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Article

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Amfiteatru Economic

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The Bucharest University of Economic Studies

Suggested Citation: Djokic, Ines; Milićević, Nikola; Djokic, Nenad; Malcic, Borka; Kalas, Branimir (2024) : Students' perceptions of the use of artificial intelligence in educational services, Amfiteatru Economic, ISSN 2247-9104, The Bucharest University of Economic Studies, Bucharest, Vol. 26, Iss. 65, pp. 294-310,
<https://doi.org/10.24818/EA/2024/65/294>

This Version is available at:

<https://hdl.handle.net/10419/281822>

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STUDENTS' PERCEPTIONS OF THE USE OF ARTIFICIAL INTELLIGENCE IN EDUCATIONAL SERVICES

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Please cite this article as:

Djokic, I., Milicevic, N., Djokic, N., Malcic, B. and Kalas, B., 2024. Students' Perceptions of the Use of Artificial Intelligence in Educational Services. *Amfiteatru Economic*, 26(65), pp. 294-310.

DOI: <https://doi.org/10.24818/EA/2024/65/294>

Article History

Received: 25 September 2023

Revised: 20 November 2023

Accepted: 13 December 2023

Abstract

The increased significance of artificial intelligence (AI) and the possibilities to implement it in higher education can be identified in contemporary conditions. At the same time, one cannot neglect the importance of student perceptions regarding it, since they represent the final users of educational services. Therefore, the focus of this study was on the implementation of the already developed Student Conceptions of AI in Education Scale (SCAIES) instrument on a sample of Serbian students. It is the first implementation of that eight-factor instrument modelled as a reflective-formative hierarchical construct which can be considered as its main contribution from the theoretical aspect. Thus, all eight factors positively and significantly formed the use of AI in education (UAIED) from students' perspective, whereas the largest contribution could be attributed to factors arising from weaknesses of traditional education, i.e. sentiment analysis in education, personalised learning and student performance prediction. On the other hand, the lowest contribution could be attributed to factors that could be related to privacy concerns about AI use and the domain of control, concretely, classroom monitoring and visual analysis, and students' grade and evaluation. Some general recommendations for higher education institutions were also provided.

Keywords: Artificial intelligence, education, students, perceptions, services.

JEL Classification: M31, I20

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Introduction

Taking into account the great progress in computing power, increasingly sophisticated algorithms, and the possibility of processing a large amount of data, artificial intelligence represents a new level of technological and scientific development that will have a huge impact on the way the world functions as we know it (Gasmi and Prlja, 2021, p. 324). According to Pelau, Ene and Pop (2021, p. 33), it can be considered as “one of the main paradigms of the contemporary society”. Regardless of whether people are aware of AI’s omnipresence or not, it is already a component of daily lives and, at least, it is changing the way people live (Jeffrey, 2020).

When it comes to AI history, it should be mentioned that the ideas of automation of human life have appeared throughout history, starting from the ancient period (for example, the protection of Crete with bronze robot Talos) (van der Vorst and Jelcic, 2019). However, the term artificial intelligence was first introduced by John McCarthy, an emeritus professor at Stanford, in 1955, who defined it as “the science and engineering of making intelligent machines” (Manning, 2020). From its inception until today, AI technology developed, although with certain issues in the 1970s (during the Cold War), and the 1990s (due to the use of hand-crafted rules in the expert systems), which were successfully overcome (van der Vorst and Jelcic, 2019).

A common definition of AI is one in which it is associated with a computer system capable of performing tasks usually related to intelligent beings (European Commission Joint Research Centre, 2018). It is similar to the definition of the European Commission, according to which AI relates to systems that present intelligent behaviour through the analysis of the environment and performing an action, with certain autonomy, so that the specific task can be achieved (Boucher, 2020). For Buabbas et al. (2023, p. 1) AI “simply means making machines capable of simulating intelligence by giving computer human-like capabilities, such as understanding, reasoning, and problem solving”.

There are different types of AI technology. Following the European Commission, Joint Research Centre (2018), AI can be explained through three alternative approaches based on data, logic, and knowledge. The first approach depends mainly on data and its availability, and in biological terminology, these systems could be called “datavores”. The other two approaches are set on a cognitive level, whereas logic-based AI deals with problem-solving processes, and knowledge-based AI implements simple models of inference, claiming that knowledge is more required than logic for effective decision making. Additionally, AI can be classified as narrow, general, and Artificial Superintelligence (Marrone, Taddeo and Hill, 2022). The most common is narrow AI, which applies machine learning to accomplish a certain goal. General AI is considered to be a match for humans, whereas artificial superintelligence surpasses them.

