Emerging Technologies Acceptance Within the Romanian Educational System: A Case Study Using the UTAUT Model

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Abstract: Emerging Technologies (ETs) will play an important role in our society. Despite their crucial role, the multi-faceted impact of technological innovation on society remains still under investigated. This study investigates the acceptance of Artificial Intelligence (AI) in the Romanian educational system through a survey of 187 educators, analyzed using the Unified Theory of Acceptance and Use of Technology (UTAUT) and partial least squares structural equation modeling (PLS-SEM) methods. The results reveal that Behavioral Intention strongly influences Use Behavior, driven by Performance Expectancy and Social Influence, while Effort Expectancy and Facilitating Conditions have minimal impact. Teachers are more likely to adopt AI if it improves job performance, engages students, or reduces workload. Positive attitudes are key factors, as intention strongly predicts adoption, and teachers prioritize the benefits of AI over ease of use.

1 INTRODUCTION

Emerging Technologies (ETs) can positively impact the economy, society, and work-life dynamics. As ETs evolve, understanding user acceptance has become essential. Several models, such as the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT), have been developed to explain this acceptance (Davis, 1989; Venkatesh et al., 2003).

Among these models, UTAUT is widely recognized as the most successful model for technology adoption (Marikyan and Papagiannidis, 2021). It has been used in various domains, including:

- Economics: e-commerce, mobile banking, and business apps.
- Healthcare: electronic health records, telemedicine.
- Education: e-learning platforms, online teaching (Abbad, 2021; Almaiah et al., 2019; Granić, 2022; Marques et al., 2010; Raffaghelli et al., 2022; Xue et al., 2024).
- Public Sector: e-government services and digital applications.

The goal of this paper is to assess UTAUT's applicability to the use of ETs in Romania's educational system. Despite strong international performance, Romania faces challenges in national assessments and OECD PISA scores, highlighting areas for improvement in education (EU Education and Training Monitor 2023).

This study introduces a novel questionnaire with 17 items to assess ETs acceptance in Romania's education sector. It applies the UTAUT model to analyze the data and validates the results using PLS-SEM.

Our paper has the following structure: in Section 2, we describe the growing need for novel technologies in education and the challenges of their implementation. Following this introduction, in Section 3 we describe our proposed research methodology that includes the outline of the UTAUT model, the designed questionnaire, data collection and sample characteristics. We validate the proposed model in Section 4 using the PLS-SEM method and present the

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obtained results and their analysis. The paper ends with some conclusions presented in Section 5.

2 THE GROWING NEED FOR NEW TECHNOLOGIES IN EDUCATION

Over the last years, the technologies have revolutionized also the educational system, improving teaching and learning. Nowadays, it is essentials for schools and universities to be up to date and integrate the latest discoveries and digital tools in their educational system. Educational games, video conferences, e-learning platforms are now essential to be used in the present educational system.

ETs like Artificial Intelligence (AI), virtual reality, chatbots, metaverse, etc., have the potential to transform the way students learn and collaborate with their professors and with each other. The primary benefit of AI and metaverse is reinforcement learning by identifying knowledge gaps and suggesting personalized learning paths to improve the educational outcomes, see for further information (Chiu, 2023).

We do believe that the true potential of ETs lie not just in making learning more efficient, but in their capacity to craft highly personalized educational experiences. The main challenge is how to incorporate these ETs in a way that take into consideration the diversity of students' abilities and needs.

2.1 Examples of ETs in Education

In today's evolving world, professors and students face various career challenges, and Educational Technologies (ETs) can help improve critical thinking, problem-solving, and essential competencies for success.

ETs can greatly enhance the education system by improving both research and learning processes. Key benefits include: improved performance for students and professors, personalized learning, time savings and increased efficiency, development of digital skills, trans-disciplinary learning, connecting concepts across disciplines.

Prominent ETs in education include:

- AI: Transforms teaching and accelerates learning.
- Metaverse, VR, AR: Enable "learn by doing" and simulate real-life scenarios.
- Gamification: Incorporates game elements to increase engagement (Smiderle et al., 2020).
- Adaptive Learning: Personalizes content based on individual needs.
- Online Courses/Live Streaming: Provide flexible and affordable learning options.
- Robotics: Offers hands-on STEM learning through educational robots.

