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Article

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CHALLENGES OF ARTIFICIAL INTELLIGENCE ON THE LEARNING PROCESS IN HIGHER EDUCATION

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Abstract

Artificial intelligence (AI) has expanded to unprecedented proportions in recent decades, penetrating vast areas, including education. The debates on the usefulness of incorporating AI into university education, with its subsequent opportunities and challenges, have captured the attention of the current research agenda. The fruitful exploitation of the AI advantages at the level of Romanian higher education is highly dependent on the specific set of knowledge, competences and abilities, even the capacity of the system to adapt to such a dynamic environment. Consequently, the objective of our research is to identify the skills necessary for the specific digital learning environment of Romanian higher education to encourage students as beneficiaries of the educational act to adopt AI technologies. Thus, our methodology consists of structural equation modelling applied to an original data set collected on the basis of a questionnaire addressed to undergraduate students from higher economic education. Results emphasise that the intention to adopt applications using AI among students directly depend on constructs such as perceived usefulness, attitude towards these technologies, perceived hedonic value, expected performance, or degree of compatibility, while the interactivity of the applications also has an important but indirect influence.

Keywords: artificial intelligence, higher education, learning outcomes, digital skills, structural equation modelling.

JEL Classification: D8, O33, I23, C15, J24

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Introduction

Artificial intelligence (AI) is perceived as a research subfield belonging to computer science whose nodal concern is the simulation, extension, and enhancement of human intelligence (Shi and Zheng, 2006). From 1956 until the present, AI has followed an extraordinary dynamic, with an unprecedented expansion in vast areas like industry, technology, economy, research and development, implicitly education, where the target has been from the very beginning higher education (European Commission, 2022). Currently, AI is facing an unprecedented dynamic from the perspective of constantly evolving and improving in terms of technology, with the United States, the European Union and China and being the global leaders. Reasoning in terms of specific capabilities, AI fits into the pattern of a vast area of machine learning based on intelligent behaviour built on automatic learning algorithms. On the one hand, AI supports people by helping them extend their capabilities when dealing with stressful environments and incomplete information, can provide real-time feedback, and is useful in making predictions and recommendations with increased accuracy (Binu and Rajakumar, 2021). On the other hand, the fabulous boost of AI also draws attention to the other perspective, namely the challenges it entails referring to ethical concerns (Gînguță et al., 2023), security, safety, or even fairness issues (Varshney, 2016).

In recent years, the use of AI in higher education has increased significantly, along with the development of AI tools designed for both students and educators (Chu et al., 2022). These AI tools provide valuable feedback to students on the next steps they need to take for a personalised learning experience, based on their personal profile, learning outcomes, progress, or context (Verdú et al., 2017). Other applications make it easier for students to learn independently through interactive games (Dever et al., 2020) or even evaluate student performance through computer-assisted evaluation in a fully transparent setting (Baykasoğlu et al., 2018).

Taking into account this complex framework of analysis, the present research aims to identify the challenges seen from the perspective of additional skills needed in the Romanian digital learning environment that are necessary to encourage undergraduate students to use AI technologies, thus improving the process of knowledge assimilation, with beneficial spillover effects upon their insertion into the labour market, tailored to professional profiles. Obviously, the ultimate goal is to have a positive influence on the performance of the learning system, and for this, we have taken into account that this fact depends, in turn, on the digital competence of the students and their propensity to accept AI technology in the learning process. Therefore, after a comprehensive review of the literature, we have identified the benefits and main challenges that accompany or constrain the absorption of AI-based technologies in educational services, with a clear focus on higher education.

The paper aims to explore a less researched perspective, namely the skills that encourage the adoption of AI among undergraduate students in Romania. From the literature review, it can be observed that our country has a high potential for the adoption of AI technologies through undergraduate curricula, being among the supporters of digital reform in higher education. Our research endeavour was based, in the first stage, on the design of a questionnaire addressed to undergraduate students in higher economic education to determine their positioning towards AI technologies. After identifying essential characteristics that would encourage the adoption of AI in education, a structural equation model (SEM) was designed and implemented. The model assesses the interaction between AI features and the intention to adopt AI, respectively, the attitude towards a series of applications among Romanian undergraduate students.

The results show that students' learning worries are associated with the consequences of using AI, as evidenced by the positive influence of all parameters. It provides valuable insights both for academics who want to use AI technologies to enhance the attractiveness of their disciplines, as well as for policymakers who could shape educational reforms to support digitalisation and applied learning, thus supporting the objectives of the EU 2030 Digital Decade strategy. A notable element of novelty of the research lies in the innovative way in which students' intention to adopt AI technologies is captured and analysed, through constructs such as their perceived usefulness of AI technologies, their perceived ability of AI to evoke emotions or enjoyable experiences, their attitude towards AI applications, expected performance or compatibility. Therefore, the interactivity of applications using AI becomes a nodal factor in inducing the intention to use AI. The more interactive these technologies become, the more attracted the learner will be, considering the pleasant experiences, students absorbing the application, and finding it useful in the learning act.

