Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

A Study on the Formation Mechanism and Psychological Structure of AI Emotional Dependence among Vocational High School Students

Kai-Chao Yao
National Changhua University of Education
Sumei Chiang
67848124su@gmail.com

National Changhua University of Education
Fang-Chen Yen
Student, National Chung Hsing Senior High School
Wun-Jin Lin
Chang Gung University

Research Article

Keywords: Emotional dependency, Interactive learning, AI literacy Education, vocational high school, PLS

Posted Date: April 30th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9155865/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

A Study on the Formation Mechanism and Psychological Structure of AI Emotional Dependence among Vocational High School Students

Kai-Chao Yao [1], Sumei Chiang[2*] , Fang-Chen Yen[3], Wun-Jin Lin[4]

[1.] Professor, Department of Electrical and Mechanical Technology, National Changhua University of Education, Taiwan.

[2*.] *PhD* Candidate, Department of Electrical and Mechanical Technology, National Changhua University of Education, Taiwan.

[3] Student, National Chung Hsing Senior High School, Taiwan.

[4]. Student, School of Medicine, Chang Gung University, Taiwan.

*Corresponding author(s). E-mail(s): 67848124su@gmail.com; Contributing authors: kcyao@cc.ncue.edu.tw; fangcheny2@gmail.com; wunjin1018@gmail.com; These authors contributed equally to this work.

ABSTRACT

This study investigates emotional dependency on generative artificial intelligence among vocational high school (VHS) students. In alignment with Taiwan's 108 Curriculum Guidelines, an interactive "Health and Nursing" module addressing AI reliance was implemented. The sample comprised 1000 students from five VHSs in central Taiwan (October–December 2025). Data were collected through questionnaires and classroom feedback to assess AI interaction frequency, emotional projection, and perceived effects on relationships and psychological needs. Analyses were conducted using SPSS 22.0 and SmartPLS 4. Results indicate that some students developed moderate to high emotional attachment to AI, particularly for support and stress relief, accompanied by blurred ethical boundaries. This study finds that VHS students' AI dependence is not as severe as commonly assumed. The study conceptualizes AI emotional dependence as a low-intensity, cognitively mediated, developmentally emergent psychological alignment.

KEYWORDS: Emotional dependency, Interactive learning, AI literacy Education, vocational high school, PLS

1. Introduction

1.1. Research Background and Motivation

Generative artificial intelligence, exemplified by ChatGPT from OpenAI, has rapidly entered education and adolescent life. Conversational AI combines semantic understanding and real-time responses with anthropomorphic tone and situational simulation to create interactive dialogue experiences (Giannakos et al., 2025； Chang et al., 2026). For VHS students, AI appears to be evolving from an information tool into a learning aid and a medium for emotional communication, raising key academic questions. While past studies have emphasized learning outcomes or ethics, empirical practice indicates that student–AI interaction extends beyond instrumental rationality to encompass emotion regulation and psychological support (Vieriu &

Petrea, 2025).

Researchers have examined AI acceptance using the Technology Acceptance Model (TAM) and social presence theory, extending these frameworks to include emotional attachment and dependency-behavior intentions (Davis, 1989). Within TAM, "Perceived Usefulness" (PU) and "Perceived Ease of Use" (PE) are key factors influencing VHS students' continued use of AI. When students find AI effective for homework, instant answers, and learning efficiency, usage increases. Likewise, intuitive interfaces, simple operation, and smooth responses reduce cognitive load and strengthen willingness to continue (Gerling et al., 2026). At the psychological level, these interactions generate "Perceived Social Presence" (PSP).

When AI simulates being "understood" and "listened to" through an empathetic tone and contextual memory, students may feel a connection that resembles human interaction. This anthropomorphic experience fosters a "Need for Emotional Support" (NES), particularly among adolescents who experience rejection, stress, or difficulty expressing themselves in real-life interactions. In such cases, AI provides a low-risk, non-judgmental outlet (Nayyar & Maqsood, 2026). Consequently, "Perceived Responsiveness" (PR) emerges as immediate and coherent replies create an impression of stable companionship, enhancing trust and dependence. Together, these factors shape "Emotional Dependence Behavioral Intention" (EDBI), meaning students may increasingly confide in or seek support from AI during stressful or lonely situations (Nguyen & Nguyen, 2026).

This study develops the AI Emotional Dependence Technology Acceptance Model (AEDTAM) by integrating six latent variables: perceived usefulness (PU), perceived ease of use (PE), perceived social presence (PSP), emotional support needs (ESN), perceived responsiveness (PR), and emotionally dependent behavioral intention (EDBI). It examines whether Taiwanese VHS students' AI usage shifts from functional acceptance to emotional attachment, exploring its mechanism and psychological structure. The findings aim to clarify AI's role in adolescents' lives and provide a theoretical foundation for educational counseling and digital ethics norms.

1.2. Research Purposes

1. To examine how VHS students' perceived usefulness (PU) and perceived ease of use (PE) influence AI usage behavior.
2. To analyze perceived social presence (PSP) and perceived responsiveness (PR) during AI interaction.
3. To assess whether emotional support needs (ESN) affect PSP and PR.
4. To explore the relationship among PU, PE, PSP, and PR in shaping emotionally dependent behavioral intention (EDBI).
5. To construct and validate a structural model (AEDTAM) clarifying mechanisms of emotional projection and attachment to AI.

2. Literature Review

This study integrates the TAM, Social Surrogacy Theory, Social Presence Theory, Parasocial Interaction Theory, Loneliness Theory, and Attachment Theory with adolescent psychological development to construct the AI Emotional Dependence Technology Acceptance Model (AEDTAM). The framework includes six latent variables—PU, PE, PSP, ESN, PR, and EDBI—to examine VHS students' psychological mechanisms and behavioral tendencies in their use of AI.

2.1 Applications of AI in Psychological Perspectives.

Generative AI is increasingly shaping education and mental health (Giannakos et al., 2025; Vieriu & Petrea, 2025). Studies show that Chatbots provide low-risk emotional support through empathetic language, immediate responses, and non-judgmental interaction. For adolescents, AI functions not only as an academic aid but also as an outlet for emotional regulation and psychological comfort. This dual role underscores the need to explore attachment formation mechanisms in educational and counseling contexts (Nayyar & Maqsood, 2026).

With the rapid advancement of AI technologies and their growing role as essential learning tools for younger generations, the significance of "Social Substitution Theory" (Derrick et al., 2009; Mehta et al.,2023) and "Parasocial Interaction Theory" (Horton & Wohl, 1956) has become increasingly prominent. In educational contexts, the interaction between learners and teachers is gradually shifting toward human–machine interaction, giving rise to new forms of social engagement that extend beyond traditional interpersonal dynamics. Meanwhile, "Loneliness Theory" has been shown to influence the frequency of student–teacher interaction and has even become a key reason why students increasingly withdraw from communicating with their instructors (Cacioppo et al., 2015; Morin, 2020).

