Journal of Vocational, Informatics and Computer Education
E-ISSN: 2988-6325; P-ISSN: 2988-4918
Journal Homepage: http://journal.lontaradigitech.com/VOICE

The Role of Anthropomorphism in Shaping Students' Emotional Attachment to AIED: A Triangular Theory of Love Approach and PLS-SEM Analysis in Makassar Universities

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ARTICLE INFO

Keywords:

Affective AIED experience; AI anthropomorphic perception; AI emotional attachment; Socio-emotional AIED; Student AI engagement

Received: September 7, 2025;
Accepted: November 30, 2025;
Available online: December 5, 2025

ABSTRACT

In the digital learning era, Artificial Intelligence in Education (AIED) functions not only as an academic support tool but is also becoming an object of emotional attachment among students. While such attachment may enhance learning motivation, it also raises concerns about emotional dependence and its implications for students' social and emotional well-being. This study investigates the effects of commitment, enthusiasm, emotional closeness, and anthropomorphic perceptions on students' emotional dependence on AIED. A quantitative cross-sectional survey was conducted with 109 university students in Makassar using a 1–5 Likert-scale questionnaire. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The structural model explained 62.7% of the variance in emotional dependence on AI ($R^2 = 0.627$), indicating moderate to strong explanatory power. Emotional closeness ($\beta = 0.324$; $t = 2.893$; $p = 0.004$) and anthropomorphic perception ($\beta = 0.440$; $t = 4.871$; $p < 0.001$) significantly increased emotional dependence, whereas commitment to continued AI use ($\beta = 0.092$; $t = 0.883$; $p = 0.377$) and enthusiasm toward AI ($\beta = 0.081$; $t = 0.901$; $p = 0.367$) were not significant predictors. These findings suggest that emotional dependence is driven more by affective engagement and the perception of AI as socially human-like than by cognitive motivation or usage intention. AIED interaction therefore extends beyond functional support into a relational experience resembling interpersonal connection. Given the limited geographic scope, future studies should involve broader populations and employ mixed-method approaches to deepen understanding of emotional dynamics in AIED use.

1. INTRODUCTION

In the era of digital learning, students not only utilize artificial intelligence as an academic tool, but also begin to show emotional attachment to this technology (1). This attachment has a positive impact in the form of comfort and increased motivation to learn, but it also has the potential to disrupt students' independence and emotional balance (2). A global survey shows that more than 60% of students experience increased emotional dependence on AI-based systems during online learning (3), which can reduce social interaction and empathy among students (4). This condition emphasizes the need for an in-depth study of how learning technology affects students' emotional well-being

The theoretical framework of this study refers to Sternberg's Triangular Theory of Love (1986), which explains that emotional relationships are formed through three main components, namely passion, intimacy, and commitment. In the context of AIED, these three components are adapted to represent students' enthusiasm for technology, emotional closeness to AI systems, and commitment to continue using them sustainably (3). However, this theory does not consider the technical characteristics of AI, particularly anthropomorphism, the ability of AI to display human-like behavior that can strengthen users' perceptions of emotional closeness (5,6). Thus, combining Sternberg's theory and the concept of anthropomorphism is necessary to understand how AI's human-like features shape students' perceptions of AI's ability to respond to emotions (2,3).

Previous studies have highlighted the contribution of AI to the affective aspects of learning, but have not comprehensively explained the form of students' emotional attachment to AIED. Previous studies indicate that AI can support the development of emotional intelligence through digital media, but their study focuses on early childhood, so it does not provide a clear picture of how AIED affects students' emotional attachment (7). Other studies have examined the use of chatbots and AI-based emotion detection, but have not explored the depth of students' emotional relationships with AI systems (8,9). Lastly other study also only examined user perceptions without considering complex affective aspects, especially those related to anthropomorphism (10). This gap indicates a lack of research that integrates emotional theory, anthropomorphism, and user experience to explain students' emotional attachment to AIED.

