

Exploring Relationships between Dialogue and Learners Achievement in Online English Language Courses at Al al-Bayt University

Mamon S. Alzboun ^{1,*}, Atef F. Al Mashakbh ¹, Rania A. Bataineh ², Hmoud M. Olaimat ¹, Fares A. Mohammad ³, AbdelKarim H. Makhadmeh ⁴, Karam K. Abu A'aqoulah ⁵, Rasha A. Enab ⁶, and Rehab Tharwat Abd El Ghani ⁷

¹ Department of Curriculum and Instruction, Faculty of Educational Sciences, Al al-Bayt University, Mafrqa, Jordan

² Language Center, Al al-Bayt University, Mafrqa, Jordan

³ Department of Arabic & Islamic Studies, Mohammed Jaber Al Ansari College for Teachers, University of Bahrain, Bahrain

⁴ Faculty of Physical Education, Yarmouk University, Irbid, Jordan

⁵ Department of Physical Education, school of Educational Sciences, Al al-Bayt University, Mafrqa, Jordan

⁶ Ministry of Education, Jordan

⁷ College of Arts, Imam Abdulrahman bin Faisal University, Saudi Arabia

Email: m.alzboon@aabu.edu.jo (M.S.A.); aal_masakabh@aabu.edu.jo (A.F.A.M.); raniasaad@aabu.edu.jo (R.A.B.);

hmoud68@aabu.edu.jo (H.M.O.); fmohammad@uob.edu.bh (F.A.M.); Makadmeh@yu.edu.jo (A.H.M.);

Kaboaqouleh@aabu.edu.jo (K.K.A.A.); M.alzboon@jo.edu.jo (R.A.E.); Rabdelgni@iau.edu.sa (R.T.A.E.G.)

*Corresponding author

Manuscript received December 31, 2025; revised January 31, 2026; accepted June 3, 2026; published October 26, 2026

Abstract—This study aims to explore the relationship between online dialogue and learning achievement, addressing a critical gap in educational research regarding the interpretation of dialogue into objective cognitive learning achievement. Unlike previous studies relying on subjective data, this research utilizes an objective proctored final examination to measure achievement across four hierarchical levels of Bloom's Taxonomy. Grounded in a synthesis of transactional distance theory and cognitive learning theory, the study involved 293 undergraduate students in online English courses at Al al-Bayt University. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), both dialogue and achievement were conceptualized as reflective second-order constructs. Findings empirically validate that online dialogue is a strong predictor of achievement (standardized coefficient (β) = 0.58, t-statistic (t) = 13.86, probability (p) < 0.001), accounting for 62% of the variance in student learning achievement. Finally, this research provides a conceptual framework for educators, demonstrating that dialogue serves as a cognitive qualifying condition for learning achievement. These insights suggest that strategic integration of interactive tools and peer-based tasks can effectively reduce psychological distance and enhance achievement by aligning dialogue mechanisms with specific cognitive domains.

Keywords—dialogue, learners' achievement, online learners' interactions

I. INTRODUCTION

Dialogue is defined by the interaction between a student, their peers, and their instructor, as well as with learning content [1]. Dialogue is a critical determinant of learning achievement [2]. According to Transactional Distance Theory (TDT), dialogue influences the psychological and instructional distance between participants, where the quality of dialogue directly influences student motivation and engagement [2]. Besides, integrating Cognitive Learning Theory (CLT) with Bloom's Taxonomy (BT) shows that high levels of dialogue enable the transition from basic memorizing facts to higher-order cognitive processes [3]. This integration motivates students to think critically, allowing them to analyze and evaluate information rather

than just repeating it [2].

Despite the theoretical importance of dialogue, a significant challenge remains in improving learning achievement within online environments. Many existing studies depend on self-perception data, while the challenge is about how dialogue translates into measurable cognitive learning achievement. This leaves a gap in objective evidence about how specific dimensions of dialogue (learner-content, learner-learner, and learner-instructor) influence learning achievement across diverse levels of Bloom's Taxonomy.