Education is one of the many sectors that has come under the influence of artificial intelligence. The significance of higher education belonging to that sector is widely recognised since “Universities are the main sources of highly qualified workforce and “knowledge”” and are “being instrumental in the development of societies and economies based on knowledge” (Dinu, 2011, p. 343). To understand and improve the application of AI technology for educational purposes, Artificial Intelligence in Education (AIED) has been drawing the attention of the scientific community for a couple of decades (Chen et al., 2020). The research subjects were the different aspects of AIED, including the perspectives of

teachers (Sangapu, 2018; Pisica et al., 2023) and students (Sangapu, 2018; Kuleto et al., 2021; Cheng et al., 2023; Idroes et al., 2023) as well.

In this paper, the focus was on students' perceptions of AI applications in the educational process. This population was selected in mind that they are the main users of educational services. Following the service-dominant logic approach and co-creation, students can be identified even as customers, hereby, as active participants and co-creators of services, they should be put in a central place of a value creation process (Bowden, 2011). According to Celuch and Robinson (2016), for whom higher education represents a "unique experiential service", student involvement occurs in the academic domain and also in the total educational experience as well; therefore, the process of creating value in the delivery of educational service requires a better understanding of the relations between students and the institution. Since AI technology has the potential to influence the student experience (Barrett et al., 2019), with a better understanding of student aspects, the implementation of AI in education could be facilitated and adjusted to their needs. Therefore, after presenting some main features related to AIEd, attention was paid to research that included students. Therefore, the eight-factor model was applied. It was based on an instrument that measures the use of AI in education (UAIEd), developed by Cheng et al. (2023). The use of an already developed instrument in the new context imposed several research questions. First, there was a need to determine the relations of constructs within the model and conclude to which type of hierarchical model it belonged. Second, the instrument needed to be tested for application in the new cultural context. In addition, there were research questions that emerged from additional theoretical and practical considerations. The third research question was related to the comparison of the results obtained with previous research from abroad and Serbia. Finally, there was a need to provide general recommendations (based on research findings) to higher education institutions.

To the authors' knowledge, this is the first paper that applied the mentioned model, particularly considering the way it was designed by using the reflective-formative approach. This can be understood as a main theoretical contribution of the paper. Not only did we apply the developed instrument for the first time in the new context, but we also paid attention to its specification. It is of the great importance since "measurement model misspecification severely biases structural parameter estimates and can lead to inappropriate conclusions about hypothesised relationships between constructs" (Jarvis, MacKenzie and Podsakoff, 2003, p. 216). The results obtained were followed by a discussion and conclusion section providing their consideration from the aspect of previous research, the cultural context in which the research was conducted, and consequential recommendations.

1. The use of artificial intelligence in education

Like in many other areas, artificial intelligence has been applied in education, which has been influenced by various factors and changes over the last few decades. Financial pressures on universities associated with the increased number of students and larger staff and operating costs, partly caused by the democratisation of higher education, make the use of AI technology very attractive (Popenici and Kerr, 2017). The importance of applying artificial intelligence in the educational sector was especially emphasised due to the COVID-19 pandemic, which resulted in a shift from traditional classroom teaching to a digital form of learning (Maqbool, Ansari and Otero, 2021; Pantelimon et al., 2021; Mijwil et al., 2022).

Using the methodology of writing narrative overviews, Chassignol et al. (2018) considered the following main educational areas that could be influenced by artificial intelligence content and teaching, assessment, and communication.

When it comes to content and teaching, the application of AI can contribute to its customisation. Taking into account the heterogeneity among students, a better understanding of their learning requirements is necessary and therefore the educational content to be personalised to their needs (Bhutoria, 2022). As an alternative to a traditional concept, personalised learning can be defined as an “approach in which teaching is customised according to the needs and abilities of an individual student” (Magomadov, 2020, p. 1). There are the so-called intelligent tutoring systems (ITS) that can offer step-by-step tutorials adjusted to each individual student; some of them are Spark, developed by Domoscio, and Gooru Navigator, known as Google Maps for learning (Holmes and Tuomi, 2022). When talking about personalised education, a special place belongs to the Watson Education Classroom, developed by IBM, which can help teachers gain deeper insight into the learning process and the ability of each student (European Commission Joint Research Centre., 2018). To increase the quality of education, personalised learning methods can be used in conjunction with certain gamification techniques and elements, particularly those associated with leaderboards and points (Chassignol et al., 2018). Digital games-based learning, Augmented Reality (AR) and Virtual Reality (VR) simulations can be applied for educational purposes as well (Holmes and Tuomi, 2022). Potentially, with the use of artificial intelligence, every student could have her/his own personalised learning companion, which besides the roles of a learning partner, guide, and instructor, would continuously record the student's improvements and interests (Holmes, Bialik and Fadel, 2019).

