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Article

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ARTIFICIAL INTELLIGENCE IN BUSINESS EDUCATION: BENEFITS AND TOOLS

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Abstract
Understanding the impact of artificial intelligence (AI) on education is vital for guiding teachers in developing educational tools. AI in education (AIEd) comes not only with opportunities but mostly with challenges for both educators and learners. Finding the proper tools to integrate AI into the learning framework represents a test for current and future generations. Even if most students acknowledged AI as a valuable tool, their interaction with AI in education seems more limited than expected. They mainly concentrated on few tools with higher awareness.
This paper examines AI's support for educational activities, key drivers, and tools for business education. Survey data collected from 254 learners were analysed using multivariate binary logistic regression. Two research questions were formulated to verify if AI supports educational activities and what AI tools support business educational activities. Results show learners appreciate AI for aiding teachers in administrative tasks, personalising learning plans, and saving time. However, learners are unfamiliar with most benefits of AI tools, except computer vision, edge computing, and AI chatbots. The paper highlights the need to increase the use of AI in education to make students more familiar with AI tools and capitalise on them in business education.

Keywords: artificial intelligence (AI), artificial intelligence in education (AIEd), instruments, benefits, Romania

JEL Classification: A23, I23, M15, O33

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Introduction

In envisioning future jobs and human resources specialists' requirements, teachers must equip students with a proficiency that makes them adaptable to challenges. Teachers significantly contribute to society by educating generations of upcoming students that will become future entrepreneurs. Tan (2020) underlines that the teacher exerts a triple role, being a content expert and creator, a knowledge spreader, and "an ethical-spiritual guide" with wisdom. The students should be able to chase trends and not just stay current with the events and environment (Elhajjar, Karam and Borna, 2021). Hence, the demand for innovative teachers embracing change, integrating new materials, and enabling student-AI interactions in education is increasing.

AI augments human skills in the workplace (Nuseir, Basheer and Aljumah, 2020) and serves as an educational partner, enhancing content and competencies (Tan, 2020). Elhajjar, Karam and Borna (2021) advocate integrating AI into education to equip students with skills essential for future jobs and digital society's demands, such as innovation, creativity, and design thinking. AIEd employs diverse tools, techniques, and systems in educational activities (McGrath et al., 2023). Investing in human capital to embrace AIEd tools is vital for societal development, despite widespread distrust and misconceptions about AI's role in human activities, especially in education (Antonenko and Abramowitz, 2023).

AI technology in education is expected to grow significantly in the coming decades, presenting new opportunities and challenges (Ouyang and Jiao, 2021; Zhang and Aslan, 2021; Khosravi, 2022). Researchers, policymakers, and practitioners are integrating AIEd to enhance teaching, personalised learning, assessments, and administrative services (Zhang and Aslan, 2021; Chiu et al., 2023). AI represents progress in education, offering benefits on multiple levels, and stimulates the evolution of teaching and learning through technologies like chatbots, robots, automated assessment, digitised artefacts, and intelligent tutoring systems, despite occasional organisational challenges (Chiu et al., 2023).

The demand for adaptive digital learning with AI support has surged in the past decade, driven by challenges like the Covid-19 pandemic and social conflicts in contemporary societies (Matzavela and Alepis, 2021). Online and blended learning are now prevalent in modern communities and emerging economies as they strive to integrate these methods into the educational system. AIEd provides feasible solutions to complex societal problems, enabling students to engage closely with global challenges and develop real-life problem-solving skills (Southworth et al., 2023).

In this study, we analyze the AI determining factors and tools that promote its benefits in educational activities for business.The paper is structured as follows. The next section depicts the literature review on AI in education and business education. Section two presents the research methodology. Section three reviews the data analysis and discusses the results. The last section exposes the conclusions of the paper.

The authors identify a gap in the literature regarding the students' limited knowledge of the benefits of AI in business education, even though many of them have previously used AI. Additionally, it is noted that there is a lack of preparedness among the respondents to adopt AI in the educational process. The study makes significant contributions by conducting an empirical investigation that explores the AI determining factors and tools in the context of business education. Additionally, the study addresses the need for continuous improvements in the implementation of AI in business education. The study holds both theoretical and

practical significance. By identifying existing gaps in students' knowledge and their low level of preparedness for adopting AI in business education, it provides a foundation for the further development of educational strategies. The study's findings can serve as a guide for educators, researchers, and the educational community in improving practices related to the use of AI in the learning process. By highlighting the need for active engagement in AI-assisted education innovation, the study contributes to shaping future research directions and actions to maximize the benefits derived from integrating AI into business education.

1. Review of the scientific literature

AI in education requires transdisciplinary skills to enhance the learning experience (Southworth et al., 2023). AIEd aids teachers and students in educational processes (Hopcan et al., 2022) and supports administrative tasks, educational services, assessments, and procedures.