2.1.1 Perceived Social Presence (PSP).

The theory of social presence (Short et al., 1976) suggests that users are more likely to form emotional connections when they perceive a "real presence" or "social response" in digital interactions. Through empathic language, contextual memory, and sustained dialogue, AI enables students to feel understood and listened to. Studies indicate that some VHS students even regard AI as an interactive partner with emotional responses, showing that it has moved beyond simple information exchange to approximate interpersonal communication (Suriá-Martínez et al., 2025; Chan, 2025).

2.1.2 Emotional Support Need (ESN).

Attachment theory (Bowlby, 1969) posits that individuals seek security in stressful or lonely situations. Adolescents, facing self-identity struggles, academic pressure, and interpersonal conflicts, have heightened needs for emotional support. When real-life interactions risk rejection or neglect, the AI Chatbot provides unconditional listening and non-judgmental responses as

alternative outlets. Studies show that VHS students confide in AI when distressed, suggesting emotional support needs directly drive usage and indirectly strengthen dependence by enhancing social presence and perceived responsiveness (Shen et al., 2024).

2.1.3 Perceived Responsiveness (PR).

Interaction theory (Vygotsky, 1978) suggests that immediate and coherent responses enhance immersion and trust. AI's rapid replies and semantic coherence create an impression of "stable companionship" for VHS students. Research shows that quick, appropriate responses increase trust and satisfaction, thereby strengthening emotional comfort (Volpato et al., 2025). This study infers that perceived responsiveness further influences emotional dependence by enhancing social presence.

2.1.4. Emotional Dependency Behavioral Intention (EDBI).

Attachment theory (Herath, 2008) posits that attachment relationships reflect behavioral tendencies to seek support in stressful or lonely situations. Adolescents may gradually form such relationships after repeatedly receiving stable support and positive feedback from AI. Although most students still view real-person interaction as irreplaceable, AI's companionship shows potential influence on emotional attachment.

2.2 Evolution of the TAM and the Addition of Latent Variables.

A wide range of psychological theories explain why young people adopt AI as a learning tool, but contemporary research most often applies the Technology Acceptance Model (TAM) to organize these constructs (Davis, 1989). TAM highlights four attitudinal variables: perceived usefulness (PU), perceived ease of use (PE), attitude to use (ATU), and behavioral intention (BI).

PU and PE are the core determinants. PU refers to the degree to which users believe a system enhances learning performance (Chiang et al., 2024). The rapid spread of AI in education demonstrates its value in homework support, knowledge expansion, and problem-solving. When students perceive that AI improves efficiency, deepens understanding, and provides diverse solutions, PU increases and encourages continued use (Yang et al., 2025). PE concerns the effort required to operate a system. AI's natural language interface reduces technical barriers and cognitive load, and research shows that ease of use directly increases usage intention while indirectly enhancing PU (Yao & Chiang, 2025). For VHS students, intuitive interaction and smooth responses strengthen confidence and may gradually foster dependency. Over the past three decades, TAM has been widely applied to predict ATU and BI toward high-tech products.

With the rise of generative AI, TAM has expanded to domains such as education, mental health, and human–computer interaction, incorporating social and emotional dimensions to better explain user behavior (Wang et al., 2025). Following this trend, the present study integrates TAM with Social Surrogacy Theory, Social Presence Theory, Parasocial Interaction Theory, Loneliness

Theory, and Attachment Theory to construct the AEDTAM model. This model includes six latent variables (PU, PE, PSP, ESN, PR, and EDBI). Based on current literature, four causal paths are proposed: (1) PE → PU; (2) PU and PE → EDBI; (3) ESN → PSP and PR; and (4) PSP and PR → EDBI. The actual situation in VHS contexts, however, requires empirical verification.

3. Methodology

This study applied quantitative methods using SPSS 22.0 and Smart PLS 4 for statistical analysis. PLS, a structural equation modeling technique, is particularly effective for causal analysis among latent variables. It outperforms general linear models and has been cited in over 2500 academic journals, earning recognition from experts (Chang, 2021).

3.1 Research Sample

This study recruited 1000 students from five VHSs in central Taiwan to participate in an “AI Emotional Dependence Survey” course within the Health and Nursing curriculum (October–December 2025). Among the sample, male students accounted for 56% and female students for 44%. Parental representativeness was considered in school selection. Each participant completed a 60-minute teaching experiment. Informed consent was obtained from teachers and guardians, and the study was approved by the academic ethics committee of the first author’s university.

3.2 Curriculum Design

This study constructed and designed an interactive course on "AI Emotional Dependence Survey" within the "Health and Nursing" curriculum, based on the Taiwan 108 Curriculum Guidelines. The course content consists of "situational triggering," "interactive experiences," "discussion and survey," "ethical reflection," and "conclusion report" related to AI emotional dependence. The course flow and classroom interaction scenarios are shown in Figures 1 and 2.

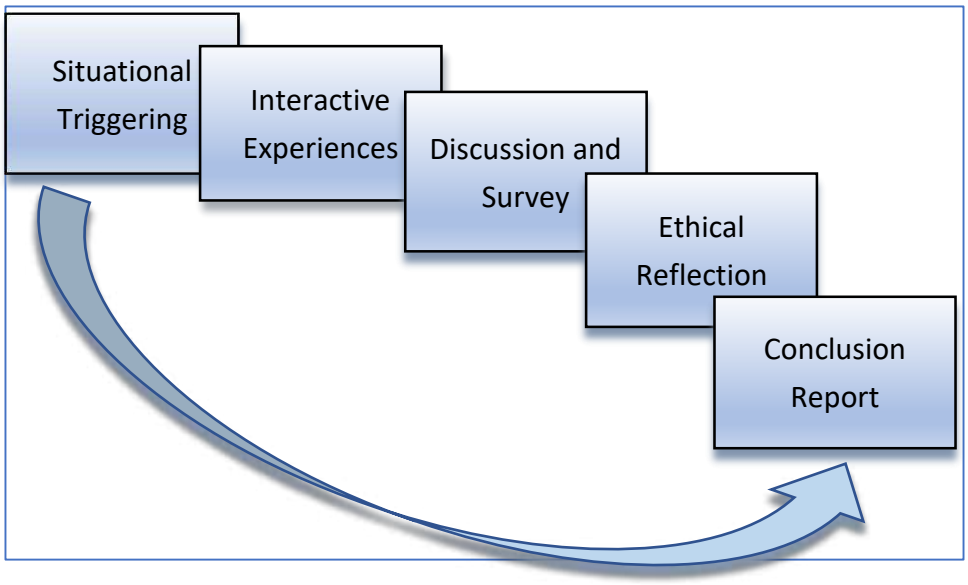


Fig. 1. Flowchart of the Interactive Course "AI Emotional Dependence Survey" in "Health and Nursing". Source: this study.



