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# Implications of Adopting Artificial Intelligence Tools for the University Educational Process

**Abstract.** *In a society governed by information and communication technology, the educational needs and aspirations of Generation Z are expressed in increasingly diverse and vivid ways. This diversity in the young generation's perception of education represents the most fertile ground for deep transformations of both the educational process and its associated tools. The field of informatics and economic cybernetics is among the most flexible in terms of the diversity of educational models, concepts, and tools. In this context, the paradigm of artificial intelligence (AI) in education should no longer be viewed merely as an innovative issue. This paper aims to inventory the specific characteristics of AI integration in education in general, highlighting its benefits and challenges. Furthermore, the study proposes an evaluation model in which five hypotheses are defined and described, focusing on the impact of AI adoption in education. The proposed model is built on the current state of research and is validated using data obtained from a survey conducted in Romania, at the Bucharest University of Economic Studies. The study employs Partial Least Squares Structural Equation Modelling (PLS-SEM model) to test and analyse the impact of the identified variables on AI use in higher education. Additionally, key recommendations are presented to support either the acceleration or the moderation of the transition toward intelligent education.*

**Keywords**: *artificial intelligence (AI), digitalisation of higher education, digital transformation in education, opportunities, impact, limitations.*

**JEL Classification:** A22, I23, O33.

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## 1. Introduction

In the same way as with some economic systems, the industrial revolution and the expansion of how information is transmitted, without which knowledge cannot occur, bring new challenges to the field of education. As Suazo Galdames (2024)

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states, artificial intelligence, a rapidly expanding technology, radically changes the way teachers teach, both regarding its inclusion and adoption, as well as the transformation of pedagogical strategies aimed at providing a well-directed and convenient educational process for the involved actors. As AI asserts its rights in the education field, challenges inevitably arise, and the relevance of studying them becomes necessary precisely to offer a suitable framework for its adoption as an inevitable process.

Considering that we are at a favourable moment for integrating AI into education, it is necessary to have a just, proportionate and responsible approach for those involved in the process, which would mean, according to Al-Zahrani & Alasmari, (2024) the development of strategies for resource management, continuous professional training, and monitoring. Ahmad et al. (2021) state that using this contemporary method of learning and teaching is a huge step in solving difficulties related to educational content, the shortage of teachers, and can even help management systems by making a massive contribution to the expansion of the educational sector, even by reducing working hours. The most useful artificial intelligence-based tools, which make a significant contribution to the expansion of the educational sector, are presented in the work of Kwid, Sarty, and Yang (2024), where they are defined as systems and applications that use AI algorithms to support the educational process in various ways (personalising learning, providing real-time feedback, automating administrative tasks, facilitating interactive experiences).

Fitria (2021) argues that AI has implications for both the learning and teaching processes and notes that the proper adoption and implementation of AI tools in the educational process (teaching-learning) can make achieving educational objectives easier. The same source (Fitria, 2021) points out that the use of technology in the educational process (such as preparing thematic plans or additional teaching materials and resources) requires the existence of specific skills for AI-based research and documentation activities. Moreover, the teaching standard also involves this research and continuous professional development throughout life, which is explicitly regulated by law in the university environment.

It is extremely clear that artificial intelligence does not only influence the life of the student or the university, but also the labour market. A relevant study is carried out by Manca (2023) where the impact of AI on the labour market and the skills needed in close connection with AI is analysed, and he notes the growing relevance in areas such as ICT or engineering and product management. Manca (2023) says that AI is associated with advanced skills and that the demand for cognitive skills developed with the help of AI will increase in relation to the expansion of the use of AI. Another relevant study is that conducted by Zhang et al. (2024), which shows that frequent use of AI tools affects individuals' personalities (who simultaneously represent the workforce) and becomes a determining factor in reducing the level of creativity and weakening the spirit of critical or independent thinking.

Given the possible transformations generated by the integration of AI in the field of education, it is necessary to understand the depth of how this technology influences the educational process, and from this we ask ourselves the following research questions: what are the main benefits and challenges offered by AI tools in university education? How does the use of these tools impact the educational process and the entities involved in it?

Given the aforementioned aspects and the need to eliminate the uncertainty related to the research questions exposed, such a study is important because it analyses an expanding phenomenon and provides relevant data for all entities involved in the higher education process so that the phenomenon is fully understood. Also, this study can provide real and clear support for the development of up-to-date educational policies, equitable for all actors in the field, as well as sustainable.