1.1. Artificial intelligence in education for learners

AI systems in education significantly enhance learners' involvement and performance (Zhang and Aslan, 2021). Chiu et al. (2023) identified essential AI roles for learners: competency-based task assignments, learner-machine discussions, feedback, and adaptive digital environments. Zhang and Aslan (2021) added other AI facilitations, including engagement, enriched learning resources, and intellectual stimuli. Southworth et al. (2023) highlight AIEd's benefits, fostering technical skills, creativity, critical thinking, and problem-solving abilities for students.

AIEd personalises learning experiences and communication to cater to individual needs and abilities, enhancing efficiency (Hopcan et al., 2022; Southworth et al., 2023). Customised learning materials are tailored based on students' evaluations, addressing their strengths and weaknesses (Hopcan et al., 2022). Li and Wang (2023) propose using advanced technology to create a comfortable communication environment, fostering learner networks with increased information accessibility for future generations.

Adapting learning experiences sustains student progress and engagement in virtual environments, promoting skill development (Southworth et al., 2023). Interactivity and participation substantially increase among students and teachers. Khosravi et al. (2022) emphasise the significance of AI in various learning interfaces. For remote learners, AI offers a crucial advantage through simulation cases on complex life topics challenging to address in traditional settings (e.g., welfare system, losses, and violence) (Asakura et al., 2020).

Ouyang and Jiao (2021) identified three AIEd paradigms: "AI-direct, learner-as-recipient", where AI leads learning with a defined pathway for the learner, "AI-supported, learner-as-collaborator", where AI optimises interaction among learners, information, and technology, and "AI-empowered, learner-as-leader", where AI enhances learners' intelligence through a complex system. Cope, Kalantzis and Searsmith (2021) acknowledge AI's intrinsic limitations, cautioning against reducing students' results to simple numbers without human thought and implications beyond AI's cognitive processes and calculations.

1.2. Artificial intelligence in education for teachers

Crompton, Jones and Burke (2022) emphasise that AIEd builds upon previous learning theories, facilitating teacher adoption of educational tools and integrating best practices to enhance learning. AIEd benefits teachers and the teaching process through tailored content for individual learners, at-risk or gifted students, learning predictive models, personalised educational resources, improved classroom management, enhanced teaching across various subjects, academic progress facilitation, and qualified development in pedagogical skills, human behaviour, and interactions (Zhang and Aslan, 2021; Chiu et al., 2023).

AI unlocks new research potential in universities by expanding experimental and investigative activities and disseminating study results (Li and Wang, 2023). Teachers can focus on complex tasks as AI provides student support and answers (Southworth et al., 2023). Khosravi (2022) advocates integrating explainable AI (XAI) in education, prioritising human-centred design of educational tools, assessing XAI implementation, and enhancing AIEd systems for reliability and knowledge transfer support. Many teachers avoid AIEd due to a lack of understanding (Crompton, Jones and Burke, 2022). To effectively integrate AI tools, teachers should update their educational practices and embrace the challenges of technology in teaching (Skavronskaya, Hadinejad and Cotterell, 2023). In the future, teachers can integrate into their pedagogical approach aspects related to learners' behaviour, such as emotions, attention, gestures, and movement, with the support of AI technologies (Crescenzi-Lanna, 2023).

1.3. Artificial intelligence in education in assessment and administration

Chiu et al. (2023) identified two main contributions of AIEd assessment: automatic grading and learners' foreseen performance in online classes. The feedback provided to students after the assessment process is immediate and constructive, and instructors can support students in improving specific skills (Hopcan et al., 2022; Southworth et al., 2023). Cope, Kalantzis and Searsmith (2021) underline the role of AI in the assessment process, not in the conventional form, but especially related to tracking progress and providing "just-in-time feedback". AI can improve assessments (Al Braiki et al., 2020), with benefits highlighting its efficiency and consistency (Chassignol et al., 2018) and presenting the possibility of automating the assessment process.

The sustenance provided by AI in education refers to supporting and enhancing the performance of management platforms, analysis of scaled data, personalisation of various academic services, increasing work efficiency of administrative staff, and consistency in the decision-making process (Zhang and Aslan, 2021; Chiu et al., 2023). The work AI can perform in education also refers to completing tasks that consume instructor's time at a faster pace, identifying students' preferences and learning styles to generate personalised learning plans, and providing them with timely and direct feedback or assisting teachers in their data-related decisions or work (Chen, Chen and Lin, 2020).

1.4. Artificial intelligence in business education and AI tools

AI-based education enhances entrepreneurial competencies and fosters creativity, benefiting businesses (Nuseir, Basheer and Aljumah, 2020). While AI offers real support in business

scenarios for students, further conceptualisation of AI's use in business and education is needed, covering critical aspects like processes, activities, and actors (Yang et al., 2022).