The potential benefits of personalised learning are numerous. Not only can its models reduce student dropout rates and support the learning process, but they can also help to achieve sustainable development goals (SDGs) presented by the UN General Assembly, such as those related to ensuring equal quality education for all (SDG4) and reducing inequalities between online and on-site approaches with special emphasis on students with disabilities (SDG 10) (Furini et al. 2022). However, there is a criticism of personalised learning, according to which this technology is redundant for meaningful learning and highly motivated students, who obtain all the necessary information by themselves (Chassignol et al., 2018).

Another area of education that was affected by artificial intelligence relates to student assessment. The development of AI technology has enabled partial or full automation of assessment practice, whereby it can be used for generating tasks, identifying adequate peers for grading, and automatically scoring student work (Swiecki et al. 2022). For example, there are systems called autograders, usually applied for the assessment of written tasks, and in mathematics and computer sciences, that are capable not only of scoring students' answers but also of diagnosing the type of error and suggesting its correction (Holmes and Tuomi, 2022). Chassignol et al. (2018) point to ITS which besides tutoring, can help in identifying learning gaps in students' works. Hereby, the models created by ITS and used for grading students' performance are based on the rules derived from previous teacher's evaluations of a sample set of students. The comparative study of Hooda et al. (2022) showed that among various artificial intelligence, machine learning, and learning analytics techniques for the assessment and provision of feedback to students, the Improved Fully Connected Network (I-FCN) had the highest performance in accuracy, precision, recall rate, and F1-score.

The use of AI can facilitate the assessment process for teachers by saving their time and effort (Holmes and Tuomi, 2022). Its techniques, such as electronic assessment platforms (EAPs) and stealth assessment, can provide continuous tracking of students' performance, while computerised adaptive testing systems (CATs) enable adjusting tasks according to students' abilities, rather than offering the same questions to all students (Swiecki et al., 2022). Despite the mentioned benefits, it should be noted that the application of AI in the assessment process related to automatic scoring, especially in the case of high-stakes testing, represents "one of the two high-risk use cases in the proposed EU AI Act, and so would be regulated by its provisions" (Holmes and Tuomi, 2022, p. 556).

AI technology influenced the area of communication in the educational process, with a focus on providing adequate feedback to students (Chassignol et al., 2018). According to Wongvorachan et al. (2022, p. 95), feedback represents „a crucial component of student learning“ that enhances the level of their understanding. Communication between teachers and students is especially important under online conditions, despite the fact that this type of interaction significantly affects student satisfaction and performance in the learning process (Seo et al., 2021). Among AI technologies that may affect this communication are, already mentioned, ITS and CATs (Wongvorachan et al., 2022). Seo et al. (2021) gave an example of an AI teaching assistant called "Jill Watson" that can improve teacher-student communication by providing autonomous responses, announcements and answers to common questions. There is also an example of the network orchestrator named "Open Tutor", which enables students to connect with other human tutors via an OT mobile app, to better understand certain topics (Holmes and Tuomi, 2022). In addition, AI techniques can be used for collaborative learning, i.e., an educational approach that includes communication, and working in a team to realise set tasks (Tan, Lee and Lee, 2022; Ramadevi et al., 2023).

The benefits of applying AI techniques in the process of communication can be reflected in the improvement of both its quantity and quality, through the efficient provision of feedback and just-in-time support to students at scale with minimal space and time barriers and with the possibility of processing a large amount of educational data (Seo et al., 2021; Wongvorachan et al., 2022). However, the research of Seo et al. (2021) revealed the existence of concerns among students and teachers that AI systems may result in responsibility, agency, and surveillance problems.

As the use of AI can have many implications for almost all stakeholders in the educational process, including both advantages and disadvantages, an important area of its implementation refers to the ethical question (Holmes and Tuomi, 2022). Thus, the focus should be on the protection of human rights (Holmes and Tuomi, 2022), the control of AI developments (Popenici and Kerr, 2017), the responsibility of AI actions, their creators and operators (Pisica et al., 2023), the digital divide and power relations between teachers, students, and AI technology (Hwang et al., 2020).

2. Student perceptions of artificial intelligence

In a number of investigations, artificial intelligence was analysed in the context of students. Among them are those in which the emphasis was on students' perceptions of AI, including their attitudes, beliefs, and/or fears. Such was the research of Gherheş and Obrad (2018), which involved undergraduate students. According to the results obtained, the majority of them believed that they had a below-average level of information about AI. A significant

number of respondents had a positive attitude towards the development of artificial intelligence, and more than half of them believed that it will positively affect society. On the other hand, the probability of humankind being destroyed by intelligent devices and the disappearance of workplaces were the greatest fears associated with the emergence of AI.

