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Digital Ethics and Learning Autonomy in Artificial Intelligence in Education: The Mediating Role of Trust in AI

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ABSTRACT

The rapid advancement of Artificial Intelligence in Education (AIED) has transformed digital learning practices while simultaneously raising critical concerns related to ethics, privacy, and user trust, which increasingly influence students' ability to develop autonomous learning behaviors in AI-driven environments. This study aims to examine the relationships among Technology Readiness, Digital Learning Motivation, Digital Privacy Awareness, and Digital Ethics on Learning Autonomy, with Trust in AI serving as a mediating variable. A quantitative cross-sectional research design was employed involving 105 undergraduate students from Universitas Negeri Makassar, and data were analyzed using Partial Least Squares–Structural Equation Modeling (PLS-SEM). The results indicate that the proposed model explains 78.8% of the variance in Trust in AI and 84.3% of the variance in Learning Autonomy. Digital Learning Motivation shows a significant positive effect on Trust in AI and Learning Autonomy, while Digital Ethics also significantly influences both constructs; however, Technology Readiness and Digital Privacy Awareness do not significantly predict Trust in AI. Mediation analysis reveals that Trust in AI partially mediates the relationships between Digital Learning Motivation and Digital Ethics with Learning Autonomy. These findings demonstrate that psychological and ethical factors play a more decisive role than technical readiness in fostering trust and supporting autonomous learning in AIED contexts, highlighting the practical importance of integrating digital ethics education and motivational support into AI-based learning systems. Future research should employ longitudinal designs, broader samples, and additional variables such as AI literacy to further explore learning autonomy in AI-driven education.

1. INTRODUCTION

The rapid development of Big Data and Artificial Intelligence (AI) technologies has significantly influenced various aspects of human life, particularly in the field of education, which is increasingly dependent on digital innovation [1]. In educational settings, AI is utilized in intelligence tutoring systems, adaptive learning environments, conversational agents, and automated assessment tools that transforms the way students interact with information [2]. However, these advancement also introduce challenges related to ethics, data security, and privacy, requiring contextual approaches and the ethical implementation of AIED (Artificial Intelligence in Education) to uphold human-centered values [3]. In addition, internal factors such as self confidence, optimism, and AI literacy influence learning autonomy among generation Z student, while declining academic integrity has become a concerning issue in today's digital era [4], [5]. Therefore, it is essential to understand the wise use of AI so that students can develop learning independence and academic integration in the future.

The integration of AI in education can be explained through technology readiness theory, wich emphasize that individuals attitudes, literacy, and technological competence influence the acceptance and effective use of digital learning systems [6]. Motivational frameworks such as self determination theory (SDT) further assert that the fulfilment of basic phycological needs autonomy, competence, and relatedness enhances intrinsic motivation and supports students learning autonomy in digital environments in AI as a learning partner plays a crucial role in the effectivisness of technology based learning [7]. Additionally, studies on digital ethics and privacy underscore the importance of moral awareness, data protection, and algorithmic transparency in the application of AI in education [3]. Collectively, these findings indicate that the success of AIED is shaped by interconnected factors, namely, technology readiness, learning motivation, ethical and privacy awareness, and trust in AI. However, existing studies rarely explain how these factors interact simultaneously within a unified mechanism that leads to learning autonomy, particularly the psychological process through which trust in AI is formed and translated into autonomous learning behavior.

Although research on AI in education has been conducted in various countries, most studies continue to focus on global contexts and have yet to examine technical aspects such as human AI interaction, algorithmic bias, and data privacy in depth[2], [8], [9]. These studies also do not thoroughly explain how students develop digital ethics and learning autonomy in local and culturally specific contexts in the first place. Previous research has largely concentrated on technological readiness and adoption, while the roles of moral awareness, ethical judgment, and students' digital responsibility remain underexplored. More importantly, empirical evidence explaining the mediating role of trust in AI between ethical motivational factors and learning autonomy is still limited, despite the fact that trust is widely recognized as a critical determinant of AI acceptance in education.

This gap indicates that the relationships among technology readiness, digital learning motivation, privacy awareness, digital ethics, and learning autonomy have rarely been empirically investigated [10]. Accordingly, this study aims to examine the structural relationships among technology readiness, digital learning motivation, digital privacy awareness, and digital ethics on learning autonomy, with trust in AI serving as a mediating variable in the context of Artificial Intelligence in Education (AIED). This study was conducted among undergraduate students at Universitas Negeri Makassar to provide empirical evidence from the Indonesian higher education context, where rapid AI adoption coexists with uneven digital ethics awareness and limited institutional guidance on responsible AI use.

