

Article

Students' Perceptions of the Use of Artificial Intelligence Tools in Educational Activities

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Abstract

The emergence of artificial intelligence (AI) tools, particularly generative models, in the last five years has fundamentally transformed the framework and methodologies of learning in higher education. Students are integrating AI for producing new ideas, assisted and personalized search, academic writing, advanced data analysis, and personalized learning. For this reason, an update of the theoretical and conceptual framework regarding the adoption of technologies in the educational environment is required. Based on traditional Technology Acceptance Model/Unified Theory of Acceptance and Use of Technology (TAM/UTAUT) models, we propose a new Partial Least Squares Structural Equation Modeling (PLS-SEM) model developed for the context of AI in higher education. The novelty of the model lies in the integration of the mediating relationship through trust (trust in AI outputs, TAI0) between perceived academic integrity risk (PAIR) and behavioral intention to use (BI), while anchoring perceived learning utility (PUL) and perceived effort expectancy (PEE) in AI literacy-specific self-efficacy (AILSE). The model is tested using a sample of 339 higher education students from economics and computer science specializations and validated using the R environment and the SEMinR package as specific software tools. Our proposed research hypotheses consider six reflective latent constructs and a mediating relationship, which we analyze using validated PLS-SEM techniques. All items included in the model constructs are formulated for use in university educational contexts and are adapted to specific AI tools for learning in the university environment.

Keywords: generative artificial intelligence tools; AI in higher education; trust in AI tools; AI literacy self-efficacy; statistical model



Academic Editor: Mingche Lee

Received: 15 April 2026

Revised: 26 May 2026

Accepted: 29 May 2026

Published: 2 June 2026

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1. Introduction

Artificial intelligence (AI) tools, particularly large language models (LLMs)—consult [1–3]—have proliferated in recent years in many fields such as software development [4–6], health [7,8], cognition and psychology, decision making, telecommunications, industrial engineering, human–computer interaction, economics, legislation, agriculture, and many others. Each existing approach has its benefits and disadvantages [9–14].

Obviously, the educational area is one of the most impacted by this phenomenon according to [15,16]. Generative models have rapidly changed the approach to learning in higher education [17]. Currently, students use and integrate AI for assisted search, new idea generation, advanced data analysis and personalization of the learning process [18].

This new paradigm shift clearly requires an update of the theoretical framework regarding the adoption of technologies [19].

Starting from the established Technology Acceptance Model/Unified Theory of Acceptance and Use of Technology (TAM/UTAUT) models that analyze the role of perceived usefulness, ease of use and behavioral intention [20], we propose a Partial Least Squares Structural Equation Modeling (PLS-SEM) model that brings new elements to the field of knowledge. The model proposed for analysis is specialized for the context of AI in education and we introduce constructs regarding AI literacy self-efficacy (AILSE), trust in AI outputs (TAIO) and perceived academic integrity risk (PAIR). A novelty of our model is that the trust mediation relationship (TAIO) between perceived academic integrity risk (PAIR) and behavioral intention to use AI tools (BI) is analyzed. Our model also anchors perceived usefulness for learning (PUL) and perceived effort expectancy (PEE) in AI literacy self-efficacy (AILSE).

While the proliferation of generative artificial intelligence (GenAI) has transformed operations across numerous industries, its integration into higher education introduces unique socio-cognitive dynamics and ethical dilemmas that demand localized empirical scrutiny. Extant research on technology acceptance in educational settings has heavily relied on traditional frameworks, such as the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT), primarily focusing on functional aspects like perceived usefulness and ease of use [21,22].

Nevertheless, these conventional models often overlook the tension between the functional utility of GenAI and the specific socio-ethical anxieties experienced by students. In the academic ecosystem, the decision to adopt GenAI tools is not merely a matter of technical efficiency, but a complex trade-off balancing operational benefits against systemic integrity risks. Consequently, there is a critical need to synthesize functional adoption drivers with domain-specific risk variables to fully comprehend students' behavioral intentions.

To bridge this gap, this study establishes a novel theoretical framework that anchors the core operational constructs—perceived usefulness and effort—within the cognitive boundaries of AI literacy self-efficacy (AILSE), while integrating perceived academic integrity risk (PAIR) as a critical ethical-behavioral factor. Unlike recent GenAI adoption studies that treat technology risk as a generic form of system anxiety [23], our approach isolates PAIR to specifically reflect students' awareness of plagiarism, cognitive dependence, and potential institutional penalties.

Within this framework, AILSE serves as a foundational psychological anchor. We argue that students' self-perceived capacity to critically understand, evaluate, and interact with certain GenAI tools does not operate in a vacuum; rather, it directly shapes their assessment of the tool's cognitive effort and subsequent utility.

By synthesizing AILSE as an upstream cognitive antecedent and evaluating how it calibrates both functional expectations and the specific dimensions of trust in AI outputs (TAIO), this paper provides a nuanced, multi-dimensional perspective that is theoretically distinct from unidimensional acceptance studies. A pivotal contribution of this conceptual integration lies in positioning TAIO as a vital mediator between the perceived ethical risks (PAIR) and the ultimate behavioral intention (BI). In high-stakes educational environments, risk and trust are inherently intertwined constructs. While PAIR captures the structural and normative anxieties associated with GenAI use, it does not automatically translate into an immediate cessation of use. Instead, following the tenets of risk calculus theories in human-computer interaction, the presence of risk activates a cognitive re-evaluation process wherein students assess the reliability, transparency, and accuracy of the output provided by a given software system [24].

