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Likelihood of AI Tools Adoption and Interest in Professional Development Opportunities in Higher Education: An Ordinal Logistic Regression Analysis

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Abstract: This study explored the factors influencing academic staff's readiness to use artificial intelligence (AI) tools and participate in AI-related professional development, utilizing a quantitative approach. Data from 95 academic staff members of the University of Vlora "Ismail Qemali" were gathered via an online survey. The analysis, conducted using univariate ordinal logistic regression, pinpointed key predictors of educational AI tools adoption likelihood and interest in attending AI professional development opportunities. Rigorous evaluation of model fit, influence diagnostics, and cross-validation was conducted to ensure the findings' reliability and accuracy. Results highlight the critical role of interest in AI educational tools development, technological proficiency, and past use of AI educational tools in determining the likelihood of adopting educational AI tools, underscoring the pivotal importance of fostering a genuine interest in AI. Furthermore, the research identifies gender as a significant factor influencing interest in attending AI professional development opportunities, while negative perceptions of AI's role in education tend to reduce such interest. These findings stress the need for targeted efforts to enhance educators' readiness for AI, mitigate gender disparities, and correct misconceptions about AI. By revealing the complex factors affecting educators' willingness to adopt AI technologies, this study advocates for a holistic strategy encompassing a broader range of influences. It provides actionable insights for educational policymakers, curriculum developers, and AI tool creators to create an environment conducive to AI adoption in higher education. Although limited by its use of convenience sampling and focus on a single institution, this research offers essential insights into the dynamics of AI adoption in education. It lays a foundation for strategies that encourage innovation, inclusivity, and a forward-thinking approach to integrating AI into future teaching and learning.

Keywords: Artificial intelligence, Ordinal logistic regression, AI tools adoption, AI professional development

Introduction

The integration of artificial intelligence (AI) into academic environments and communities holds the potential to bring significant changes in pedagogical approaches. Through this integration, it will be possible to improve the quality of learning and optimize administrative procedures. To guarantee the effective integration and utilization of AI-driven tools and applications, the academic community must be opened and prepared to accept these technological developments. As the educational landscape progresses under the influence of AI, UNESCO advocates for the protection of teachers' rights and working conditions. It underscores the importance of AI as a complementary tool that enhances, rather than replaces, the vital human elements of learning and cooperation. The requirement to strengthen teacher training and implement capacity-building initiatives is prioritized by UNESCO in its call (UNESCO [7387], 2019).

The private sector has mainly influenced AI adoption and implementation in higher education institutions, despite challenges posed by the absence of comprehensive public policies and sufficient governmental support. Collaboration among policymakers, educational institutions, and both private and public research entities is of critical importance to ensure that the infrastructure for AI integration is adequately established (Lainjo & Tmouche, 2023). Countries such as France, Australia, Estonia, South Korea, China, and the United States are recognizing the potential of AI to enhance educational equity and quality, and are actively integrating AI into their educational programs. However, these efforts encounter barriers, especially in developing countries, due to inadequate technological infrastructure and the lack of highly trained AI professionals, underscoring a global disparity in readiness for AI-driven educational reforms (Pedró et al., 2019).

Albania, an upper-middle-income country (World Bank Blogs, 2023), has been adjusting its educational policies to incorporate recent technological advancements more effectively, particularly in the field of AI. A specialized study (Tataj & Kola, 2021) examined the consequences of these strategic changes in Albania on the development of innovative educational methodologies. This examination illustrated how the Albanian education system responds to labor market demands by incorporating AI-related college faculties and courses. The study highlights the challenges inherent in AI education in Albania, including a deficiency of AI-specialized faculty and a limited availability of AI curricula, especially in private establishments. These circumstances underscore the critical need for more thorough AI educational opportunities. One of the prerequisites for EU integration in Albania is the digitization of higher education. However, a significant lack of specialized information and communication technology (ICT) educators prevents this objective, with 77% of vocational instructors acknowledging the need for further ICT methodological training. The country's strategic plan for higher education and ICT (2021–2027) focuses on the inclusive integration of ICT to strengthen the educational digital infrastructure through technological enhancements and e-learning platforms (Xhindi & Toci, 2023).