This study addresses this gap within the setting of Al al-Bayt University (AABU) in Jordan by modeling the relationship between online dialogue and learning achievement. AABU is a public university that is undergoing a significant pedagogical transition, adapting to a student-centered approach. At AABU, students who enrolled in the compulsory online English language courses (E099 and E101) face the challenge of adapting to a new learning management system. Through the proposed model, this research provides university administrators with essential data to refine the online learning environment.

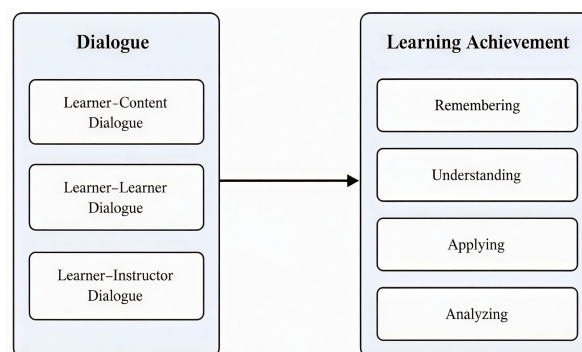


Fig. 1. Conceptual framework.

Fig. 1 presents the research model's conceptual framework to guide modeling the proposed relationship between learner dialogue and learning achievement. Firstly, the dialogue dimension consists of three components: Learner-Content

Dialogue (D-LC), Learner-Learner Dialogue (D-LL), and Learner-Instructor Dialogue (D-LI). Secondly, the learning achievement dimension includes four levels: Remembering (R), Understanding (Un), Applying (Ap), and Analyzing (An).

To guide model development, the research evaluates the following hypotheses:

H1: Learners' learning achievement is explained by four dimensions: Remembering (R), Understanding (Un), Application (Ap), and Analyzing (An).

H2: Learning dialogue explained by three dimensions: Learner-Content Dialogue (D-LC), Learner-Learner Dialogue (D-LL), and Learner-Instructor Dialogue (D-LI)

H3: Learners' dialogue influences their learning Achievement.

The present study is expected to offer several theoretical and methodological contributions. First, it provides a conceptual framework for understanding how interaction types foster cognitive learning outcomes in online English courses. Second, it provides institutions with a comprehensive analysis of how pedagogical shifts toward student-centered online learning influence the quality and function of dialogue.

II. LITERATURE REVIEW

A. Learning Achievement and Bloom's Taxonomy

Learning achievement is a measurement of "what is learned" [4]. It is the specific content a student learned throughout a predetermined period of a course. To assess this achievement accurately, educational objectives are often operationalized through Bloom's Taxonomy (BT). In 1956, Bloom and Engelhart established BT to assess students' academic achievement [5] and a classification system for learning objectives [6]. Within the cognitive domain, learning consists of six ordered levels: remembering, comprehending, applying, and analyzing. These levels range from the most basic to the most complicated [5, 6]. These levels of remembering, understanding, applying, and analyzing (within the scope of this study) range from basic recognition to complex cognitive processing. Research highlights that the categorization highlighted the usage of specific cognitive activities to completely occur in learning [7]. Every level builds upon the accomplishment of earlier levels [8].

The first three cognitive application levels are remembering, understanding, and application. At the level of remembering, the students must understand concepts, facts, techniques, and procedures as well as recognize a task based on their prior knowledge [6, 9], while at the understanding level, students must be able to describe previously learned content and recognize facts and principles. Thus, understanding the significance and then explaining the instructions for problem-solving [9]. However, at the application level, they must be able to apply learned material theories in new everyday situations [10]. The higher-order cognitive levels, which require the use of higher-order thinking skills, include analysis, synthesis, and evaluation. The analysis level requires students to recognize and find the material they have studied [7], while the synthesis level

requires students to think critically, understand added information, and make connections between it and what they have already learned [6, 7]. However, the level of assessment requires students to make implicit assumptions about the relevance of the material they have studied. Regardless of the established nature of BT, there is a need to explore how specific dialogue types in online environments assist these diverse cognitive domains.