Therefore, evaluating TAIO as a mediator allows us to model the psychological mechanism through which students rationalize academic vulnerabilities. This specific pathway addresses a critical omission in the current GenAI-in-education literature, demonstrating that the behavioral trajectory from risk perception to actual tool utilization is fundamentally governed by the caliber of trust established in the generative system's performance.

Paper Structure

Section 2 enumerates the research goals of our study, followed by the materials and methods described in Section 3. The results obtained are presented in Section 4. We also include a discussion about the multifaceted perspective on how the respondents perceive the AI tools and intend to use them (Section 5). In the last section, future work and conclusion are presented.

2. Research Goals

The model we propose brings into the analysis a triadic structure between integrity risk–trust–intention, being different from classical adoption frameworks in that the academic integrity dimension is explicitly isolated as a determinant of trust, and not just as generic technological anxiety.

In the established TAM model, perceived usefulness is a determinant of behavioral intention to use technology [25]. In the context of using AI technologies in the university educational process, the construct perceived usefulness for learning (PUL) captures the belief that AI tools improve content understanding, quality and efficiency of academic performance [26]. Thus, the PUL construct in our proposed model retains the affiliation with perceived usefulness from TAM, but specializes it for educational outcomes such as clarification of difficult concepts, personalized feedback, etc. Based on the adaptation to the original TAM model, we hypothesize that PUL has a direct and significant effect on behavioral intention (H1) and, in addition, strengthens trust in AI outputs (TAIO)—hypothesis H8. This approach is justified by the fact that experiences that are perceived as valuable facilitate the internalization of technological reliability [27].

In classical models [28,29], perceived effort expectancy (PEE) represents the expectation of effort or perceived ease when the user interacts with a new technology [25]. In our proposed model, the technology in question is one that uses AI tools in the university educational process. Thus, from an adoption perspective, if the graphical and auditory user interfaces are intuitive, and the configuration effort is reduced, then the probability of behavioral intention to use increases (hypothesis H2). Within our analysis model, we intend to find out whether PEE has a direct effect on BI.

AILSE brings a particularly important psychological component that refers to the confidence in one's ability to use AI tools and technologies responsibly and informedly [30–32]. In the context of university education, students who have high values for AILSE have the ability to critically evaluate the outputs generated by AI technologies, identifying cases of bias or hallucinations. They can also choose the right tools and are able to correctly integrate ethical practices and citation systems. In our proposed research model, AILSE is an “upstream” construct and we postulate that it significantly influences both perceived usefulness for learning (PUL) (hypothesis H3) and trust in AI outputs (TAIO) (hypothesis H4). Thus, we test whether perceived competence allows for the achievement of educational benefits and the establishment of a stronger trusting relationship with AI technology in the educational process.

Our conceptual framework has as a distinctive element perceived academic integrity risk (PAIR) because the literature on educational technologies [33–35] has frequently addressed risk/concern, but in the current context generative artificial intelligence (GenAI) technologies bring specific problems such as the potential for plagiarism, manipulation and influencing of academic evaluation, addiction, etc. Considering these arguments, we develop the research hypothesis H5 according to which PAIR directly influences TAIO. Continuing this approach, we also analyze the mediating relationship $PAIR \rightarrow TAIO \rightarrow BI$ by defining the research hypothesis H7. Accordingly, we actually evaluate whether integrity risks affect the intention to use through trust mechanisms: when trust decreases, students will be less willing to adopt the use of AI technologies, although they recognize a certain utility.

Trust in AI outputs (TAIO) [27,36] is approached as an attitudinal pivot that has the role of connecting risk and utility assessments with behavioral intention to use AI technologies in higher education. We propose the research hypothesis H6 according to which trust in AI outputs (reliability, transparency, and accuracy) directly influences the intention to use. In the same vein, through the research hypothesis H8 we also analyze the possibility that perceived usefulness for learning (PUL) stimulates TAIO because positive experiences can reinforce favorable perceptions about the performance of the system. The goal is to analyze whether TAIO can become a central mechanism through which universities can intervene by increasing transparency, explainability and practices for assessing the quality of outputs and results.

The proposed relationships and related hypotheses (H1, . . . , H8) are presented synthetically in the following list.

- H1.** $PUL \rightarrow BI$;
- H2.** $PEE \rightarrow BI$;
- H3.** $AILSE \rightarrow PUL$;
- H4.** $AILSE \rightarrow TAIO$;
- H5.** $PAIR \rightarrow TAIO$;
- H6.** $TAIO \rightarrow BI$;
- H7** (mediation). $PAIR \rightarrow TAIO \rightarrow BI$ (mediation through trust);
- H8.** $PUL \rightarrow TAIO$;
- H9.** $PAIR \rightarrow BI$.

Therefore, TAIO mediates the effect of PAIR on BI. Also, AILSE acts as an upstream determinant for PUL and TAIO, and PEE and PUL directly influence BI.

3. Materials and Methods

3.1. Data Sample and Software Tools

The research was conducted under the agreement of the Research Ethics Committee of the Faculty of Economics and Business Administration of Alexandru Ioan Cuza University of Iași, Romania. The ethics agreement has the number 505/24.02.2026, and data collection was carried out exclusively in an online format through a Google Forms questionnaire.

During the questionnaire, the authors of this research did not have physical contact with the respondents and did not affect their physical or mental integrity in any way. At the beginning of the questionnaire, each respondent gave their written consent for voluntary participation in the research process. The questionnaire did not collect personal data, and the answers were used strictly for the purpose of academic research. Respondents were informed that they could interrupt the questionnaire whenever they felt uncomfortable because of the questions.