In this research, we aim to examine the influence of a set of predictors—demographic characteristics, educational background, technological proficiency, perceptions of AI's role in education, past use of AI educational tools, and interest in AI educational tools development—on understanding their impact on two outcome variables: the likelihood of academic staff at the University of Vlora "Ismail Qemali" adopting AI tools in their future pedagogical and scholarly endeavors (educational AI tools adoption likelihood) and their interest in engaging with professional development opportunities related to AI in education (interest in attending AI professional development opportunities). Our objective is to ascertain the degree to which these predictors, separately, can predict each of the outcome variables. This investigation aims to contribute to a deeper understanding of the variables that promote or slow the adoption of AI technologies among higher educators. The findings of this study are important to cultivate the academic dialogue on AI in higher education and inform the development of interventions, training programs, and policies that enhance educators' skills and readiness for AI integration.

This research paper's organization is as follows: The second section gives an overview of the literature relevant to the subject under investigation. The third section details the methods used for collecting, processing, and analyzing data. The fourth section presents the study's findings, while the fifth provides a discussion of these results. The sixth section presents the research conclusions.

Literature Review

Research into the adoption and integration of virtual and digital technologies within higher education across various regions, including the Western Balkans and Albania, underscores a complex landscape of engagement and readiness among educators and institutions. In the Western Balkans it is pointed out a moderate familiarity but low implementation (9%) of augmented reality (AR) and virtual reality (VR) technologies among academic staff, despite a high interest and positive attitude towards these technologies. Factors such as teaching experience, hardware infrastructure, and lab usage frequency come out as significant determinants of educators' confidence and the timeline for integrating VR into pedagogy (Kamińska, et al., 2022). Furthermore, the integration of virtual learning environments into education is expected to fundamentally transform the creation and distribution of content, necessitating adjustments to accommodate learners' digital competence. This highlights the significance of AI in promoting educational fairness, and a sustainable framework consistent with socioeconomic goals (Jokhan et al., 2022). In addition, the advocacy for improved accessibility to education and technology marks the potential of AI and Fourth Industrial Revolution technologies to further sustainable development objectives, specifically in the realms of equitable education and lifelong learning (Ally & Perris, 2022).

Evaluating higher education's response to the AI labor market's demands, an investigation pinpointed fundamental technical, interdisciplinary, and soft skills, affirming the need for educational institutions to certify graduates' proficiency (Benhayoun & Lang, 2021). A three-stage framework at a pedagogical university promotes advancing digital proficiency, creating digital portfolios, and installing a competency-based evaluation system to augment educational processes with digital technologies, aiming to boost both digital infrastructure and educational outcomes (Voronin et al., 2020). Furthermore, in (Al-Slehat et al., 2023), faculty perceptions underscored the necessity for upgrading educational environments and infrastructure to ease AI adoption, aligning with international educational advancements. Also, in (Huang et al., 2021) it is found that the integration of AI in education needs new digital teaching skills, adjustments in students' learning styles, and a collaborative effort to develop an AI-based educational ecosystem that ensures fairness, ethical data handling, and safe technology use.

The productiveness of AI in education, particularly in personalized learning for primary grades, relies on its lining up with the different needs and perspectives of both learners and educators, necessitating advancements in AI technologies like reinforcement learning (Chaudhry & Kazim, 2021). The supportive potential of AI and its learning analytics in enhancing teaching activities, while stressing the need for greater emphasis on ethical considerations and data privacy in the evolving landscape of teacher training is revealed in (Salas-Pilco, Xiao, & Hu, 2022). An exploratory review accentuates the ethical integration of AI into pedagogy as the primary focus of the field of AI in education. It emphasizes the central role of educators in leveraging AI to facilitate personalized learning experiences (Lameras & Arnab, 2022). A comprehensive analysis focusing on teachers' perspectives underscores their essential role in AI-based educational research, regardless of challenges related to AI's technical capacity, reliability, and the sector's infrastructural deficiencies. Further analysis highlights AI's multifaceted utility in academia, including personalized teaching, risk identification, and administrative automation, indicating its transformative potential in both the pedagogical and operational domains of higher education (Tarisayi, 2023). Nevertheless, AI is recognized for its ability to facilitate educational planning, implementation, and assessment, suggesting a generally positive outlook on its contribution to teaching methodologies (Celik et al., 2022).