Theoretically, students' emotional attachment to AIED is important to study because it is related to learning motivation and psychological well-being in higher education. This study strengthens our understanding of human interaction with AI from an affective perspective, which has rarely been researched. The theoretical findings are expected to enrich the literature on emotional dynamics in the use of learning technology. This study aims to analyze the effect of student interaction with AIED on commitment, enthusiasm, and emotional closeness in the learning process. In addition, this study assesses how students' perceptions of AI's ability to understand emotions are formed from their experience of using it. This analysis provides an empirical description of the patterns of emotional attachment between students and the AIED system. In line with these objectives, this study formulates the following research questions:

RQ1. To what extent do students' commitment, enthusiasm, and emotional closeness to AI influence their emotional attachment to Artificial Intelligence in Education (AIED)?

RQ2. How does anthropomorphic perception of AI mediate the relationship between students' emotional interactions and their attachment to AIED?

RQ3. Which factor contributes most to shaping students' emotional attachment to AIED based on the Triangular Theory of Love approach?

2. METHOD

Data collection

This study uses a quantitative approach to measure the relationship between commitment, enthusiasm, emotional closeness, and anthropomorphic perceptions of AI with students' perceptions of AI's ability to understand emotions through numerical data analysis (11,12). This approach was chosen because it allows for empirical assessment of students' emotional attachment in the context of AI-based learning (AIED). The research design used is a cross-sectional survey because it is suitable for objectively describing the relationship between variables in a single period of time (13) and representing the actual conditions of students' affective engagement without direct intervention (5). Thus, this research design also serves as the basis for determining the sampling technique and data collection instruments in the next stage.

The research participants were active students from various universities in Makassar who had used AI systems such as ChatGPT, Gemini, or similar platforms in their academic activities and showed higher emotional involvement than other age groups (Tran et al., 2025). The sample size was determined following the PLS-SEM rule of thumb, namely the 10-times rule based on the number of indicators, with five indicators per variable, resulting in a minimum limit of 50 respondents (14,15). However, the latest methodological literature recommends 100–200 respondents for more stable estimates (14,15). Thus, the selection of respondents from among university students is considered appropriate because this group has high relevance and strong academic and emotional involvement in the use of modern learning technologies.

The population in this study included all active students at various universities in Makassar who had used artificial intelligence-based learning systems. The sampling technique used was purposive sampling, because this study required respondents with specific characteristics, namely students who had direct experience using AI to support the learning process (5). This approach is commonly used in social research that targets specific respondent profiles so that the data obtained remains relevant and in-depth (Memon et al., 2024). The inclusion criteria for respondents included: (1) active students at one of the universities, (2) having interacted with an AI system, and (3) residing in the Makassar area. The sample size was determined based on the guidelines for determining the minimum sample size in correlational quantitative research so that the results would have adequate statistical power ((14).

Instrument

This research instrument consists of two main parts. The first part covers the demographic data of respondents, including name, gender, university of origin, major (STEM or Non-STEM), semester, frequency of AI system use, and the main purpose of using AIED (Artificial Intelligence in Education). This data is used to identify respondent profiles and link individual characteristics to the intensity of interaction with AI systems in an academic context (16). The second part contains statement items that measure commitment, enthusiasm, emotional closeness, anthropomorphic perceptions, and perceptions of AI's ability to understand emotions. All items use a 1–5 Likert scale, with categories ranging from 1 = Strongly Disagree to 5 = Strongly Agree, as this is effective in assessing attitudes and perceptions of technology (17). Data collection was conducted online via Google Form to facilitate rapid and real-time dissemination across universities (17). Data collection was conducted online via Google Form to facilitate rapid and real-time dissemination across universities (18).