A total of 339 responses were collected between February and March 2026 from students of both economics and computer science specializations provided by the same university. Several characteristics of the respondent group are as follows:

- Gender—females: 53%; males: 47%;
- Age—between 18 and 30 years: 96.7%; 31–40 years: 0.3%; 41–50 years: 1.5%; between 51 and 60 years: 0.9%; over 60 years: 0.6%.
- Level of study—undergraduates: 63%; postgraduates such as master’s studies: 34.9%; PhD students: 0.9%; post-doctoral students: 1.2%.

The collected data were processed using several tools and technologies: Google Forms for collecting questionnaire responses; Microsoft Excel for data aggregation; R and R-Studio for data analysis, including the SEMinR package [37] for PLS-SEM model analysis.

3.2. Methods

The research method was based on Partial Least Squares Structural Equations Modelling (PLS-SEM), and we built the constructs, paths and the research model using the SEMinR package commands from R-Studio. Within the model, each research hypothesis was defined and described with specific commands, according to the official documentation. The information obtained during the analysis was exported and interpreted according to the thresholds and conditions from the literature. According to the “10 times rule” recommended by [38], the minimum number of respondents is calculated as $10 \times$ the maximum of the number of indicators of the most complex construct or the number of relationships (arrows) that enter a construct. In our case, it would be $10 \times 4 = 40$. Furthermore, according to modern methods of sampling, we used the sample size calculator for structural equation models available at [39]. We set the following values for determining the sample size:

- Anticipated effect size = 0.3;
- Desired statistical power level = 0.8;
- Number of latent variables = 6;
- Number of observed variables = 19;
- Probability level = 0.01.

The result provided was a value of 203 respondents for the recommended minimum sample size. Considering that our sample has 339 responses, it is obvious that the specified rule is met.

Each construct contains indicators from the literature, and the full list of questions are listed in Table 1.

Additionally, a set of questions regarding the actual use of GenAI tools was included:

- What favorite AI tools do you use or have you used (most) often in educational activities?
- What activities do you mainly use AI tools for?
- Should the college/university offer optional free training on the use of AI tools?

Table 1. Constructs and indicators.

Construct	Indicator	Question (Likert 1–7)	References (Adapted from)
PUL	PUL_1	Using AI tools improves my understanding of course content.	[25,28]
	PUL_2	AI tools help me learn more effectively than without them.	[25,26]
	PUL_3	Using AI improves the quality of my academic results.	[20,25]
	PUL_4	AI helps me solve learning tasks faster.	[25]
PEE	PEE_1	It is easy for me to learn how to use AI tools for academic tasks.	[28]
	PEE_2	Interaction with AI tools is clear and understandable.	[25,28]
	PEE_3	I find that using AI tools requires little effort on my part.	[28]
AILSE	AILSE_1	I feel capable of critically evaluating AI-generated outputs.	[30,32]
	AILSE_2	I can use AI tools responsibly while respecting citation and academic integrity rules.	[18,32]
	AILSE_3	I am confident that I can choose the right AI tool for a learning task.	[30]
PAIR	PAIR_1	The use of AI tools increases the risk of violating academic integrity rules.	[33,34]
	PAIR_2	There is a risk of becoming too dependent on AI to complete tasks.	[18,35]
	PAIR_3	There is a risk that my performance evaluation will be unfairly influenced by the use of AI.	[19,35]
TAIO	TAIO_1	The results generated by AI are generally accurate.	[27,40]
	TAIO_2	I believe that AI tools are transparent in how they produce results.	[27,41]
	TAIO_3	I can rely on AI outputs to guide my learning decisions.	[40]
BI	BI_1	I intend to use AI tools frequently in my academic activities.	[28]
	BI_2	I will continue to use AI tools in the coming semesters.	[20]
	BI_3	If I have access, I will prefer to use AI for learning tasks.	[28,42]

4. Results

To obtain the results related to the analysis of the proposed research model, we followed the methodological steps for PLS-SEM. Thus, first we evaluated the measurement model (outer model), and then we analyzed the structural model (inner model) and tested the research hypotheses.

During the evaluation stage of the measurement model (outer model), we considered the calculation, analysis and interpretation of the following relevant aspects: indicator reliability, internal consistency, convergent validity and discriminant validity.

Regarding the evaluation of the structural model (inner model) and the testing of research hypotheses, we analyzed the problems of collinearity and predictive power by calculating and interpreting the *R*-squared coefficient of determination for the endogenous constructs within the model. Also, to test the research hypotheses, we considered statistical significance by running the bootstrapping algorithm and analyzed the path coefficient for each hypothesis. To finalize our research, we examined the mediation relationship outlined in our model by calculating and analyzing the specific indirect effect.

4.1. Evaluation of the Measurement Model

To evaluate the measurement model, we calculated several specific indicators that we present below.

Thus, to determine indicator reliability, we checked outer loadings, and the results are available in Table 2.

Table 2. Indicator reliability—outer loadings.

	PUL	PEE	AILSE	PAIR	TAIO	BI
BI1						0.912
BI2						0.911
BI3						0.897
PUL1	0.896					
PUL2	0.903					
PUL3	0.911					
PUL4	0.903					
PEE1		0.931				
PEE2		0.922				
PEE3		0.939				
AILSE1			0.919			
AILSE2			0.909			
AILSE3			0.919			
PAIR1				0.934		
PAIR2				0.935		
PAIR3				0.947		
TAIO1					0.908	
TAIO2					0.912	
TAIO3					0.905	

According to the rules in the literature [37], an indicator is considered reliable if its factor loading is greater than 0.708. In the data from this study, all of our values are between 0.896 and 0.947. This means that each item (question) explains more than 80% of the variance of its construct, thus certifying that the criterion regarding the reliability indicator is met. The data obtained from the analysis allowed us to make the decision not to eliminate any indicator because the proposed model has strong internal consistency.