2.2 The Challenges of Implementing ETs in Education

Implementing emerging technologies (ETs) in education presents both opportunities and challenges. ETs can transform teaching and learning, foster innovation, enhance access to information, and equip students with essential technological skills for the future workforce.

However, we need more studies to understand how to balance the benefits and risks of using ETs in the education system and how we can design more effective the teaching and learning process without any risk on the student development and academic integrity.

3 THE PROPOSED RESEARCH METHODOLOGY

3.1 Description of the UTAUT Model

In our paper, we use the Unified Theory of Acceptance and Use of Technology (UTAUT) model to investigate the factors influencing the adoption of artificial intelligence (AI) technology in education. UTAUT is a theoretical framework intended to explain the user intentions regarding the utilization of an information system and subsequent usage behavior. It integrates elements from multiple models related to technology acceptance and use.

The key components of the UTAUT model are:

- **Performance Expectancy (PE).** The degree to which a person trusts that using the system will improve his job performance.
- **Effort Expectancy (EE).** The level of ease associated with using the system.
- **Social Influence (SI).** The degree to which an individual discerns that significant others believe they should use the novel system.
- **Facilitating Conditions (FC).** The degree to which a person trusts that there is adequate organizational and technical infrastructure to permit the system usage.

The influence of core constructs on Behavioral Intention and Usage Behavior depends on factors like Gender, Age, Experience, and Willingness to Use. In the UTAUT model, Behavioral Intention (BI) reflects a person's decision to engage in a future behavior, while Usage Behavior (UB) denotes the actual system use.

In Figure 1, we illustrate graphically the UTAUT model as described by Venkatesh et al. [13].

3.2 The Designed Questionnaire

To evaluate the variables in the UTAUT framework, we used a questionnaire with 17 items, presented in Table 1. Each item was evaluated using a rating between one and five, where one represented "not at all" and five represented "extremely." The respondents were motivated to base their evaluations on their own knowledge and experience.

The chosen constructs in this investigation form the foundation for the considered hypotheses, which are subsequently outlined below:

H1: ***Performance expectancy (PE)*** has a positive impact on the behavioral intention to use AI technologies in their educational work.

H2: ***Effort expectancy (EE)*** has a positive impact on the behavioral intention to use AI technologies in their educational work.

H3: ***Social Influence (SI)*** positively influences the behavioral intention to use AI technologies in their educational work.

H4: ***Facilitation condition (FC)*** has a positive effect on the behavioral intention to use AI technologies in their educational work.

H5: ***Behavioral Intentions (BI)*** positively affects the behavioral intention to adopt AI technologies in their educational work.

The survey instrument used to implement the questionnaire from this study is Microsoft Forms. The questionnaire was then disseminated across various social media platforms and educational groups. Participants were encouraged to share the questionnaire link within their networks. During a one-week period, the questionnaire-based investigation gathered a total of 187 valid responses.

The survey participants were predominantly female (74%), and all the respondents were Romanian, working in the education sector. Most of the respondents were teachers (93%), with 38% being college teachers, 37% high school teachers, and 18% university instructors. Regarding educational qualifications, 43% of the participants have a Ph.D. degree, 31% of them have a Master's degree, and the rest 26% have a Bachelor's degree. In terms of age, 43% of the participants were between 46-55 years old, 28% were between 36-45 years old, 9% were between 26-35 years old, and 5% were between 20-25 years old.

Table 2 summarizes the demographic details of the respondents.

4 THE ACHIEVED RESULTS AND THEIR ANALYSIS

To assess the validity the proposed model, we eployed the Partial Least Squares Structural Equation Modeling (PLS-SEM) method, which is an extremely valuable method for assessing complex theoretical relationships among multiple variables. For further information concerning the PLS-SEM method we refer to (Hair and Alamer, 2022). Using SmartPLS 4.0 software, the data collected from the survey underwent PLS-SEM analysis to evaluate the model and test the hypotheses.