The paper is organised into six major sections. The introduction highlights the conceptual framework of how AI is integrated into education and its implications in higher education. The second section presents the current state of AI adoption in universities and highlights the benefits and challenges of this technology. This is followed by the section dedicated to the research methodology, where the hypotheses are formulated, described, and supported, both empirically and theoretically, regarding the impact of AI on the processes of learning, teaching, evaluation, research, and on the way of training new professionals. In the fourth section, the data collection tools, the analysis techniques are described, and then the research results are presented by outlining a profile of the respondents and validating a theoretical model, as well as recommendations regarding the integration of AI in education. The end of the paper shows its limitations and proposals on future research directions.

## 2. Current state of adoption of AI tools in the educational process

An extremely interesting report is given by Virtue Market Research (2024) which, in addition to estimating that by the end of 2025 more than 60% of teachers will adopt AI in various forms, also offers a forecast regarding investments in educational technologies that says that they will exceed 10 billion dollars by 2026, while also stating that adoption increases student performance by up to 30%.

A Eurostat (2024) report indicates that in the European Union, at the level of all economic activities, the use of AI is highest in Denmark and Finland (15%), and the lowest rate of use is in Romania (2%). From the data presented we can extract the idea that, although Romania has a low level of use of AI compared to other states, there is a high interest and also a considerable potential in the field of education, and this can help to catch up with other countries.

### *2.1 Benefits of using AI in education*

Özer (2024) makes an analysis of the main advantages offered by the integration of artificial intelligence in the education system, referring to increasing literacy levels and reducing inequalities in education, and to an inclusive and interdisciplinary approach by continuously updating teachers' skills to adapt to new contemporary requirements and transforming assessment and grading methods through the accuracy provided by Pisica et al. (2023) also show that in higher education, AI improves the teaching-learning process by personalising with the help of voice assistants, virtual reality or instant feedback, facilitates data analysis, interdisciplinary collaboration and automation of processes, leading to the optimisation of the resources of educational institutions. The same source (Pisica et al., 2023) states that educational institutions that adopt this technology will be able to prepare students for the job market of the future, and this will be a major competitive advantage. Hannan & Liu (2021) point out that AI can transform higher education by personalising curricula for each student, help tailor teaching to their needs (with facial expression recognition), support academic advising, and improve administrative efficiency, both through automation and redesigning workflows.

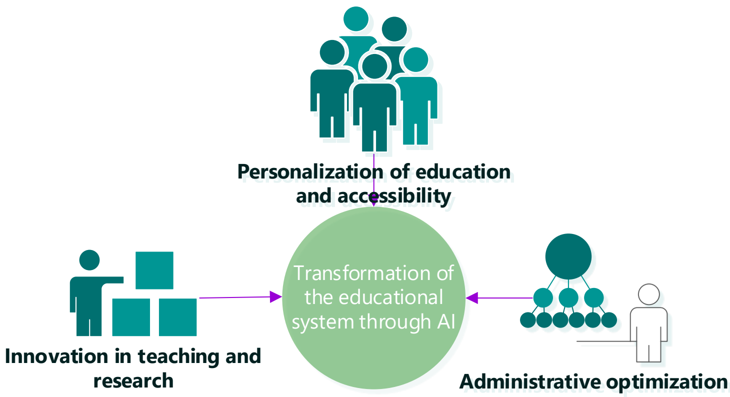


**Figure 1. AI implications in education system**
*Source*: Authors' own creation.

Knowing the tools and how AI is integrated into the educational process (as seen in figure 1) and, of course, its implementation provides a framework, a solid basis for strategies that help to:

a. Personalisation of the educational process and its accessibility - by adapting to the needs of each student;
b. Changing the way of teaching and creating new skills - by technologizing teaching methods;
c. Optimising administrative processes - by providing support in decision-making and streamlining working time and, implicitly, by reducing the waste of resources.

### *2.2 Challenges and prospects for the adoption of AI in the educational process*

The ethical implications of using AI in education are an increasingly controversial perspective. Despite the potential benefits, challenges remain, including ethical ones, data quality issues, and data security risks (Su & Yang, 2023). The European Commission considers the use of AI to pose a high risk, recommending clear guidelines to promote its transparency and ethical use. Current research emphasises the need for responsible integration of AI to ensure that it benefits in equity and access to the educational act, without affecting its quality (Khreisat, 2024). Data security and privacy also remain major concerns when using AI in education. AI systems can be vulnerable to data security and privacy breaches, exposing sensitive information. In universities, it is essential to have rigorous security protocols and ethical data management practices.

Based on the current stage of AI tool adoption in the educational process, this paper aims to analyse the interdependence among various factors through a model that conceptualises the university educational process. The model functions as a system composed of multiple interdependent dimensions: the learning process (LP), the teaching process (TP), the evaluation process (EP), the research process (RP), the New Generation of Professionals (NGP), as well as AI adoption in Higher education (AIE). Each of these dimensions can interact directly or indirectly with specific AI tools, influencing how education is designed, delivered, and received by its beneficiaries.