To verify internal consistency, we calculated the corresponding values for Cronbach's *Alpha* (although it is considered conservative) and Composite Reliability (*rhoA* and *rhoC*). According to the criteria in the literature [37], both must be greater than 0.70. Regarding convergent validity, it is measured by Average Variance Extracted (AVE), the criterion being that AVE should have values greater than 0.50, meaning that the construct should explain at least 50% of the variance of its indicators. All of these values are presented in Table 3.

Table 3. Internal consistency and convergent validity.

	Alpha	rhoA	rhoC	AVE
PUL	0.925	0.926	0.947	0.816
PEE	0.923	0.925	0.951	0.866
AILSE	0.904	0.904	0.940	0.838
PAIR	0.933	0.934	0.957	0.881
TAIO	0.894	0.894	0.934	0.825
BI	0.892	0.894	0.933	0.823

As we can observe, all values in the columns of the table indicate that the Cronbach *Alpha* is greater than the threshold of 0.7. Also, the *rhoA* and *rhoC* values meet the validity condition for internal consistency. At the same time, convergent validity is demonstrated by the fact that all of the AVE values are superior to the threshold of 0.50.

We also calculated the values related to the discriminant validity criterion. The Fornell–Larcker criterion (Table 4) has long been used in the specialized literature [43], but recent research [44] suggests the use of the HTMT (heterotrait–monotrait ratio) criterion as a measure of similarity between latent variables.

Table 4. Fornell–Larcker criterion.

	PUL	PEE	AILSE	PAIR	TAIO	BI
PUL	0.903	NA	NA	NA	NA	NA
PEE	0.022	0.931	NA	NA	NA	NA
AILSE	0.590	0.100	0.916	NA	NA	NA
PAIR	−0.030	0.129	0.022	0.939	NA	NA
TAIO	0.290	0.110	0.456	0.528	0.908	NA
BI	0.506	0.344	0.450	0.209	0.540	0.907

The Fornell–Larcker criterion analyzes whether the constructs are different from each other, and the rule says that the square root of the AVE for a construct must be greater than any correlation of that construct with any other within the model. In our model, the values on the diagonal in Table 4 are higher than the values corresponding to the correlations between constructs, which means that discriminant validity is confirmed from the point of view of the Fornell–Larcker criterion.

Regarding the HTMT criterion, it is currently considered the most rigorous indicator for discriminant validity in PLS-SEM, because it is much more sensitive than the Fornell–Larcker criterion that we analyzed previously. To demonstrate that the two constructs are different and we have discriminant validity, HTMT values must be below the HTMT threshold <0.85, which is a conservative threshold—recommended by [44].

The values in Table 5 are all well below the 0.85 threshold, indicating an excellent discriminant validity for the proposed research model.

Table 5. HTMT criterion values.

	PUL	PEE	AILSE	PAIR	TAIO	BI
PUL	NA	NA	NA	NA	NA	NA
PEE	0.038	NA	NA	NA	NA	NA
AILSE	0.645	0.109	NA	NA	NA	NA
PAIR	0.032	0.139	0.032	NA	NA	NA
TAIO	0.317	0.122	0.507	0.578	NA	NA
BI	0.555	0.379	0.499	0.228	0.603	NA

Based on the earlier findings regarding indicator reliability, internal consistency, convergent validity, and discriminant validity, we can conclude that the measurement model is valid. This prepares us to proceed with analyzing and evaluating the structural model, along with testing our research hypotheses.

4.2. Evaluation of the Structural Model and Hypotheses Testing

In order to validate the structural model, we will continue to analyze the collinearity situation, the predictive and explanatory power, and the statistical significance of the direct effects in the model, and we will test the mediation relationship.

Thus, before we can analyze the influences, we must ensure that the predictive variables are not strongly correlated, and as a criterion we have the corresponding VIF (variance inflation factor) threshold which must be lower than 3 (conservative criterion) or lower than 5—an accepted criterion in social research according to [45]. Based on the data obtained in Table 6, we find that our model does not present collinearity problems, most of the VIF values are less than 3 and all of them are below 5.

Table 6. VIF values.

Indicator	VIF
PUL1	2.911
PUL2	3.131
PUL3	3.348
PUL4	3.287
PEE1	3.491
PEE2	3.234
PEE3	3.738
AILSE1	3.054
AILSE2	2.700
AILSE3	2.951
PAIR1	3.605
PAIR2	3.851
PAIR3	4.280
TAIO1	2.631
TAIO2	2.785
TAIO3	2.630
BI1	2.801
BI2	2.637
BI3	2.529

To evaluate the potential threat of Common Method Bias (CMB) arising from the cross-sectional nature of the data, a comprehensive collinearity variance inflation factor (VIF) approach was implemented, adhering to the guidelines outlined in [46]. The structural variance inflation factors (VIFs) were computed and the results indicated that all structural VIF values are below the conservative threshold of 3.3. Consequently, the model can be considered free from common method variance definitive distortions.

To analyze the predictive and explanatory power, we calculated the R^2 (R-squared) coefficient for the endogenous constructs. In this case, these are BI, TAIO and PUL. The coefficient of determination actually shows what percentage of the variance of these constructs is explained by the analyzed model. The values are presented in Table 7.

Table 7. R-squared values.