The remainder of the paper is organised as follows: the first part presents a review of the literature on artificial intelligence (AI) and its impact on the learning process in the higher education system. The second section describes the variables used, the research hypotheses, and the research methodology applied through structural equation modelling. The third section is devoted to results and discussions. The final section summarises conclusions, but also limitations, and future research directions.

1. Higher education and the challenges of artificial intelligence: a systematic review of the literature

Artificial intelligence (AI) embeds multiple definitions in the relevant scientific literature. Thus, AI is defined as an assembly of systems that denote intelligent behaviour involving analysis of the environment and the ability to act, with some autonomy, to meet predetermined goals (Boucher, 2020). Artificial intelligence belongs to computer science and is attributed entirely to machines, computers (Pan, 2016). AI is designed to solve specific tasks in all fields of activity undertaken by humans (Makridakis, 2017). In other words, AI is the automated version of human intelligence (Fenwick and Molnar, 2022).

As part of the development of contemporary society, the use of AI in the context of digitisation has become an intrinsic component of individuals' lives and education. In this perspective, the higher education sector is frequently associated with highly dynamic environments, interdependent with information systems or digitalisation, making it suitable for the adoption of artificial intelligence technology for educational acts (Escotet, 2023). Although AI is promoted as a tool that can be used to improve the lives of individuals to its full potential, its implementation in higher education is strongly encouraged by the advancement of information and communication technologies. Technological progress has opened up a wide range of opportunities for both students and teachers, as the delivery of educational materials online and the rapid distribution of information with a fast and secure connection between the educational service provider and the beneficiary fuels increased accessibility to tertiary education. Moreover, on-line learning technologies allow for a greater degree of customisation for academic materials and the use of blended learning models, giving students the freedom to study at their own pace while having flexible access to courses. While in theory, the use of AI is easy, once transposed into practice, it can produce several effects, which differ from one field of study to another. For this reason, the

metamorphosis of the teaching-learning act involves a continuous effort from both sides, teachers, and students (Escotet, 2023). Today, the pressure exerted by the use of digital technology is determining an increased pace of change in universities, opening them up to the world of digital skills. Thus, their competitiveness is often reflected in the ability to update their disciplines, making them more attractive to students and available to all through distance learning platforms. The traditional pattern of student presence in the classroom must be replaced with a modern one in which technology captures the attention. New forms of learning combine digital instruments with AI technologies such as Grammarly, ChatGPT, Brainly, Mendeley, DeepL Write, or others that stimulate problematisation, hands-on activities through interactive experiences such as virtual classrooms, virtual apps or experiments, and access to various forms of online educational resources, simulations, tutorials, or practical team projects (Pellas, Mystakidis and Kazanidis, 2021).

However, the call for interactivity comes with some challenges. Thus, studies show that reading, one of the essential instruments for human intellectual development, is gradually being replaced by sounds or images, which makes the large-scale implementation of AI pave the way toward perpetuating behaviour that can sabotage human intelligence in the long run (Pan, 2016). This is not the only risk of widespread adoption of AI in education. Moreover, we can mention issues such as invasion of personal space and security, as most applications using AI request and collect users' personal data, sometimes even without their consent. Furthermore, excessive automation can lead to individual isolation and decrease the level of social interaction, severely diminishing the role of the teacher in the teaching-learning act. Another aspect is the learning process limited to a specific context or set of data, which could sabotage the human need for lifelong learning, implicitly ethical issues (Gînguță et al., 2023), and moral ones (Saghiri et al., 2022). Based on these shortcomings, which required a well-defined framework for deployment, the European Parliament and the European Commission initiated in 2021 the first proposal to regulate AI at the EU level, giving it precise guidelines for use based on a legal framework that would turn AI into a support for European citizens while limiting its risks.

Education and training are strategic directions for the prosperity of all nations. Therefore, as a complement to the Act, the European Commission (European Commission, 2021, p. 9) has developed an AI Monitoring Index (2021) to include the most relevant dimensions for policy makers, to target those areas that need further investment. University education is part of this index, specifically the *Societal Aspects* pillar, and is assessed on three levels: (1) *AI in EU university programmes*, which measures the intensity of use of AI in university curricula, seen as an indicator of the AI skills of current students (future employees). From this point of view, at the level of the 2020-2021 academic year, Romania had a modest performance of only 5% of AI programmes in total undergraduate programmes (European Commission, 2022, p.45); (2) *places in AI-content universities*, which shows the number of places available in AI-content university programmes and provides an overview of the AI skills acquired by the potential AI workforce trained in university education. In this respect, Romania ranks third in Europe, after Germany and Poland, with more than 55.000 undergraduate places in universities; (3) *AI intensity in places offered by universities*, an indicator showing the proportion of places available in university programmes with a high AI content out of the total number of places. Even at this dimension, Romania occupies a leading position, second after Estonia, with a share of about 14% in the total number of undergraduate places (European Commission, 2022, p.47).