A thorough synthesis of research examining the integration of AI technologies in education in Romania, Serbia, and other regions emphasizes the complex relationship between educators' readiness and the complicated nature of AI implementation in higher education institutions. Empirical evidence supports the notion that, despite the fact that AI tools have a large capacity to improve educational aims, their integration into pedagogical practices is hindered by barriers that impede teachers' tendency to employ them (Bucea-Manea-Țoniș, et al., 2022). Another study probed generative AI's dual impact in developing countries, focusing on its potential to advance or slow down progress across sectors, including education, while calling for strategic interventions to provide broad development and diminish disparities in technology access (Mannuru et al., 2023). According to Cathrin and Wikandaru (2023), the integration of AI technology into education is considered an inevitable trend, necessitating the development of academic and ethical standards in a balanced manner to tackle contemporary social challenges. A bibliometric analysis further demonstrates a lack of literature on the pedagogical implications of AI and machine learning (ML), identifying significant barriers to their effective integration in educational settings. This analysis predicts the development of sophisticated AI and ML tools to overcome these challenges, enhancing teaching and learning, especially for learners with disabilities (Okagbue et al., 2023).

As a result of increased academic recognition and the impact of AI on education during the COVID-19 pandemic, a bibliometric analysis conducted since 2018 reveals a substantial increase in AI-related educational research, with the United States and China making the most significant contributions (Karaca & Kılcan, 2023). Surveys and quantitative assessments of educators' engagement with generative AI tools and ChatGPT for teaching and research purposes disclose a foundational use among participants and a moderately positive bias towards these technologies, despite a low frequency of participation in related training initiatives (Ruiz-Rojas et al., 2023; Abbas et al., 2023).

Method

Study Design and Data

The research strategy employed in this study was a comprehensive quantitative analysis aimed at exploring the impact of various predictors on the likelihood of academic staff at the University of Vlora "Ismail Qemali" to adopt AI tools in their future pedagogical and scholarly endeavors (Y1), and their interest in engaging with professional development opportunities related to AI in education (Y2). Specifically, the strategy consisted of a structured approach to data collection through a survey, capturing responses across demographic characteristics (X1, X2), educational background (X3, X4), technological proficiency (X5), perceptions of AI's role in education (X6), past use of AI educational tools (X7), and interest in AI educational tools development (X8).

Table 1 provides an overview of the survey's items, categories, codes, measurement scales, and response frequencies.

Table 1. Overview of survey items, categories, codes, measurement scales, and response frequencies

Variable	Question	Shorten version of question	Categories	Code	Measurement scales	Frequency
X1	What is your gender?	Gender	Male	1	Nominal	26
			Female	2		69
X2	What is your age?	Age	25-34	1	Ordinal	12
			35-44	2		34
			45-54	3		31
			55 or older	4		18
X3	Which field of study are you currently in?	Field of study	Humanities and social sciences	1	Nominal	22
			Natural sciences	2		23
			Engineering and technology	3		22
			Medical and health sciences	4		11
			Business and economics	5		17
X4	What is your level of education?	Education level	Master's degree	1	Ordinal	20
			Doctoral degree	2		75
X5	How would you describe your level of proficiency in using technology?	Technological proficiency	Beginner	1	Ordinal	1
			Intermediate	2		15
			Proficient	3		60
			Expert	4		19
X6	How do you perceive the role of AI in education?	Perception of AI's role in education	Don't know	1	Nominal	3
			Worsen	2		4
			No impact	3		7
			Moderately	4		42
			Significantly improve	5		39
Y1	How likely are you to use AI-powered tools or applications in your studies or teaching in the future?	Educational AI tools adoption likelihood	Not very likely	1	Ordinal	12
			Somewhat likely	2		27
			Very likely	3		56
X7	Have you used any AI-powered tools or applications in your studies or teaching?	Past use of AI educational tools	No	0	Nominal	58
			Yes	1		37
Y2	Would you be interested in attending a workshop or training on the use of AI in education?	Interest in attending AI professional development opportunities	No	1	Ordinal	5
			Not sure	2		11
			Yes	3		79
X8	Are there any AI-powered tools or applications that you would like to see developed for use in education?	Interest in AI educational tools development	No	0	Nominal	72
			Yes	1		23

We collected the data by distributing an online survey via Gmail and using computer-assisted self-enumeration, which allowed the academic staff to complete the survey on their own. A sample frame of 145 academic staff members' private email addresses was used for the investigation. The study's sample population consisted of 95 academic staff members who answered the survey.