AI tools have proven firmly and vastly helpful in various fields, in education or business education. Amongst them, there are computer vision, prediction systems, data mining (Das et al., 2015), intelligent learning or teaching systems, learning analytics (Ley et al., 2023), facial recognition systems, voice or speech recognition systems, virtual laboratories, augmented reality, virtual reality, hearing and sensing technologies, edge computing, virtual personalised assistants, real-time analysis, AI chatbot, image recognition, personalised learning approach, academic analytics, and adaptive learning method (al-Zyoud, 2020; Han, Park and Lee, 2022).

2. Research methodology

The article uses quantitative research to examine how AI supports educational activities, significant drivers, and tools for business education. The study aimed to determine whether respondents thought of AI as a tool that supported educational activities and which AI technologies supported business academic endeavours.

Students are direct beneficiaries of the educational process, and therefore, the study focuses on their situation to highlight the immediate impact of AI in educational activities. It is crucial to understand in detail how AI can influence them, improving the quality of the learning process and academic outcomes. Based on the analysis of the literature (Das et al., 2015; Asakura et al., 2020; Al Braiki et al., 2020; Chen, Chen and Lin, 2020; Nuseir, Basheer and Aljumah, 2020; al-Zyoud, 2020; Ouyang and Jiao, 2021; Cope, Kalantzis and Searsmith, 2021; Zhang and Aslan, 2021; Hopcan et al., 2022; Khosravi et al., 2022; Crompton, Jones and Burke, 2022; Yang et al., 2022; Han, Park and Lee, 2022; Chiu et al., 2023; Southworth et al., 2023; Li and Wang, 2023; Skavronskaya, Hadinejad and Cotterell, 2023; Crescenzi-Lanna, 2023; Ley et al., 2023), two main research questions have been formulated, namely:

Q1: Have you used AI in educational activities?

Q2: Do you consider AI beneficial in business educational activities?

To perform multivariate statistical analysis, binary logistic regression is often recommended (Toumi, 2020; Rahman et al., 2021). To respond to these questions, the econometric model deployed for data analysis was binary logistic regression, which can be written as (Bangdiwala, 2018):

$$\mathrm{P}(Y = 1 \mid X) = logit^{-1}(X\beta) = \frac{e^{X\beta}}{1+e^{X\beta}} \quad (1)$$

In the equation, $\mathrm{P}(Y = 1 \mid X)$ represents the probability that variable Y would be affected if the predictor variables X are taken into consideration; Y is the dependent variable with only one of two outcomes (1 – the outcome that is trying to predict; 0 – the other outcome), $X\beta$ is the linear predictor function. The inverse of the logit function gives the probability of Y having the value of 1.

The coefficient β shows if a direct or an inverse association exists between the dependent variable and its predictors. The odds ratios higher than 1 indicate that as the independent variable increases, so do the odds of the dependent variable, but the values of less than

1 suggest that if the independent variable increases, the odds of the dependent variable decrease (Field, 2013). The response variable is binary, and in our research, the first dependent variable used was AIEd corresponding to the question from the questionnaire: Have you used AI in educational activities? Starting from the literature review, eighteen independent variables were used to explain AI usage by learners. The AIEd predictors are described in table no. 1.

Table no. 1. Artificial intelligence in education (AIEd) and predictors

Predictors	Coding
AI performs administrative tasks instead of teachers	AI_AD
AI identifies the degree of fulfilment of students' work tasks	AI_DW
AI enables learning outside the classroom	AI_CLASS
AI helps teachers develop personalised learning plans for each student	AI_P
AI discovers learning gaps in students	AI_DIS
AI helps generate ideas for projects / other curricular and extracurricular activities	AI_NI
AI reduces human error (e.g., corrections)	AI_HE
AI identifies copyright issues	AI_HR
AI will eliminate the role of the teacher in the future	AI_T
AI will increase tuition costs	AI_COST
AI cannot give me emotional support	AI_ES
AI, together with teachers, creates a complete approach to the educational act	AI_CA
AI allows the connection with the business environment	AI_BE
AI can be used to train teachers	AI_TT
AI improves school performance	AI_SP
AI reduces the time allocated to learning	AI_TIME
AI increases the employability of students in the business environment	AI_EMPLOY
AI stimulates the desire to learn and assimilate new knowledge	AI_LD

The second research question is Q2: Do you consider AI beneficial in business educational activities? The respondents were asked to select from nineteen AI tools that learners can use in business education (AIEd_B) (Table no. 2).