B. The Dialogue Dimension in Online Learning

The dialogue dimension of online learning is crucial. It explains the constructive interactions that occur between students, instructors, and content in instructional environments [11, 12]. Based on Transactional Distance Theory (TDT), dialogue is a process where each party is a respectful, active contributor, building on the ideas of others to foster a better understanding of knowledge [13]. The impact of dialogue is well-documented: the study of 130 university students studied across 73 courses found that students' participation in classroom dialogue is positively related to their knowledge in the field and their understanding of cooperation [14], while Aziz *et al.* [15] and Comingking *et al.* [16] identified that instructor communication patterns as significant predictors of learning achievement and they classified specific dialogic actions that support learning in inquiry environments. Particularly, Labib [17] reported that the communication strategy contributed 57.76% to learning quality.

Online learning settings dialogue improves the learner's understanding [18]. TDT guides the plan of three types of dialogue: Learner-Content Dialogue (D-LC), Learner-Learner Dialogue (D-LL), and Learner-Instructor Dialogue (D-LI). Moore [19] showed D-LC as "the process of intellectually interacting with content that results in changes in the learner's understanding, the learner's perspective, or the cognitive structures of the learner's mind". D-LC is essential for the required changes in a learner's learning cognitive structures [18–20]. D-LL occurs through learning management systems, discussion boards, and social networks such as Facebook, Instagram, and WhatsApp, which expand these dialogues for better knowledge acquisition [20]. There is a strong correlation between student dialogues and their degree of satisfaction with online learning [21]. These social environments empower collaborative learning [20]. As well as providing a positive experience, which is essential to cognitive and social development [22]. According to the study of Halim *et al.* [23], students are more likely to approach their peers for advice and clarification than they are to ask their teachers. In other words, the social learning environments help students construct their learning goals effectively. D-LI is a crucial factor of online learning interaction [20]. It involves the teacher giving comments, motivating the student, and imparting knowledge. Additionally, this can interest the student in engaging with the teacher by responding to inquiries or exchanging ideas about the course assignments [24]. The instructor plays the role of facilitator of student learning.

C. Theoretical Framework

The two learning theories that form the basis of this research paradigm are Transactional Distance Theory (TDT)

and Cognitive Learning Theory (CLT). Both theories discuss how learning happens, but they emphasize different facets of the educational process.

TDT focuses on distance learning and the mental and communicative space between students and teachers [25]. The theory identifies three significant variables: first, dialogue, which mainly includes three forms: Learner-Content Dialogue (D-LC), Learner-Learner Dialogue (D-LL), and Learner-Instructor Dialogue (D-LI). The second variable refers to the structure of the course's layout and design. The third variable is learner autonomy, which refers to the level of independence a student exercises [13]. According to Moore [2], the theory posits that the greater the transactional distance, the more autonomy a learner requires.

CLT is concerned with human cognition, learning, and memory [26]. It highlights internal functions, including memory, problem-solving, information processing, and representation creation [23, 24]. According to CLT, learners actively construct new knowledge by drawing on their prior knowledge during the learning process [27]. On the relationship between CLT and TDT, Mayer [28] emphasized CLT's reliance on the mental processes involved, while Fan and Chen [29] clarified that TDT is more about the environment and context of learning. Dialogue improves engagement to encourage deeper thinking, and developing dialogue facilitates cognitive processing [3]. To reduce psychological distance, TDT emphasizes the need for dialogue [2]. Phillipson and Wegerif [3] clarify that CLT supports dialogue in the form of discussion boards and feedback, which improves cognitive engagement and knowledge production.

This research integrates TDT and CLT with BT to provide a comprehensive framework to explore the online dialogue learning achievement relationship. BT divides learning objectives into six hierarchical levels of cognitive complexity [30]. Interact with Bloom's Levels, dialogue aids in concept clarification and misunderstanding correction in lower-order thinking (remember, understand, apply) [1]. Instructor comments and content interactions enhance retention and understanding [31]. Suen and Hung [31] emphasized that regular engagement aids students in understanding and keeping material so they may use it in structured assignments. Also, peer talks and group projects promote deeper analysis and synthesis [1].