A general positive perception of college students regarding artificial intelligence was also found in the study by Jeffrey (2020). When it comes to the level of understanding of the meaning of AI by the student and information about its current development, the largest number of respondents fell in the moderately high and moderately low range, respectively. Furthermore, the research findings indicated the existence of both affirmative beliefs related to the positive impacts of AI on society and well-being and concerns related to the rapid developments in AI, replacing human jobs and surpassing human intelligence. Thus, it was proven that those perceptions were affected by the student's level of information about AI.

The focus of some studies was students' AI learning intention. Wang et al. (2022) examined this variable in the context of AI anxieties (learning and job replacement), learning motivations (intrinsic and extrinsic), and learning self-efficacy, taking university students as participants. In addition to the positive impacts of learning self-efficacy and learning motivations on AI learning intention, this research highlighted the importance of AI anxieties, especially the learning one, which negatively influenced the two motivation variables. Besides university students, the intention or readiness to learn AI was analysed among secondary school students (Chai, Wang and Xu, 2020) and elementary school students (Dai et al., 2020).

There are studies that examined artificial intelligence from the point of view of students with special reference to the educational process. Students' perception regarding the use of artificial intelligence in education was examined in the research of Idroes et al. (2023). The results of their survey conducted among undergraduate students pointed to the existence of a generally positive perception of the usefulness of artificial intelligence in education. Furthermore, the perceived advantages and disadvantages of AI in education were analysed. In terms of the teaching process, the main advantage perceived by the students was the virtual assistant. In the case of learning, the most important advantage was universal access, while when considering the evaluation process, most students identified constant feedback as the main benefit. The main disadvantage of AI in the educational process was found to be the lack of a relationship between students and their teachers.

To develop an instrument to evaluate undergraduate students' conceptions of artificial intelligence in education, Cheng et al. (2023) conducted a study that resulted in eight AI factors: intelligent tutoring system (AI1) – the use of AI to offer learning experiences to students in the appropriate time and place; student grading and evaluation (AI2) – the use of AI to grade and evaluate student performance; students' retention and dropout of students (AI3) – the application of AI in developing intervention and warning systems intended for at-risk students so that adequate support could be provided in a timely manner; sentiment analysis in education (AI4) – the application of AI techniques to detect student opinions (negative and positive) concerning their learning experiences; recommendation systems (AI5) – the use of AI in making helpful suggestions to students; classroom monitoring and visual analysis (AI6) – the application of AI in assessing students' face-to-face class attendance with the emphasis on their emotions and engagement; personalised learning (AI7) – the use of AI technologies, usually based on learner data, in creating learner profiles that can be applied for providing timely learning support, curricular pathways and feedbacks; and

student performance prediction (AI8) – the application of AI models in anticipating students' future performance. Based on these factors, the Student Conceptions of AI in Education Scale (SCAIES) was developed.

Kuleto et al. (2021) paid attention to artificial intelligence and machine learning (ML) taking into account their opportunities and challenges in higher education institutions (HEI). In addition to content analysis, they implemented the survey among students; the results of the regression model have shown that the enhancement of personalised learning driven by AI and ML can be performed through the development of student skills, the provision of a collaborative learning environment in the HEI, and the development of an accessible research environment.

The study by Sangapu (2018) explored the students' and teachers' perceptions of AI use in the classroom, relying on online surveys. When it comes to students, half of the respondents perceived artificial intelligence as useful, while the lowest percent of them felt that it was harmful. Approximately two-thirds of the students had a positive perception of the teaching pattern in which a teacher uses AI as a support, while nearly eighty percent of them had negative responses about the complete replacement of teachers by robots. More than 50% of the students received positive feedback that the use of AI by teachers would improve their teaching performance. On the other hand, more than half of them thought that it was not possible for robot classrooms without teachers to fill the gaps in teaching performance.