Table no. 2. Artificial intelligence in education (AIEd_B) and predictors

Predictors	Coding	Predictors	Coding
Computer-Vision	CV	Virtual Reality	VR
Prediction Systems	PS	Hearing and Sensing Technologies	HST
Data Mining	DM	Edge computing	EC
Intelligent Learning Systems	EIS	Virtual Personalized Assistants	VPA
Learning Analytics	LA	Real-Time Analysis	RTA
Facial Recognition Systems	FAS	AI chatbot	CBT
Voice Recognition Systems	VAS	Image recognition	IR
Virtual Laboratories	VL	Personalised Learning Approach	PLA
Augmented Reality	AR	Academic Analytics	AA
		Adaptive Learning Method	ALM

The data were collected through a questionnaire administrated via Google Forms in June – July 2023, comprising dichotomic questions (2) and close-ended questions with Likert scale answers. The study had 254 respondents. The gender distribution was 41.7% male and 58.3% female (Table no. 3). Regarding age, 94.9% were 18-26 years old, while 5.1% were 26 years old or above. Concerning income, 34.6% had 3,000 lei or less, 25.9% had more than

3,000 lei, and 39.5% did not declare any income. Education-wise, 27.2% had a bachelor's degree or higher, and 72.8% had high school, post-secondary, or professional studies. As for occupation, 15.0% were employees, and 85.0% were students. The convenience sampling technique was applied to select respondents conveniently (Edgar and Manz, 2017). This sampling technique involves selecting respondents from a convenient subset of the population (Baxter et al., 2015). Although this technique may be perceived as the weakest method of non-probabilistic sampling, it is often used to obtain a range of attitudes and opinions that can be further tested in future research (Albert et al., 2010).

The questionnaire was administered to assess how AI influences educational activities and to evaluate AI tools supporting business educational activities. The respondents are students from business education programs. The provided responses are anonymous, ensuring the confidentiality of the collected data.

The statistical analysis was conducted using IBM SPSS Statistics version 29.0, employing binary logistic regression. The variables were assessed for multicollinearity (Field, 2013), using the variance inflation factor (VIF) to estimate how much the change of a regression coefficient rises if the independent variables are correlated. A VIF between 5 and 10 indicates a high correlation between predictors.

$$VIF_j = \frac{1}{1-R_j^2} \quad (2)$$

In the above equation, R_j^2 is the coefficient of determination (R-squared) for linear regression.

Table no. 3. Descriptive statistics of respondents' profile

Measure	Item	Frequency (%) N = 254
Gender	Male	106 (41.7%)
	Female	148 (58.3%)
Age	18-25	241 (94.9%)
	26 or above	12 (5.1%)
Average monthly income	3,000 lei or less	88 (34.6%)
	More than 3,000 lei	66 (25.9%)
	No income	100 (39.5%)
Education	High school / post-secondary studies/ professional studies	185 (72.8%)
	Bachelor's degree / Postgraduate studies	69 (27.2%)
Occupation	Employee	38 (15.0%)
	Student	216 (85.0%)

To test the model fit, we employed Omnibus Tests of Model Coefficients to determine if there was a significant improvement compared to the null model. The Hosmer and Lemeshow test was also used to assess the difference between the observed and predicted models (Field, 2013).

$$H = \sum_{i=1}^{G} \frac{(O_i - E_i)^2}{E_i * (1 - \frac{E_i}{N})} \quad (3)$$

In the above equation, G represents the number of groups created based on the probabilities predicted by the model, O_i represents the observed frequency in group i, E_i represents the expected frequency in group i, and N represents the total number of observations.

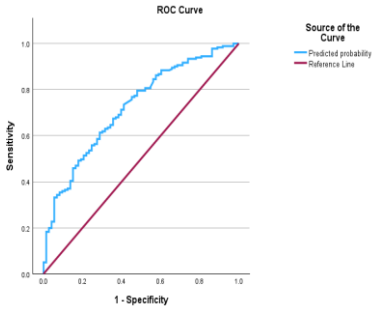
The model summary used Nagelkerke's R-square, an adjusted version of the Cox and Snell R-square ranging from 0 to 1 (Pallant, 2005). Model validation included receiver operating characteristic curve (ROC curve) analysis, measuring the area under the ROC curve (AUC).

Within the analysis, the issue of endogeneity has not been addressed. Since both independent and dependent variables are based on opinions expressed by the same individual, there is a risk that the observed relationship may not only reflect direct causality but also reciprocal influences or effects of an unobserved variable. This may affect the generalizability of the results to other populations or contexts. Thus, the findings of this study may be influenced by the specific characteristics of the subjects and the context in which the data were collected, and the extrapolation of results to other groups or situations may be limited. It is necessary for future research to adopt specific methods to manage these aspects.