Fig. 2. Classroom Interaction Situation. Source: this study

3.3 Research Hypotheses

To achieve the research objectives, this study implemented an interactive “AI Emotional Dependence Survey” course within the Health and Nursing curriculum of a vocational high school (VHS). Drawing on prior literature, we integrated the TAM, Social Presence Theory, and Attachment Theory with adolescent psychological development to construct the AEDTAM. This model centers on six latent variables: Perceived Usefulness (PU), Perceived Ease of Use (PE), Perceived Social Presence (PSP), Emotional Support Needs (ESN), Perceived Responsiveness (PR), and Emotionally Dependent Behavioral Intention (EDBI). Following the course experiment, we validated the structural relationships among these latent variables to clarify the mechanisms underlying VHS students’ emotional projection and attachment tendencies toward AI. The proposed AEDTAM framework is illustrated in Figure 2.

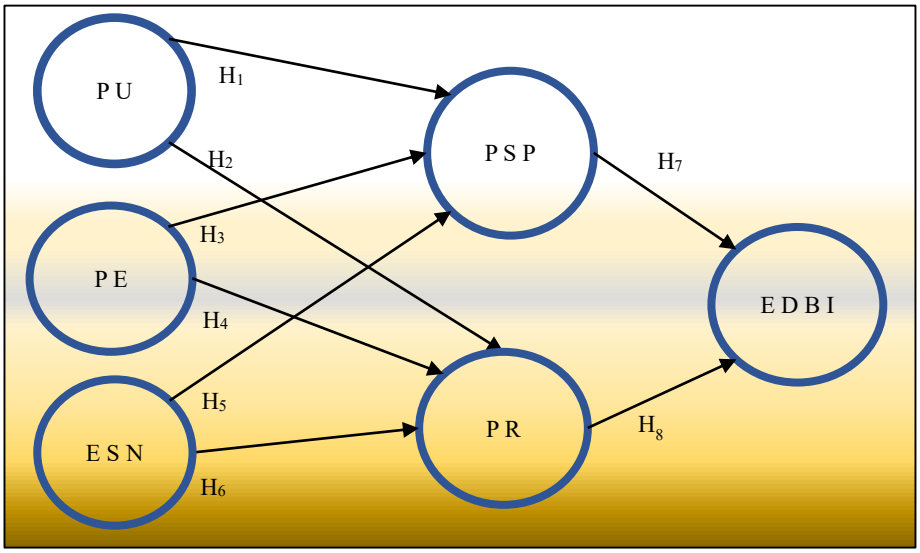


Fig. 2. The Hypothetical Theoretical Framework of AEDTAM.

Based on AEDTAM, this study applies an interactive teaching approach in the Health and Nursing course on "AI Emotional Dependence Survey" to validate the structural model of six latent variables. It clarifies the mechanisms of students' emotional projection and attachment to AI and proposes the following null hypotheses.

H_1: VHS students' perceived usefulness (PU) of AI for emotional dependence does not positively influence their perceived social presence (PSP).

H_2: PU of AI for emotional dependence does not positively influence perceived responsiveness (PR).

H_3: Perceived ease of use (PE) of AI for emotional dependence does not positively influence PSP.

H_4: PE of AI for emotional dependence does not positively influence perceived responsiveness (PR).

H_5: Emotional support needs (ESN) in AI use for emotional dependence do not positively influence perceived social presence (PSP).

H_6: ESN in AI use for emotional dependence do not positively influence perceived responsiveness (PR).

H_7: PSP in AI use for emotional dependence does not positively influence emotional dependency behavioral intention (EDBI).

H_8: PR in AI use for emotional dependence does not positively influence emotional dependency behavioral intention (EDBI).

3.4. Questionnaire Development Reliability and Validity

To achieve the research objectives, a questionnaire was designed to collect participant feedback on the interactive AI Emotional Dependence Survey course. The instrument was developed based on prior studies (Chiang, 2025; Yao et al., 2025). It contained two sections: (1) basic information such as gender and age, and (2) content covering six research dimensions—perceived usefulness (PU), perceived ease of use (PE), perceived social presence (PSP), emotional support needs (ESN), perceived responsiveness (PR), and emotionally dependent behavioral intentions (EDBI). Items were measured using a 7-point Likert scale ranging from "Strongly disagree" to "Strongly agree." A pilot test with 30 VHS students yielded a split-half reliability coefficient of 0.92. Three professors from domestic educational institutions reviewed and revised the questionnaire, confirming strong expert validity. The questionnaire contents are presented in Table 1.

Table 1. Questionnaire Contents of the AEDTAM Model Among VHS Students

Facets	Questionnaire items
	Definition: The degree to which users believe AI can improve their learning or life efficiency.

PU	U_1. AI can improve my learning efficiency. U_2.The information provided by the AI helped solve my problem. U_3. Using AI makes me more expressive in my coursework.
PE	Definition: The degree to which users find AI simple to operate and easy to use. E_1. I think AI is very easy to operate. E_2. I can easily understand the AI's responses.
ESN	Definition: The degree to which an individual desires to be understood and supported in emotional or stressful situations. N_1. When I'm in a bad mood, I hope someone will listen to me. N_2. When I feel stressed, I need emotional support. N_3. I sometimes feel lonely because of a lack of support.
PSP	Definition: The degree to which users perceive AI as having "understanding," "companionship," or "emotional presence" when interacting with it. P_1. I feel like the AI is having a real conversation with me. P_2. I felt understood when chatting with AI. P_3. AI makes me feel like I'm being listened to. P_4. I think AI's responses have emotional warmth.
PR	Definition: User's subjective evaluation of the speed, appropriateness, and continuity of AI response. R_1. AI can accurately understand my question. R_2. AI's suggestions usually meet my needs. R_3. AI's response reassured me.
EDBI	Definition: The tendency to prioritize AI as a source of emotional support in emotional distress or stressful situations. B_1. Without AI, I would feel like I've lost someone to listen to. B_2. I may continue to rely on AI for companionship. B_3. In the future, I will still regard AI as a source of emotional support.