The following table displays a complete list of variables, item codes, statements, and reference sources used in the preparation of this research instrument:

Table 1. Research Instruments

No	Concstruct	Item
1.	Commitment to Continue Using AI (CC)	1, 2, 3, 4, 5
2.	Enthusiasm Toward AI (EA)	6, 7, 8, 9, 10
3.	Emotional Closeness Between Students and AI (EC)	11, 12, 13, 14, 15
4.	Perceived Anthropomorphism Toward AI (PA)	16, 17, 18, 19, 20
5.	Emotional Dependence on AI (ED)	21, 22, 23, 24, 25

Procedure

This research procedure was carried out sequentially and through several systematic stages to ensure that each step produced valid data. The first stage began with a literature review and the development of a theoretical framework based on studies of emotional attachment and anthropomorphism in artificial intelligence-based learning (3,19). Next, research instruments were developed and validated based on relevant theoretical indicators, taking into account the suitability of the academic context (1). Once the instruments were validated, the questionnaire was distributed online via Google Form to students from various universities to ensure a wide range of respondents (6). Thus, this entire series of procedures formed a strong methodological basis for scientifically examining students' emotional attachment to AIED systems.

The stages of this research procedure are described visually to clarify the flow of the research process, from the formulation of the problem to the drawing of conclusions. The following figure shows the sequence of activities carried out by researchers in the process of developing, validating, and analyzing instruments to obtain systematic, efficient, and measurable research results.

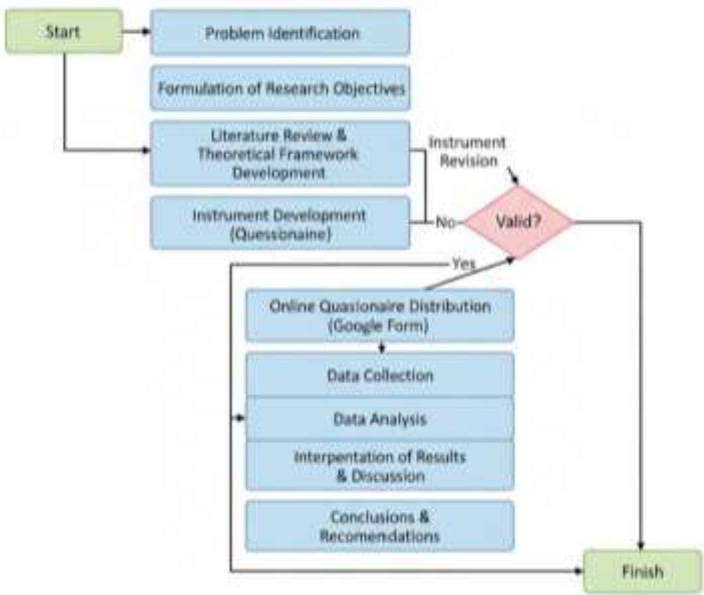

Figure 1. Research Procedures

Data analysis was conducted in two stages. First, descriptive analysis was used to describe the characteristics of respondents based on demographic variables and response patterns for each research variable (3). Descriptive analysis was used to display respondent characteristics based on variables such as gender, university of origin, major, semester, and frequency of AI use (1). All of this data was then processed into basic statistics such as mean, median, mode, minimum, and maximum so that the distribution pattern could be clearly seen (2). The descriptive results provide an initial overview of the participants' conditions and help to understand the context before testing the structural model (4).

The inferential stage was conducted using PLS-SEM through SmartPLS, which is suitable for non-normal data and theoretical models involving relationships between latent constructs (20,21). The outer model was evaluated through reliability and validity measurements using outer loading, Cronbach's alpha, composite reliability ≥ 0.70, as well as AVE ≥ 0.50 and Fornell Larcker criteria and HTMT < 0.90 (13,15,21–23). The Inner Model was analyzed using path coefficients and R^2 values to examine the strength of the relationship between endogenous variables (20,23). Significance testing was conducted through bootstrapping to obtain t-statistic and p-value values so that each hypothesis could be assessed objectively ((21). A relationship was considered significant if it met the criteria of p-value < 0.05 and t-statistic > 1.96 (22).