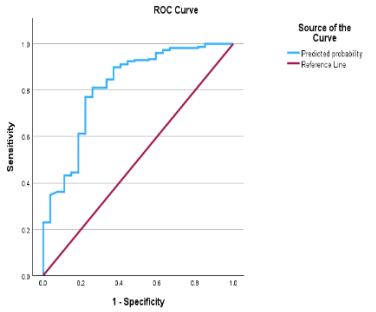
3. Results and discussion

For multivariate binary logistic regression, we used AIEd as dependent variable, and the variables AI_AD, AI_DW, AI_CLASS, AI_P, AI_DIS, AI_NI, AI_HE, AI_HR, AI_T, AI_COST, AI_ES, AI_CA, AI_BE, AI_TA, AI_SP, AI_TIME, AI_EMPLOY, and AI_LD as independent variables fitted into the model as will appear in table no. 5. The model fitting effect was tested by ROC (figure no. 1 (a)). The variables AI_AD, AI_DW, AI_CLASS, AI_P, AI_DIS, AI_NI, AI_HE, AI_HR, AI_T, AI_COST, AI_ES, AI_CA, AI_BE, AI_TA, AI_SP, AI_TIME, AI_EMPLOY, and AI_LD jointly projected the AIEd with an AUC of 0.723. According to Hosmer, Lemeshow and Sturdivant (2013), we consider this acceptable discrimination if $0.7 \leq ROC < 0.8$. Consequently, this regression model has good sensitivity and specificity. For the model, Chi-square (df:18) = 43.369 was statistically significant, with p-value < 0.05 (=0.011) showing that the full model has a considerable prediction performance. Moreover, the model explained 18.1% of the variance of AIEd (Nagelkerke R-square), predicted percentage correct at 73.2%. For the model fit, we also evaluated Hosmer and Lemeshow test, Chi-square (df:8) = 5.143, df=8, p-value > 0.05 (=0.742), which showed that the deployed model fitted the data. The collinearity statistics suggest that there isn't any collinearity relationship between predictors as their VIF values range between 1.433 and 3.298, as is to be seen in table no. 4.

The second dependent variable used in the multivariate binary logistic model was AIEd_B. The independent variables were: CV, PS, DM, EIS, LA, FAS, VAS, VL, AR, VR, HST, EC, VPA, RTA, CBT, IR, PLA, AA, and ALM, as to be mentioned in table no. 6. The model fitting effect tested by ROC and the predictors jointly projected the AIEd_B with an AUC of 0.817 (figure no. 1 (b)). According to Hosmer, Lemeshow and Sturdivant (2013), we consider this excellent discrimination if $0.8 \leq ROC < 0.9$. Therefore, the second regression model has good sensitivity and specificity. In this model, Chi-square (df:19) = 38.941 was statistically significant, p-value < 0.01 (=0.004). According to Nagelkerke R-square, the model explained 28.9% of the variance of AIEd_B, predicted percentage correct at 90.2%. Hosmer and Lemeshow test, Chi-square (df:8) = 12.550, df=8, p-value > 0.05 (=0.128) showed that the deployed model fitted the data.



(a)



(b)

Figure no. 1. ROC curve

The collinearity statistics indicate that there isn't a collinearity relationship between mentioned predictors, as the VIF values are greater than 1 and below 5, ranging between 2.092 and 4.339 (table no. 4).

Within the study, the learners' reasons for using AI in educational activities were identified, a multivariate binary logistic model being used. In this model, AIEd was considered as the dependent variable. Thus, considering the first research question (Q1: Have you used AI in educational activities?), the analysis results show that four factors are statistically significant at the 95% confidence level (p-value < 0.1) among the predictors, as will be observed in table no. 5. Those factors were: AI_AD (AI performs administrative tasks instead of teachers), AI_P (AI helps teachers develop personalised learning plans for each student), AI_SP (AI improves school performance), and AI_TIME (AI reduces the time allocated to learning).

Table no. 4. Collinearity statistics

Factor	Tolerance	VIF	Factor	Tolerance	VIF
AI_AD	0.406	2.461	**CV**	0.478	2.092
AI_DW	0.397	2.516	**PS**	0.379	2.639
AI_CLASS	0.449	2.229	**DM**	0.472	2.119
AI_P	0.315	3.173	**EIS**	0.437	2.288
AI_DIS	0.409	2.447	**LA**	0.380	2.634
AI_NI	0.460	2.175	**FAS**	0.244	4.102
AI_HE	0.534	1.871	**VAS**	0.264	3.788
AI_HR	0.570	1.755	**VL**	0.359	2.786
AI_T	0.557	1.794	**AR**	0.393	2.544
AI_COST	0.560	1.785	**VR**	0.375	2.665
AI_ES	0.698	1.433	**HST**	0.393	2.546
AI_CA	0.368	2.714	**EC**	0.336	2.976
AI_BE	0.382	2.619	**VPA**	0.354	2.826
AI_TA	0.374	2.671	**RTA**	0.343	2.912
AI_SP	0.303	3.298	**CBT**	0.437	2.286
AI_TIME	0.512	1.951	**IR**	0.365	2.743
AI_EMPLOY	0.378	2.643	**PLA**	0.302	3.315
AI_LD	0.404	2.474	**AA**	0.247	4.041
			ALM	0.230	4.339