Based on this description, this study is important because advances in AI in education require students to balance technological competence with digital ethical awareness. Several key factors influence the degree of trust In AI as a reliable learning partner, namely technological readiness, digital learning motivation, privacy awareness, and digital ethics. This level of trust ultimately determines the extent to which students can achieve autonomy and responsibility in AIED-based learning intelligently and ethically. Therefore, the findings of this study are expected to contribute meaningfully to educational theory and practice, particularly in fostering a generation of learners who are adaptive, independent, and uphold integrity in the digital era.

Research Question:

1. Does the level of technological readiness influence trust in AI in learning contexts?
2. Does digital learning motivation influence the formation of students' trust in AI?
3. Does digital privacy awareness influence students' trust in the use of AIED?
4. Does digital ethics influence students' level of trust in AI learning?
5. Does students' trust in AI affect their learning autonomy?
6. Does trust in AI play a role in the relationship between technological readiness, digital learning motivation, digital privacy awareness, and digital ethics, and student learning autonomy?

2. RESEARCH METHODS

Research Design

This study uses quantitative methods, namely research procedures conducted in a structured manner using numerical data and statistical analysis to solve a problem [11]. In addition, this study used a cross-sectional design, collecting data once in a period of time to analyze the relationship between variables based on the actual conditions of students. The use of this design is in line with the view that [12], that mapping digital learning behavior through a one-time survey is effective for capturing patterns of interaction and technology acceptance in the context of AIED. The unit of analysis in this study is individual undergraduate students who actively use AI-based learning tools

Data Collection Technique

This study used 105 samples with characteristics of active students at Makassar State University who have used AI technology in their learning activities, both to understand the material, engage in academic discussions, and assist them in completing their college assignments. The research population comprised 110 active UNM students. The population was selected at the university level because the use of AI has spread to various faculties, not only in the field of technology [13]. This population size also meets the minimum limit generally recommended for PLS-SEM models[14]. The sampling technique used was purposive sampling, in which respondents were selected based on criteria relevant to the research objectives. Purposive sampling was chosen because, according to [15], purposive sampling is an appropriate technique for research that requires participants with direct experience related to the phenomenon being studied, so that the information obtained is more accurate and contextual.

Instrument

The instrument used in this study was a questionnaire as supporting data to obtain a general picture of the attitudes, perceptions, and opinions of respondents towards the phenomenon being studied. As mentioned in Table 1, this questionnaire consists of 30 statement items with four independent variables (five TR items, five DLM items, five DPA items, and five DE items), one mediator variable (five TA items), and one dependent variable (five LA items). The content and formulation of the statements in the questionnaire were verified by expert judgment. This item was measured using a 6-point Likert scale (1 = Strongly Disagree, 2 = Somewhat Disagree, 3 = Neither Agree Nor Disagree, 4 = Somewhat Agree, 5 = Agree, 6 = Strongly Agree) in accordance with the measurement guidelines from [16].

Table 1. Research Instruments

No	Variables	Variable Symbols	Statement	Reference
1	Technology Readiness	TR	1-5	[17], [18]
2	Digital Learning Motivation	DLM	6-10	[19], [20]
3	Digital Privacy Awareness	DPA	11-15	[21], [22]
4	Digital Ethics	DE	16-20	[23], [24]
5	Trust in AI	TIA	21-25	[25]
6	Learning Autonomy	LA	26-30	[26]

Sumber : Data diolah , 2025

The procedure followed a structured sequence, as shown in Figure 1. The procedure began with the preparation of literature and questionnaire instruments based on relevant theoretical research. The instruments were then validated by expert judgment using the Index of Item Congruence (IOC) to ensure the suitability and clarity of the statements. Once the instruments were deemed suitable for use, the questionnaire was distributed online via Google Forms in November 2025. The next step was to determine the sample using purposive sampling, as this technique allows for the selection of respondents who have direct experience with the phenomenon being studied, so that the data collected are relevant and valid for the research objectives. Finally, data collection was conducted, which was then compiled, summarized, and analyzed.

Figure 1. Research procedure flow

Data Analysis

Data analysis in this study used two techniques: descriptive statistical analysis and partial least square-structural equation modeling (PLS-SEM) analysis. Descriptive analysis is the accumulation of basic data that explains without drawing conclusions or making predictions [27]. These descriptive statistics consist of mean values, standard deviations, and percentages to illustrate students' tendencies in utilizing AI in learning [9], [19]. Jamovi will be used for this descriptive analysis. Jamovi is R-based statistical software that is useful for descriptive and inferential statistical analysis, and is compatible with various data formats [28].