4. Results and Discussion

4.1 AEDTAM Model Measurement.

Confirmatory factor analysis (CFA) was conducted to test the convergent and discriminant validity of the six latent variables in the AEDTAM model. Smart PLS 4 was employed, executing the bootstrap algorithm 5000 times, with statistical significance achieved at $p < .05$. CFA, average variance extracted (AVE), and other indicators were also applied to validate the hypothesized model and analyze path coefficients and causal relationships among latent variables.

4.2 Confirmatory Factor Analysis (CFA).

In the preliminary analysis stage, convergent validity was examined. Item loadings, average variance extracted (AVE), and composite reliability (CR) were analyzed to validate the hypothesized model. The model included five independent variables—perceived usefulness, perceived ease of use, perceived social presence, emotional support needs, and perceived responsiveness—and one dependent variable, emotionally dependent behavioral intention. Latent variables (perceived usefulness, perceived social presence, perceived responsiveness, and emotionally dependent behavioral intention) each had three indicators, while emotional support needs and perceived ease of use had four and two indicators, respectively.

Preliminary analysis of the AEDTAM model fit showed AVE values above 0.5 and factor loadings above 0.6, meeting recommended thresholds for latent structures. Hair Jr et al. (2009) noted that AVE must exceed 0.5 to be acceptable. Indicators with lower loadings were modified or removed to optimize the model. After adjustment, AVE values ranged from 0.61 to 0.81, confirming validity.

The overall CR values of latent variables ranged from 0.72 to 0.92, consistent with recommended standards (Hair et al., 2009). Thus, the hypothesized model was validated. Results are presented in Table 2.

Table 2. Confirmatory Factor Analysis.

Variables	Factor loadings	Cronbach α	CR	AVE
PE		0.71	0.72	0.78
E_1	0.87			
E_2	0.90			
PU		0.85	0.86	0.77
U_1	0.85			
U_2	0.88			
U_3	0.87			
ESN		0.73	0.73	0.65
N_1	0.84			
N_2	0.81			
N_3	0.78			
PSP		0.92	0.92	0.81
P_1	0.89			
P_2	0.90			
P_3	0.90			
P_4	0.90			
PR		0.73	0.73	0.66
R_1	0.86			
R_2	0.70			
R_3	0.87			
EDBI		0.70	0.83	0.61
B_1	0.75			
B_2	0.85			
B_3	0.75			

4.3 Correlation between Construction and Extraction of Average Variance Extracted (AVE).

In this study, all latent variables exhibited satisfactory discriminant validity (Fornell & Larcker, 1981). To determine whether the hypothetical theoretical model proposed in this study has good discriminant validity, the criterion is that the square root of the mean variance extracted (AVE) for each latent variable must be higher than the correlation coefficient between all other variables (Chang, 2021). Table 3 shows that this study validated that the square root of the AVE

for each latent variable in the theoretical model is higher than the correlation coefficient between all other variables and that latent variable. The test results are sufficient to demonstrate that the hypothetical theoretical model proposed in this study has good discriminant validity. The analysis results are shown in Table 3.

Table 3. Correlation Between Constructed and Extracted Average Variation.

Item	EDBI	ESN	PE	PR	PSP	PU
EDBI	0.79					
ESN	0.31	0.81				
PE	0.28	0.70	0.88			
PR	0.31	0.63	0.55	0.81		
PSP	0.32	0.37	0.34	0.41	0.90	
PU	0.24	0.49	0.41	0.82	0.39	0.88

4.4. Structural Equation Model Evaluation.

This study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using Smart PLS 4.0 to examine the hypothesized relationships in the AEDTAM model. Bootstrapping with 5000 resamples was conducted to evaluate the significance of path coefficients. Table 4 shows the path coefficients, t values, and β of the AEDTAM model, and the SEM PLS Algorithm is shown in Figure 3.

Table 4. Path Coefficients, *β and t*-value of the Hypothetical Theoretical Model.

	Relationship Between Variables	*β*	Standard Error	*t*-value	Decision Making
H_1	PU→PSP	0.27	0.04	7.08***	PASS
H_2	PU→PR	0.66	0.03	24.48***	PASS
H_3	PE→PSP	0.12	0.05	2.54**	PASS
H_4	PE→PR	0.13	0.03	4.89***	PASS
H_5	ESN→PSP	0.16	0.05	3.31**	PASS
H_6	ESN→PR	0.21	0.03	6.92***	PASS
H_7	PSP→EDBI	0.24	0.04	6.41***	PASS
H_8	PR→EDBI	0.21	0.04	5.74***	PASS

Note: ***p < .001; **p < .01

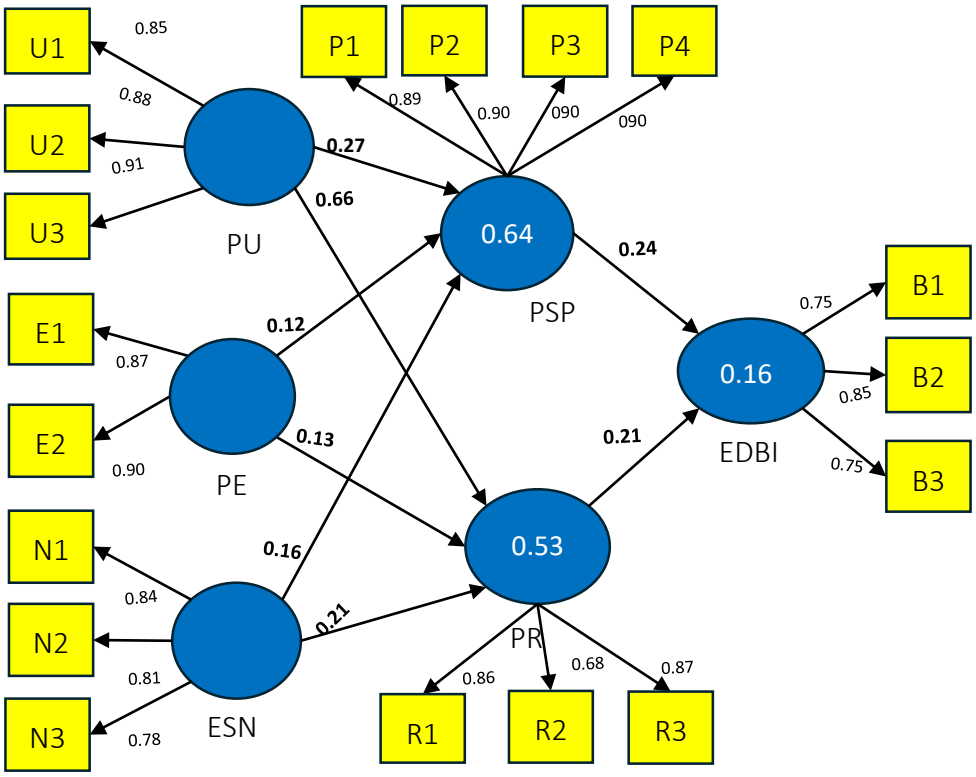


Fig. 3. The Hypothetic Theoretical Model (AEDTAM) Verification Results.