The variable AI_AD was found to have a significant relationship with AIEd (p-value < 0.05). The results in the model indicated that the probability of using AI in educational activities

increases by 1.488 times when considering that AI performs administrative tasks instead of teachers, considering all the other variables being constant. Such tasks may include analysing students' work, providing feedback, grading, or detecting plagiarism (Chen, Chen and Lin, 2020; Pokrivcakova, 2019). These results are consistent with the previous findings (Zhang and Aslan, 2021; Chiu et al., 2023).

The variable AI_P was significant at a 95% confidence level in the model (p-value < 0.05) (table no. 5). The results indicate that learners' perception of AI helping teachers develop personalised learning plans increases the likelihood of AIEd by 1.651 times, holding other factors constant. This finding aligns with previous research highlighting AI's value in personalising and adjusting individual learning plans (Hopcan et al., 2022; Southworth et al., 2023).

The variable AI_SP (AI improves school performance) was a significant factor in the model (p-value < 0.1). The probability of learners considering using AI tools in educational activities is ambiguous as the value of the odds ratio of AI_SP is 0.668 (< 1), and the lower limit is 0.416. In contrast, the upper limit is 1.074 (Field, 2013). These findings are in line with previous studies that show how instrumental AI tools can positively influence the current school performance or satisfaction of students (Steenbergen-Hu and Cooper, 2014; Ouyang, Zheng and Jiao, 2022) and identify some gaps that have an impact on their learning performance (Chassignol et al., 2018). Better performance can also be achieved by linking AI to innovative assessment practices (Yang et al., 2021).

Table no. 5. Binary logistic regression results, AIEd as dependent variable

Factor	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)
AI_AD	0.397	0.182	4.741	1	0.029**	1.488	1.040 - 2.128
AI_DW	-0.214	0.195	1.204	1	0.272	0.807	0.551 - 1.183
AI_CLASS	0.065	0.192	0.114	1	0.736	1.067	0.732 - 1.556
AI_P	0.501	0.222	5.112	1	0.024**	1.651	1.069 - 2.549
AI_DIS	-0.247	0.202	1.498	1	0.221	0.781	0.526 - 1.160
AI_NI	0.157	0.179	0.768	1	0.381	1.169	0.824 - 1.660
AI_HE	0.039	0.177	0.048	1	0.827	1.039	0.735 - 1.470
AI_HR	-0.261	0.189	1.903	1	0.168	0.770	0.531 - 1.116
AI_T	-0.137	0.149	0.852	1	0.356	0.872	0.651 - 1.167
AI_COST	-0.123	0.157	0.615	1	0.433	0.884	0.650 - 1.202
AI_ES	-0.061	0.150	0.165	1	0.684	0.941	0.700 - 1.263
AI_CA	0.290	0.210	1.913	1	0.167	1.337	0.886 - 2.016
AI_BE	-0.319	0.221	2.082	1	0.149	0.727	0.472 - 1.121
AI_TA	-0.059	0.222	0.070	1	0.791	0.943	0.611 - 1.456
AI_SP	-0.403	0.242	2.769	1	0.096*	0.668	0.416 - 1.074
AI_TIME	0.461	0.187	6.104	1	0.013**	1.586	1.100 - 2.288
AI_EMPLOY	0.238	0.215	1.226	1	0.268	1.269	0.832 - 1.934
AI_LD	-0.129	0.214	0.365	1	0.546	0.879	0.578 - 1.337
Constant	0.040	0.635	0.004	1	0.949	1.041	

Model summary: n=254; -2Log likelihood=270.334, Cox and Snell R-square=0.127, Nagelkerke R-Square=0.181; Step 0: Predicted Percentage Correct 71.3%; Step 1: Predicted Percentage Correct: 73.2%; Omnibus Test: Chi-square = 43.369, df=18, p-value=0.011; Hosmer and Lemeshow test: Chi-square = 5.143, df=8, p-value=0.742; ***Significance at the 1% level, ** at the 5% level, and *at the 10% level.