Based on these considerations, higher education in Romania (undergraduate level) presents a high potential for the implementation of technologies using AI, being on the same wavelength as the EU digitisation strategy. Romania's openness towards AI offers the necessary prerequisites for reforming the education system to support the digital skills and training of the younger generation. This is in line with the objectives of the EU's Recovery and Resilience Mechanism by ensuring that the workforce has access to retraining and further qualification that is valid across the EU, based on the recognition of specialised higher education programmes in AI in all member states (European Commission, 2021). Given this potential concerning the openness toward interactivity and AI in the Romanian university education system, which was dominated until recently by the traditional teaching-learning formula, our study completes the overall framework with feedback provided by the beneficiaries of the educational act. It reveals the defining constructs that would lead students to adopt and use, with confidence, AI technologies in their university training. These characteristics become all the more important, as the openness of undergraduate programmes in Romania towards AI denotes boldness and creativity, first of all, on the part of higher education institutions that are committed to a permanent exercise of curriculum development and adaptation. Then, on the part of teachers, who must redefine themselves in the effort to model competences by selecting the proper AI applications able to add value to the educational act, in conditions of increased attractiveness for their students.

2. Methodology

The main research objective of this study is to identify the attributes needed by the specific digital learning environment for Romanian higher education that will allow students to adopt AI technologies. Therefore, the research activity was designed using a cascade approach, being fully planned and executed in stages. To achieve this objective, we rely on newly compiled data and advanced econometric procedures that incorporate simultaneous equation reasoning/structural equation modelling (SEM). Therefore, to gather the necessary data, in the initial phase of the research, an online questionnaire was administered using Google Forms to undergraduate students within the Faculty of Economics and Business Administration, West University of Timisoara, between June and July 2023.

The data used in the SEM application were obtained by administering the online questionnaire with questions based on 5-point Likert scale responses. Data processing and analysis were performed using SmartPLS v4 econometric software. Thus, we obtained a database with 267 valid responses, out of a total of 293 respondents – students in higher education in economics, undergraduate level, the structure of the respondents being the following: 51% female and 49% male. The allocation of respondents was first made according to the year of study for the undergraduate level, thus: first-year students – 26%, second-year students – 32%, and third year – 42%. Regarding the distribution according to the birthplace counties, there were 140 students from Timiș county (52.43%), 29 students from Arad (10.86%); 27 students from Hunedoara, (10.11%); 23 students from Caraș-Severin (8.62%); 19 students from Gorj (7.12%); 17 students from Mehedinți (6.37%); 12 students from other counties (like Bihor, Vrancea, Maramureș, Botoșani, and Sălaj), which represent 4.91%. The AI applications that were mostly used by students are ChatGPT (all respondents); Bard or Microsoft Bing (62%); under 24% of the respondents

use other AI applications like Grammarly, My AI on Snapchat, Wolfram Alpha, Duolingo, Bloomai, Merlin AI, Tutor AI, Anthropic or Cohere.

In shaping the constructs that lead respondents to adopt AI applications, the following ten attributes were taken into consideration in this research according to which a number of 12 hypotheses were established, which are illustrated in Table no.1