	BI	TAIO	PUL
Rsq	0.509	0.480	0.348
AdjRsq	0.504	0.475	0.346

Taking into consideration that the adjusted R^2 values are 0.504 for BI, 0.475 for TAIO and 0.346 for PUL, it can be said that the model explains 50.4% of the variation in behavioral intention (BI), while the variations in TAIO and PUL are also solid, indicating a substantial predictive effect. For both BI and TAIO, moderate predictive power was achieved, thereby providing strong validity to the structural hypotheses. Additionally, given that the difference between R^2 and adjusted R^2 is very small (e.g., 0.509 versus 0.504), that means the proposed research model is robust and does not suffer from unnecessary complexity.

Regarding hypothesis testing and the statistical significance of direct effects, we ran the bootstrap algorithm with 5000 subsamples, obtaining the corresponding values in Table 8.

Table 8. Hypotheses testing results.

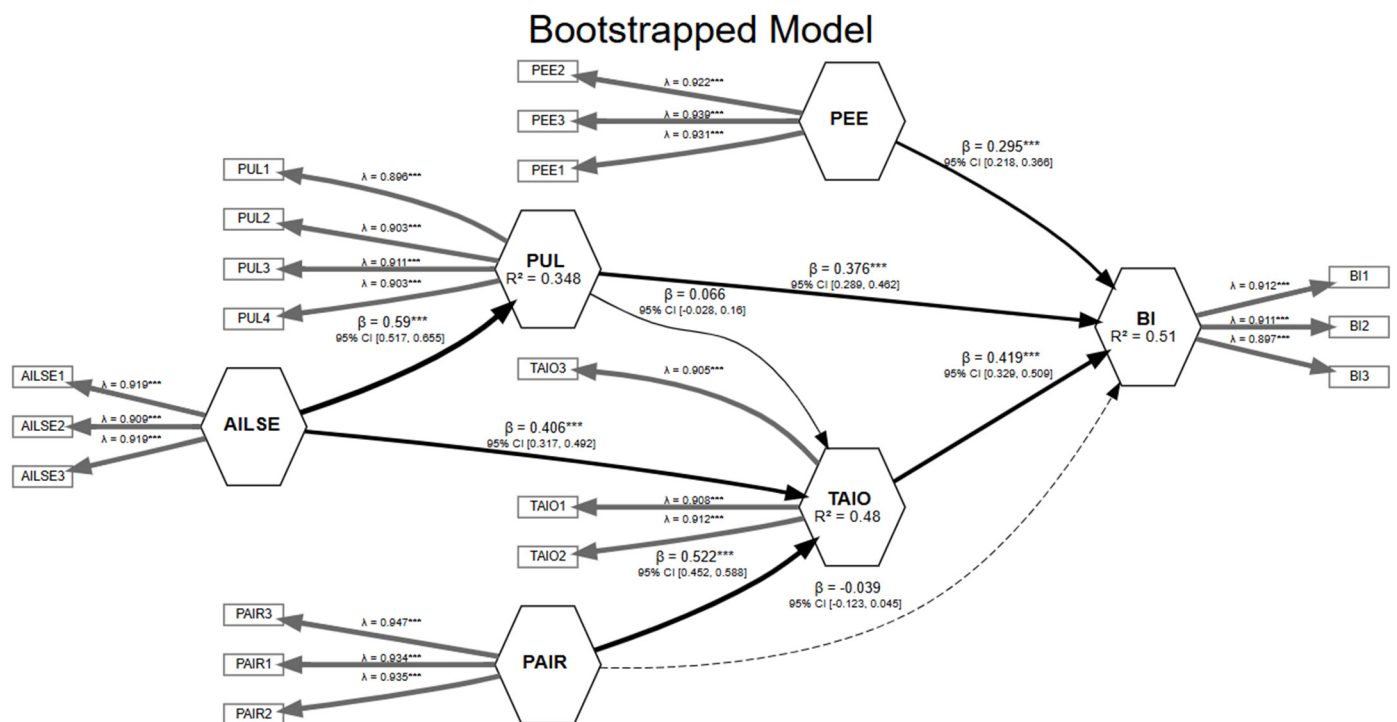
Path	Beta	Bootstrap SD	T Stat.	2.5% CI	97.5% CI	Bootstrap <i>p</i> Val
PUL → TAIO	0.066	0.048	1.376	−0.028	0.160	0.160
PUL → BI	0.376	0.043	8.546	0.289	0.462	0.000
PEE → BI	0.295	0.038	7.849	0.218	0.366	0.000
AILSE → PUL	0.590	0.036	16.395	0.517	0.655	0.000
AILSE → TAIO	0.406	0.045	9.022	0.317	0.492	0.000
PAIR → TAIO	0.522	0.035	14.908	0.452	0.588	0.000
TAIO → BI	0.419	0.046	9.056	0.329	0.509	0.000
PAIR → BI	−0.039	0.043	−0.924	−0.123	0.045	0.349

Based on the bootstrap *p*-values, the complete situation of the research hypotheses from the proposed model is presented in Table 9.

Table 9. Status of the research hypotheses.

Hypothesis	Path	Bootstrap <i>p</i> Val	Status
H9	PAIR → BI	0.349	Not Supported
H8	PUL → TAIO	0.160	Not Supported
H1	PUL → BI	0.000	Supported
H2	PEE → BI	0.000	Supported
H3	AILSE → PUL	0.000	Supported
H4	AILSE → TAIO	0.000	Supported
H5	PAIR → TAIO	0.000	Supported
H6	TAIO → BI	0.000	Supported

Using the *plot* command from the SEMinR package in RStudio v2026.01.1, we obtained the visual analytic research model in Figure 1.

**Figure 1.** The relevant values of the research model.

To analyze the effect size, f^2 values were calculated, and the result is presented in detail in Table 10. The effect size tells us how much a specific variable contributes to the R^2 of the dependent variable.