3. Research methodology

When analysing the use of AI in education (UAIEd) from the perspective of students, eight factors proposed by Cheng et al. (2023) were considered. Bearing in mind that the mentioned factors represent latent phenomena, partial least squares structural equation modelling (PLS-SEM, also known as PLS path modelling (Hair et al., 2017, p. 31)) was applied. Following Hair et al. (2017), SEM refers to second-generation advanced statistical techniques, which use can help overcome the weaknesses of first-generation techniques (such as logistic regression, multiple regression, and cluster analysis). Representing a combination of regression and factor analysis, SEM is suitable for examining unobservable variables (constructs) indirectly measured by one or more manifest variables (indicators) (Hair et al., 2017). Moreover, PLS-SEM enables the analyses of hierarchical (higher-order) constructs, which implementation leads to better theoretical parsimony and the reduction of model complexity (Becker, Klein and Wetzels, 2012). Hereby, the UAIEd was presented as a multidimensional latent variable that was modelled as a hierarchical construct. When it comes to the construct mode (Crocetta et al., 2021), the AI factors were set as reflective lower-order dimensions, while UAIEd was set as a formative higher-order construct, that is, it was “formed” by AI factors. The relations of the items with corresponding dimensions can be considered as reflective in accordance to Jarvis, MacKenzie and Podsakoff (2003) since those items are actually manifestations of the dimension and changes in them should not cause changes in the dimensions (but opposite); the items have similar content/share a common theme and dropping one of them should not alter the conceptual domain of the dimension; finally, a change in one of the items is associated with changes in another and they have the same antecedents and consequences. On the other hand, the relations of the dimensions of their underlying higher-order construct correspond to formative relations (as suggested by Jarvis, MacKenzie and Podsakoff, 2003). Concretely, those dimensions are defining characteristics of the construct and changes in them cause changes in it (not

opposite); those dimensions do not have similar content, nor share a common theme, and dropping one of the dimensions will alter the conceptual domain of the construct; dimensions do not necessarily covary, nor have the same antecedents and consequences. This type of hierarchical model is very popular among researchers in regard to the application of partial least squares structural path modelling (Cheah et al., 2019).

Figure 1 presents the research model. The meaning of abbreviations and the source of the corresponding items can be seen in this section of the paper when the instrument was described.