## 3. Research objectives and hypotheses

The research objectives of the study aim to analyse the impact of the adoption of artificial intelligence in university-level education and are formulated as follows:

- O1. Identifying the main benefits and challenges related to the adoption of AI in the university educational process.
- O2. Validation of the proposed theoretical model based on studies/practices in the field and empirical data and recommendations for modernisation of the educational process.

This study proposes five main hypotheses about the potential impact of AI in higher education, which are detailed below.

*H1: The adoption of AI in university education can help the learner/student in the learning process.*

Baillifard et al. (2023) reveal that AI helps in a multitude of learning activities over the course of a semester and that it has a promising effect relative to improving the learning process, increasing the percentile of students who have used it as a tool by 15 points. In addition to providing informational support in learning to the student, AI also comes with a dose of motivation, and Mclaren & Nguyen (2023) demonstrate that combining entertainment with educational goals is a success in accumulating knowledge. Sajja et al. (2023) illustrate how an intelligent virtual assistant can provide real-time feedback and personalised support, which makes this technology give the possibility of learning adapted to the pace and style of students.

*H2: The adoption of AI in higher education can help the trainer/teacher in the teaching process.*

AI in education is not only a tool that helps students, but also their trainers in various ways. Dickey & Bejarano (2024) emphasise the idea that teachers can use it to generate content, and they are left with the task of refining and elaborating information. Pesovski et al. (2024) show how AI provides, through specific tools, access to various content variants to help students' learning process and demonstrate that the choice of summary or extended solutions influences educational performance. In this way, AI adapts to different modes of understanding and provides the possibility for teachers to personalise and give dynamics to teaching materials (Sajja et al., 2023).

*H3: The adoption of AI in higher education can help in the process of evaluating learners/students.*

The work carried out by Pallathadka et al. (2022) demonstrates that AI can help in the entire process of predicting student performance based on data collected also with the help of AI tools. The possibility of personalised feedback based on the data collected by AI stimulates learners' motivation and engagement in the learning process (Yaseen et al., 2025). Artificial intelligence not only intervenes on the content but also provides, after careful analysis, recommendations in line with the students' gaps (Delianidi et al., 2024). Moreover, it can replace standardised tests and create a continuous and more accurate assessment of student performance (Van Der Vorst & Jelicic, 2019).

*H4: The adoption of AI in higher education can positively influence the academic scientific research process.*

A recent study shows that we can use AI in multiple phases of the research process, such as creating hypotheses, simplifying statistical data analysis, or refining text grammatically (Heidt, 2025). Khalifa & Albadawy (2024) made a more thorough analysis and showed that at all stages of the research process, we can make use of various AI tools, and the six areas of applicability are: development of ideas and design of research, review and synthesis of literature, development and structuring of content, editing and support for the publication of the work, maintaining ethical compliance and data management and analysis.

*H5: The adoption of AI in higher education can negatively influence the personality of new generations of professionals.*

The integration of AI in all spheres of human existence is constantly increasing. With the potential benefits of using AI, further analysis of the risks and challenges of its adoption is needed, especially in the training of new generations of professionals. The impact of the use of AI in education on the *development of the individual* is an important challenge to analyse. As evidenced by the study conducted by (Malik et al., 2023), the most common concern of learners/students is the prospect of the lack of originality and innovation in their work (86%). Learners/students also worry about the potential limitation of critical thinking skills when relying on AI (75%) and the possibility of over-relying on technology (73%). Also challenging is how the use of AI in education influences the *human value system*. In this regard, further analysis needs to be undertaken on the possible social injustice and inequality noted by some participants, as well as how the use of AI affects human relationships (Chan & Hu, 2023).

Following the previous theoretical analysis, which allowed the substantiation of the research hypotheses, we created Table 1 that details the key constructs of the proposed conceptual model. This table highlights how the use of AI tools impacts the transformation of the university educational environment.