We executed this procedure from May 11, 2023, to June 22, 2023, using convenience sampling to ensure efficient response collection. Despite this limitation, the results obtained from this sample remain representative of the academic community at the University of Vlora "Ismail Qemali". This method was chosen because of its efficiency and accessibility to a readily available subset of the target population. However, the method's reliance on academic staff who were more readily available or prone to participate introduced the possibility of bias, which may have compromised the sample's representativeness.

Model Analysis and Performance

In pursuit of the research objective—distinguish the direct effects of different predictors on an ordinal outcome variable—the following subsubsections provide the rigorous statistical methods employed. To determine the relationship between the ordinal outcome variable Y and the predictor variable X, the univariate ordinal logistic regression model, known also as the Proportional Odds Cumulative Logit Model (POLR), was utilized. The formula for the POLR model (McCullagh, 1980; Agresti, 2010; Scott & Freese, 2014) is presented as:

$$P(Y \le j \mid X) = \frac{1}{1+\exp(-(\alpha_j - X\beta))},$$

where $P(Y \le j \mid X)$ denotes the probability of the response Y being less than or equal to category j, given predictor matrix X, α_j represent category-specific intercepts (threshold for category j), and β denotes the vector of regression coefficients. For the POLR model (Venables & Ripley, 2002; R Core Team, 2023), the `polr` function from the MASS package in R was used to perform model fitting. By employing the variance-covariance matrix estimate, this method calculates standard errors for ordinal response variables. In order to ensure that the Hessian matrix is computed correctly, the `Hess=true` option is provided. After the model was built, its assumptions were checked to ensure they were met. Throughout the subsequent statistical analysis, a significance level of 0.05 is used as the threshold for statistical significance.

Model Assessment

Through the utilization of various diagnostic tests, the univariate POLR model's adequacy was evaluated. The degrees of freedom were calculated as the discrepancy between the number of observations and the model parameters. t-values were derived for each coefficient in order to assess its significance. The purpose of calculating p-values is to examine the null hypothesis that each coefficient has no impact or is equivalent to zero. This is accomplished through the application of the t-distribution, in which the calculation for the negative absolute value of the t-statistic (Agresti, 2010; Venables & Ripley, 2002) entails doubling the cumulative distribution function value. Odds ratios were calculated by exponentiating the coefficients in order to quantify the influence of predictor variables.

The model's fit was assessed using likelihood ratio tests (LRT) with the `lrtest` function from the `lmtest` package (Zeileis & Hothorn, 2002). This involved comparing a fitted model with a single predictor to a null model consisting simply of the baseline intercept. The objective was to ascertain whether the predictor's inclusion improved the explanatory capability of the model. The LR, defined as

$$LR = -2(\log(L_{\text{null}}) - \log(L_{\text{model}}))$$

compares the log-likelihoods of the fitted model and null (intercept-only) model using a chi-square distribution with degrees of freedom representing the difference in parameter counts between the models. To identify observations that had a large impact on the model's estimates, we performed systematic evaluations as part of the analysis of influence and outliers (Kutner, Nachtsheim, Neter, & Li, 2005). The standard errors for the POLR model coefficients were calculated from the diagonal of the variance-covariance matrix. Influence measures for each observation were computed by recalculating the model coefficients with each observation excluded in turn. The change in coefficients was normalized by the standard errors, squared, and summed to quantify the influence of each observation.

Outliers were identified using deviance residuals of the model. Residuals that exceeded the 95th percentile of their absolute values were classified as outliers. Influential observations were those where the influence measure exceeded the 95th percentile of all calculated influence measures. Two new models were fitted after removing the outliers and influential points separately. Their quality was evaluated through a comparison of the Akaike Information Criterion (AIC) (Akaike, 1974) values with the original model.

Model Evaluation

We employed a 10-fold cross-validation strategy, facilitated by the caret package (Kuhn, 2008), to assess the predictive capability and generalizability of our univariate ordinal logistic regression model. The data set was partitioned at random into ten subsets. The validation set was assigned to each subset in a sequential manner, and the remaining data was utilized as training. By systematically applying the cross-validation method to each subset, we ensured that each subset served as the validation set exactly once.