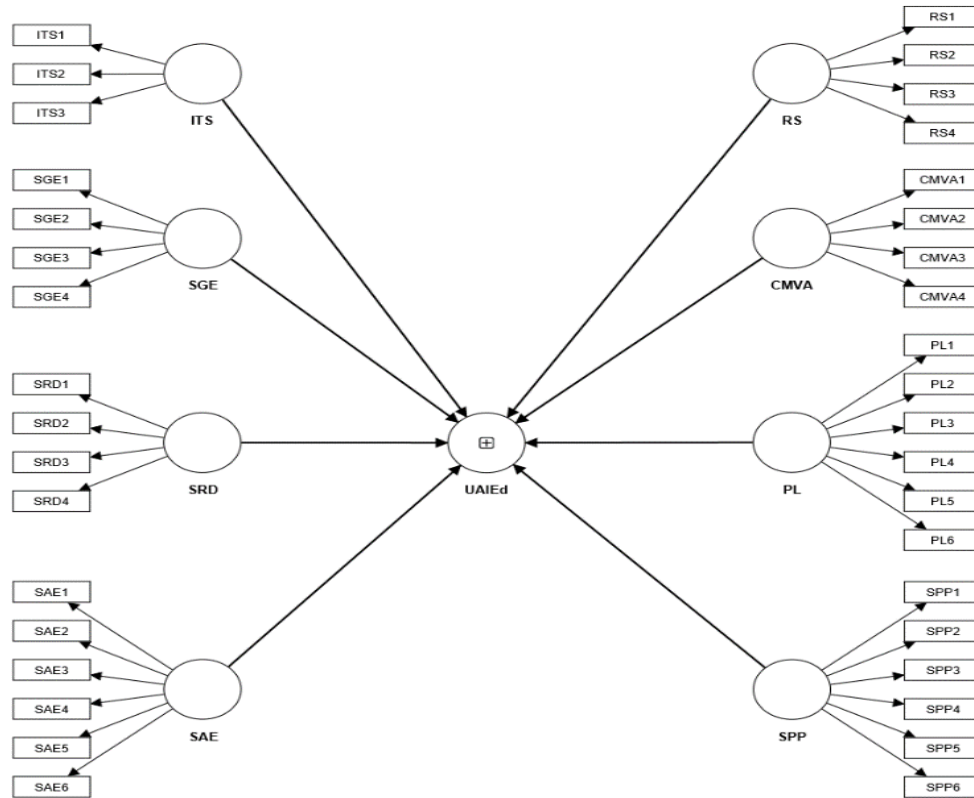


Figure no. 1. Research model

The instrument applied for the purpose of the research was an anonymous questionnaire. In addition to some demographic questions, it included statements that were evaluated on a 5-point Likert scale. For assessing eight AI factors, 37 SCAIES statements were taken from Cheng et al. (2023) and formulated as conditional sentences: 3 statements for intelligent tutoring system (ITS) – ITS1, ITS2, and ITS3; 4 statements for students' grading and evaluation (SGE) – SGE1, SGE2, SGE3, and SGE4; 4 statements for students' retention and dropout (SRD) – SRD1, SRD2, SRD3, and SRD4; 6 statements for sentiment analysis in education (SAE) – SAE1, SAE2, SAE3, SAE4, SAE5, and SAE6; 4 statements for recommendation systems (RS) – RS1, RS2, RS3, and RS4; 4 statements for classroom monitoring and visual analysis (CMVA) – CMVA1, CMVA2, CMVA3, and CMVA4; 6 statements for personalized learning (PL) – PL1, PL2, PL3, PL4, PL5, and PL6; and 6 statements for students' performance prediction (SPP) – SPP1, SPP2, SPP3, SPP4, SPP5, and SPP6. Hereby, it should be noted that the repeated indicator approach (Becker, Klein and

Wetzels, 2012) was implemented to model the higher-order construct; hence, all 37 statements (indicators) employed for measuring previously mentioned lower-order dimensions were also used for specifying the higher-order construct – UAIED.

For evaluating both reflective lower-order dimensions (AI factors) and higher-order formative construct (UAIED) in PLS-SEM, recommendations provided by Hair et al. (2017) were used. Therefore, when it comes to reflective dimensions, several steps were taken including the analyses of: indicator reliability (each indicator's outer loading must be greater than 0.70), internal consistency reliability (the value of composite reliability value (CR) for each dimension must be greater than 0.70), convergent validity (the value of the average variance extracted (AVE) for each dimension must be above 0.50), and discriminant validity (the evaluation of the Fornell-Larcker and HTMT criterion). On the other hand, the assessment of the higher-order formative construct included convergence validity (the application of redundancy analysis based on the use of a single global item), collinearity statistics, and path coefficients.

The convenience sample consisted of 285 students from the University of Novi Sad. When considering the sample size, our sample exceeded the "10 times rule", according to which "the minimum sample size should be 10 times the maximum number of arrowheads pointing at a latent variable anywhere in the PLS path model" (Hair et al., 2017, p. 47), which was 80 in this case. Additionally, the sample size in this research exceeded samples sizes in most similar studies. Idroes et al. (2023) researched 91 students, Kuleto et al. (2023) had a sample of 103 participants, while in the case of Jeffrey's research (2020), there were 230 respondents. The size of our sample was similar to the sample of 301 participants investigated by Wang et al. (2022). Only in two cases (Cheng et al. (2023) relied on the sample of 445 students, while Gherheş and Obrad (2018) researched 928 students) sizes of samples from similar research were larger (to a higher extent) than in this research.

The questionnaire was available online and professors from different faculties belonging to the University of Novi Sad had asked students to fill in the survey on the topic that may be of special importance for the future of, among others, higher education. Most of them were women (55.1%). The gender structure of the sample was very similar to the gender structure of the student population in the autonomous province of Vojvodina in which, within the state university, i.e. University of Novi Sad, there were 23,042 female students enrolled in school year 2022/23, out of the total of 40,867 students enrolled in that school year, i.e. 56.43% (Statistical Office of the Republic of Serbia, 2023, p. 118). Their average age was 22.4. In addition to the fact that students represent the primary users of educational services, as stated by Gherheş and Obrad (2018) this population is well informed and will be an active population category under the greater influence of AI development in the future. Data were collected and processed in 2023, using the SmartPLS 4 software.

4. Results and discussion

When testing the UAIED model, the lower-order reflective dimensions were analysed first, after which the higher-order formative construct was examined. Table no. 1. presents the values related to the assessment of the reflective dimensions – indicator's outer loadings, composite reliability, and the average variance extracted – and as can be seen all assumptions are satisfied. The meaning of abbreviations and the source of the corresponding items can be seen within the Research methodology section of this paper when the instrument was described.