Table no. 1. The establishment of working hypotheses

No.	Attributes	Hypotheses
1-2	<i>AI adoption intention</i> refers to individuals' feelings, positive or negative, related to the achievement of the target behaviour, respectively, AI adoption (Venkatesh et al., 2003; Chatterjee and Bhattacharjee, 2020); <i>Attitude towards AI applications</i> defines the positive or negative emotions of a person related to a particular activity or affective response triggered by an application (Chauhan and Jaiswal, 2016; Chatterjee and Bhattacharjee, 2020; Almaraz-López, Almaraz-Menéndez and López-Esteban, 2023).	<i>H1. Attitude towards AI applications positively influences the intention of AI adoption.</i>
3	<i>Perceived usefulness</i> refers to the conscious benefits students would gain from using AI (Dubey and Sahu, 2021; Malik et al., 2021).	<i>H2. Perceived usefulness has a positive impact on the intention to adopt AI.</i>
4	<i>The perceived hedonic value</i> illustrates the personal and subjective satisfaction gained from using a service (Alam et al., 2023).	<i>H3. The perceived hedonic value has a positive effect on the intention to adopt AI.</i>
5	<i>Compatibility</i> captures how appropriate AI is to the student's values and habits (Rogers, 1962; Venkatesh et al., 2003).	<i>H4. Compatibility has a positive impact on the intention to adopt AI.</i>
6	<i>Performance expectancy</i> represents a construct that reflects a person's attitude toward the use of a new system and its noticeable contribution to his increased professional achievements (Venkatesh et al., 2003).	<i>H5. Performance expectancy has a positive influence on AI adoption intention.</i>
7	<i>Immersion</i> is an important construct as it allows the learner to be totally immersed in applications using AI, practising real skills in a realistic setting but consumed in a virtual space (Luan et al., 2020; Hannan and Liu, 2023; Rodway and Schepman, 2023).	<i>H6. Immersion positively influences the attitude towards AI applications.</i>
8	<i>System quality</i> refers directly to the openness of the education system to e-learning (Maisha and Shetu, 2023).	<i>H7. The quality of the system has positive inferences on immersion.</i>
9	<i>Interactivity</i> is the ability of AI technology to allow the user to participate actively in the communication process (Pillai et al., 2023).	<i>H8. Interactivity positively influences immersion.</i> <i>H9. Interactivity has a notable inference on perceived usefulness.</i> <i>H10. Interactivity significantly shapes the perceived hedonic value.</i>
10	<i>Personalisation</i> is the construct that indicates the usefulness of an application that is intended to enhance the user's perceived value. Its role is to improve the user's experience, helping him achieve greater productivity (Asif and Krogstie, 2013).	<i>H11. Personalisation influences perceived usefulness.</i> <i>H12. Personalisation influences the perceived hedonic value.</i>

To test the research hypotheses, we designed a research model containing the constructs listed above, namely: intention to adopt AI; attitude towards AI applications; perceived usefulness; perceived hedonic value; compatibility; performance expectancy; immersion; system quality; interactivity; and personalisation (Figure 1 and Figure 2).

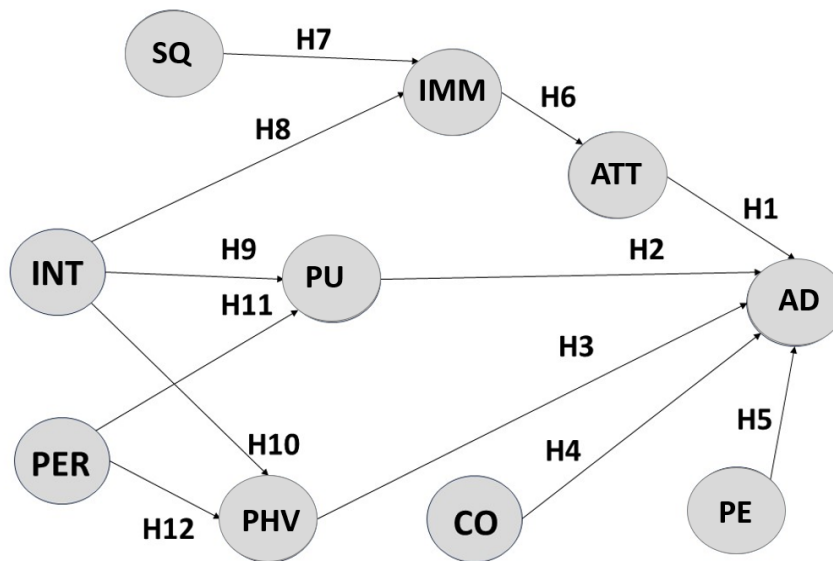


Figure no. 1. The structural conceptual model

Note: IA (AI adoption intention); AT (Attitude towards AI applications); UP (Perceived usefulness); VHP (Perceived hedonic value); CO (Compatibility); PA (Performance expectancy); IM (Immersion); CS (System quality); INT (Interactivity); PER (Personalisation).

The research methodology consists of structural equation modelling (SEM) and analyses the interaction between the features of the learning system and the willingness of the students to accept AI technology in order to transfer part of their tasks into a digitisation-based automated programme. This methodology belongs to multivariate statistics (Kaplan, 2001) and offers the possibility to model complex relationships between *observed or manifest variables*, in our case students' propensity to integrate AI technologies in the act of learning and *latent variables*, respectively, that are also called *constructs* represented by the features of the learning system, providing in-depth information of the correlations between them.

3. Results and discussion

To estimate the research model (Figure 1), partial least squares equation modelling (PLS-SEM) (Hair et al., 2021) was applied using SmartPLS v4 statistical software. Thus, we were able to determine the links between the variables and their corresponding latent constructs in the estimation model and the relationships between the constructs in the structural model. We also examined whether there is predictive relevance of endogenous latent variables (Henseler, 2018). From the perspective of model validity and reliability, the results of Table 2 confirm the internal consistency of the model presented in Figure 1.