**Table 1. The latent variables contained in the model**

| Construct | Construct items | Conceptual rationale |
|---|---|---|
| Learning Process (LP) | LP1: Facilitates exhaustive documentation for a specific topic<br>LP2: Provides synthetic solutions on a theme of your choice<br>LP3: Can generate various solutions to the same problem<br>LP4: Trains the learner/student in educational games<br>LP5: Provides support for differentiated learning | Reflects the role of AI in supporting personalised learning, problem-solving, and exercises (Baillifard et al. (2023); Mclaren & Nguyen (2023); Sajja et al. (2023)). |
| Teaching Process (TP) | TP1: Facilitates exhaustive documentation for a specific teaching topic<br>TP2: Provides synthetic solutions on a topic of your choice for teaching<br>TP3: Can generate various solutions to the same problem<br>TP4: Offers solutions for customising teaching materials in the teaching act | Captures AI support for educators in personalising and planning teaching (Dickey & Bejarano (2024); Pesovski et al. (2024); Sajja et al., 2023)). |
| Evaluation Process (EP) | EP1: Provides solutions for collecting learner/student performance data<br>EP2: Can generate personalised feedback<br>EP3: Can make recommendations for improving educational performance<br>EP4: Can support the development of custom tests | Show the role of AI in assessing and monitoring student performance (Pallathadka et al. (2022); Yaseen et al. (2025); Van Der Vorst & Jelicic (2019). |
| Research Process (RP) | RP1: Review of the literature<br>RP2: Organisation of bibliographic references<br>RP3: Formulation of research hypotheses<br>RP4: Manuscript development<br>PR5: Summary of scientific conclusions<br>RP6: Detecting grammatical errors<br>RP7: Verification of scientific plagiarism situations<br>RP8: Translation of manuscripts | Covers the importance of AI in academic research activities, including various stage of the research process (Heidt, 2025; Khalifa & Albadawy (2024)). |
| New Generation of Professionals (NGP) | NGP1: The adoption of AI can have a negative impact on the development of the individual (through the inability to develop creative skills and intellectual development)<br>NGP2: The adoption of AI can affect the human value system, posing a threat to humanity in general | Considers the effects of the development of students' creativity and value systems (Malik et al. (2023); Chan & Hu (2023)). |
| AI adoption in higher Education (AIE) | AIE1: Rather, AI needs to be adopted in targeted areas, through pilot projects<br>AIE2: AI solutions should rather be introduced only in the primary education cycle (grades 1-4)<br>AIE3: AI should not be used in academic scientific research | It addresses the relevance of the gradual introduction of AI in universities (Al-Zahrani & Alasmari, (2024); Manca (2023); Pisica et al. (2023); Hannan & Liu (2021)). |

*Source*: Authors' processing.

## 4. Data and research methodology

The technical tools used and the manner of data collection for defining the model and verifying the hypotheses of the study are presented below.

### *4.1 Tools used*

In this research, we used the Google Forms platform, which allowed us to efficiently manage the questionnaire to the respondents. Subsequently, for the analysis of the data obtained, we used the WarpPLS software tool, which facilitated the testing of the theoretical model and the estimation of the relationships between its variables, but also the performance of statistical analyses that would allow us a valid interpretation of the studied constructs. The relevance of using this software is given by its unique ability to identify nonlinear relationships between latent variables used in the model to be created.

Considering the research objectives, the characteristics of the data, and the complexity of the proposed model for hypothesis validation, PLS-SEM was used. The method is recommended for exploratory studies, complex models that include reflective and formative constructs, small sample size, and non-normal data, as noted by Hair et al. (2014) and Hair, Ringle, and Sarstedt (2013). Additionally, other studies recommend PLS-SEM as a standard practice, particularly through the use of SmartPLS software (Garson, 2016).

### *4.2 Data collection*

Data collection was done using a survey, using a Google form distributed to 350 possible respondents. The survey targeted respondents who were students in the bachelor's cycle of state university education from the Bucharest University of Economic Studies (BUES). The research authors' experience in the adoption of ICT in different fields of activity made it possible to create an appropriate survey and obtain an appropriate number of valid responses (274). For two consecutive years, BUES has been the leader among higher education institutions in economics in Romania and South Europe, as confirmed by the prestigious Times Higher Education World University Ranking 2021. Additionally, its leading position in economic sciences at the national level is also confirmed by TopShanghai (Bucharest University of Economic Studies, 2024a; Bucharest University of Economic Studies, 2024b).

For our study, a stratified sampling scheme was considered relevant (Cochran, 1977), given that the method allows the inclusion of heterogenous population with significant differences between years of study. The method ensures that all subgroups are appropriately represented, as will be shown in Table 2. Considering the exploratory nature of the study and the available resources, students represented a relevant group, and the conclusions regarding the relationships between variables can be cautiously generalised to populations with similar characteristics.

The questions in the survey considered the respondents' profile, educational level, educational specialisation (economic informatics and/or economic cybernetics), level of knowledge about artificial intelligence, appreciation of the need for a study on the adoption of AI in education and research, and 25 questions to measure latent variables (Table 1). A 5-point Likert scale was used to measure the responses to the items in Table 1 (from 1 – strong disagreement to 5 – strong agreement).

## 5. The results of the research

In this section we aim to analyse the collected data, verify the validity of the model, draw the main conclusions regarding the impact of the adoption of AI in education and research and issue recommendations on the way in which AI should be present or not in the university educational process.

