January 2024).
53. Statistical Office of the Republic of Serbia. *Statistical Yearbook of the Republic of Serbia*; Statistical Office of the Republic of Serbia: Belgrade, Serbia, 2022. Available online: <https://publikacije.stat.gov.rs/G2022/pdf/G20222055.pdf> (accessed on 19 January 2024).

54. Statistical Office of the Republic of Serbia. *Statistical Yearbook of the Republic of Serbia*; Statistical Office of the Republic of Serbia: Belgrade, Serbia, 2023. Available online: <https://publikacije.stat.gov.rs/G2023/Pdf/G20232056.pdf> (accessed on 19 January 2024).
55. Hair, J.F.; Hult, G.T.M.; Ringle, C.M.; Sarstedt, M. *A Primer on Partial Least Squares Structural Equation Modeling*; Sage: Thousand Oaks, CA, USA, 2017.
56. Raub, S.; Blunschi, S. The power of meaningful work: How awareness of CSR initiatives fosters task significance and positive work outcomes in service employees. *Cornell Hosp. Q.* **2014**, *55*, 10–18. [[CrossRef](#)]
57. Becker, J.-M.; Cheah, J.-H.; Gholamzade, R.; Ringle, C.M.; Sarstedt, M. PLS-SEM's most wanted guidance. *Int. J. Contemp. Hosp. Manag.* **2023**, *35*, 321–346. [[CrossRef](#)]
58. Ilić, M.P.; Păun, D.; Popović Šević, N.; Hadžić, A.; Jianu, A. Needs and Performance Analysis for Changes in Higher Education and Implementation of Artificial Intelligence, Machine Learning, and Extended Reality. *Educ. Sci.* **2021**, *11*, 568. [[CrossRef](#)]
59. Kuleto, V.; Ilić, M.; Dumangiu, M.; Ranković, M.; Martins, O.M.D.; Păun, D.; Mihoreanu, L. Exploring Opportunities and Challenges of Artificial Intelligence and Machine Learning in Higher Education Institutions. *Sustainability* **2021**, *13*, 10424. [[CrossRef](#)]
60. Bucea-Manea-Toniș, R.; Kuleto, V.; Gudei, S.C.D.; Lianu, C.; Lianu, C.; Ilić, M.P.; Păun, D. Artificial Intelligence Potential in Higher Education Institutions Enhanced Learning Environment in Romania and Serbia. *Sustainability* **2022**, *14*, 5842. [[CrossRef](#)]
61. Chen, X.; Xie, H.; Hwang, G.-J. A multi-perspective study on Artificial Intelligence in Education: Grants, conferences, journals, software tools, institutions, and researchers. *Comput. Educ. Artif. Intell.* **2020**, *1*, 100005.
62. Foffano, F.; Scantamburlo, T.; Cortés, A. Investing in AI for social good: An analysis of European national strategies. *AI Soc.* **2023**, *38*, 479–500. [[CrossRef](#)]
63. Chan, C.K.Y. A comprehensive AI policy education framework for university teaching and learning. *Int. J. Educ. Technol. High. Educ.* **2023**, *20*, 38. [[CrossRef](#)]

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