Applying PLS-SEM to the UTAUT model involves specifying the structural and measurement models, estimating the models iteratively, assessing their validity and reliability, performing bootstrapping to test significance, and interpreting the results. This approach helps in understanding the factors influencing technology acceptance and use, providing insights into how constructs like performance expectancy, effort expectancy, social influence, and facilitating conditions influence behavioural intention and use behaviour.

Prior to analysing the measurement model, we examined the mean, median, standard deviation, excess kurtosis, and skewness of the observed variables. These values are illustrated in Table 3.

The mean is the average of a data set, representing its central point. In UTAUT models, it reflects overall respondent tendencies, such as perceptions of performance or effort expectancy, helping to understand general attitudes toward technology adoption.

The median is the middle value when data is ordered. In UTAUT, it shows typical opinions about technology adoption factors when data is not uniformly distributed.

Standard deviation indicates the spread of data around the mean. Low values show consistency, while high values indicate varied opinions. In UTAUT, this helps assess agreement on technology perceptions.

Excess kurtosis measures the "tailedness" of a distribution. Positive values indicate extreme responses, while negative values suggest uniformity. In UTAUT, it highlights concentration or extremes in responses.

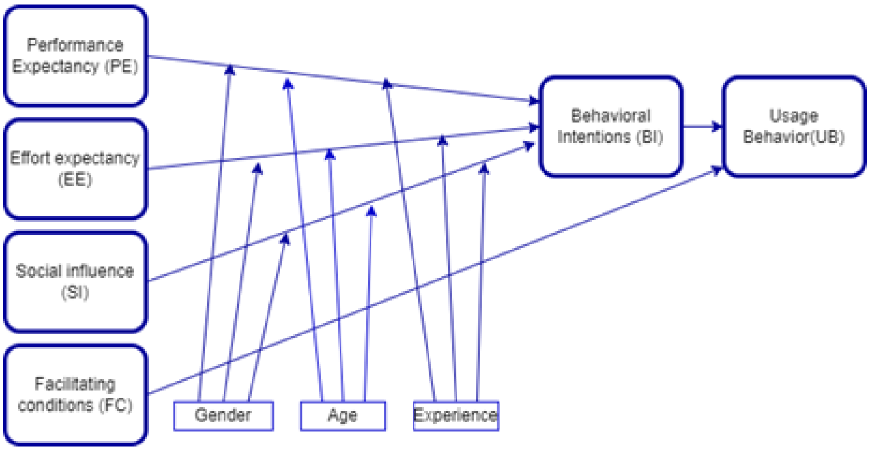

Figure 1: Illustration of the UTAUT model (Venkatesh et al., 2003).

Table 1: Constructs and measurements items.

Item code	Item description
PE	PE1: Use of AI technologies will help to complete the lessons and tests for the class faster. PE2: Use of AI technologies will help to teach more effectively in the classroom. PE3: Use of AI technologies will make students learn more effectively.
EE	EE1: Learning how to use AI technologies will be easy. EE2: To integrate AI technologies into the teaching process will be easy. EE3: To integrate AI technologies into the student's evaluation process will be easy. EE4: To integrate AI technologies into the preparation of lessons and tests in class will be easy.
SI	SI1: There is a pressure to adopt AI technologies into the teaching process. SI2: There is a pressure to adopt AI technologies into the student evaluation process. SI3: There is a pressure to adopt AI technology into the class hours.
FC	FC1: I believe that the education system provide good support to be able to adopt the AI technologies. FC2: There are necessary resources (materials, tools) available to integrate AI technologies in education. FC3: There are necessary technical support to be able to use AI technologies in education.
BI	BI1: I intend to use AI technologies in the near future. BI2: I feel comfortable to use AI technologies.
UB	UB1: I am familiar with AI technologies. UB2: I am using AI technologies in my work.

Skewness shows distribution asymmetry. Positive skewness means most responses are favorable, while negative skewness reflects unfavorable clustering. In UTAUT, this helps identify response biases.

These measures provide insights into perceptions in UTAUT models, aiding understanding of technology adoption. The achieved results revealed mean scores ranging from 2.578 to 3.364 and standard deviations ranging from 0.765 to 1.097, suggesting respondents found AI moderately easy to use.

In PLS-SEM, discriminant validity ensures constructs are distinct, confirming factors like performance expectancy and social influence measure different aspects of technology adoption.