### *5.1 Respondents' profile*

The survey took place between May and June 2025. Following the survey, a number of 300 forms were collected, representing 85.71% of the total number of questionnaires distributed (350). Out of the 300 forms received, only 274 forms were taken into account, which is a sufficient input for the use of the PLS-SEM method.

The remaining 26 forms were removed from the analysis, corresponding to respondents who did not have sufficient knowledge about AI and its use in the educational process.

Synthetically, the characteristics of the studied sample are presented in Table 2. First of all, there is a distribution of respondents of 2 to 1 according to gender (182 female vs. 92 male) and a balanced student participation in terms of the specialisation they study (142 vs. 132). Most of the survey participants are at the age appropriate to the level of undergraduate university education (271) and have thorough knowledge of AI tools (169), which gives the survey a correct architecture in relation to the objectives of the study. Also, most of the respondents graduated from high school in an educational institution outside Bucharest (61.7%). These aspects support in the first instance the qualitative representativeness of the sample, but also the relevance of the study undertaken.

**Table 2. Characteristics of the survey sample**

| Characteristics | Choice | (N) | (%) |
|---|---|---|---|
| Gender | Masculine | 92 | 33.6 |
| | Feminine | 182 | 66.4 |
| Age | 21-25 years old | 271 | 98.9 |
| | 26 years or older | 3 | 1.1 |
| Bachelor's degree specialisation you are studying | Business Informatics | 142 | 51.8 |
| | Cyber Economics | 132 | 48.2 |
| The locality where you graduated from high school | Bucharest | 98 | 35.8 |
| | Outside Bucharest | 169 | 61.7 |
| | Outside Romania | 7 | 2.5 |
| Your level of knowledge/experience about AI | I've heard about the concept/technology | 105 | 38.3 |
| | I can define concepts/technologies, but not | 76 | 27.8 |

| Characteristics | Choice | (N) | (%) |
|---|---|---|---|
| | I personally experienced | | |
| | I have experience with the concepts/ specific technologies, with the advantages and their disadvantages | 93 | 33.9 |

*Source*: Authors' processing.

In support of the study and to draw sustainable conclusions, a multiple-choice question was asked to measure the popularity of AI tools in education currently on the market (Table 3). Table 3 reflects the dominance of ChatGPT in the market for educational AI tools, in its version dedicated to the mathematical field. Also, the diversity of such instruments is reflected by the size of the "Other" feature in Table 3 (52.2%).

**Table 3. Characteristics of the survey sample**

| Characteristics | Choice | (N) | (%) |
|---|---|---|---|
| What AI tool for education do you know/use (multiple choice) | MathGPTPro | 109 | 39.8 |
| | Course Hero | 73 | 26.6 |
| | Ivy Chatbot | 39 | 14.2 |
| | Socrat | 29 | 10.6 |
| | Fetchy | 13 | 4.7 |
| | Cognii | 13 | 4.7 |
| | Gradescop | 9 | 3.3 |
| | Carnegie Learning | 9 | 3.3 |
| | Century Tech | 6 | 2.2 |
| | *Other* | *143* | *52.2* |

*Source*: Authors' processing.

The representativeness of the survey is directly supported by the characteristics of the respondents, who are undergraduate students, most of whom are familiar with the use of emerging technologies specific to the information society, including AI solutions and tools.

### *5.2 Evaluation of the Measuring Model*

Following the input of the data obtained from the respondents, the validity and reliability of the model in Figure 2 was calculated in WarpPLS. The model is statistically significant and shows a mean global fit (GoF - 0.292), and this value shows that the model has a mean to superior predictive value, also indicated in Table 4. The values of the collinearity (VIF) and paradox (SPR) indicators have at least acceptable values, and the contributions of the variables to the explanation of the model are ideal. The model-explained variability (ARS) and the adjusted value (AARS) indicate a modestly explanatory power of the model, the value of 0.152 shows that 15.2% of the variability of the variables is explained by the model in accordance with the values (between 0 and 1, where 0 signals the lack of model fit, and 1 reflects the perfect fit). However, the p-value indicates that the result is statistically significant, its values being in the case of all connections within the appropriate limits ($p<0.01$).

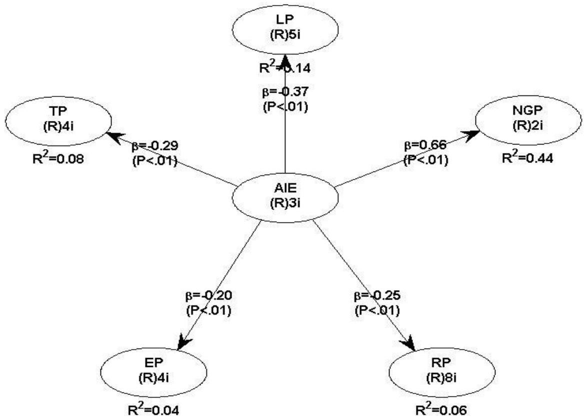


**Figure 2. The proposed model for the analysis of the impact of AI adoption in the university educational process**

*Source*: Authors' own creation from WarpPLS.