Table no. 1. Reflective dimensions: Outer loadings, CR and AVE

Indicators	Outer loadings	CR	AVE
Intelligent tutoring system - ITS		0.945	0.851
- ITS1	0.903		
- ITS2	0.937		
- ITS3	0.926		
Student grading and evaluation - SGE		0.942	0.804
- SGE1	0.896		
- SGE2	0.849		
- SGE3	0.915		
- SGE4	0.924		
Students' retention and dropout - SRD		0.919	0.740
- SRD1	0.923		
- SRD2	0.860		
- SRD3	0.903		
- SRD4	0.743		
Sentiment analysis in education- SAE		0.948	0.752
- SAE1	0.827		
- SAE2	0.849		
- SAE3	0.896		
- SAE4	0.845		
- SAE5	0.895		
- SAE6	0.888		
Recommendation systems - RS		0.930	0.768
- RS1	0.875		
- RS2	0.877		
- RS3	0.867		
- RS4	0.885		
Classroom monitoring and visual analysis - CMVA		0.916	0.731
- CMVA1	0.847		
- CMVA2	0.811		
- CMVA3	0.905		
- CMVA4	0.855		
Personalised learning -PL		0.950	0.759
- PL1	0.891		
- PL2	0.858		
- PL3	0.911		
- PL4	0.872		
- PL5	0.839		
- PL6	0.855		
Student performance prediction - SPP		0.949	0.755
- SPP1	0.895		
- SPP2	0.883		
- SPP3	0.885		
- SPP4	0.849		
- SPP5	0.843		
- SPP6	0.859		

Source: Authors

With regard to discriminant validity, no problem was identified, as shown by the Fornell-Larcker criterion. As can be seen in Table no. 2 the square root of each construct's AVE was greater than its correlations with other constructs. The meaning of abbreviations can be seen within the Research methodology section of this paper when the instrument was described.

Table no. 2. Reflective dimensions: Fornell-Larcker criterion

	CMVA	ITS	PL	RS	SAE	SGE	SPP	SRD
CMVA	0.855							
ITS	0.306	0.923						
PL	0.354	0.541	0.871					
RS	0.166	0.552	0.623	0.876				
SAE	0.488	0.482	0.556	0.378	0.867			
SGE	0.283	0.349	0.276	0.190	0.327	0.897		
SPP	0.514	0.427	0.447	0.294	0.649	0.232	0.869	
SRD	0.429	0.519	0.577	0.555	0.543	0.260	0.451	0.860

Source: Authors

The establishment of discriminant validity was also confirmed by the application of the HTMT approach, which according to Henseler, Ringle and Sarstedt (2015) has superior performance over traditional methods of its assessment. The HTMT₉₀ criterion was met because the HTMT ratio for each pair of constructs was less than 0.90 (Table no 3).

Table no. 3. Reflective dimensions: HTMT ratio

	CMVA	ITS	PL	RS	SAE	SGE	SPP	SRD
CMVA								
ITS	0.331							
PL	0.379	0.583						
RS	0.189	0.606	0.671					
SAE	0.527	0.522	0.592	0.409				
SGE	0.313	0.381	0.298	0.208	0.352			
SPP	0.554	0.460	0.474	0.314	0.691	0.252		
SRD	0.469	0.569	0.620	0.620	0.579	0.287	0.479	

Source: Authors

When it comes to the higher-order formative construct (UAIED), the results of the redundancy analysis (a path coefficient had a magnitude greater than 0.70 (0.711) and R^2 was greater than 0.50 (0.506)) confirmed its convergent validity. For examining path coefficients, a bootstrapping procedure with 5000 sub-samples was applied. As can be seen in table no. 4, all path coefficients were positive and statistically significant with $p < 0.001$, whereby VIF values below 3 indicated that there were no collinearity issues. In addition, it should be mentioned that due to the application of the repeated indicator approach, the value of R^2 for the UAIED construct equalled 1.

When it comes to the results of the model, as already suggested, all lower-order constructs form a higher-order construct positively and significantly. The largest path coefficients (all above 0.2) can be attributed to sentiment analysis in education, personalised learning, and prediction of student performance. The next group of first-order constructs have path coefficients ranging from 0.123 to 0.152 and here belong (in the following order): students' retention and dropout of students, recommendation systems, and intelligent tutoring system.

Finally, two constructs with the smallest values of path coefficients are classroom monitoring and visual analysis, and students' grading and evaluation.

Table no. 4. Path coefficients and VIF values

Relations	Path coefficient	Standard deviation	T statistics	P values	VIF value
CMVA → UAIEd	0.119	0.010	11.835	p<0.001	1.563
ITS → UAIEd	0.123	0.008	15.333	p<0.001	1.840
PL → UAIEd	0.250	0.010	25.818	p<0.001	2.192
RS → UAIEd	0.136	0.010	14.183	p<0.001	2.029
SAE → UAIEd	0.256	0.011	23.878	p<0.001	2.263
SGE → UAIEd	0.098	0.015	6.598	p<0.001	1.211
SPP → UAIEd	0.235	0.012	19.681	p<0.001	1.956
SRD → UAIEd	0.152	0.007	21.935	p<0.001	2.007