To assess the discriminant validity in PLS-SEM, we used the Fornell & Larcker Criterion, as shown in Table 4. This criterion implies comparing the square root of the Average Variance Extracted (AVE) for every construct with the correlations between that construct and the other constructs within the model. The discriminant validity is supported if the square root of the AVE for each construct is greater than its correlations with other constructs.

The Fornell & Larcker Criterion evaluates two key aspects: how well each concept (represented by the diagonal values in the table) explains itself, and how much each concept correlates with the others (represented by the off-diagonal values). The diagonal values in the table show how well each concept measures itself, and all of these values are higher than 0.7. This is a good indication that each concept is explained well by its own indicators, meaning the model is measuring each concept accurately. This is an important step in confirming the validity of the model.

To confirm discriminant validity, the diagonal values should be higher than the correlations between different concepts. Effort Expectancy (EE), Facilitating Conditions (FC), and Performance Expectancy

Table 2: Demographic details of the respondents (N=187).

Category	Sub-category	Frequency	Percent
Gender	Female	138	74
	Male	49	26
Age	20-25	9	5
	26-35	17	9
	36-45	52	28
	46-55	80	43
	≥ 56	33	18
Education	Bachelor's degree	58	26
level	Master's degree	80	31
	Ph.D.	48	43
	Other	1	
Role	High school teacher	69	37
	College teacher	71	38
	University teacher	34	18
	Other	13	7
ET Usage	Not at all	0	0
	Slightly	7	4
	Moderately	43	23
	Very much	99	53
	Extremely	38	20

Table 3: Data for AI adoption using UTAUT.

Item code	**Mean**	**Median**	**Standard deviation**	**Excess kurtosis**	**Skewness**
PE1	3.364	3	0.893	0.171	-0.422
PE2	3.294	3	0.904	0.162	-0.311
PE3	3.246	3	0.933	-0.012	-0.271
EE1	3.123	3	0.808	0.609	0.2
EE2	3.043	3	0.773	0.693	-0.004
EE3	3.053	3	0.765	0.38	0.125
EE4	3.011	3	0.781	0.403	0.117
SI1	2.578	3	1.023	-0.564	0.076
SI2	2.594	3	1.052	-0.7	0.014
SI3	3.048	3	1.046	-0.578	-0.295
FC1	2.861	3	1.025	-0.579	-0.048
FC2	3.043	3	0.912	-0.168	-0.213
FC3	3.048	3	1.015	-0.392	-0.283
BI1	3.267	3	0.966	0.208	-0.452
BI2	2.337	2	1.089	-0.299	0.55
USE1	2.989	3	0.931	-0.02	-0.019
USE2	2.642	3	1.097	-0.621	0.112

Table 4: Fornell & Larcker Criterion analysis for checking Discriminant validity.

	BI	**EE**	**FC**	**PE**	**SI**	**USE**
BI	0.880					
EE	0.217	0.835				
FC	0.483	0.186	0.860			
PE	0.549	0.186	0.488	0.934		
SI	0.365	0.427	0.314	0.351	0.882	
USE	0.908	0.176	0.453	0.458	0.372	0.924

(PE) clearly show distinct validity, as their diagonal values are significantly higher than their correlations with other concepts. For Behavioral Intention (BI), which has a diagonal value of 0.880, its highest correlation is with USE at 0.908. While these values are quite close, this overlap is both expected and acceptable, particularly in models where BI (intentions to use) and USE (actual use) are naturally linked. Given their close relationship in technology adoption models, this slight overlap between BI and USE is perfectly normal and understandable.

The model is valid based on the Fornell & Larcker Criterion, as most diagonal values are higher than the off-diagonal correlations, confirming discriminant validity. This means that the model successfully differentiates between the various concepts, ensuring that they are distinct from one another.

The path coefficients represent the relationships between latent constructs in the structural model. These coefficients indicate the strength and direction of the relationships.

In Figure 2, we illustrate the path coefficients, outer loadings and the coefficient of determination R^2 for each variable in the respective structural models.

Assessing the measurement model in PLS-SEM relies significantly on outer loadings, which indicate the strength of relationships between indicators and their respective constructs, thereby ensuring the construct's validity and reliability.