To evaluate the relationship between variables and research hypotheses, partial least square-structural equation modeling (PLS-SEM) will be used with the help of Smart-PLS software. This method was chosen because it can analyze complex relationships between latent variables and is suitable for small sample data and does not require data normality assumptions [29], [30]. The analysis was conducted by testing the outer and inner models and testing the significance using the bootstrapping technique with 105 samples. Testing using the bootstrapping technique is a special resampling process in which data are randomly selected and then returned. This process produces a new sample (bootstrap sample) that has the same size as the original data but allows for replicated data [31].

Outer model testing is a measurement stage for the validity and reliability of indicators against the latent variables. In outer model testing, constructs (latent variables) are tested using Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE) [32]. Inner model testing was used to show the relationships between the constructs in the PLS-SEM model. This model evaluates the relationships, strength, significance, and predictive ability between constructs in the PLS-SEM model. Inner model testing was conducted through four main stages, Path Coefficient Test (β), Coefficient of Determination (R^2), T-test and Effect Size (f^2), and Predictive Relevance (Q^2) [33]. Figure 2 shows the PLS algorithm model, which describes the relationship between the variables analyzed, namely Technology Readiness, Digital Ethics, Digital Privacy Awareness, and Digital Learning Motivation, which act as independent variables for Trust in AI, as well as their overall influence on Learning Autonomy.

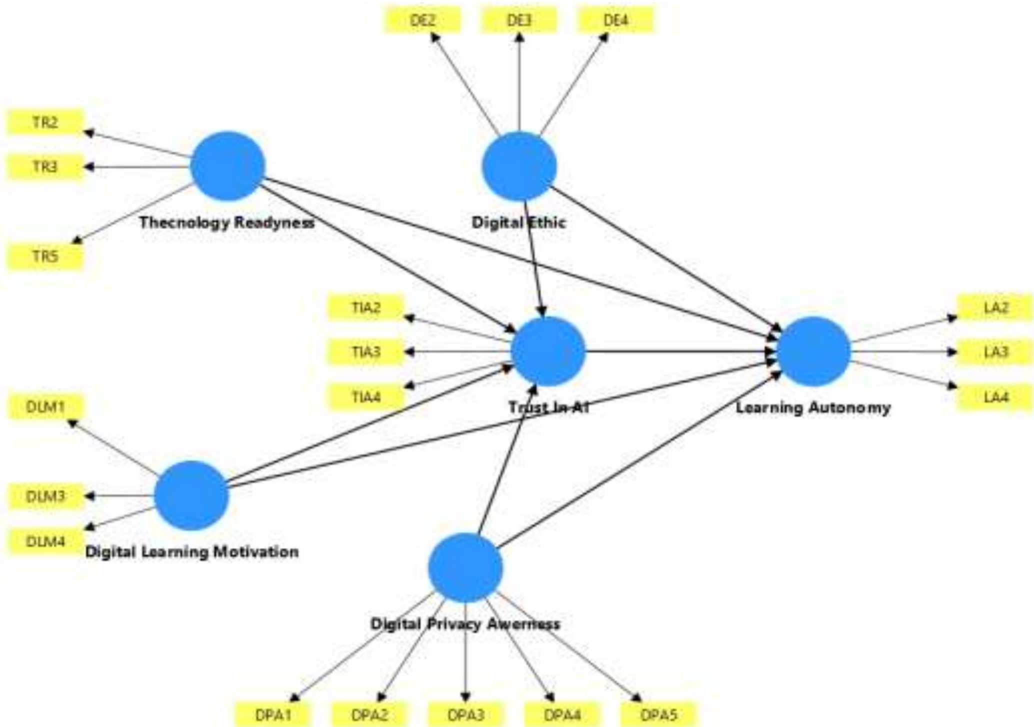

Figure 2. Model proposed in this study

Hypotesis

H_1: Technology Readiness has a significant positive influence on Trust in AI and on Learning Autonomy.

H_{1a}: Technology Readiness has a significant positive influence on Trust in AI

H_{1b}: Technology Readiness has a significant positive influence on Learning Autonomy.

H_2: Digital Learning Motivation has a significant positive influence on Trust in AI and on Learning Autonomy.

H_{2a}: Digital Learning Motivation has a significant positive influence on Trust in AI.