4.4.1 Path Coefficients and Statistical Significance.

As shown in Table 4 and Figure 2, all hypothesized structural paths were statistically significant at p< .01 or p< .001 levels. These results indicate that perceived usefulness, perceived ease of use, and emotional support needs significantly predict perceived social presence and perceived responsiveness. Furthermore, both perceived social presence (PSP) and perceived responsiveness (PR) significantly predict emotional dependency behavioral intention (EDBI). However, statistical significance does not necessarily imply substantive explanatory strength. Therefore, R^2 and effect sizes (f2) were further examined.

4.4.2 Coefficient of Determination (R^2).

The explanatory power of the endogenous constructs was evaluated using R^2 values: (1) PSP = 0.64; (2) PR = 0.53; (3) EDBI = 0.16. According to PLS-SEM guidelines (Hair et al., 2019), $R^2 \approx 0.75$ indicates substantial explanatory power, ≈ 0.50 moderate, and ≈ 0.25 weak. The PR value (R^2 = 0.53) reflects moderate explanatory strength, showing that perceived usefulness (PU), perceived ease of use (PE), and emotional support needs collectively provide strong predictive capability for perceived responsiveness.

In contrast, PSP (R^2 = 0.64) and EDBI (R^2 = 0.16) demonstrate strong and weak explanatory power, respectively. In this study's theoretical model, the latent variable PSP shows a moderate level of explanatory power for the overall model (R^2 = 0.64), whereas the latent variable EDBI

exhibits a weaker explanatory power ($R^2 = 0.16$). However, perceived social presence (PSP) exerts a significant direct effect on EDBI (emotional dependency behavioral intention) ($\beta = 0.24$, $p < .001$), and perceived responsiveness (PR) also has a significant direct effect on EDBI ($\beta = 0.21$, $p < .001$). Both effects reach statistically significant levels (**p < .01; ***p < .001). Therefore, all latent variables constructed within the hypothesized theoretical model serve as statistically valid explanatory variables.

4.4.3 Structural Interpretation.

The structural relationships reveal a statistically supported pathway: functional and emotional antecedents → perceptual responses (PSP, PR) → emotional dependency intention. Perceived usefulness shows the strongest predictive effect on perceived responsiveness ($\beta = 0.66$), indicating that responsiveness perception is primarily grounded in functional evaluation. This suggests that students' view of AI as accurate and helpful derives mainly from its instrumental value. Although both PSP and PR significantly predict EDBI, their coefficients are moderate, and explanatory power remains limited ($R^2 = 0.16$). Thus, emotional dependency intention should be interpreted as a statistically identifiable but modest outcome rather than a strongly determined behavioral construct. Low R^2 values are common in early-stage psychological intention research involving emerging technologies.

Overall, the model demonstrates significant structural relationships, with strong explanatory power for responsiveness perception but relatively weak explanatory power for emotional dependency intention, suggesting adolescents' emotional attachment to AI develops gradually and remains limited in magnitude.

4.4.4 Summary of Structural Findings.

The SEM analysis supports the following conclusions: functional cognition (PU, PE) and emotional support needs (ESN) significantly shape perceived responsiveness (PR) and social presence. Perceived responsiveness (PR) is strongly predicted by functional cognition (PU, PE). Emotional dependency behavioral intention (EDBI) is significantly but weakly explained by perceptual constructs. Overall, AEDTAM model demonstrates statistical validity, revealing significant yet low-intensity psychological conversion mechanisms, with emotional dependency formation among VHS students limited in explanatory strength within the present framework.

4.5. Verification of Mediation

To examine whether perceived social presence (PSP) and perceived responsiveness (PR) mediate the relationships between the three exogenous variables (PU, PE, ESN) and emotional dependency behavioral intention (EDBI), indirect effects were calculated using the bootstrapping procedure with 5000 resamples.

4.5.1 Indirect Effect of Perceived Usefulness (PU) on EDBI.

The total indirect effect of PU on EDBI was calculated as: (1) PU → PSP → EDBI (0.27 × 0.24) = 0.065; (2) PU → PR → EDBI (0.66 × 0.21) = 0.139. Total indirect effect = 0.203. Bootstrapping results indicate that the indirect effect is statistically significant ($p < .001$). Because no direct path from PU to EDBI was moderated, this pattern represents indirect-only mediation. The results suggest that perceived usefulness influences emotional dependency intention through perceptual mechanisms, particularly via perceived responsiveness. However, although the indirect coefficient (0.203) is the largest among the three antecedents, the ultimate explanatory power of EDBI remains weak ($R^2 = 0.16$), and the effect sizes of PSP → EDBI and PR → EDBI are very small ($f^2 < 0.02$). Therefore, the mediation should be interpreted as statistically supported but substantively modest.

4.5.2 Indirect Effect of Perceived Ease of Use (PE) on EDBI.

The total indirect effect of PE on EDBI was calculated as: (1) PE → PSP → EDBI (0.12 × 0.24) = 0.029; (2) PE → PR → EDBI (0.13 × 0.21) = 0.028.

Total indirect effect = 0.056. The indirect effect is statistically significant ($p < .01$). Compared with PU, the magnitude of the indirect effect is relatively small, indicating that ease of use functions primarily as a supportive condition rather than a central driver of emotional dependency intention.

4.5.3 Indirect Effect of Emotional Support Needs (ESN) on EDBI.

The total indirect effect of ESN on EDBI was calculated as:(1) ESN → PSP → EDBI (0.16 × 0.24) = 0.038; (2) ESN → PR → EDBI (0.21 × 0.21) = 0.044. Total indirect effect = 0.083. Bootstrapping confirmed statistical significance ($p < .01$). As with the previous constructs, the absence of a direct ESN → EDBI path indicates indirect-only mediation. Although emotional support needs significantly influence perceptual mechanisms (PSP and PR), their translation into emotional dependency intention is limited in magnitude. This suggests that emotional support needs may facilitate perceptual sensitivity toward AI interaction but do not independently generate strong dependency tendencies.