In Table 5, we present the outer loading values received along with their interpretations. Indicators with outer loadings equal to or exceeding 0.7 are deemed to exhibit robust associations with their corresponding constructs, signifying their reliability in measuring the construct and substantial contribution to its variance. Loadings falling within the range of 0.4 to 0.7 are considered acceptable but may suggest the necessity for further refinement, indicating that while these indicators contribute to the construct, they may benefit from additional indicators or reassessment to enhance their reliability. Notably, all the obtained results demonstrate high loading values, except for $EE1 \leftarrow EE$, which displays a moderate value.

Table 5: Outer loadings value.

	Outer loadings value
$USE1 \leftarrow USE$	0.924
$USE2 \leftarrow USE$	0.924
$BI1 \leftarrow BI$	0.880
$BI2 \leftarrow BI$	0.880
$EE1 \leftarrow EE$	0.590
$EE2 \leftarrow EE$	0.889
$EE3 \leftarrow EE$	0.913
$EE4 \leftarrow EE$	0.905
$FC1 \leftarrow FC$	0.760
$FC2 \leftarrow FC$	0.910
$FC3 \leftarrow FC$	0.902
$PE1 \leftarrow PE$	0.934
$PE2 \leftarrow PE$	0.936
$PE3 \leftarrow PE$	0.932
$SI1 \leftarrow SI$	0.934
$SI2 \leftarrow SI$	0.916
$SI3 \leftarrow SI$	0.789

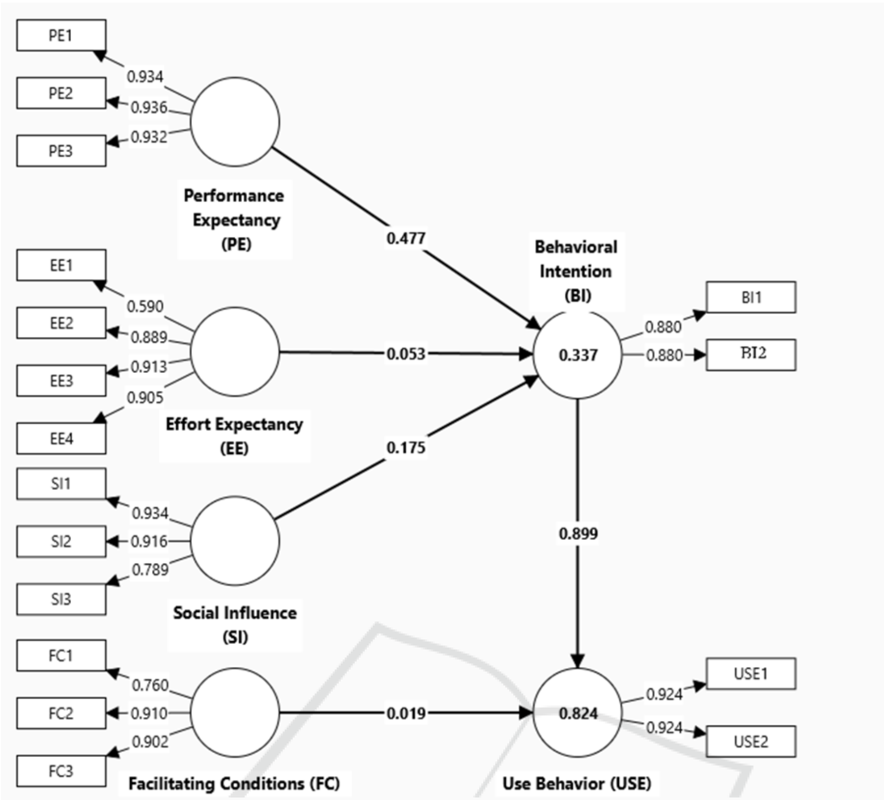

Figure 2: UTAUT model: outer loadings, path coefficients and R^2.