As presented in Table 2, the item loadings range from 0.701 to 0.934. These values are greater than 0.70, meaning that they make a substantial contribution to the constructs assigned to them (Hair et al., 2021). The recommended values for rho_c and rho_a are greater than 0.70, with the Cronbach's Alpha coefficient associated with internal reliability (Taber, 2018). Consequently, for each variable, Cronbach's Alpha >0.838; composite reliability rho_a > 0.847; rho_c > 0.892. The values of the average variance extracted (AVE) indicator show, on average, how much of the variance of the associated items can be explained by the construct. The literature recommends values greater than 0.50. In our research, the results synthesised in Table 2 entail an average variance extracted (AVE) higher than 0.628.

Table no. 2. Validation of the constructs and scales used in the questionnaire

Construct	Code	Item	Adapted after the authors	Loading	$\alpha/\rho_a/\rho_c$ AVE
AI adoption intention	ADI1	I will continue to use AI apps as often as I do now.	Chatterjee and Bhattacharjee (2020)	0.701	0.862/0.874/0.902/0.649
	ADI2	Next time I have to work on a project with a colleague, I would like to use AI applications.	Chatterjee and Bhattacharjee (2020)	0.739	
	ADI3	I intend to use AI applications in the future when preparing my projects.	Chatterjee and Bhattacharjee (2020)	0.854	
	ADI4	I would like to use AI applications in the future when learning.	Chatterjee and Bhattacharjee (2020)	0.869	
	ADI5	I would recommend to my friend to use AI applications when learning.	Chatterjee and Bhattacharjee (2020)	0.864	
Attitude towards AI applications	ATT1	I love talking to friends, family, or colleagues about AI applications.	Chauhan and Jaiswal, 2016	0.892	0.91/0.913/0.937/0.787
	ATT2	I recommend AI applications to friends, family or colleagues.	Chauhan and Jaiswal, 2016	0.897	
	ATT3	I share information through social networks that I have learnt using AI applications.	Almaraz-López, Almaraz-Menéndez and López-Esteban, 2023	0.869	
	ATT4	I share content from AI applications with colleagues.	Almaraz-López, Almaraz-Menéndez and López-Esteban, 2023	0.890	
Perceived usefulness	PU1	AI applications ...improve my ability to learn.	Dubey and Sahu, 2021	0.897	0.901/0.902/0.931/0.772
	PU2	...I save time when I study.	Malik et al., 2021	0.842	
	PU3	... improve the way I search for information.	Malik et al., 2021	0.905	
	PU4	...allow me to get information faster.	Malik et al., 2021	0.870	

Construct	Code	Item	Adapted after the authors	Loading	$\alpha/\rho_a/\rho_{cAVE}$
Perceived hedonic value	PHV1	AI applications are ...fun.	Alam et al., 2023	0.874	0.927/0.929/ 0.948/0.821
	PHV2	... interesting.	Alam et al., 2023	0.923	
	PHV3	... delightful.	Alam et al., 2023	0.934	
	PHV4	... exciting.	Alam et al., 2023	0.891	
Compatibility	CO1	AI applications fit well with my learning style.	Venkatesh et al., 2003	0.851	0.839/0.848/ 0.904/0.758
	CO2	With AI applications, I can learn the way I like.	Venkatesh et al., 2003	0.928	
	CO3	Using AI applications, I can find new ways to learn in an enjoyable way.	Venkatesh et al., 2003	0.830	
Performance expectancy	PE1	Using AI applications when learning helps me to ... understand concepts faster.	Chatterjee and Bhattacharjee (2020)	0.921	0.87/0.874/ 0.920/0.793
	PE2	... achieve higher grades.	Chatterjee and Bhattacharjee (2020)	0.886	
	PE3	I believe that AI applications make learning more efficient.	Chatterjee and Bhattacharjee (2020)	0.864	
Immersion	IMM1	While using AI learning applications, I was ...absorbed by what I was doing.	Hannan and Liu, 2023	0.880	0.904/0.908/ 0.929/0.725
	IMM2	... immersed in the task that I was performing.	Hannan and Liu, 2023	0.887	
	IMM3	When they use AI applications, I can discover and explore many concepts.	Luan et al., 2020	0.883	
	IMM4	I would like to spend more time with AI applications when I am learning.	Luan et al., 2020	0.817	
	IMM5	Working with AI applications is fascinating.	Rodway and Schepman, 2023	0.784	
System quality	SQ1	AI applications respond promptly to my requests and deliver reliable results.	Maisha and Shetu, 2023	0.876	0.887/0.888/ 0.922/0.747
	SQ2	AI applications ...perform their functions quickly and efficiently.	Maisha and Shetu, 2023	0.861	
	SQ3	... are reliable (they are always up and running, they run error-free and do what they are supposed to do).	Maisha and Shetu, 2023	0.845	
	SQ4	... provides accurate information.	Maisha and Shetu, 2023	0.874	