4.5.4 Summary of Mediation Findings.

The mediation analysis reveals three consistent indirect pathways: (1) functional cognition/emotional needs → perceptual responses (PSP, PR), and (2) functional cognition/emotional needs → emotional dependency intention. All mediation patterns represent indirect-only mediation, not full mediation. The magnitude of effects is modest, particularly given the weak explanatory power of EDBI ($R^2 = 0.16$). Perceived responsiveness contributes most to the indirect effect in the PU pathway, yet its ultimate impact on emotional dependency intention remains small. Thus, the mediation structure should be interpreted as a statistically identifiable

but low-intensity psychological transmission process rather than a strong dependency mechanism.

The research findings suggest that functional cognition and emotional needs shape perceptual interpretations of AI interaction, while emotional dependency intention emerges gradually, multifactorially, and with limited strength. In summary: (1) all three exogenous variables exhibit complete mediation for EDBI; (2) PR is the key mediator, highlighting accuracy and immediacy of AI responses as core mechanisms of attachment; (3) PU shows the largest total effect (0.203), exceeding ESN (0.083) and PE (0.056), confirming functional value as the foundation of emotional attachment. The AEDTAM model thus reveals a stable structural chain: functional cognition/emotional needs → response and presence perception → emotional attachment intention, strengthening its theoretical validity.

4.5.5 Assessment of the Contribution of Exogenous Variables to Endogenous Variables.

In addition to testing the significance of the pathway and the mediating effect, this study further calculated the Effect Size (f^2) to assess the substantial contribution of each exogenous variable to the endogenous variable. Based on the recommendations of Cohen (1988) and Hair et al. (2019):

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}} \quad (1)$$

The results indicate that the path PU → PR (f^2 = 1.270) demonstrates an exceptionally large effect size, far exceeding the threshold for a large effect. This finding confirms that perceived usefulness is the dominant substantive predictor of perceived responsiveness. In contrast, PE and ESN show only small effects on PR (f^2 = 0.079; 0.069).

For PSP, all three predictors (PU, PE, ESN) show small effect sizes (0.034–0.055), suggesting that social presence perception is jointly influenced but not strongly driven by any single antecedent. More importantly, although PSP and PR significantly predict EDBI, their effect sizes are very small (f^2 = 0.014; 0.008), both below the 0.02 threshold. This indicates that emotional dependency behavioral intention is weakly explained by these perceptual constructs, despite statistical significance.

Therefore, while the structural paths are significant, the formation of emotional dependency intention appears to be multifactorial and weak in effect, as shown in Table 5.

Table 5. Assessment of the Contribution of Exogenous Variables to Endogenous Variables.

Exogenous variables	Endogenous variables	f^2	Determination
PU	PSP	0.043	Small
PE	PSP	0.034	Small
ESN	PSP	0.055	Small

PU	PR	1.270	Large
PE	PR	0.079	Small
ESN	PR	0.069	Small
PSP	EDBI	0.014	Very Small
PR	EDBI	0.008	Very Small

4.6 Model Fit Assessment: SRMR

To further assess the overall fit of the AEDTAM model, this study adopted the Standardized Root Mean Square Residual (SRMR) recommended by PLS-SEM as the fit index. SRMR reflects the difference between the correlation matrix predicted by the theoretical model and the observed matrix; smaller values indicate a better fit. According to Henseler et al. (2014) and Hair et al. (2019): (1) SRMR < 0.08 → good fit, (2) SRMR < 0.10 → acceptable fit, (3) NFI > 0.90 → good fit, NFI > 0.80 → acceptable fit, and (4) d_ULS and d_G below the 95% bootstrap confidence limit → model rationality. The SRMR results of this study are presented in Table 6.

Table 6. Model Fit Analysis of the Hypothetical Theoretical Model.

Index	**Saturated Model**	**Estimated Model**
SRMR	0.08	0.08
d_ULS	1.16	1.21
d_G	0.47	0.47
Chi-Square	2674.95	2690.68
NFI	0.8	0.8

The SRMR of the AEDTAM structural model in this study is 0.08, indicating: (1) moderate residuals between predicted latent correlations and actual data, (2) good overall fit between the theoretical framework and observed data, and (3) no obvious misspecification. Therefore, the AEDTAM model demonstrates strong overall validity. The SRMR results further confirm that the model is significant not only in local paths but also interpretable and predictive at the structural level. In short, the AEDTAM model is supported in terms of statistical significance, effect size, and overall fit.

4.7 Harman's Single-Factor Test.

To further ensure the robustness of the AEDTAM model, Harman's single-factor test was conducted to assess potential common method bias (CMB). All measurement items from the six latent constructs (PU, PE, PSP, ESN, PR, EDBI) were subjected to an unrotated exploratory factor analysis. Results showed that the first factor accounted for 28.7% of the total variance, which is well below the critical threshold of 50% (Podsakoff et al., 2024). This indicates that no single factor dominated the variance structure and that common method bias was not a serious concern in this study.

Combined with the confirmatory factor analysis (CFA) and discriminant validity checks, these findings reinforce the distinctiveness of the latent constructs and enhance confidence in the structural relationships identified. Thus, the validity of the AEDTAM model is supported not only by convergent and discriminant validity but also by the absence of significant method bias.

4.8 Discussion

Although all structural paths were statistically significant, the explanatory power for emotional dependency behavioral intention ($R^2 = 0.16$) was relatively weak. Rather than treating this as a limitation alone, the findings provide important theoretical insights into the early-stage psychological structure of AI-related emotional orientation among adolescents.

4.8.1 Emotional Dependency as a Low-Intensity Construct.

One key finding of this study is that emotional dependency intention toward AI is statistically identifiable but modest. Although perceived social presence and perceived responsiveness significantly predict EDBI, their effect sizes are very small ($f^2 < 0.02$). This suggests adolescents' emotional dependency on generative AI is not a dominant or strongly structured tendency.

The result challenges deterministic claims that AI rapidly replaces human attachment figures. Instead, emotional orientation toward AI among high school students appears subtle, situational, and weakly consolidated. Emotional dependency should thus be interpreted as an emerging psychological inclination rather than a stable attachment. Accordingly, AEDTAM reflects a low-intensity affective alignment process that may precede deeper relational shifts.

4.8.2 Functional Trust as the Cognitive Foundation.

Perceived usefulness demonstrated a strong effect on perceived responsiveness ($\beta = 0.66$; $f^2 = 1.270$), indicating that adolescents' perception of AI responsiveness is fundamentally grounded in functional evaluation. Emotional interpretation does not emerge independently of instrumental trust; students first assess AI's utility and problem-solving effectiveness, then perceive responsiveness and presence.