In the context of UTAUT, the total effects can help understand the comprehensive influence of each construct on users' behavioral intentions and use behavior. Table 6 presents key statistics (path coefficients, standard deviations, t-statistic, and p-values) from our study that examines how different factors influence the adoption of AI technologies in education. The results reveal the following key insights:

- The relationship between Behavioral Intention and Use Behavior is strong and highly significant (0.899, $p < 0.001$), indicating that teachers with high intentions are likely to use AI technologies.
- Performance Expectancy has a significant positive effect on both Behavioral Intention (0.477, $p < 0.001$) and Use Behavior (0.429, $p < 0.001$). This shows that the perceived usefulness of AI tools is crucial for adoption.
- Social Influence moderately affects Behavioral Intention (0.175, $p < 0.05$) and Use Behavior (0.157, $p < 0.05$), suggesting that social expectations play a role, though to a lesser degree.
- Effort Expectancy and Facilitating Conditions have weak or non-significant effects, with paths such as $EE \rightarrow BI$ (0.053, $p = 0.483$) and $FC \rightarrow USE$ (0.019, $p = 0.594$) indicating minimal influence. Teachers' ease of use or available resources are less decisive factors in their decisions.

The findings suggest that promoting AI technologies among educators should prioritize enhancing behavioral intentions and emphasizing practical benefits, as these significantly influence usage. While ease of use and support systems are less critical, the role of intention and perceived value aligns with the UTAUT framework, emphasizing behavioral intention as a key driver.

Table 6: Total effects.

	Original sample	Sample mean	Standard deviation	t-statistic	P-values
$BI \rightarrow USE$	0.899	0.898	0.020	44.809	0.000
$EE \rightarrow BI$	0.053	0.053	0.076	0.702	0.483
$EE \rightarrow USE$	0.048	0.047	0.068	0.704	0.481
$FC \rightarrow USE$	0.019	0.018	0.036	0.533	0.594
$PE \rightarrow BI$	0.477	0.475	0.081	5.905	0.000
$PE \rightarrow USE$	0.429	0.428	0.076	5.638	0.000
$SI \rightarrow BI$	0.175	0.174	0.085	2.058	0.040
$SI \rightarrow USE$	0.157	0.156	0.076	2.066	0.039

Our results indicate that teachers' intentions to use AI technologies in education are strongly influenced by their behavioral intentions. Other factors, such as ease of use and facilitating conditions, have less impact on their decisions. The strong confidence in the relationship between intention and actual use suggests that promoting AI tools among teachers will likely be effective, provided they are motivated to engage with the technology.

Collinearity statistics, specifically the Variance Inflation Factor (VIF), are used to assess how much the variance of a regression coefficient is increased due to collinearity with other predictors in the model. The Variance Inflation Factor (VIF) helps determine whether two or more independent variables in a regression model are too closely related to each other. When VIF values are low, it suggests that there is little overlap between the variables, indicating that each variable provides unique information to the model.

In our research, the VIF values range from 1.143 to 1.349, indicating an acceptable level of independence among the variables. A common rule of thumb is that a VIF value greater than 5 or 10 may indicate problematic collinearity. Since all the VIF values in this table are below those thresholds, it suggests that the constructs in the model, such as Behavioral Intention, Use, Effort Expectancy, Facilitating Conditions, Performance Expectancy, and Social Influence, are not highly collinear. This means each variable contributes valuable and distinct information to the model, allowing for more reliable analysis of their relationships and impacts.

Table 7: Collinearity statistics (VIF).

	Collinearity statistics (VIF)
$BI \leftarrow USE$	1.304
$EE \leftarrow BI$	1.225
$FC \leftarrow USE$	1.304
$PE \leftarrow BI$	1.143
$SI \leftarrow BI$	1.349

Analyzing the obtained values presented in Table 7, we can conclude that the relationships between the model's constructs are clear, independent, and reliably estimated. This ensures that the model offers valid insights into the factors that influence users' acceptance and use of technology, facilitating informed decision-making and effective intervention strategies.

In Table 8, we displayed the convergent validity and the reliability of the constructs and their measuring items.

Table 8: Convergent validity and reliability of constructs and their measuring items

	Cronbach's alpha	Composite reliability	Composite reliability	Average variance extracted (AVE)
BI	0.710	0.710	0.873	0.775
EE	0.846	0.880	0.900	0.698
FC	0.820	0.834	0.894	0.739
PE	0.927	0.927	0.954	0.873
SI	0.854	0.866	0.913	0.778
USE	0.829	0.829	0.921	0.854

As shown in Table 8, all constructs exhibit strong internal consistency and reliability, with acceptable to excellent values for Cronbach's alpha and composite reliability. Additionally, good convergent validity confirms that the items effectively capture their intended constructs, supporting the measurement model's validity and reliability.