D. Synthesis of Gaps and Justification for the Current Study

A significant methodological and theoretical gap exists in current literature. First, there is no consensus on which dialogue types most effectively drive success; while some scholars prioritize D-LI and D-LC, others emphasize the importance of D-LL for clarifying learning goals [3, 31]. Second, many studies rely on perception-based instruments (e.g., satisfaction questionnaires) that lack a robust cognitive framework for measuring achievement. Furthermore, earlier research often treats dialogue as a scalar variable rather than exploring how diverse types of functions cognitively across hierarchical levels. For example, while D-LI is vital for retention and understanding, higher-order outcomes like analysis and creation require more intensive, interactive dialogue to bridge transactional distance. Moreover, the

current literature does not typically (i) assess D-LC, D-LL, and D-LI in relation to achievement in a Bloom taxonomy framework, (ii) validate reflective second-order factors for dialogue and achievement, or (iii) use a common, course-delivered assessment for measuring achievement sub-dimensions. This study addresses these limitations by conceptualizing dialogue and achievement as reflective second-order constructs.

III. METHODOLOGY

A. Method

This study employed quantitative research methods to explore the relationships between online learners' dialogue and learning achievement in online English language courses at AABU. The participants were AABU undergraduate students who enrolled in required English language courses, namely English Language 101, during the 2020–2021 second semester academic year. The population consisted of 992 students from thirty-five online sections. Ten instructors utilizing the Moodle Learning Management System taught these course sections. Two instructors with the same qualifications and experiences teach the randomly selected sample that consists of four sections with 293 learners, and an 89% return rate (261 returned). The study participants were composed of 57% females and 43% males from different majors in the university, extend over first year level and multiple majors across the university. Participant demographic characteristics are presented in Table A1 of Appendix A.

B. Research Instruments

This study utilizes two measuring tools: the dialogue questionnaire and the English 101 final exam learning achievement test.

1) Dialogue questionnaire

This research adopted the Mashakbh [32] dialogue questionnaire, a validated scale for the Jordanian context. The scale consists of 21 items that measure the latent construction of a student's online learning dialogue. The questionnaire employs a five-point Likert scale: 1 for major disagreement, 2 for somewhat-disagreements, 3 for neutralities, 4 for agreements, and 5 for strong agreements.

2) Achievement test development

Developing the final examination for the English 101 course according to a detailed plan, which a priori placed the test items into one of the four Bloom levels examined for the purposes of the current study, namely, Remembering, Understanding, Applying, and Analyzing. checking the alignment of the individual items with the relevant Bloom levels independently by two EFL subject-matter experts and one assessment specialist, with agreement on any areas of difference to ensure the cognitive validity of the individual subscales. Corresponding to Al al-Bayt University's assessment policy, transforming the raw scores into categorical proficiency levels (1 = poor, 2 = fair, 3 = good, 4 = very good, 5 = excellent) was conducted as a practical choice to align with AABU's established assessment policy. While providing actionable feedback for administrators. To ensure the robustness of the results, repeating the PLS-SEM

analysis with the use of percentage scores for the individual Bloom levels, with the results being substantively similar.

To measure the reliability of the PLS-SEM results, using Cronbach's alpha (α), Construct's Internal Consistency Reliability (ρ_A), and Composite Reliability (CR), all of which should exceed the threshold of 0.70. The Average Variance Extracted (AVE) for the individual dimensions of the model, which corresponds to the individual Bloom levels, should exceed 0.50, thus supporting the results for the validity of the model. The use of Classical Test Theory indices, namely, item difficulties and item discriminant validity are applicable only for the analysis of binary item responses, which is not the case for the current study.

C. Research Implementation Procedures

Administering learner dialogue scale and the final learning achievement test after students complete twelve weeks of the online course.