Construct	Code	Item	Adapted after the authors	Loading	$\alpha/\rho_a/\rho_{cAVE}$
Interactivity	INT1	... have interaction functions that help me make decisions when solving problems.	Pillai et al., 2023	0.702	0.852/0.872/ 0.893/0.628
	INT2	I can interact with AI application to get information tailored to my specific needs.	Pillai et al., 2023	0.733	
	INT3	By interacting with AI applications, I can get a deep understanding of the concepts I am learning.	Pillai et al., 2023	0.844	
	INT4	AI applications have remarkable interaction features.	Pillai et al., 2023	0.845	
	INT5	I can interact with AI application to get new information.	Pillai et al., 2023	0.837	
Personalisation	PER1	AI applications ...fit my needs well when I am learning.	Asif and Krogstie, 2013	0.818	0.857/0.862/ 0.897/0.637
	PER2	... gives me information that is useful to understand the concepts I am studying.	Asif and Krogstie, 2013	0.794	
	PER3	...understand my requirements.	Asif and Krogstie, 2013	0.832	
	PER4	... understand what I want to learn.	Asif and Krogstie, 2013	0.825	
	PER5	... allow me to learn at my own pace.	Asif and Krogstie, 2013	0.716	

Rönkkö and Cho (2020) showed that, through discriminant validity, items correlate more with each other than they correlate with other items from other constructs. In our research, we used the Fornell-Larcker criterion to determine the discriminant validity, as entailed in Table no. 3 below.

Table no. 3. Discriminant validity analysis (Fornell and Larcker criterion)

	ATT	SQ	CO	IMM	ADI	INT	PE	PER	PU	PHV
ATT	0.887									
SQ	0.652	0.864								
CO	0.713	0.749	0.871							
IMM	0.744	0.73	0.781	0.851						
ADI	0.725	0.77	0.77	0.741	0.806					
INT	0.598	0.789	0.736	0.685	0.74	0.792				
PE	0.62	0.684	0.651	0.568	0.757	0.711	0.891			
PER	0.629	0.757	0.742	0.66	0.727	0.752	0.643	0.798		
PU	0.567	0.775	0.686	0.656	0.802	0.762	0.747	0.719	0.879	
PHV	0.669	0.743	0.758	0.757	0.802	0.764	0.697	0.654	0.736	0.906

According to the data in Table no. 3, following the Fornell-Larcker criterion, it can be seen that the square root of the average variance extracted is higher than the absolute value of the correlation coefficients, thus confirming the discriminant validity of each construct in the model. In assessing the structural model, the perspective offered by Streukens and Leroi-Werelds (2016, p.626) that “from a statistical explanatory modelling point of view, hypothesis testing is a critical element in developing a relevant and rigorous theory. In a PLS-SEM context, hypothesis testing relies on bootstrapping”. The recommendations refer to the use of P-values and bootstrap confidence intervals. If $P \leq 0.05$, the hypothesis is accepted; otherwise, it is rejected.

In our research, the bootstrapping procedure was implemented as a statistical resampling method, often reported in the scientific literature because of its advantage to generate pseudo-observations that will ensure a good convergence of the estimators towards real values. We performed the robustness check for the accuracy of the results obtained after processing our research model and concluded that all hypotheses are supported, as shown in Table 4.

Table no. 4. Validity of the assumptions

Direct effects	Coefficients of Effect	T statistic	P Value	Hypotheses
Attitude towards AI applications -> Adoption intention	0.202	3.395	0.001	H1- supported
Perceived usefulness -> Adoption intention	0.311	5.013	0	H2- supported
Perceived hedonic value -> Adoption intention	0.224	3.775	0	H3- supported
Compatibility -> Adoption intention	0.146	2.607	0.009	H4- supported
Performance expectancy -> Adoption intention	0.149	2.482	0.013	H5- supported
Immersion -> Attitude towards AI applications	0.744	19.815	0	H6- supported
Sistem Quality -> Immersion	0.502	6.147	0	H7- supported
Interactivity -> Immersion	0.289	3.215	0.001	H8- supported
Interactivity -> Perceived usefulness	0.509	7.724	0	H9- supported
Interactivity -> Perceived hedonic value	0.336	5.732	0	H10- supported
Personalisation -> Perceived utility	0.625	10.968	0	H11- supported
Personalisation -> Perceived hedonic value	0.185	3.334	0.001	H12- supported

In the evaluation of the structural model, the effects coefficients were used. According to Nakagawa, Johnson and Schielzeth (2017), the decomposition of total effects coefficients into direct and indirect effects takes place. In our case, the effect coefficients are presented in Figure 2 of the structural model and Table 4, respectively.