In Table 9, we present the confidence intervals.

Drawing from the interpretations of all the results thus far and considering the values of the confidence intervals, we can determine whether the formulated hypotheses are supported or not:

H1. With a path coefficient of 0.477 and a 95% confidence interval from 0.303 to 0.618 (excluding zero), there is a statistically significant link between Performance Expectancy and Behavioral Intention. Our findings confirm that believing AI improves educational performance strongly correlates with the intention to use it.

H2. With a path coefficient of 0.053 and a 95% confidence interval from -0.104 to 0.194 (including zero), there is no statistically significant link between Effort Expectancy and Behavioral Intention. While ease of use might encourage trying AI, the results show no significant connection, and the hypothesis is not supported.

H3. The path coefficient for Social Influence and Behavioral Intention is 0.175, with a 95% confidence interval from 0.011 to 0.347 (excluding zero), indicating statistical significance. Results confirm that encouragement from others positively influences the intention to use AI, supporting this hypothesis.

H4. The path coefficient for Facilitating Conditions and Use Behavior is 0.019, with a 95% confidence interval from -0.053 to 0.087 (including zero), indicating no statistical significance. Results show that resources and support do not significantly influence AI use, so this hypothesis is not supported.

H5. The path coefficient for Behavioral Intention and Use Behavior is 0.899, with a 95% confidence interval of 0.856 to 0.936 (excluding zero), indicating a statistically significant relationship. The strong link shows that intention strongly predicts actual AI use, supporting this hypothesis.

5 CONCLUSIONS

Using the UTAUT model analyzed through PLS-SEM in SmartPLS, we can assess the adoption of AI technologies in education. By evaluating constructs like

Table 9: Confidence intervals.

HYPOTHESIS	Original sample	Sample mean	Bias	2.5%	97.5%	Decision
H1	0.477	0.475	-0.002	0.303	0.618	SUPPORTED
H2	0.053	0.053	-0.000	-0.104	0.194	NOT SUPPORTED
H3	0.175	0.174	-0.001	0.011	0.347	SUPPORTED
H4	0.019	0.018	-0.001	-0.053	0.087	NOT SUPPORTED
H5	0.899	0.898	-0.000	0.856	0.936	SUPPORTED

Performance Expectancy, Effort Expectancy, Social Influence, and Behavioral Intention, we gain insights into the factors impacting the acceptance and utilization of AI technologies in educational settings. The analysis provides a comprehensive understanding of the attitudes, perceptions, and intentions of educators and students towards AI integration in education. By validating hypotheses and interpreting path coefficients, we can ascertain the significance of these factors in driving the adoption of AI technologies. Ultimately, this analytical approach enables us to draw conclusions about the readiness and propensity of educational stakeholders to embrace AI innovations, thereby informing strategies for successful implementation and integration of AI technologies in educational practices.

In conclusion, the UTAUT model highlights Behavioral Intention as a strong predictor of Use Behavior, driven mainly by Performance Expectancy and Social Influence. Effort Expectancy and Facilitating Conditions show no significant impact. The significant indirect effect of Performance Expectancy on Use Behavior underscores the importance of perceived performance benefits.

Teachers are more likely to adopt AI if they believe it enhances job performance, such as making lessons engaging or reducing workload. Clear benefits are essential for AI adoption in education.

Another important finding is that when teachers express a desire or intention to use AI, they are very likely to actually use it. This shows that developing a positive attitude toward AI early on is key because once teachers decide they want to use it, they will probably follow through.

Social pressure from colleagues or administrators has some influence but isn't as important. While it can help to have others around them encouraging AI use, teachers are mostly driven by their own beliefs about the technology's benefits.

Finally, having access to resources and support does not strongly affect teachers' decision to adopt AI. While it helps, what really matters is whether teachers see value in using AI. Schools should focus more on showing the practical benefits of AI rather than just providing resources.

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