**Table 4. Model Quality Ratings**

| **Model fit and quality indices** |
|---|
| Average path coefficient (APC)=0.355, P<0.001 |
| Average R-squared (ARS)=0.152, P=0.003 |
| Average adjusted R-squared (AARS)=0.149, P=0.003 |
| Average block VIF (AVIF) not available |
| Average full collinearity VIF (AFVIF)=1.974, acceptable if <= 5, ideally <= 3.3 |
| Tenenhaus GoF (GoF)=0.292, small >= 0.1, medium >= 0.25, large >= 0.36 |
| Sympson's paradox ratio (SPR)=1.000, acceptable if >= 0.7, ideally = 1 |
| R-squared contribution ratio (RSCR)=1.000, acceptable if >= 0.9, ideally = 1 |
| Statistical suppression ratio (SSR)=1.000, acceptable if >= 0.7 |
| Nonlinear bivariate causality direction ratio (NLBCDR)=1.000, acceptable if >= 0.7 |

*Source*: Authors' own creation from WarpPLS.

As we can see in Table 5, all constructs have a composite reliability indicator with CR>0.7 values, which means that the model has a high internal consistency, the constructs being coherently connected and measuring the same thing, having a good reliability.

**Table 5. Model Quality Ratings**

| **Composite reliability coefficients (CR)** | | | | | |
|---|---|---|---|---|---|
| LP | TP | EP | RP | NGP | AIE |
| 0.833 | 0.841 | 0.879 | 0.806 | 0.833 | 0.79 |
| **Cronbach's alpha coefficients** | | | | | |
| LP | TP | EP | RP | NGP | AIE |
| 0.749 | 0.748 | 0.817 | 0.727 | 0.599 | 0.599 |

*Source*: Authors' own creation from WarpPLS.

Cronbach's alpha indicator shows us (at least in the exploratory phase of our research and given the resources used for data collection) that the model is a valid one. Its values in the case of most constructs are acceptable, but in the case of NGP and AIE the reliability is low. Given that the diversity of study participants is demographically varied and taking into account the complexity of measuring the NGP and EIA constructs, which are relatively new concepts and the perception of them can be diverse, the internal coherence of the model is affected. Starting from this idea, we decided to analyse and interpret factor loads and cross-loads, and they can be found in Table 6.

All loads for the items of each construct are large, except for items RP6, RP7, and RP8 (below 0.5) which may be less relevant in the definition of the RP construct, as in the case of item AIE1. Even if in the case of RP and AIE constructs there is a greater variation between items, we can consider that each construct is properly measured by its items. Also, the p-values are very small (<0.001) and this suggests that all loads are statistically significant.