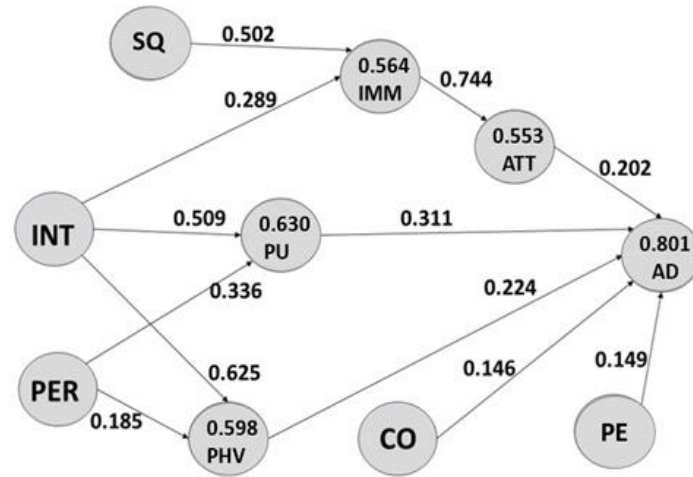


Figure no. 2. The structural model

Note: IA (AI adoption intention); AT (Attitude towards AI applications); UP (Perceived usefulness); VHP (Perceived hedonic value); CO (Compatibility); PA (Performance expectancy); IM (Immersion); CS (System quality); INT (Interactivity); PER (Personalisation)

Table 5 illustrates the total effects (consisting of direct and indirect effects) of the variables in the structural model listed in Figure 2.

Table no. 5. Total effects

Total effects	Coefficients of Effect	T statistic	P Value
Interactivitt -> Adoption intention	0.341	6.745	0.000
Perceived usefulness -> Adoption intention	0.311	5.013	0.000
Perceived hedonic value -> Adoption intention	0.224	3.775	0.000
Attitude towards AI applications -> Adoption intention	0.202	3.395	0.001
Immersion -> Adoption intention	0.150	3.300	0.001
Performance expected -> Adoption intention	0.149	2.482	0.013
Compatibility -> Adoption intention	0.146	2.607	0.009
Personalisation -> Adoption intention	0.146	4.046	0.000
Sistem Quality -> Adoption intention	0.075	2.761	0.006
Immersion -> Attitude towards AI applications	0.744	19.815	0.000
Sistem Quality -> Attitude towards AI applications	0.373	5.582	0.000
Interactivity -> Attitude towards AI applications	0.215	3.150	0.002
Sistem Quality -> Immersion	0.502	6.147	0.000
Interactivity -> Immersion	0.289	3.215	0.001
Interactivity -> Perceived usefulness	0.509	7.724	0.000
Personalisation -> Perceived usefulness	0.336	5.732	0.000
Interactivity -> Perceived hedonic value	0.625	10.968	0.000
Personalisation -> Perceived hedonic value	0.185	3.334	0.001

The standardised root mean square residual (SRMR) reported in Table 5 was calculated in SmartPLS. According to Henseler et al. (2014), values less than 0.10 are considered to show a good model fit. In our research, we obtained an SRMR value of 0.069, which indicates a good fit of the model. Stone-Geisser values (Q²) are 0.691 (Adoption intention), 0.623 (Perceived usefulness) and 0.59 (Perceived hedonic value), 0.554 (Immersion), and 0.426 (Attitude towards AI applications). They also describe the important predictive relevance of the PLS path model.

The purpose of our research was to identify the additional skills needed in the Romanian digital learning environment specific to higher education that would lead undergraduate students to adopt AI technologies, thus improving their knowledge assimilation process. Romania has significant potential from this point of view; the biggest challenge is to identify the optimal approach in the selection of AI applications that can be easily assimilated by students while bringing a real added value to the whole educational act. This is a necessary transition to the digital era, and the fact that Romanian universities have shown openness to insert AI into the matrix of the educational act since the academic year 2020-2021 offers not only proof of courage, but implicitly an undeniable proof that the necessary prerequisites to deepen the process already exist (European Commission, 2022).

The results of our analysis show that the intention to adopt AI-containing applications is directly supported by constructs embedding challenges, such as: perceived usefulness (0.311), perceived hedonic value (0.224), attitude towards AI applications (0.202), performance expectancy (0.149) and compatibility (0.146). In other words, students are open to these new technologies only if they are convinced that it is appropriate for their own needs and increase their satisfaction with the act of learning, a perspective also shared by Malik et al., 2021; Alam et al., 2023; Almaraz-López, Almaraz-Menéndez and López-Esteban, 2023. Considering the total effects, the intention to adopt AI is influenced by interactivity (0.341), perceived usefulness (0.311), perceived hedonic value (0.224), attitude towards AI applications (0.202), immersion (0.150), performance expectancy (0.149), compatibility (0.146), and personalisation (0.146). Consequently, the holistic perspective shows us that all the attributes inserted in the analysis are relevant in shaping students' intention to adopt AI. Being familiar with various social networks, students combine the efficiency and usefulness of AI applications with their personal needs, becoming sensitive to the ability of AI to test their real-life skills in a virtual space placed on the same wavelength as their own needs. Also, our analyses reveal that although interactivity does not directly affect the intention to adopt AI applications, it is nevertheless the factor with the highest influence, determining directly and significantly perceived hedonic value (0.625), perceived usefulness (0.509), and immersion (0.289), an aspect also confirmed by the studies of Pillai et al. (2023) or Dubey and Sahu (2021).