H_{2b}: Digital learning motivation has a significant positive influence on Learning Autonomy.

H_3: Digital Privacy Awareness has a significant positive influence on Trust in AI and Learning Autonomy.

H_{3a}: Digital Privacy Awareness has a significant positive influence on Trust in AI.

H_{3b}: Digital Privacy Awareness has a significant positive influence on Learning Autonomy.

H_4: Digital Ethics has a significant positive influence on Trust in AI and Learning Autonomy.

H_{4a}: Digital Ethics has a significant positive influence on Trust in AI.

H_{4b}: Digital Ethics has a significant positive influence on Learning Autonomy.

H_5: Trust in AI has a significant positive influence on Learning Autonomy.

H_6: Trust in AI mediates the influence of Technological Readiness, Digital Ethics, Digital Privacy Awareness, and Digital Learning Motivation on Learning Autonomy.

H_{6a}: Trust in AI mediates the influence of Technology Readiness on Learning Autonomy.

H_{6b}: Trust in AI mediates the influence of Digital Ethics on Learning Autonomy.

H_{6c}: Trust in AI mediates the influence of Digital Privacy Awareness on Learning Autonomy.

H_{6d}: Trust in AI mediates the influence of Digital Learning Motivation on Learning Autonomy.

3. RESULT AND DISCUSSION

The sample in this study consisted of 105 respondents. The demographic information of the respondents is summarized in the table below, which includes information on gender, age, semester, class year, and frequency of technology use for learning purposes.

Table 2. Demographic Data of the Respondents

No	Category	Description	Percentage (%)
1	Gender	Female	60.0 %
		Male	40.0 %
2	Age	22 Years	2.9 %
		21 Years	4.8 %
		20 Years	24.8 %
		19 Years	44.8 %
		18 Years	21.0 %
		17 Years	1.9 %
3	Semester	I	18.1 %
		III	66.7 %
		V	7.6 %
		VII	7.6 %
4	Class Year	2022	7.6 %
		2023	7.6 %
		2024	66.7 %
		2025	18.1 %
5		Every day	78.1 %

Frequency of Technology Use for Learning	3-5 times a week	14.3 %
	1-2 times a week	6.7 %
	Rarely	1.0 %

Sumber: Data diolah, 2025

As shown in Table 2, a total of 105 students participated in the study. The demographic profile indicates that most respondents were female (60%), within the age range of 18-20 years, and predominantly enrolled in their third semester. Most (78.1%) reported daily technology use for learning. These characteristics suggest that the respondents represent a young, digitally exposed student population with substantial experience in technology-assisted learning.

Convergent Validity and Construct Reliability

The measurement model was evaluated to ensure that all constructs met the requirements for convergent validity and internal consistency before proceeding to the structural analysis. Convergent validity was assessed using three criteria: factor loadings, composite reliability (CR), and Average Variance Extracted (AVE). Reliability was assessed using Cronbach's measurement assessment.

Table 3. Convergent Validity and Construct Reliability Evaluation Results

Construct	Items	Outer Loadings	Cronbach's Alpha	Rho_A	Composite Reliability (CR)	Average Variance Extracted (AVE)
Technology Readiness	TR1	0.826	0.899	0.905	0.926	0.717
	TR2	0.900				
	TR3	0.899				
	TR4	0.866				
	TR5	0.729				
Digital Privacy Awareness	DPA1	0.823	0.869	0.872	0.906	0.659
	DPA2	0.850				
	DPA3	0.864				
	DPA4	0.786				
	DPA5	0.727				
Digital Learning Motivation	DLM1	0.753	0.904	0.904	0.929	0.725
	DLM2	0.868				
	DLM3	0.888				
	DLM4	0.851				
	DLM5	0.890				
Digital Ethics	DE1	0.730	0.846	0.852	0.891	0.622
	DE2	0.793				
	DE3	0.835				
	DE4	0.870				
	DE5	0.702				
Trust in AI	TIA1	0.840	0.887	0.890	0.918	0.691
	TIA2	0.798				
	TIA3	0.880				
	TIA4	0.865				
	TIA5	0.768				
Learning Autonomy	LA1	0.877	0.917	0.919	0.938	0.751
	LA2	0.900				
	LA3	0.843				
	LA4	0.859				
	LA5	0.853				

Sumber : Data diolah, 2025

The results in Table 3 show that all constructs met the recommended criteria for convergent validity and internal consistency. All indicator loadings exceeded the threshold of 0.70, indicating that each item strongly represented its corresponding latent variable. Furthermore, Cronbach's alpha, rho_A, and composite reliability were assessed across the measurement model.