Based on the structural model in Figure 2, the research hypothesis is:

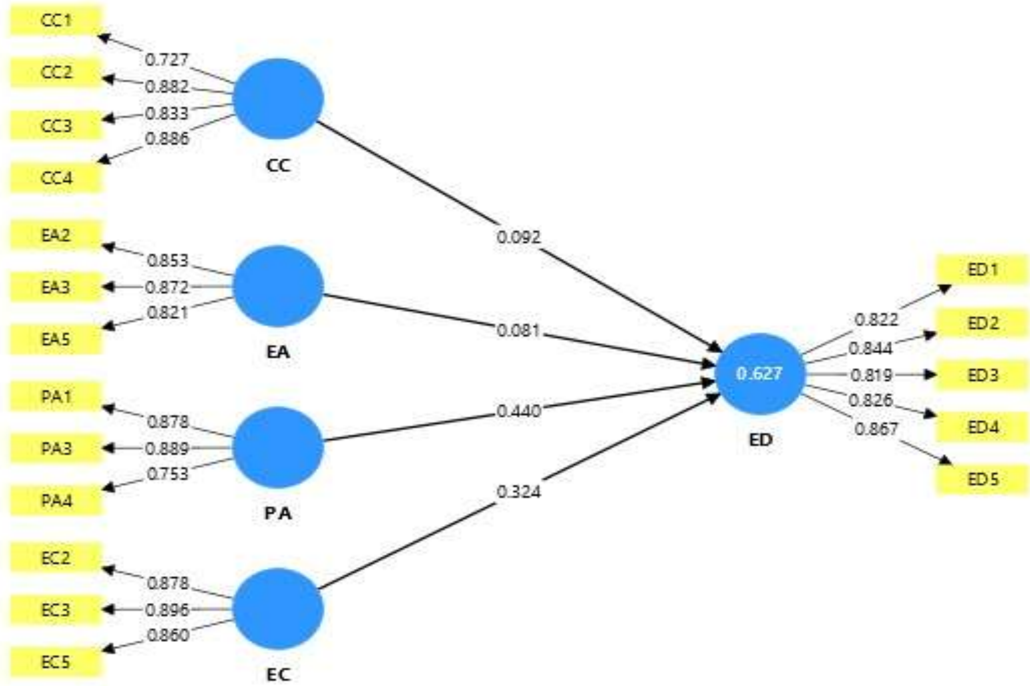

Figure 2. Research Structural Model

H1: Students' commitment to continue using AI affects their emotional dependence on AIED.
H2: Students' enthusiasm for AI influences their emotional dependence on AIED.
H3: Students' anthropomorphic perceptions of AI influence their emotional dependence on AIED.
H4: Students' emotional closeness to AI affects their emotional dependence on AIED.

3. RESULT AND DISCUSSION

Result

This study involved 109 respondents from various universities in the city of Makassar. The respondents were students of diverse genders, universities, and fields of study. This variation in background indicates that the sample reflects a fairly heterogeneous academic environment. Respondents also had varying frequencies of interaction with AI, ranging from low to intensive use. This demographic overview provides initial context regarding the characteristics of the participants in the study.

Table 2. Respondent Characteristics

Category	Description	Frequency	Percentage
Gender	Male	32	29,1%
	Female	78	70,9%
University	Makassar State University	65	59,1%
	Hasanuddin University	32	29,1%
	Alauddin State Islamic University Makassar	6	5,4%
	Indonesian Muslim University	1	0,9%
	Bosowa University	2	1,8%
	Muhammadiyah University Makassar	1	0,9%
	Megarezky University	1	0,9%
	Ujung Pandang State Polytechnic	1	0,9%
Department	STEAM	47	42,7%
	NON STEAM	63	57,3%
Frequency of AI Interaction	Every day	72	65,5%
	3–5 times a week	26	23,6%
	1–2 times a week	9	8,2%
	Rarely	3	2,7%
Purpose of AIED Use	To assist with academic assignments	94	85,5%
	For discussion/practice	83	75,5%
	For personal exploration/entertainment	42	38,2%

In general, respondents showed a high level of AIED utilization, especially for academic needs such as completing assignments and learning discussions. This usage pattern confirms that AIED has become part of students' learning routines, with most respondents integrating it into their daily activities. The composition of their backgrounds and interaction patterns indicate that the majority of respondents are active users who utilize AIED in a targeted manner. This profile supports the relevance of the data for analyzing how psychosocial factors shape affective experiences in students' interactions with AI systems.