The results of the model indicated that the variable AI_TIME (AI reduces the time allocated to learning) had a significant relationship with AIEd at a 95% confidence level (p-value < 0.05). The estimate of the odds ratio for AI_TIME is 1.586, which indicates that the odds of learners using AIEd, because they consider that AI reduces the time allocated to learning, is 1.586, more significant than the odds of not considering AI_TIME. A study conducted by Cen, Koedinger and Junker (2007) has proven that using intelligent tutoring systems reduces students' learning time and, nowadays, AI intelligent tutoring systems can provide a relatively well-rounded human-like learning experience. Furthermore, Kong (2020) mentioned that AI shortens the learning time, and, thus, students have the capability of learning more content within the same time frame, an affirmation in line with other findings (Dahotre et al., 2011; Munir, Vogel and Jacobsson, 2022) showing that when compared to using traditional training materials, students use less time for training whilst improving their performance. AIEd requires continuous improvement to address learners' diverse needs and preferences (Zhang and Aslan, 2021). To achieve this, educators, researchers, and the education community must actively participate in the AIEd innovation process, integrating theoretical, practical, conceptual, and empirical dimensions.

Little evidence exists for educational data mining, particularly in offering speculative and predictive analyses (Cope, Kalantzis and Searsmith, 2021). AI in education has drawbacks, including higher costs, scalability challenges, ethical concerns, privacy issues, and limited teacher expertise (Zhang and Aslan, 2021). Integrating AI into education depends on government support for educational institutions, research, training, and private sector efforts in developing AI applications (Knox, 2020) for teaching.

The second multivariate binary logistic model was developed to identify the predictors for AI in business educational activities (the key question in the questionnaire Q2: Do you consider AI beneficial in business educational activities?). The binary logistic regression on AIEd_B and its predictors shows that the variables CV, EC, CBT, and ALM are the best predictors.

The variable CV (computer vision) was found to be a significant factor in the binary regression model at a 95% confidence level (p-value<0.05). The results indicated that the odd ratio of CV increased the probability of AIEd_B by 2.169 times, which was in line with the results of the previous studies (Bebis, Egbert and Shah, 2003). CV has various applications in education activities with multiple purposes (He et al., 2017; Kusumota, Aroca and Martins, 2018; Savov, Terzieva and Todorova, 2018) that show various benefits such as creating an interactive educational environment (Sophocleus et al., 2021).

The variable EC (edge computing) had a significant influence on AIEd_B at a 90% confidence level (p-value<0.10). The results showed that the probability of EC familiarity for learners increased by 2.028 in the likelihood of AIEd_B. These findings are consistent with the motivations of Hua et al. (2023), highlighting that, on the one hand, AI algorithms can optimise EC, and, on the other hand, EC is an enabler for AI to bring faster response speeds for AI applications in various other fields. Hwang and Nurtantyana (2022) emphasise that using AI and EC can extend the education of students.

The variable CBT significantly influenced AIEd_B at a 95% confidence level (p-value <0.05). The increase in the odds ratio of CBT is a 0.443 decrease in the odds of considering AI beneficial for business educational activities, and the decrease could be as much as

0.227-fold or a 0.865-fold drop. This result follows similar conclusions as Chen, Chen and Lin (2022), showing favourable student perceptions.

The variable ALM (adaptive learning method) had a significant influence on AIEd_B at a 90% confidence level (p-value<0.1). Still, the effect of ALM on AIEd_B is not apparent, as the value of the odds ratio is 0.528 (< 1), with the lower limit of 0.256 and the upper limit is 1.088 (Hosmer, Lemeshow and Sturdivant, 2013). The findings are in line with Muñoz et al. (2022) that adaptive learning technology enables students to obtain instruction and practice at a faster pace and is also suited to their capabilities. A possible negative impact may be seen in the challenges of adaptive learning in education, such as "the lack of cognition of brain and technology, the bottleneck of the model of emotion domain, the separation of education and technology, the security of data management and the risk of privacy leakage" (Li, He and Xue, 2021). Also, implementing adaptive technologies in the educational process depends highly on the teachers' role (Morze et al., 2021). Other studies also show the effectiveness of adaptive learning in enabling students to become proficient in specific content (Shelle et al., 2018).

The results of the binary logistic regression specific to IAEd_B and the dependent variables mentioned above (table no. 6.) indicate that the significant impact is exerted by CV, EC, CBT and ALM.