Table 10. f^2 values (effect size).

	PUL	PEE	AILSE	PAIR	TAIO	BI
PUL	0.000	0.000	0.000	0.000	0.005	0.275
PEE	0.000	0.000	0.000	0.000	0.000	0.170
AILSE	0.534	0.000	0.000	0.000	0.206	0.000
PAIR	0.000	0.000	0.000	0.000	0.520	0.000
TAIO	0.000	0.000	0.000	0.000	0.000	0.289
BI	0.000	0.000	0.000	0.000	0.000	0.000

Interpretation thresholds—according to [47]—were used to interpret the values by following the standard benchmarks: 0.02 denotes a small effect, 0.15 signifies a medium effect, 0.35 indicates a large effect, and values below 0.02 represent a negligible effect (practically does not contribute to the explanation).

Based on the data obtained in Table 8, we can observe several important aspects about the endogenous variables of the model:

- For BI (behavioral intention), TAIO $\rightarrow$ BI (0.289): Medium to large effect. TAIO is a very important predictor for behavioral intention.
- PUL $\rightarrow$ BI (0.275): Medium to large effect. Similar to TAIO, PUL has a substantial contribution to explaining BI.
- PEE $\rightarrow$ BI (0.170): Medium effect. It contributes to the model, but less than the first two.
- For TAIO: PAIR $\rightarrow$ TAIO 0.520, showing a very large effect, above the 0.35 threshold. PAIR is the main driver explaining the variation in TAIO.
- AILSE $\rightarrow$ TAIO 0.205: Medium effect. It is a solid contribution, but subordinate to the influence of PAIR.
- PUL $\rightarrow$ TAIO (0.005): Negligible effect. It is not statistically significant in bootstrap, so its practical influence on TAIO's R^2 is zero.
- For PUL: AILSE $\rightarrow$ PUL 0.533: Very large effect. AILSE explains a huge part of the variation in PUL.

Based on the above data, we can draw the following conclusions:

- Strongest predictors: The relationships AILSE $\rightarrow$ PUL ($f^2 = 0.533$) and PAIR $\rightarrow$ TAIO ($f^2 = 0.520$) have the largest effect sizes in the model.
- Moderate predictors: For the final variable BI, both TAIO and PUL have medium–large effects, meaning that both are essential for understanding behavioral intention.
- Weak predictors: The relationship PUL $\rightarrow$ TAIO has a negligible effect size, suggesting that PUL does not play a practical role in shaping TAIO in this model.

Regarding hypothesis H7 of the proposed research model, we calculated the values related to the mediation effect (Table 11).

Table 11. Mediation analysis results.

	Original Est.	Bootstrap Mean	Bootstrap SD	T-Stat.	2.5% CI	97.5% CI	Bootstrap p Val
PAIR $\rightarrow$ TAIO $\rightarrow$ BI	0.219	0.219	0.029	7.62	0.164	0.277	0.000

The results of the mediation analysis (Table 11) indicate a significant indirect effect of PAIR on BI through TAIO ($\beta = 0.219$, $t = 7.62$, $p < 0.001$). The confidence interval calculated by the bootstrap procedure (95% CI: [0.164, 0.277]) does not contain the value zero, which confirms the mediator role of the TAIO variable in the relationship between PAIR and BI.

To establish the type of mediation, we analyzed the relationship between the direct and indirect effect. In consequence, the value of the indirect effect (PAIR $\rightarrow$ TAIO $\rightarrow$ BI) is 0.219, while the value of the direct effect (PAIR $\rightarrow$ BI) is not statistically significant. Since the direct effect became non-significant ($p = 0.349$) while the indirect effect remained significant, a full (only-indirect) mediation via TAIO is established. Therefore, the hypothesis of a direct effect was rejected. As per the methodological guidelines outlined in [37], this finding suggests a complete mediation effect mediated by the trust in AI outputs (TAIO) construct.

4.3. Most Popular AI Tools and Their Uses

Considering the question “What favorite AI tools do you use or have you used (most) often in educational activities?”, the top five favorite tools indicated by the respondents are (multiple answers were permitted):

- OpenAI ChatGPT—82.5%;
- Google Gemini—76.6%;
- Microsoft Copilot—26.4%;
- Anthropic Claude—22%;
- Perplexity.ai—7.7%.

Among other AI solutions, the following tools/technologies are mentioned (in alphabetical order): Apple Intelligence, DeepSeek, and Google NotebookLM.

The answers provided by the students to the question “What activities do you mainly use AI tools for?” are listed below (multiple answers were permitted):

- Information synthesis—77.4%;
- Research on various topics—73.3%;
- Creating and/or adjusting textual content—67.7%;
- Source-code generation—39.2%;
- Creating and/or adjusting graphical/multimedia content—37.5%.

4.4. Pros and Cons Regarding the Academic Training on AI Tools Usage

We also provide a selection of some opinions regarding the question “Should the college/university offer optional free training on the use of AI tools?”:

- Yes. With the help of AI tools, students can learn new things much more easily.
- I think AI is a useful tool if used properly. We are always informed by professors to filter information, but it is all our responsibility. While I do not consider such training mandatory, I consider that if university staff asks for it, we can be trained on how to properly filter that information at least at a basic level.
- Yes. Some students do not know how to properly use the AI tools; they just copy and paste. Students should understand that the use of AI tools does not have to be addictive. AI tools are very useful when used correctly and can augment the learning process.
- Yes. Inexperienced students who do not have a solid foundation of knowledge about how AI works may take all content as correct without filtering it through their own thinking. They should be aware of the possibility of hallucination in the display of information, security issues regarding what they upload into these tools. Such training can make students more aware of the risks they are exposing themselves to.