**Table 6. Model Quality Ratings**

**Composite reliability coefficients (CR)**

| | LP | TP | EP | RP | NGP | AIE | Type (a | SE | P value |
|---|---|---|---|---|---|---|---|---|---|
| LP1 | 0.713 | -0.182 | -0.002 | -0.044 | -0.005 | -0.023 | Reflect | 0.054 | <0.001 |
| LP2 | 0.667 | 0.299 | -0.126 | 0.002 | 0.241 | -0.278 | Reflect | 0.054 | <0.001 |
| LP3 | 0.683 | 0.146 | 0.117 | -0.007 | 0.008 | 0.019 | Reflect | 0.054 | <0.001 |
| LP4 | 0.699 | -0.171 | 0.063 | 0.081 | 0.006 | 0.063 | Reflect | 0.054 | <0.001 |
| LP5 | 0.77 | -0.065 | -0.05 | -0.028 | -0.217 | 0.188 | Reflect | 0.053 | <0.001 |
| TP1 | 0.218 | 0.723 | 0.085 | -0.013 | -0.093 | 0.074 | Reflect | 0.054 | <0.001 |
| TP2 | -0.122 | 0.778 | -0.1 | -0.008 | 0.105 | -0.144 | Reflect | 0.053 | <0.001 |
| TP3 | 0.044 | 0.793 | -0.013 | 0.057 | -0.033 | 0.062 | Reflect | 0.053 | <0.001 |
| TP4 | -0.135 | 0.725 | 0.036 | -0.04 | 0.016 | 0.013 | Reflect | 0.054 | <0.001 |
| EP1 | 0.039 | -0.008 | 0.766 | -0.016 | -0.117 | 0.18 | Reflect | 0.053 | <0.001 |
| EP2 | 0.064 | -0.195 | 0.83 | -0.004 | -0.024 | 0.033 | Reflect | 0.053 | <0.001 |
| EP3 | -0.146 | 0.228 | 0.828 | 0.026 | 0.03 | -0.045 | Reflect | 0.053 | <0.001 |
| EP4 | 0.049 | -0.027 | 0.789 | -0.007 | 0.108 | -0.161 | Reflect | 0.053 | <0.001 |
| RP1 | 0.099 | -0.096 | -0.055 | 0.711 | -0.047 | 0.096 | Reflect | 0.054 | <0.001 |
| RP2 | 0.164 | -0.157 | 0.054 | 0.57 | -0.164 | 0.034 | Reflect | 0.055 | <0.001 |
| RP3 | 0.009 | -0.035 | 0.117 | 0.714 | 0.199 | -0.109 | Reflect | 0.054 | <0.001 |
| RP4 | 0.041 | -0.096 | 0.011 | 0.712 | -0.201 | 0.298 | Reflect | 0.054 | <0.001 |
| RP5 | -0.02 | 0.122 | -0.07 | 0.675 | -0.021 | -0.058 | Reflect | 0.054 | <0.001 |
| RP6 | -0.224 | 0.244 | -0.153 | 0.367 | -0.105 | -0.002 | Reflect | 0.057 | <0.001 |
| RP7 | -0.156 | 0.044 | 0.135 | 0.399 | 0.062 | -0.001 | Reflect | 0.057 | <0.001 |
| RP8 | -0.086 | 0.127 | -0.071 | 0.485 | 0.324 | -0.374 | Reflect | 0.056 | <0.001 |
| NGP1 | 0.113 | -0.038 | -0.074 | -0.022 | 0.845 | 0.076 | Reflect | 0.053 | <0.001 |
| NGP2 | -0.113 | 0.038 | 0.074 | 0.022 | 0.845 | -0.076 | Reflect | 0.053 | <0.001 |
| AIE1 | 0.09 | -0.037 | 0.087 | -0.028 | 0.373 | 0.539 | Reflect | 0.055 | <0.001 |
| AIE2 | 0.015 | -0.026 | 0.012 | 0.044 | -0.232 | 0.819 | Reflect | 0.053 | <0.001 |
| AIE3 | -0.071 | 0.048 | -0.067 | -0.025 | -0.013 | 0.856 | Reflect | 0.052 | <0.001 |

Notes: Loadings are unrotated and cross-loadings are oblique-rotated. SEs and P values are for loadings. P values < 0.05 are desirable for reflective indicators.

*Source*: Authors' own creation from WarpPLS.

### *5.3 Assessment of the Structural Model*

In order to evaluate the structural model, we also examined its validity in relation to the data obtained in order to determine its degree of adequacy and robustness. To observe in detail the causal relationships between the variables, we can follow the data in Table 7 and Table 8.

Regarding the measurement of the model's performance shown by the R2 coefficient, it can be seen that the NGP item has the variability best expressed by the model, specifically 43.7% of its variability being explained by the model.

The values of the Q2 indicator are very similar, the predictive power of the model being not very high, but which provides a solid basis for exploring the phenomenon of AI integration in the educational system. Also, our model has a significant predictive capacity for the NGP variable (0.437), and this shows that it is effective in capturing essential causal relationships.

Based on the path coefficient presented in Table 7, the following can be observed:

- The LP-AIE relationship (-0.37) – is a negative one and may suggest that as the learning process becomes more complex, AI adoption becomes irrelevant;
- The TP-AIE ratio (-0.288) - is a negative one and indicates that if the traditional teaching process is more efficient, the relevance of AI adoption decreases;
- The EP-IEA ratio (-0.202) - is a negative one and reflects the idea that the traditional evaluation system is to a greater extent accepted;
- The RP-AIE ratio (-0.252) - is a negative one that proposes the use of traditional methods in the university research activity, rather in relation to new technologies;
- The NGP-AIE relationship (0.661) - is a positive one and signals that the adoption of AI in university education can negatively affect the personality of the new generations of professionals (it can have an unfavourable impact on the development of the individual, through the inability to develop creative skills and intellectual development and can negatively affect the human value system).

In the process of validating the created model, we also aimed to measure and evaluate the statistical significance of the relationship between the model variables, as we assumed in the section dedicated to hypotheses. As highlighted in Table 8, the five assumptions of the proposed model are validated and accepted.

We can note that the effect considered, in the case of all constructs, is a very significant one, with less than 1% chance that the result is random, therefore, there is an extremely significant relationship between the learning process (LP), the teaching process (TP), the evaluation process (PE), the research process (PR), the personality of the new generations of professionals (NGP), and the integration of AI in the higher education system (AIE).