The AVE values, ranging from 0.622 to 0.752, also surpass the minimum requirement of 0.05, which means that each construct can explain more than half of the variance of its indicators. These results confirm that the convergent validity of the measurement model was fully achieved. Overall, the findings are consistent with the PLS-SEM guidelines outlined [34], [35], indicating that the constructs are valid and reliable for use in subsequent structural model analysis.

Discriminant Validity

Table 4 presents the discriminant validity assessment using the Fornell-Larcker criterion, wich compares the square root the AVE of each construct with its correlations with other constructs. The results show that for all variables, including Technology Readiness, Digital Privacy Awareness, Digital Learning Motivation, Digital Ethics, Trust In Ai, and Learning Autonomy, the square root of the AVE is higher than the inter-construct correlations.

Table 4. Results of The Fornell-Lacker Criterion Validity Test

	Digital Ethics	Digital Learning Motivation	Digital Privacy Awareness	Learning Autonomy	Trust in AI	Technology Readiness
Digital Ethics	$\sqrt{AVE_{DE}}$ =0.788					
Digital Learning Motivation	0.677	$\sqrt{AVE_{DLM}}$= 0.851				
Digital Privacy Awareness	0.840	0.720	$\sqrt{AVE_{DPA}}$=0. 812			
Learning Autonomy	0.708	0.795	0.699	$\sqrt{AVE_{LA}}$=0. 867		
Trust in AI	0.802	0.813	0.750	0.887	$\sqrt{AVE_{TIA}}$= 0.831	
Technology Readiness	0.768	0.739	0.735	0.684	0.757	$\sqrt{AVE_{TR}}$=0. 788

Sumber : Data diolah, 2025

This pattern indicates that each construct is empirically distant and captures a unique conceptual dimension in the model. In other words, the indicators of each latent variable did not overlap with other variables, fulfilling the discriminant validity threshold suggested [35]. Therefore, the constructs in this study demonstrated adequate discriminant separation and were suitable for further structural analysis.

Inner Model

Table 5 summarizes the result of the hypothesis testing conducted through PLS-SEM, including path coefficients, t-statistics, and p-values. The finding show that some relationships in the model are statiscally significant, while others are not

Table 5. Result of Testing The Relationship Between Latent Constructs

Hypothesis	Track	Path Coefficienst	T-Statistics	P-Values	Decision
H1a	TR → TIA	0.064	0.461	0.322	Rejected
H1b	TR → LA	0.053	0.678	0.249	Rejected
H2a	DLM → TIA	0.455	4.522	0.000	Accepted
H2b	DLM → LA	0.240	2.324	0.010	Accepted
H3a	DPA → TIA	0.057	0.374	0.354	Rejected
H3b	DPA → LA	0.226	2.081	0.019	Accepted
H4a	DE → TIA	0.289	1.785	0.037	Accepted
H4b	DE → LA	-0.209	1.752	0.040	Accepted
H5	TIA → LA	0.594	6.886	0.000	Accepted
H6a	TR → TIA → LA	0.073	0.928	0.177	Rejected
H6b	DLM → TIA → LA	0.339	5.037	0.000	Accepted
H6c	DPA → TIA → LA	-0.007	0.092	0.463	Rejected
H6d	DE → TIA → LA	0.311	2.489	0.006	Accepted

Sumber : Data diolah, 2025

Technology Readiness (TR) did not significantly predict Trust in AI or Learning Autonomy. The low coefficients and high p-values suggest that students' technical readiness alone does not translate into trust in AI systems or greater learning autonomy. This supports the findings by Dwianto et al, [2] who argue that readiness primarily reflecs technical familiarity rather than cognitive or affective acceptance of AI.

Unlike TR, Digital Learning Motivation (DLM) exhibited a strong and significant relationship with both Trust in AI and learning autonomy. This reflects the role of intrinsic motivation in shaping students' engagement with AI tools, consistent with Self-Determination Theory, which posits that motivation enhances perceived competence and autonomy [19]. Motivated learners are more likely to value AI support and engage independently in digital learning motivation, [7].

Digital Privacy Awareness (DPA) showed a mixed effect; it did not significantly predict trust in AI but significantly predicted Learning Autonomy. Students who are aware of privacy concerns may be cautious toward AI system, sich reduces the likelihood of developing trust [36], however, thid awareness simultaneously strengthens autonomus decision-making, as privacy conscious student trend to regulate their use of technology more deliberatly [37].