- Yes, because AI is often used in the IT industry and it is good for students to know how to work with AI to increase productivity. With proper training, users would use AI more effectively and responsibly.
- I believe that most people are familiar with AI, which is why this type of training would not be of interest to students. However, how the training would be presented/structured matters a lot.
- Yes, because we need to know how to use AI tools correctly and to our advantage. Especially regarding correct citation and use without violating ethical rules regarding plagiarism.
- No, because it would teach us to “cheat” correctly.
- I don’t think the faculty should provide training because students have unlimited resources on the internet regarding this aspect, all they need is the desire to learn.
- It should not. On the contrary, emphasis should be placed on not using AI during studies. No, AI should still be banned in colleges, not because it is not used, but because it is very easy to learn to use an AI tool, but the college still has to focus on original solutions, because an exercise solved with AI is nothing, a problem solved by a student, who maybe when he gets stuck on a certain thing asks the AI to explain it to him or to find hard-to-find errors. This only speeds up the process and is efficient, but using AI tools too much leads to no accumulated knowledge.

5. Discussion

5.1. An Analysis of the Results

Considering the results presented in this research, we can provide an ample discussion about a complex perspective on how the respondents perceive the AI tools and intend to use them in their own educational activities. Taking into account the research objectives that we have proposed, the empirical model considers extensions of the already validated TAM and UTAUT models. It was objectively validated by applying the PLS-SEM methodology, unequivocally highlighting the important role of some constructs specific to the AI context. These constructs are AI literacy self-efficacy (AILSE), trust in AI outputs (TAIO) and perceived academic integrity risk (PAIR).

We consider it relevant to mention that the validation of the measurement model confirms that the constructs included in the model are robust. The high numerical results and the analyzed thresholds for factor loadings, Cronbach Alpha, rhoA, rhoC and convergent validity AVE validate that the analyzed items truly reflect the theoretical concepts that we have included in the research model. Regarding discriminant validity, both criteria widely used in the literature (HTMT and Fornell–Larcker) show unequivocally that each construct is conceptually individualized. The combined findings support the interpretations related to the structural relationships within the model.

By carefully analyzing the structural model, we can argue that the behavioral intention to use artificial intelligence (BI) tools is explained in a substantial proportion, because $R^2 = 0.509$. This value indicates a significant explanatory power. The results obtained by us are consistent with previous results from the TAM/UTAUT models, in the context in which we extended these models with relevant contextual variables. The numerical results show that the hypothesis H1 is confirmed, which means that PUL (perceived usefulness for learning) has a substantial, direct and positive effect on the behavioral intention to use AI tools (BI). According to the classical theory of technology acceptance [25], perceived usefulness is one of the strongest predictors of intention to use, which means that in the context of current AI technologies, students are determined to use them when they perceive direct and immediate benefits in aspects such as the quality of learning and increased academic performance.

Another important hypothesis that was validated by the proposed research model is hypothesis H2 which demonstrates that perceived effort expectancy (PEE) has a determining influence on behavioral intention. The data obtained from the econometric analysis show that, in this case, the effect is smaller compared to PUL. The impact remains notable, demonstrating that the PEE construct plays a crucial and pertinent role, even if it is not the sole determining factor. We consider that the result can be interpreted in the context of students' familiarity with information technologies, which reduces the impact of perceived effort on their decision to use modern AI tools.

From our point of view, the confirmation of hypotheses H3 and H4 is a very relevant aspect because it highlights the central role of AI literacy self-efficacy (AILSE), since it has a significant effect on PUL and TAIO. In the case of PUL, the effect is strong. With respect to TAIO, the effect has a moderate impact. These hypotheses indicate that students who believe in their ability to use AI tools tend to view them as more trustworthy and beneficial for their educational activities. We can conclude that the result has important implications because it suggests an approach regarding educational strategy in the university field. The incorporation of AI tools into the educational framework must go hand in hand with initiatives aimed at cultivating the skills needed for the responsible use of these advanced technologies. This necessitates a reevaluation of the existing structure in universities. Hypothesis H5 in the research model analyzed in this study considered the relationship between perceived academic integrity risk (PAIR) and trust in AI outputs (TAIO). The data confirms that the effect is noteworthy, which makes the result indicate an apparent contradiction. In this context, the result is particularly interesting. Students are aware of the risks of intensive AI use in education, but develop advanced adaptation and critical evaluation mechanisms. This allows them to use AI tools in an informed and assumed manner.

Nevertheless, this positive and apparently counter-intuitive relationship should be interpreted with some academic caution. On the one hand, it is possible that this result reflects a specificity effect related to the way respondents interpreted the items of the PAIR construct; students may associate high risk not with a lack of technology performance, but with the strictness of institutional norms. On the other hand, this phenomenon may be closely related to the specific profile of the analyzed sample, composed of students majoring in economics and computer science. Among these young people, who possess a high level of trust and digital literacy, acute awareness of ethical risks and trust in the technical accuracy of the results provided by AI (TAIO) are not mutually exclusive, but can coexist as facets of a pragmatic and assumed use of technology.

The validation of the research model confirms that hypothesis H6 is also validated, which means that TAIO has a direct and significant impact on BI. Hypothesis H6 supports the notion that trust plays an essential role in the adoption of modern technologies, aligning with research on trust in automated systems. H6 specifically demonstrates that students are more inclined to embrace AI technologies when they perceive their outcomes as relevant.