Outer Model

To ensure the quality of the research instruments, convergent validity and construct reliability tests were conducted on all variables used. This evaluation included outer loading analysis, Average Variance Extracted (AVE), and internal reliability through Cronbach's Alpha, rho_A, and Composite Reliability. Details of the test results are presented in Table 3.

Table 3. Convergent Validity and Construct Reliability

Construct	Item	Outer Loading	Cronbach's Alpha	Rho_A	Composite Reliability	AVE
Commitment to Continue Using AI (CC)	CC1	0,727	0,855	0,884	0,901	0,697
	CC2	0,882				
	CC3	0,833				
	CC4	0,886				
Enthusiasm for AI (EA)	EA2	0,853	0,807	0,817	0,885	0,720
	EA3	0,872				
	EA5	0,821				
Emotional Closeness between Students and AI (EC)	EC2	0,878	0,852	0,853	0,910	0,771
	EC3	0,896				
	EC5	0,860				
Perceptions of Anthropomorphism toward AI (PA)	PA1	0,878	0,795	0,818	0,880	0,710
	PA3	0,889				
	PA4	0,753				
Emotional Dependence on AI (ED)	ED1	0,822	0,892	0,894	0,921	0,699
	ED2	0,844				
	ED3	0,819				
	ED4	0,826				
	ED5	0,867				

The evaluation of the measurement model shows that all constructs meet the methodological criteria required in PLS-SEM, so that the instrument is considered capable of measuring the defined concepts consistently. The indicators in each construct show stable performance and do not need to be removed. This confirms that the measurement model has met the technical requirements to proceed to the structural analysis stage. Thus, the interpretation of the relationship between variables in the inner model can be carried out without any concerns about bias or weaknesses at the measurement level.

Inner Model

After the measurement model meets the validity and reliability criteria, the next step is to test the structural model (inner model) to evaluate the direction and strength of the relationships between constructs according to the research hypothesis. The bootstrapping procedure with 5,000 subsamples was used to obtain estimates of Path Coefficients, T-Statistics, and P-Values, as recommended in modern PLS-SEM practice (21,23,24). The results of testing the hypothesis describing the influence of commitment, enthusiasm, emotional closeness, and anthropomorphism perception on students' emotional dependence on AI are presented in the following table

Table 4. Hypothesis Testing

Hypothesis	Path	Path Coefficient	T-Statistics	P-Values	Decision
H1	Commitment to Continuing AI Use → Emotional Dependence on AI	0,092	0,883	0,377	Not Significant
H2	Enthusiasm for AI → Emotional Dependence on AI	0,081	0,901	0,367	Not Significant
H3	Emotional Closeness between Students and AI → Emotional Dependence on AI	0,324	2,893	0,004	Significant
H4	Perception of Anthropomorphism in AI → Emotional Dependence on AI	0,440	4,871	0,000	Significant

Based on the hypothesis testing results presented in Table 4, only emotional closeness and anthropomorphic perception show statistically significant effects on students' emotional dependence on AI, while commitment and enthusiasm do not demonstrate significant influence. To further assess the overall predictive capability of the structural model, the coefficient of determination (R^2) for the endogenous construct was subsequently examined. Table 5 presents the R^2 value for emotional dependence on AI, indicating the extent to which the exogenous variables jointly explain variance in the dependent construct.