Meanwhile, Digital Ethics (DE) significantly influences both Trust in AI and Learning Autonomy. Ethical awareness help students critically evaluate issues as algorithmic fairness, transparency, and accountability, wich contribute to forming informed trust in AI system [8], such ethical literacy also equips students to use AI tools responsibly and independently, leading to grater learning autonomy [38] .

Mediation analysis showed that Trust in AI mediated the effects of digital learning motivation and digital ethics on learning autonomy but did not mediate technology readiness or digital privacy awareness. This suggest that motivational and ethical factors shape autonomy primarily through the development of trust, whereas technical readiness and privacy concerns operate through alternative patways. [30], [39] describe, trust is a cognitive affective mechanism that is shaped more by values, motivation, and experience than by technical compentence alone. Overall, Table 5 highlights that psychological and ethical factors, rather than technical or privacy-related considerations, play the most influential role in building trust and fostering autonomous learning in AI-supported educational contexts.

The findings of this study indicate that learning autonomy in Artificial Intelligence in Education (AIED) environments is primarily influenced by psychological and ethical factors rather than technical readiness alone. This supports recent critiques of technology-centered approaches in AIED, which argue that effective AI integration depends on human-centered dimensions such as values, motivation, and trust, rather than mere technological capability [1], [2].

Digital Learning Motivation emerged as a strong predictor of both Trust in AI and Learning Autonomy. From a Self-Determination Theory perspective, motivated learners are more likely to perceive AI systems as autonomy-supportive tools that enhance their competence and self-regulation [19]. When students experience intrinsic motivation, they tend to engage more confidently with AI technologies, develop trust in AI-supported feedback, and manage their learning processes independently. This finding aligns with prior research emphasizing motivation as a critical driver of trust formation and meaningful engagement in AI-powered educational environments [7].

Digital Ethics also play a significant role in shaping Trust in AI and Learning Autonomy. Ethical awareness enables students to critically assess issues such as transparency, fairness, and accountability in AI systems, which are central concerns in contemporary AIED discourse [3], [8]. Rather than acting as a barrier, ethical sensitivity appears to foster informed trust, allowing students to use AI responsibly while maintaining their autonomy. This result extends existing ethical frameworks by empirically demonstrating that digital ethics can function as an enabler of autonomous learning, rather than merely a normative constraint.

In contrast, Technology Readiness did not significantly predict Trust in AI or Learning Autonomy. This suggests that technical competence alone is insufficient to generate trust and autonomy in AI-driven learning contexts. Students may be technologically proficient but remain hesitant to rely on AI systems if ethical alignment and motivational engagement are lacking [6]. Similarly, Digital Privacy Awareness does not significantly influence Trust in AI, although it contributes to Learning Autonomy. Heightened privacy awareness may encourage self-regulation while simultaneously limiting trust in AI systems that process personal data [21], [37].

The mediation analysis further confirmed that Trust in AI functions as a key psychological mechanism linking Digital Learning Motivation and Digital Ethics to Learning Autonomy. Trust serves as a cognitive bridge that translates students' values and motivational orientations into autonomous learning behavior. This finding reinforces the central role of trust as a human-centered construct in AIED, shaped more by ethical and motivational considerations than by technical readiness.

4. CONCLUSION

This study demonstrates that digital learning motivation and digital ethics are the most influential factors in fostering students' learning autonomy in Artificial Intelligence in Education (AIED), with trust in AI serving as a key mediating mechanism. In contrast, technology readiness and digital privacy awareness did not show significant direct effects on learning autonomy, indicating that technical competence alone is insufficient to support autonomous learning in AI-driven environments. These findings emphasize that psychological and ethical dimensions play a more decisive role than technological readiness in shaping meaningful and responsible AI-supported learning experiences.

From a theoretical perspective, this study contributes to the AIED literature by validating a trust-mediated model that integrates motivational and ethical factors to explain learning autonomy beyond technology-centric adoption frameworks. The results suggest that higher education institutions should prioritize the development of digital ethics literacy, motivational support, and transparent AI practices to strengthen students' trust and autonomy in AI-based learning. Despite these contributions, this study is limited by its cross-sectional design and single-institution sample, which may restrict its generalizability. Future research should employ longitudinal designs, involve more diverse populations, and incorporate additional variables, such as AI literacy and AI usage experience, to further advance the understanding of autonomous learning in AIED contexts.

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