Thus, affective interpretation appears cognitively scaffolded rather than emotionally driven. However, the strong explanatory power of perceived responsiveness (PR, $R^2 = 0.53$) does not proportionally extend to emotional dependency behavioral intention (EDBI, $R^2 = 0.16$). This asymmetry suggests responsiveness is central to perceptual processing but limited in behavioral internalization. Emotional dependency behavioral intention (EDBI) remains weakly structured despite strong responsiveness perception, highlighting that adolescents may cognitively trust AI without fully integrating it into their emotional support hierarchy.

4.8.3 Revisiting Attachment Theory in Human–AI Contexts.

Traditional attachment theory (Bowlby, 1969) defines attachment as a stable emotional bond

formed under security-seeking conditions. However, findings show that emotional support needs (ESN) influence emotional dependency behavioral intention (EDBI) only indirectly through perceptual constructs (PSP, PR), with weak behavioral tendencies. This suggests AI is not automatically positioned as a primary attachment figure, even when emotional support needs are high. Instead, AI functions as a supplementary coping resource under situational conditions.

Attachment toward AI in adolescence may thus be context-dependent, cognitively mediated, and low in behavioral consolidation. This modifies attachment theory in human–computer interaction by highlighting that technological attachment requires reinforcement and broader psychosocial alignment before achieving stronger structural status.

4.8.4 Social Presence Versus Responsiveness.

Both perceived social presence (PSP) and perceived responsiveness (PR) significantly predicted EDBI, though effect sizes were small. PR was more strongly explained by antecedent variables than PSP, suggesting that "being effectively responded to" is more psychologically salient than anthropomorphic warmth in generative AI interaction. Yet, even this salient perceptual experience does not automatically produce dependency.

Emotional alignment with AI may rely more on functional stability than anthropomorphism, but translation into attachment-like behavioral intention (EDBI) remains gradual and weak. This finding refines social presence theory, showing that presence perception alone is insufficient without broader psychosocial reinforcement.

4.8.5 A Developmental Interpretation.

Given the low R^2 of emotional dependency intention, AEDTAM is interpreted as an early-stage developmental configuration rather than a mature dependency structure. Adolescents: (1) recognize AI's functional value, (2) perceive responsiveness and presence, and (3) show limited but statistically detectable emotional orientation. However, EDBI is neither dominant nor strongly explained within the current model.

AI-related emotional dependency among VHS students may represent a transitional psychological state, a low-risk exploratory orientation, or a situational coping mechanism. This aligns with developmental theories emphasizing identity experimentation during adolescence rather than stable relational replacement.

4.8.6 Theoretical Contributions.

This study offers three theoretical contributions:

(A) AI attachment is reframed as a low-intensity, cognitively mediated, and context-dependent form of psychological alignment. Rather than supporting alarmist narratives about technological dependency, the AEDTAM framework positions adolescent AI attachment as emergent rather than entrenched, with weak effect sizes indicating that emotional reliance has not yet developed

into a stable bond structure.

(B) Emotional dependency toward AI is statistically observable but modest. In this study, emotional dependency is operationalized at the behavioral-intention level rather than as a full attachment system. Accordingly, the findings should not be interpreted as evidence of deep or enduring relational bonding with AI.

(C) Functional cognition serves as the primary scaffold for responsiveness perception. Adolescents' interpretations of AI responsiveness are shaped more by cognitive appraisal than by affective immersion, underscoring the central role of functional evaluation in early-stage AI relational processes.

5. Conclusions, Implications, Limitations, and Future Works.

5.1 Conclusions

This study integrates the Social Surrogacy Theory, Social Presence Theory, Parasocial Interaction Theory, Loneliness Theory, and Attachment Theory. Building on Davis' (1989) TAM, we constructed the AI Emotional Dependence Technology Acceptance Model (AEDTAM) and examined VHS students' emotional attachment to generative AI. PLS-SEM analysis yielded four conclusions as follows:

5.1.1. Emotional attachment is weak but significant.

This study finds that VHS students' AI dependence is not as severe as commonly assumed. The results show that perceived usefulness strongly shapes responsiveness perception. However, the effects of responsiveness and social presence on emotional dependency intention are small. Adolescents' attachment to AI appears gradual, situational, and limited rather than dominant.

5.1.2. Response quality is central.

Immediacy, accuracy, and appropriateness of AI responses are critical conditions for triggering attachment.

5.1.3. Emotional support needs act indirectly.

Findings revise the assumption that emotional deprivation directly produces attachment, showing instead that attachment emerges through interaction processes.

5.1.4. Attachment remains multifactorial.

Emotional attachment is also influenced by factors not included in the model, such as personality traits, loneliness, family support, and peer relationships.

Together, these results highlight AEDTAM's theoretical validity while emphasizing that adolescent attachment to AI is modest, context-dependent, and shaped by multiple psychological and social variables.

5.2 Implications for Counseling, AI Ethics, and Adolescent Mental Health.

The findings yield three implications. First, for counseling, emotional dependency on AI should be viewed not as a binary disorder but as a situational coping pattern shaped by perception and

interaction. Counselors can use students' emotional support needs (ESN) AI literacy to identify at-risk individuals and embed AI literacy into therapeutic programs. Second, for AI ethics, the central role of functional trust (perceived usefulness) in fostering attachment shows that design choices—response quality, immediacy, and empathic tone—can unintentionally cultivate adolescent dependency, requiring transparent standards and age-appropriate safeguards. Third, although current dependency levels among VHS students are modest, vulnerabilities linked to loneliness, low family support, and unmet peer needs suggest the need for monitoring and integrating digital emotional wellness into school mental-health frameworks.

5.3 Limitations and Future Works.

Although the AEDTAM model was validated using survey data from VHS students, the causal relationships among latent variables require longitudinal verification. Because this study collected data at a single time point, the analysis relied on a cross-sectional design, which allows inference of structural relationships rather than long-term developmental processes. All variables were measured through self-reports, which may raise concerns about social desirability bias and common method variance. Future researchers are encouraged to conduct longitudinal studies to further examine the causal pathways among the AEDTAM model's latent variables.

Declarations

Funding: The authors appreciate the financial support from the National Science Council, Taiwan, under the Grant NSTC 112-2410-H-018-030-MY3.

Conflicts of Interest: The authors declare no conflicts of interest.

Ethics approval and consent to participate: Before conducting the experiments, this research project was submitted to and approved by the Academic Ethics Review Committee of the first author's affiliated university, National Changhua University of Education. We obtained informed consent from all participants involved in the study. The authors informed the participants before the experiment about the voluntary nature of their participation and the confidentiality of the collected information.

Data Availability: The data supporting this study's findings are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Author Contribution: Conceptualization, S.C. and F-C.Y.; data curation, S.C., F-C.Y., and W-J. L.; investigation, S.C.; methodology, S.C. and K.-C.Y.; project administration, K.-C.Y.; software, S.C.; validation, S.C.; writing—original draft, S.C.; writing—review and editing, K.-C.Y. All authors have read and agreed to the published version of the manuscript.