This approach aimed to obtain a reliable estimate of the model's predictive accuracy. Using the train function in conjunction with the polr method, the model was trained on nine subsets and its performance was assessed on the tenth subset. A random `seed()` was established prior to the initiation of model training in order to ensure the reproducibility of our findings. To evaluate the explanatory power of our univariate ordinal logistic regression model, we calculated pseudo-R-squared values using McFadden's (McFadden, 1974), Cox and Snell's (1989), and Nagelkerke's (1991) metrics. Each version of these metrics provides a distinct viewpoint regarding the adequacy of the model:

$$R^2_{\text{McFadden}} = 1 - \frac{\log(L_{\text{model}})}{\log(L_{\text{null}})}$$

$$R^2_{\text{Cox\&Snell}} = 1 - \left(\frac{L_{\text{null}}}{L_{\text{model}}}\right)^{2/n}$$

$$R^2_{\text{Nagelkerke}} = \frac{R^2_{\text{Cox\&Snell}}}{1 - \left(L_{\text{null}}\right)^{2/n}}$$

where L_{model} and L_{null} are the likelihoods of the fitted and null model, respectively, and n is the sample size.

Results

Model Assessment

The associations between outcome variables (Y1 and Y2) and a variety of predictors (X1, X2, X3, X4, X5, Q6, Q7, and Q8) is investigated using univariate POLR models. The results indicated that only a subset of the predictors (X1, X5, X6, X7, and X8) showed statistically significant associations with the outcome variables (Y1 and Y2). Details related to these models are presented in Table 2.

Assumptions Checks for Univariate Logistic Regression Models

The outcome variables Y1 and Y2 were treated as ordinals, given that their categories possess an inherent order, yet the precise distances between these categories were neither constant nor quantifiable. Furthermore, the assumption of the independence of observations was satisfied, ensuring that the data collected from one participant did not influence the data collected from another. The assumption of linearity in the log-odds of the predictors was not applicable due to the ordinal nature of these variables; in particular, the predictors lacked continuity.

Table 2. Summary of the univariate POLR models for Y1 and Y2

	Component	Estimate	Stand. Error	t-value	Coef. p-value	Odd ratios	Residual Deviance	AIC	LR test p-value
Y1~X5	Coefficients:						173.03	183.03	0.2888
	X5.L**	-8.67	0.33	-25.92	<0.0001	0.0002			
	X5.Q***	7.44	0.38	19.44	<0.0001	1710.4			
	X5.C****	-3.23	0.36	-8.89	<0.0001	0.0397			
	Intercepts:								
	Not very likely|Somewhat likely	-5.39	0.32	-17.01	<0.0001				
	Somewhat likely|Very likely	-3.79	0.24	-15.57	<0.0001				
Y1~X7	Coefficients:						167.21	173.21	0.0019
	X7Yes	1.35	0.46	2.95	0.0040	3.8647			
	Intercepts:								
	Not very likely|Somewhat likely	-1.53	0.33	-4.63	<0.0001				
	Somewhat likely|Very likely	0.15	0.26	0.55	0.5833*				
Y1~X8	Coefficients:						155.62	161.62	<0.0001
	X8Yes	3.22	1.05	3.07	0.0028	24.925			
	Intercepts:								
	Not very likely|Somewhat likely	-1.62	0.32	-5.13	<0.0001				
	Somewhat likely|Very likely	0.12	0.24	0.49	0.6227*				
Y2~X1	Coefficients:						101.77	107.77	0.0393
	X1Female	1.17	0.56	2.08	0.0400	3.2249			
	Intercepts:								
	No|Not sure	-2.19	0.54	-4.01	0.0001				
	Not sure|Yes	-0.85	0.42	-2.02	0.0459				
Y2~X5	Coefficients:						104.70	114.70	0.7261
	X5.L	-9.00	0.39	-22.73	<0.0001	0.0001			
	X5.Q	6.05	0.46	13.28	<0.0001	425.05			
	X5.C	-2.90	0.55	-5.32	<0.0001	0.0549			
	Intercepts:								
	No|Not sure	-6.11	0.46	-13.39	<0.0001				
	Not sure|Yes	-4.80	0.31	-15.63	<0.0001				
Y2~X6	Coefficients:						97.51	109.51	0.0747
	X6Worsen	-16.60	0.88	-18.96	<0.0001	<0.0001			
	X6No impact	-15.59	0.64	-24.28	<0.0001	<0.0001			
	X6Moderately improve	-14.06	0.47	-30.14	<0.0001	<0.0001			
	X6Significantly Improve	-13.99	0.49	-28.58	<0.0001	<0.0001			
	Intercepts:								
	No|Not sure	-17.31	0.39	-43.44	<0.0001				
	Not sure|Yes	-15.89	0.33	-48.58	<0.0001				