The main empirical findings of the study carried out in the current research emphasise the importance of incorporating AI applications in teaching activities to encourage students to use them in their learning process. To achieve this, AI applications should possess both interactivity and facilitation features. In this way, AI applications can directly contribute to enhancing learning capabilities, saving time, and obtaining information quickly. Professors play a crucial role in the teaching-learning process by implementing interactive strategies that enable students to use AI applications to acquire new skills and knowledge, leading to better learning outcomes. Furthermore, AI applications can adapt to student learning needs,

while providing useful information to understand various notions and to assimilate information at their own pace.

The answers provided by our respondents show that the new generation of young people needs to validate the usefulness of this technology. Even more, the specific benefits they could get from AI could materialise into an improved ability to learn, saving time in the learning process, facilitating the search for information, allowing faster retrieval of information, etc. Considering the pattern of the target group – undergraduate students – here, interactivity is very important. The more interesting the AI applications, the easier it will be for the students to adopt them. This feature highlights that students do not feel comfortable with rigid applications that put pressure on them, but rather prefer AI technologies that provide them freedom of choice and generate accurate results in terms of knowledge accumulation. Teachers also have the opportunity to track students' engagement, their level of immersion, and whether they feel useful performing some tasks in the learning process using AI applications. This way students can be stimulated in the learning process and can be checked to see whether the AI applications selected by teachers are compatible with the students' learning style or not.

Conclusions

The findings of our research show that students are open to using AI applications that give them satisfaction and are compatible with their own learning needs. The present study applied to the Romanian university area, even if on a micro-scale (undergraduate students from one faculty), validates the overall theoretical framework regarding the contribution of AI technologies to the learning process. Its added value lies in providing milestones with the status of challenges that need to be validated when encouraging the adoption of AI in the act of learning by Romanian students. With a rather more traditional educational culture, Romania needs this new impulse to bring tertiary education in line with Western standards.

The usefulness of the present research derives from the fact that it highlights the need to adopt a set of measures, in the Romanian university area, aimed at stimulating and exploiting the benefits of AI to the advantage of students in the learning process, based on the strong identified constructs. Currently, AI is present in the Romanian university educational act, either in the form of plagiarism detection applications such as Turnitin or Copyscape, which can be used by both teachers and students, or through tools that facilitate correct expression in foreign languages such as Grammarly or DeepL Write. ChatGPT, which provides students with complex information on various topics, in real time, or Mendeley, which supports citation and the organisation of bibliographic references for various projects, are other common examples. Thus, their widespread applicability still requires time to adapt and embed into daily behaviour.

After processing the questionnaire, it was found that the respondents have indicated a number of AI applications they are already using in the educational process, such as: ChatGPT (100%); Bard or Microsoft Bing (62% of respondents); less than 24% of respondents use Grammarly, My AI on Snapchat, Wolfram Alpha, Duolingo, Bloomai, Merlin AI, Tutor AI, Anthropic, or Cohere.

The paper also has some limitations arising from the fact that the data was collected from a single university centre. To gain additional representativeness in the application of AI in Romanian higher education, it would be beneficial to extend the application of the Universitaria Consortium. Also, another element worth of consideration refers to the insertion in the analysis of new constructs such as: *AI support conditions* (showing us whether AI has the necessary support for implementation, or if it has been used before by the students) and *the perceived risk of adopting AI*. On the one hand, students who already know the usefulness of AI, trust it, and are open to discover more via new applications. For students who have not used AI in the past, their expectations may go far beyond the actual results of using these technologies. This provides valuable conclusions concerning the need for a proper awareness-raising campaign on AI technologies among students, in order to familiarise them with the real benefits of AI for stimulating and supporting learning, before the actual implementation of the technologies. On the other hand, the construct of perceived risk of AI adoption may implicitly signal beneficiaries' fears related to an AI-assisted learning act. Student feedback can be relevant to the academic or higher education management decision-making process regarding the choice of AI-based technologies or applications.

As future research directions, we propose not only to insert the above-mentioned constructs into the analysis, but inherently to extend the perspective concerning the intention to adopt AI also to teachers who manage the educational process with the support of AI. This perspective will provide an overall picture with respect to AI - higher education relationship so that the associated challenges can be addressed for the benefit of all parties involved in raising the performance of higher education.

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