Source: Authors

Before discussing the obtained results, two remarks should be made. Firstly, the instrument used in this research (Cheng et al., 2023) is rather new and has not been implemented in any other studies so far. Therefore, the space for direct comparison of the obtained results with results from other studies is rather limited. Second, the authors of the implemented instrument focus on its development and present only mean values for each of the factors. In this research, since the implementation of the instrument is in its focus, the authors consider the SCAIES as a second-order reflective-formative construct. The justification for such an approach can be found in literature dealing with that topic (Jarvis, MacKenzie and Podsakoff, 2003) and can be considered as a specific contribution of this paper due to the large presence of construct misspecification within the published research. Therefore, it additionally limits the comparison of the obtained results with those obtained when the instrument was developed. However, both remarks do not prevent the authors from considering the results from the point of view of their meaning and the specificities of the country in which the research was conducted.

If we focus on the three most important factors in student perceptions of the use of AI in higher education, we could attempt to find out if there is something common among them. It can be seen that they are related to detecting the opinions of students (negative and positive) considering their learning experiences; providing timely learning support, curricular pathways, and feedback; and anticipating their future performance. All of them may be related to the overcoming of different aspects of challenges arising from classical education, including working with large groups of students and not providing them feedback continuously. It is all in line with one previous research on student perception of higher education in Serbia (Rodic Lukic, 2015), indicating that students do not receive as high a level of quality as they expect when it comes to, among others, gaining personal attention, understanding their own specific needs, and reacting promptly to their needs.

On the other hand, two factors that contribute the least to students' perceptions of AI use in higher education are related to assessing the attendance of students' face-to-face classes with an emphasis on their emotions and participation, as well as grading and evaluating student performance. Both of those factors belong to the control area and could be connected to anxiety about AI. Namely, AI anxiety is the fear or agitation associated with AI and may

affect learning motivation (Wang et al., 2022) and other variables, such as attitude toward using AI and intention to learn AI (Chai, Wang and Xu, 2020).

When considering the obtained results, two other aspects should be emphasised. Namely, in this research students' perceptions are measured. The authors of the original questionnaire also stress that these perceptions may be influenced by students' pre-faculty educational experiences or "other views of AI found in movies, television shows, news, social media, and the like" (Cheng et al., 2023, p. 303). In addition, AI literacy can be mentioned, i.e., the level of knowledge and skills related to AI (Dai et al., 2020). It can be considered a significant antecedent of students' attitudes and perceptions regarding AI (Chai, Wang and Xu, 2020).

Conclusions

The development of artificial intelligence is changing the world by affecting almost every segment of human life and work. Based on the process of "making intelligent machines" it was supposed to help people in different sectors and activities. Therefore, the implementation of AI technology has drawn the attention of researchers in various scientific fields. One of them refers to education, which represents a sector of special importance for the entire society. Taking into account the sensitivity of the educational sector, the application of AI systems should be approached with great caution.

To get deeper insights into this field of interest, the paper examined the use of artificial intelligence in education. In its theoretical part, the focus was on certain educational areas (content and teaching, assessment, and communication) that can be affected by AI technology. In addition, the subject of the analysis was the perceptions of the students about artificial intelligence. Therefore, in addition to their general attitudes and beliefs towards AI technology, perceptions regarding the educational process were also analysed.

In the empirical part of the paper, the hierarchical model related to students' perceptions regarding the use of AI in education was assessed. The model was based on the SCAIES scale, where its eight factors were presented as reflective lower-order dimensions forming the higher-order UAIED construct. It can be understood as the main theoretical contribution of the paper. Following the results obtained, all dimensions positively and significantly contributed to the UAIED. Therefore, for students, particularly significant domains were sentiment analysis in education, personalised learning, and prediction of student performance, while classroom monitoring and visual analysis and student rating and evaluation were the ones with the lowest contribution.

The results obtained suggest that the largest contribution can be attributed to factors arising from weaknesses of traditional education, while the lowest contribution is to factors that could be connected to privacy concerns regarding AI use and the domain of control. When considering the results in line with Cheng et al. (2023), the results obtained must be interpreted from the aspect of implications for higher education institutions. Therefore, the use of AI is supported in areas where students lack personal attention, understanding of their own specific needs, and prompt response to their needs. Even before implementing AI, management representatives in higher education institutions should improve the quality of this aspect of service. On the other hand, if they want to implement AI in higher education, institutions should address all fears students express about privacy, control, or lack of human interaction. These suggestions present a practical contribution to the research.

Similar to the study of Cheng et al. (2023), the limitation of this research refers to the insufficient knowledge of students' experiences associated with artificial intelligence. Therefore, future studies could be expanded with new variables, such as AI literacy and/or AI anxiety.

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