*The significance of coefficients relative to intercepts can vary based on the model’s objective. Given that the primary interest in this research lies in assessing how particular predictors influence the outcome variable, the significance of these coefficients is deemed more crucial than that of the intercepts; ** “L” stands for “Linear”; *** “Q” stands for “Quadratic”; *** “C” stands for “Cubic”

We excluded the examination of multicollinearity in this context because each model exclusively included a single predictor. Nevertheless, frequency distribution analysis verified the requirement for predictor variability, ensuring that the predictor did not assume a single value across the dataset. Critical to the models' validity, the proportional odds assumption was validated for each model, as indicated by the p-values (>0.05) derived from the Brant test outcomes (see Table 3). The verification results showed a consistent correlation between the predictors and the log-odds of achieving a higher or lower outcome category across all outcome categories.

Table 3. Brant test results

Outcome	Predictor	Omnibus Test χ^2	df	Omnibus Probability	Specific Test for Predictors	Specific Predictor χ^2	Specific Predictor Probability
Y1	X5	0.8	3	0.85	X5.L, X5.Q, X5.C	0, 0, 0	1, 1, 1
	X7	0	1	0.99	X7Yes	0	0.99
	X8	0	1	0.99	X8Yes	0	0.99
Y2	X1	0.56	1	0.46	X1Female	0.56	0.46
	X5	0.03	3	1	X5.L, X5.Q, X5.C	0, 0, 0	1, 1, 1
	X6	5.32	4	0.26	X6Worsen, X6No impact, X6Moderately improve, X6Significantly improve	0, 0, 0, 0	1, 1, 1, 1

The models were assessed by examining them for outliers and influential data points and comparing model fits using AIC values. Table 4 presents the AIC values for each model, detailing the number of detected outliers and influential points. Interestingly, we identified no outliers in any model, as all counts were zero. However, we noted the presence of influential points for each model. When comparing the AIC values of the original models, those without non-existent outliers, and those without influential points, it became clear that removing influential points reduced the AIC values.

Table 4. Comparison of AIC values across models with and without influential observations and outliers

Model description	Y1 ~ X5	Y1 ~ X7	Y1 ~ X8	Y2 ~ X1	Y2 ~ X5	Y2 ~ X6
Original model	183.03	173.21	161.62	107.77	114.70	109.51
Number of outliers	0	0	0	0	0	0
Number of influential points	5	4	4	5	5	5
Model excluding outliers	183.03	173.21	161.62	107.77	114.70	109.51
Model excluding influential observations	159.59	157.74	152.99	68.41	89.89	93.31

Significance of Model Coefficients and Performance Metrics

The examination of POLR models, targeting the predictors X5 (technological proficiency), X7 (past use of AI educational tools), and X8 (interest in AI educational tools development), provided thorough insights into their impact on Y1 (educational AI tools adoption likelihood). For X5, the presence of significant p-values (<0.0001) underscored a strong statistical relationship with Y1. The extreme odds ratios, particularly 1710.4 for the quadratic term, suggested that different levels of technological proficiency had a significant effect on Y1. However, the likelihood ratio test, yielding a p-value of 0.2888, implying that technological proficiency by itself did not significantly improve the model's capacity to explain Y1 compared to a baseline model without any predictors.

In the case of X7, its coefficient, which showed a significant p-value (<0.0001), confirmed its important association with Y1. The odds ratio of 3.8647 for X7Yes underscores that past use of AI educational tools is a strong predictor of their continued use. This conclusion is strongly supported by a likelihood ratio test with a p-value of 0.0019. This results highlights the critical role of prior experience with AI tools in predicting future usage.