References

Bowlby, J (1969). *Attachment and loss: Vol. 1. Attachment*. Basic Books.

Cacioppo, JT, Cacioppo, S, & Boomsma, DI (2015). Evolutionary mechanisms for loneliness. *Cognition and Emotion, 28*(1): 3–21. https://doi.org/10.1080/02699931.2013.837379.

Chan, CKY (2025). AI as the therapist: Student insights on the challenges of using generative AI for school mental health frameworks. *Behavioral Sciences, 15*(3): 287. https://doi.org/10.3390/bs15030287.

Chang, SH (2021). *Structural equation modeling by partial least squares method (PLS-SEM): Application of Smart PLS*. Wunan Books. Taiwan.

Chang, SH, Chang, RF, & Chang, BY (2026). *An introduction to the fundamentals of artificial intelligence.* Wunan Books. Taiwan.

Chiang, S, Chang, SH, Yao, KC, & Kuo, MC (2025). Vocational high school weave hair learning in virtual reality: An application of extended technology acceptance model with flow theory. *Interactive Learning Environments,* 1–16. Advance online publication. https://doi.org/10.1080/10494820.2025.2535675

Cohen, J (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Davis, FD (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3): 319–340. https://doi.org/10.2307/249008.

Derrick, JL, Gabriel, S, & Hugenberg, K (2009). Social surrogacy: How favored television programs provide the experience of belonging. *Journal of Experimental Social Psychology, 45*(2): 352–362. https://doi.org/10.1016/j.jesp.2008.12.003.

Fornell, C, & Larcker, DF (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1): 39–50. https://doi.org/10.1177/002224378101800104.

Gerling, C, Teubner, T, & Braesemann, F (2026). Who uses general-purpose AI? A typology of ChatGPT early adopters. *Electronic Markets, 36*(1): 15. https://doi.org/10.1007/s12525-025-00853-0.

Giannakos, M, Azevedo, R, Brusilovsky, P, Cukurova, M, Dimitriadis, Y, Hernandez-Leo, D, et al (2025). The promise and challenges of generative AI in education. *Behaviour & Information Technology, 44*(11): 2518–2544. https://doi.org/10.1080/0144929X.2024.2394886.

Hair, JF Jr, Black, WC, Babin, BJ, & Anderson, RE (2009). *Multivariate data analysis* (7th ed.). Prentice Hall.

Herath, D (2008). Development discourse of the globalists and dependency theorists: Do the globalisation theorists rephrase and reword the central

concepts of the dependency school? *Third World Quarterly, 29*(4): 819–834. https://doi.org/10.1080/01436590802052961.

Horton, D, & Wohl, RR (1956). Mass communication and para-social interaction: Observations on intimacy at a distance. *Psychiatry, 19*(3): 215–229.

Mehta, H, & Bapu, VKG (2023). Parasocial interactions, intolerance of uncertainty and loneliness. *The International Journal of Indian Psychology, 11(*2). https://doi.org/10.25215/1102.158.

Morin, AH (2020). Teacher support and the social classroom environment as predictors of student loneliness. *Social Psychology of Education, 23*: 1687–1707.

Nayyar, A, & Maqsood, A (2026). From human bonds to artificial support: Perceived AI empathy, dependence on AI Chatbots, and social disconnection among emerging adults. *Qlantic Journal of Social Sciences and Humanities, 7*(1): 70–82. https://doi.org/10.55737/qjssh.vii-i.26463.

Nguyen, TDX, & Nguyen, KM (2026). Demystifying how emotional and cognitive resonance to AI-driven content consistency sparks customer engagement and impulse buying in short-video E-commerce. *Journal of Retailing and Consumer Services, 89:* 104312. https://doi.org/10.1016/j.jretconser.2025.104312.

Podsakoff, PM, Podsakoff, NP, Williams, LJ, Huang, C, & Yang, J (2024). Common method bias: It's bad, it's complex, it's widespread, and it's not easy to fix. *Annual Review of Organizational Psychology and Organizational Behavior, 11*(1): 17–61. https://doi.org/10.1146/annurev-orgpsych-110721-040030.

Shen, J, DiPaola, D, Ali, S, Sap, M, Park, HW, & Breazeal, C (2024). Empathy toward artificial intelligence versus human experiences and the role of transparency in mental health and social support Chatbot design: Comparative study. *JMIR Mental Health, 11:* e62679. https://doi.org/10.2196/62679

Short, J, Williams, E, & Christie, B (1976). *The social psychology of telecommunications*. John Wiley & Sons.

Suriá-Martínez, R, García-Castillo, F, López-Sánchez, C, & García del Castillo, JA (2026). Artificial intelligence and emotional support: A comparative study of university students with and without disabilities. *Healthcare, 14*(1): 75. https://doi.org/10.3390/healthcare14010075.

Vanhoffelen, G, Vandenbosch, L, & Schreurs, L (2025). Teens, tech, and talk: Adolescents' use of and emotional reactions to Snapchat's My AI Chatbot. *Behavioral Sciences, 15*(8): 1037. https://doi.org/10.3390/bs15081037.

Vieriu, AM, & Petrea, G (2025). The impact of artificial intelligence (AI) on students' academic development. *Education Sciences, 15*(3): 343. https://doi.org/10.3390/educsci15030343

Volpato, R, DeBruine, L, & Stumpf, S (2025). Trusting emotional support from generative artificial intelligence: A conceptual review. *Computers in Human Behavior: Artificial Humans, 5*: Article 100195. https://doi.org/10.1016/j.chbah.2025.100195.

Vygotsky, LS (1978). *Mind in society: The development of higher psychological processes.* Harvard University Press.

Wang, Y, Guan, X, Sun, Y, Wang, H, & Chen, D (2025). The cognitive acceptance of generative AI image tools based on TPB-TAM model and multi-theory integration. *Advanced Design Research, 3*(1): 38–54. https://doi.org/10.1016/j.ijadr.2025.08.001.

Yang, TC, Hsu, YC, & Wu, JY (2025). The effectiveness of ChatGPT in assisting high school students in programming learning: Evidence from a quasi-experimental research. *Interactive Learning Environments, 33*(6): 3726–3743. https://doi.org/10.1080/10494820.2025.2450659

Yao, KC, & Chiang, S (2025). Mathematical modeling and structural equation analysis of acceptance behavior intention to AI medical diagnosis systems. *Mathematics, 13*(15): 2390. https://doi.org/10.3390/math13152390.

Disclosure statement

The authors reported no potential conflict of interest.