In contrast, the invalidation of hypothesis H8 denotes the fact that perceived usefulness for learning (PUL) and trust in AI outputs (TAIO) are distinct constructs, but do not directly influence each other in the context that we analyzed within the model. A plausible interpretation of this result may be that students may consider a certain tool as useful, without necessarily having full confidence in the results provided by it. This interpretation actually reflects a critical and selective attitude towards artificial intelligence tools that can be used in the educational process.

Our research also considered the analysis of the mediation relationship within hypothesis H7. Consequently, the results of the analysis highlight the mediating role of TAIO between PAIR and BI, indicating a full mediation. This result determines impor-

tant theoretical and practical implications. Therefore, from a theoretical perspective, we have demonstrated that the relationship between risk and behavior is not straightforward; instead, it is influenced by cognitive processes that act as mediators. One of these mechanisms is trust. This result also has a relevant practical implication because it indicates that educational strategies in the university environment should also aim to strengthen trust in the responsible use of AI tools, not only to reduce the risks that students perceive. Students' perceptions of academic integrity risks (PAIR) do not directly influence their intention to use AI (BI). Risk alone does not determine whether people use GenAI tools more or less. Risk operates exclusively through an intermediary psychological mechanism: it influences how individuals evaluate and trust AI tools' outputs (TAIO), and this trust ultimately determines their intention to use AI. In essence, without cultivating confidence in the system's performance, mere awareness of risk does not directly influence their decision to adopt the technology.

5.2. Related Work

Regarding the previous results from the literature, a similar approach on using a mixed-method approach (PLS-SEM and fsQCA) in the corporate context by investigating how personal beliefs, interactive qualities, and technical characteristics jointly shape the intention to use AI is presented by [48].

Also, a recent systematic study [49] indicates that while current educational practices tend to approach highly automated AI interaction modes with caution, there is a notable trend emerging towards a hybrid model that combines high human control with significant AI automation. This approach shows great promise for leveraging the distinct strengths of both humans and AI in the educational landscape.

Another recent research study considers the interaction between LLM-based tools and humans in the context of performing complex creative tasks, by conducting a randomized controlled experiment [50].

The paper [24] explores the use of generative AI tools and research integrity assessments of use cases by researchers, including PhD students, at Danish universities. The study evaluated 32 AI use cases across five research phases—idea generation, research design, data collection, data analysis, and writing/reporting—but it took into consideration only a limited use of statistical analysis methods.

Similar approaches focused on various educational aspects are described in [21–23,51].

6. Future Work and Conclusions

In terms of limitations, the sample used in this study is limited to students in the fields of economics and computer science. This approach may affect the generalizability of the results we obtained. Also, the use of a questionnaire as a data collection technique may introduce biases related to the subjective perceptions of the study participants. Moreover, the cross-sectional nature of the study does not provide a complete view of the evolution over time of the proposed research model. A major limitation of this study, which directly affects the generalizability of the empirical results, derives from the methodological design adopted. The external validity of the proposed structural model is restricted by the use of a non-probability sampling method, convenience, as well as the concentration of data collection at the level of a single public university in Romania and within only two fields of study (economics and computer science). For these reasons, the sample of 339 respondents cannot be considered a strict representation of the entire national student population or of other academic specializations (such as humanities or arts), where the dynamics of technological adoption and the perception of ethical risks may vary significantly.

We also consider it important to mention that students in these specific fields often exhibit higher levels of digital literacy and distinct attitudes towards technological risk. These elements may influence their perceptions of generative AI tools. Given the results obtained and the objective limitations we identified, future research should address these limitations by implementing a probabilistic sampling framework and expanding data collection to include a broader spectrum of academic fields. Another feasible approach is to incorporate and analyze institutional contexts and geographical regions to strengthen and validate the external validity of our structural model.

Based on the results obtained and the objective limitations that we identified, we consider that the study opens up new future research directions of interest. Consequently, as a first future direction, we recommend expanding the research by applying the study to a sample that includes students from several relevant university fields/specializations. A second direction for continuing the research consists of implementing the study at a longitudinal level, so as to have a vision of the evolution of students' perceptions over time regarding the use of generative AI technologies in education. This path is also justified by the fact that the use of actual AI tends to become more and more integrated in educational processes. We also believe that in the future it would be interesting to analyze the possible moderating effects of some variables on the initial model that we presented in this paper.

In summary, the findings of this research highlight a significant contribution to the existing literature by confirming an integrated model that sheds light on how students perceive and intend to use AI tools in their educational experiences. The results allowed us to offer clear directions for proposals for the development of educational strategies that are adapted to the current technological context.

Author Contributions: Conceptualization, S.C.B., O.D. and N.D.; methodology, S.C.B., O.D. and N.D.; software, S.C.B. and O.D.; validation, S.C.B., O.D. and N.D.; formal analysis, O.D. and N.D.; investigation, S.C.B., O.D. and N.D.; data curation, S.C.B., O.D. and N.D.; writing—original draft preparation, S.C.B., O.D. and N.D.; writing—review and editing, S.C.B., O.D. and N.D.; visualization, O.D.; supervision, S.C.B.; project administration, O.D.; funding acquisition, S.C.B. All authors have read and agreed to the published version of the manuscript.

Funding: For the author Octavian Dospinescu, this research was developed within the project “PIONIER AI—Robot Autonom Pentru Afaceri”. Cod SMIS: 338328.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Research Ethics Committee of the Faculty of Economics and Business Administration, Alexandru Ioan Cuza University. Approval Code: 505 and Approval Date by 24 February 2026.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data is publicly available at the following web address: <https://doi.org/10.6084/m9.figshare.31986933>.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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