For X8, the coefficient's significance (p<0.0001) directly tied the interest in AI educational tools development to educational AI tools adoption likelihood. An odds ratio of 24.925 for X8Yes underscored the impact of this interest on educational AI tools adoption likelihood. Additionally, a marked improvement in the model's fit was observed, as indicated by the likelihood ratio test p-value (<0.0001). Based on the analyses that evaluated the influence of X1 (gender), X5, and X6 (perceptions of AI's role in education) on Y2 (interest in attending AI professional development opportunities), the findings are as follows:

Gender (X1Female) significantly influenced Y2, as indicated by the p-value of 0.0400 and odds ratio of 3.2249; this suggested that females were more inclined than males to attend AI professional development opportunities. This discovery was further supported by the likelihood ratio test (p = 0.03928).

For X5, highly significant coefficients and substantial effect sizes, as demonstrated by an odds ratio of 425.053 for X5.Q, indicated that Y2 varied significantly with technological proficiency levels. Yet, the likelihood ratio test (p=0.7261) suggested that X5, by itself, did not significantly boost the model's explanatory capability beyond a baseline model without predictors.

Regarding X6, significant p-values (<0.0001) highlighted its strong impact on interest in attending AI professional development opportunities. Extremely low odds ratios for all categories revealed the significant impediment effect of negative perceptions. However, a likelihood ratio test resulting in a p-value of 0.07472 pointed to only a slight, non-significant model fit enhancement when considering perceptions. This fact underscors the nuanced role of perceptions in influencing interest in attending AI professional development opportunities.

Table 5. Cross-validation method, with 10-fold and performance metrics

Outcome	Cross-validation				Performance metrics		
	Predictor	Accuracy	Kappa	Selected Method	$R^2_{McFadden}$	$R^2_{Cox\&Snell}$	$R^2_{Nagelkerke}$
Y1	X5	0.589	0	cauchit	0.0213	0.0388	0.0459
	X7	0.590	0	cloglog	0.0541	0.0959	0.1135
	X8	0.590	0	cloglog	0.1197	0.1997	0.2365
Y2	X1	0.835	0	cauchit	0.0401	0.0437	0.0650
	X5	0.829	0	cloglog	0.0124	0.0137	0.0204
	X6	0.813	-0.0118 to -0.025	cloglog	0.0802	0.0856	0.1274

Model Evaluation

Table 5 introduces the cross-validation analysis that evaluated the predictive performance of various models using separate predictors X5, X7, X8 for the outcome Y1, and X1, X5, X6 for Y2. For the outcome Y1, the models achieved moderate accuracy levels around 0.59. However, the zero Kappa statistic suggested that the accuracy might not significantly deviate from chance, indicating limited predictive effectiveness. Predictor X8 seemed to have the greatest predictive power, as shown by its gradually rising pseudo-R-squared values (0.1197, 0.1997, and 0.2365), which means it fits the model better than X5 and X7.

In contrast, the models predicting outcome Y2 displayed higher accuracy, especially the model with predictor X1, which achieved an accuracy of 0.835. Despite this high accuracy, negative Kappa values for predictor X6 warned of potential overfitting or non-generalizability, underscoring the importance of careful interpretation of these metrics. The high pseudo-R-squared values for predictor X1 suggested that it had a lot of explanatory power, which could be a sign of how well it captured important changes in the data.

Discussion

The statistical analysis indicated that predictors—technological proficiency, past use of AI educational tools, and interest in AI educational tools development—all significantly affected the educational AI tools adoption likelihood. Interest in AI educational tools development emerged as the most influential, as evidenced by the highest odds ratio and a significant p-value from the likelihood ratio test, underscoring a strong connection with educational AI tools adoption likelihood. These findings imply that although technological skills and past use of AI educational tools are relevant, a strong interest in AI educational tools development plays a central role in forecasting educational AI tools adoption likelihood. The low accuracy of the predictions and the pseudo-R-squared values found across these models show how hard it is to accurately model educational behaviors.

Moreover, gender emerged as a positive factor for interest in attending AI professional development opportunities, contrasting with the potential impediment effect of negative perceptions of AI's role in education. Although technological proficiency was important, its isolated impact did not significantly improve model accuracy, revealing the challenges in accurately forecasting interest in attending AI professional development opportunities. These findings suggest that a more complex approach, such as using multiple predictors or interaction between them, might make likelihood of AI tools adoption and interest in attending AI professional development opportunities, more predictable.