Table no. 6 Binary logistic regression results, AIEd_B as dependent variable

Factor	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)
CV	0.774	0.308	6.327	1	0.012**	2.169	1.186 – 3.965
PS	-0.325	0.333	0.957	1	0.328	0.722	0.376 – 1.386
DM	-0.375	0.302	1.534	1	0.216	0.688	0.380 – 1.244
EIS	0.195	0.322	0.366	1	0.545	1.215	0.646 - 2.285
LA	0.629	0.382	2.709	1	0.100	1.875	0.887 – 3.966
FAS	-0.375	0.413	0.825	1	0.364	0.687	0.306 – 1.544
VAS	0.063	0.367	0.030	1	0.863	1.066	0.519 – 2.189
VL	0.047	0.375	0.016	1	0.900	1.048	0.503 – 2.187
AR	0.133	0.277	0.232	1	0.630	1.143	0.664 – 1.966
VR	0.398	0.360	1.224	1	0.269	1.488	0.736 – 3.011
HST	-0.158	0.313	0.253	1	0.615	0.854	0.462 – 1.578
EC	0.707	0.395	3.198	1	0.074*	2.028	0.934 – 4.402
VPA	-0.508	0.324	2.450	1	0.117	0.602	0.319 – 1.136
RTA	-0.027	0.337	0.006	1	0.936	0.973	0.503 – 1.883
CBT	-0.814	0.341	5.695	1	0.017**	0.443	0.227 – 0.865
IR	0.502	0.313	2.573	1	0.109	1.652	0.895 – 3.049
PLA	0.538	0.360	2.234	1	0.135	1.712	0.846 – 3.467
AA	0.017	0.367	0.002	1	0.962	1.018	0.496 – 2.089
ALM	-0.639	0.369	2.997	1	0.083*	0.528	0.256 – 1.088
Constant	-0.221	0.814	0.074	1	0.786	0.801	

Model summary: n=254; -2Log likelihood=133.122, Cox and Snell R-square=0.142, Nagelkerke R-Square=0.289; Step 0: Predicted Percentage Correct 89.4%; Step 1: Predicted Percentage Correct: 90.2%; Omnibus Test: Chi-square = 38.941, df=19, p-value=0.004; Hosmer and Lemeshow test: Chi-square = 12.550, df=8, p-value=0.128; ***Significance at the 1% level, ** at the 5% level, and *at the 10% level.

Table no. 5 and table no. 6 present the Wald test values, which are used to assess the statistical significance of each coefficient in the regression models. The obtained value for the Wald test is used to test the null hypothesis that the associated coefficient is zero. A higher value of the Wald test indicates a significant influence of the independent variable on the dependent variable. Additionally, for each coefficient, the associated probability value with the Wald test is important, as lower probability values suggest rejecting the null hypothesis and considering the coefficient as different from zero.

Conclusions

This study empirically investigated the triggers and AI tools fostering AI benefits in business educational activities. Research among students revealed their limited familiarity with AI's benefits for education, despite 87.8% having used AI previously. Only 71.3% of respondents used AIEd, indicating little awareness of AI tools and their benefits. Additionally, 46.8% of learners declared being unprepared to embrace AI in business education, although they were more prepared than teachers for AIEd_B (only 27.2% of the teachers were prepared). The authors employed multivariate binary logistic regressions to respond to two research questions. For the first question, if AI supports educational activities, the results of the study revealed that the respondents used AI mainly because it performs administrative tasks instead of teachers; AI helps teachers develop personalised learning plans for each student; AI improves school performance, and AI reduces the time allocated to learning. The second research question focused on AI tools used in AIEd, revealing limited learner knowledge and practice regarding CV, PS, DM, EIS, LA, FAS, VAS, VL, AR, VR, HST, EC, VPA, RTA, CBT, IR, PLA, AA, and ALM in business education.

The questionnaire used in the study is an original tool, and the analysis focuses on a specific group of subjects and a unique context that has not been extensively covered in the existing literature. This research contributes to existing knowledge by highlighting unique aspects that enrich the understanding in the analyzed field.

The paper highlights the limited degree of awareness regarding the benefits of using AI in business education, even though respondents have used AI in various activities. Additionally, the lack of preparedness among respondents to effectively adopt AI in the educational process has been emphasized. The study contributes to existing literature through empirical investigation of AI determining factors and tools in the context of business education, underscoring the need for continuous improvements in the implementation of AI in this domain.

A limitation of this study refers to the sample, its size and level of knowledge. It considers the students' opinions from Romania without the possibility of expanding the analysis to other situations encountered in different universities. Future research should use larger and more diverse samples to enhance the generalizability of results to a significant population. Additionally, it is important to consider the impact of AI on teachers and administrative components in education, and future research should focus on exploring these aspects.

Throughout this investigation, binary logistic regression models were employed, acknowledging their limitations in capturing the entire complexity of the studied phenomenon. Looking ahead to future research, we consider transitioning to a Generalized Ordered Logit model beneficial, as it allows for a more detailed and precise approach to the relationships between variables. Through this model, we intend to thoroughly explore the

influence of each explanatory variable on different levels of the dependent variable, highlighting consistent contributions across various value tiers. The study may appear timely based, viewing the students' understanding of the field and the limited use of AI in the Romanian educational system for business students. It may fail to present a holistic and deepened view of the topic.

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