Table 5. R Square (R^2) of Endogenous Variable

Endogenous Variable	R Square (R^2)	Kategori
Emotional Dependence on AI	0.627	Moderate to Strong

The evaluation of the measurement model shows that emotional dependence as a core variable in the model is shaped more by affective and perceptual mechanisms than by rational impulses. The structural model reveals that students do not develop emotional attachment simply because of their intention to use AI or their initial interest, but rather because of the closeness they feel and the way they perceive AI as an entity with human-like characteristics. Thus, the endogenous variables in this study do not only function as statistical outputs, but reflect psychological processes that place emotional interaction and social perception as the foundation for forming relationships with technology. This pattern reinforces the view that human relationships with AI move beyond instrumental functions, towards more personal and symbolic forms of relationship.

Discussion

The research findings confirm that commitment to continue using AI (H1) and enthusiasm for AI (H2) do not have a significant effect on students' emotional dependence. These findings show that the intention to use and initial interest in technology are not enough to form a deep emotional connection, so that student engagement is still utilitarian in nature. This pattern is consistent with several previous studies that confirm that cognitive motivation does not always transform into affective attachment (6,19,22) However, these findings also show inconsistency with previous studies that emphasized that commitment to use can encourage emotional attachment in certain digital systems, thus indicating that the AIED context has different dynamics. Conversely, emotional closeness between students and AI (H3) proved to be a significant predictor of emotional dependence. Positive and supportive interactions made AI not only an academic tool, but also a learning partner that provided emotional comfort. These findings are in line with research stating that positive affective experiences tend to strengthen users' emotional bonds with technology.

In addition, anthropomorphic perceptions of AI (H4) showed the strongest influence, confirming that the more AI is perceived to have human-like characteristics, the greater the tendency for students to form emotional attachments. This pattern is consistent with the Computers as Social Actors (CASA) theory and a number of studies showing that anthropomorphic features can increase perceptions of artificial empathy and deepen affective relationships (11,12,25,26). Critically, these results differ from several studies that found that anthropomorphism does not always produce significant emotional effects on more transactional systems, suggesting that the educational context appears to amplify these social-emotional effects.

The R^2 result shows that the model has adequate explanatory power for the dependent variable, so that the relationship between constructs does not only stand individually but forms a coherent pattern of influence. In the context of PLS-SEM, R^2 serves as an indicator that reflects the extent to which the model structure describes the psychological processes underlying emotional dependence, thereby strengthening the conceptual validity of the findings of this study (27). Overall, the pattern of relationships between variables confirms that affective factors and social perceptions play a more dominant role than cognitive factors in shaping students' attachment to AIED. Commitment to use and enthusiasm do not appear as major predictors, while emotional closeness and anthropomorphism form the foundation for attachment. These findings are consistent with contemporary literature showing that technologies that evoke interpersonal experiences have the potential to influence users' emotional well-being and the quality of their relationship with (2,7,9).

From both a theoretical and practical perspective, these findings emphasize the importance of balancing instrumental functions and socio-emotional characteristics in AIED design. Anthropomorphic features need to be implemented in a measured manner so as not to trigger excessive emotional closeness, especially among students with high usage intensity, while educational institutions need to integrate emotional literacy and an understanding of technological limitations to keep user interactions adaptive and psychologically safe.

4. CONCLUSION

This study shows that the formation of students' emotional attachment to Artificial Intelligence in Education (AIED) is not determined by cognitive factors such as commitment to continued use or enthusiasm for technology, which have been proven to have no significant effect, but rather by emotional closeness and perceptions of anthropomorphism, which have the strongest influence, indicating that students perceive AI as an entity that is capable of warm, adaptive, and human-like. Conceptually, this study expands the understanding of human interaction with AI by emphasizing the role of emotional experiences and social perceptions in building attachment, while practically, these findings emphasize the importance of developing humanistic, empathetic, and responsive AIED systems to support students' emotional well-being and learning effectiveness.

Although these findings provide a strong picture of the patterns of students' emotional attachment to AIED, this study still has a number of limitations. These limitations include a sample that is limited to one region, meaning that generalizations must be made with caution, as well as a survey approach that limits understanding of the situational emotional dynamics during interactions with AI. The variables tested also did not include psychological factors or AI design characteristics that could enrich the understanding of emotional dependence. Further research is recommended to involve a more diverse sample and a mixed-method approach.

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