Reflecting on our statistical analysis, which identified technological proficiency, past use of AI educational tools, and especially interest in AI educational tools development as crucial predictors for educational AI tools adoption likelihood, and comparing these with broader research, we reveal similarities and divergences. An evident similarity with a cross-sectional study (Ahmad et al., 2024) lies in the critical gap in AI awareness and its impact on perceptions within higher education, underscoring the universal challenge of cultivating interest in AI. However, while our study highlighted the overall importance of fostering a specific interest in AI educational tools development, further research (McGrath et al., 2023; Chou et al., 2023) dives into the nuanced discrepancies in AI knowledge among educators, influenced by gender and educational settings. These studies suggest that while interest in AI is important, the factors that affect it—such as gender, institution, and learning environment—are also very important. This nuanced view complements our findings by illustrating the varied nature of AI adoption challenges, indicating that efforts to build up AI integration in education must address not only the broad interest and proficiency but also the detailed landscape of educators' experiences and perceptions.

These findings have several practical implications for educational policymakers, curriculum designers, and AI tool developers. Firstly, the essential role of interest in educational AI tools development suggests that educational programs should include components that stimulate and develop this interest, such as project-based learning and real-world problem-solving activities involving AI. Secondly, the positive influence of gender on interest in attending AI professional development opportunities highlights the opportunity to tailor marketing strategies to encourage greater female participation in AI-related education and careers. Lastly, addressing negative perceptions of AI's role in education requires clear communication of AI's benefits and ethical considerations, along with the development of privacy-preserving and inclusive AI tools.

The present study acknowledges some limitations in its investigation. Specifically, the reliance on convenience sampling and the concentration on a single academic university may limit our findings' broader applicability. The structured nature of the primary quantitative approach may not fully capture academic staff's nuanced perspectives on AI integration. Moreover, the exponential progression of AI technologies poses a difficulty in ensuring that our conclusions remain current and pertinent over time.

Conclusion

This research investigated the influence of various factors on the likelihood of academic staff at the University of Vlora "Ismail Qemali" adopting AI tools in future pedagogical endeavors and their interest in professional development related to AI. The study identified significant predictors of educational AI tools adoption likelihood and interest in attending AI professional development opportunities. Here are included: technological proficiency, past use of AI educational tools, interest in AI educational tools development, gender, and perceptions of AI's role in education.

Among these, interest in AI educational tools development emerged as a particularly strong predictor, underscoring the importance of fostering a specific interest in educational AI tools adoption. We found that gender positively influences interest in attending AI professional development opportunities, underscoring the potential to encourage female participation in AI-related education and careers. Conversely, negative perceptions of AI were shown to potentially diminish interest in attending AI professional development opportunities, suggesting a need for clear communication of AI's benefits and ethical considerations.

Emphasizing the critical role of fostering interest in AI educational tools development and addressing gender disparities and negative perceptions, this research informs the development of targeted interventions, training programs, and policies aimed at enhancing educators' skills and readiness for AI integration. Finally, the research underscores the multifaceted nature of academic staff's readiness and interest in AI technologies within academic settings. It reveals the importance of addressing both broad and nuanced factors influencing AI adoption, from technological proficiency to personal attitudes towards AI. By providing a deeper understanding of these dynamics, the study offers a foundation for more effective AI integration strategies in education, fostering an ecosystem that nurtures innovation, inclusivity, and preparedness for the AI-driven future of teaching and learning.

Recommendations

Further research should be conducted to increase the variety of samples and incorporate comparative studies that span different educational contexts in order to increase the generalizability of the findings. The integration of qualitative methods may provide more profound insights into educators' perspectives and encounters with AI. It is advisable to conduct longitudinal studies to track the development of AI technologies and their potential impact on the field of education. We could discern optimal strategies for integrating AI by investigating the efficacy of particular AI interventions implemented in educational environments. To guarantee that technology deployment fosters fairness, safeguards privacy, and enhances educational environments, conducting an in-depth examination of the ethical considerations and inclusiveness of AI tools is essential.

Scientific Ethics Declaration

The author declares that the scientific ethical and legal responsibility of this article published in EPESS journal belongs to the author.

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