**Table 7. Performance coefficients and statistical significance of the model**

| R-squared coefficients | | | | | | |
|---|---|---|---|---|---|---|
| LP | TP | EP | RP | NGP | AIE | |
| 0.137 | **0.**083 | 0.041 | 0.064 | 0.437 | | |
| **Q-squared coefficients** | | | | | | |
| LP | TP | EP | RP | NGP | AIE | |
| 0.133 | 0.083 | 0.04 | 0.062 | 0.437 | | |
| **Path coefficients** | | | | | | |
| | LP | TP | EP | RP | NGP | AIE |
| LP | | | | | | -0.37 |
| TP | | | | | | -0.288 |
| EP | | | | | | -0.202 |
| RP | | | | | | -0.252 |
| NGP | | | | | | 0.661 |

*Source*: Authors' own creation from WarpPLS.

Also, the robotism of the structural model is a very firm one, and the P values in Table 6 demonstrate that the model is statistically reliable.

**Table 8. Statistical significance test results**

| | | | | | | **P values** | | |
|---|---|---|---|---|---|---|---|---|
| | LP | TP | EP | RP | NGP | AIE | HYPOTHESIS | STATUS |
| LP | | | | | | <0.001 | H1 | Supported |
| TP | | | | | | <0.001 | H2 | Supported |
| EP | | | | | | <0.001 | H3 | Supported |
| RP | | | | | | <0.001 | H4 | Supported |
| NGP | | | | | | <0.001 | H5 | Supported |

*Source*: Authors' own creation from WarpPLS.

### *5.4 Discussions and recommendations*

Returning to the conclusion formulated above and going through the last column of Table 6, we can discuss the confirmation of the five hypotheses proposed by the model, the empirical findings thus supporting the theoretical assertions described by these hypotheses. Moreover, each of the five hypotheses is supported to a greater or lesser extent by referring to various dimensions of the PLS-SEM analysis. The model demonstrated generally high validity and the reliability, and path coefficients and $R^2$ values indicate that it captures the casual relationships between the variables.

The results of our study show the need for a gradual adoption of AI in higher education. The contrast between the efficiency of traditional methods and the potential offered by AI reveals that the direct substitution of traditional methods is not a suitable option, but rather contextualised integration can be widely accepted by the actors involved in the educational process, which is in line with the observations of Al-Zahrani & Alasmari (2024), who consider that we are at an opportune moment for the responsible integration of this form of technology in education.

Our study also confirms and aligns with the conclusion of Fitria (2021), namely that AI intervenes in both the learning and teaching processes, influences the development of competencies for new professionals (Zhang et al., 2024), and provides complementary support to traditional methods.

The integration of AI in education should be carried out gradually, in compliance with the ethical considerations well specified at the level of universities, with well-defined objectives, which should complement traditional methods.

## 6. Conclusions, limitations, and directions of research

The main conclusions of the proposed study surprise the fact that the transition towards a new paradigm of academic scientific education and research that encompasses specific AI tools will have to follow a genuine process of smooth change, without sudden, abrupt metamorphoses. The main dimensions of the university educational process captured by the proposed study – the learning process (LP), the teaching process (TP), the evaluation process (PE), the research process (PR), the personality of the new generations of professionals (NGP), and the integration of AI in the higher education system (AIE) – may tangentially or directly interfere with specific AI tools. For higher education, the pedagogical dimension delivered by the human resource involved in educational processes is important and must remain a constant.

The limitations of the study can be given by the extent to which it targets only the public university environment in Romania, the level of undergraduate studies. An extension to other educational levels (doctoral, master's, high school or secondary school) can be one of the research directions. Whichever side of the barricades we are on regarding the adoption of AI tools in the university educational process, we must take very seriously the spectacular technological development of current times and the increasingly futuristic trends of generative AI and its impact on the universe of human existence. And, last but not least, a very important aspect must be, as our study highlights, the ethical dimension of the adoption of artificial intelligence in education, in general.

Ethical issues can be an emergence of subjectivism in education and can refer to prejudices and stereotypes that can affect the educational experiences and outcomes of learners and teachers alike, leading to discrimination and inequality. Thus, educational prejudices arise when preconceived notions about individuals or groups influence the way they are treated in educational settings. These can manifest themselves in various forms, including prejudices based on gender, race, ethnicity, socioeconomic status, and special educational needs. Such prejudices can lead to stereotyping, decision-making subjectivism and discrimination, ultimately affecting students' learning experiences and academic success. In this case, we are talking about the so-called educational bias, which can manifest itself through malicious encapsulation under the AI screen through implicit prejudices (unconscious attitudes or stereotypes that affect our understanding, actions and decisions), stereotyping (generalisation of characteristics, behaviours or abilities to all members of a group), or negative reaction bias (when individuals face negative reactions for not conforming to group stereotypes).

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