D. Modeling Approach and Diagnostics

This study conceptualizes dialogue and achievement as reflective second-order constructs (D-LC, D-LL, D-LI; and R, Un, Ap, An). The analytical process adopted a two-step procedure via SmartPLS 3: First, estimating the components and then estimating the higher-order constructs by Latent Variable (LV) scoring. The inclusion or exclusion of indicators was based on a loading criterion ≥ 0.70 . Removing Indicators with loadings less than 0.60 and were non-essential for improving Composite Reliability (CR) and Average Variance Extracted (AVE). To address potential Common Method Bias (CMB), the study employed an external measure for achievement. Furthermore, Harman's single factor test was used to assess CMB, which explains less than 50% of the variance, and a Variance Inflation Factor (VIF) less than 3.3.

E. Data Analysis

Performing Partial Least Square-Structural Equation Modeling (PLS-SEM) analysis using the Smart PLS 3.0 software to evaluate the research hypothesis allowed for the simultaneous evaluation of the theoretical structure and measurement model [33]. Besides, PLS-SEM was selected over CB-SEM due to its superior ability to manage complex, hierarchical models with reflective second-order constructs and its suitability for research focused on predicting key target outcomes like learning achievement and learning dialogue. Therefore, research hypotheses H1, H2, and H3, convergent and discriminant validity, and the predictive power of the model were evaluated. In other words, to see if the theoretically related measures are also related according to the analysis results. The study model's conceptual framework represented in Fig. 1, outlines the study's objectives and boundaries, specifically exploring how learner dialogue supports the realization of learning achievement. Therefore, the hypothesized Confirmatory Factor Analysis (CFA) models comprise of three main phases analysis:

(1) Phase one emphasizes examining the influence of exogenous variables on the development of endogenous variables and the unobserved dependent variables. In this context, the endogenous variables represent the observed indicators corresponding to each latent construct. This stage aims to determine whether the hypothesized

dimensions significantly shape learner achievement and dialogue.

(2) Phase two investigates the role of learner achievement in contributing to the implementation of the overall framework.

(3) Phase three evaluates the model's predictive power and discriminant validity.

This study establishes the acceptance criteria for the model based on PLS-SEM, including convergent validity, discriminant validity, and predictive power. First, in terms of convergent validity, according to Kline [34], Hair *et al.* [35], and Fornell and Larcker [36], the factor loading between indicators and their corresponding latent variables must be higher than 0.5. Additionally, all latent variables should have Cronbach's alpha (α) and Composite Reliability (CR) coefficients larger than 0.7, and the final Average Variance Extracted (AVE) values must be higher than 0.5. Second, according to Fornell and Larcker [36], to be considered the measures discriminant, all the values on the diagonals must be bigger than the corresponding row and column values, as per Fornell and item cross-loadings on different constructs. However, to meet the condition of comparing the correlations between constructs and the square roots of AVEs, each diagonal value must be higher than the corresponding row and column values, confirming the discriminant nature of the measures. In addition, the Heterotrait-Monotrait (HTMT) ratio between a particular pair of reflective structures should not be greater than 0.90 according to Henseler *et al.* [37]. Third, the structural model is evaluated based on the coefficient of determination R^2 , which represents the explained variance of endogenous constructs and reflects explanatory power per Cohen [38], which indicates that there are significant magnitudes of effect when $R = 0.50$, while 0.10 is the minimum acceptable threshold, and values between 0.1 and 0.5 represent medium effects. Furthermore, Cohen [38] demonstrates that for the F^2 effect size measure, a value of 0.02 indicates a small effect, 0.15 a medium effect, and 0.35 a large effect. For predictive relevance, Q^2 values are calculated using the blindfolding procedure. Q^2 value above 0 suggests that the model exhibits meaningful predictive capability [39]. To ensure robustness, collinearity among predictor constructs examining Variance Inflation Factors (VIF) values, which should remain below conservative threshold levels to suggest stable parameter estimates and no serious multicollinearity concerns [39]. Consistent with the predictive orientation of PLS-SEM model evaluation emphasizes explanatory power, predictive relevance, and robustness diagnostics rather than global model fit indices [38].

Assess the inner model and hypotheses, evaluate the proposed correlations between constructs, dialogue, and achievements evaluated using the PLS algorithm and Smart PLS 3.0. The significance of the loadings and path coefficients was evaluated using the bootstrapping approach (5000 resamples) [40]. Additionally, Henseler *et al.* [41] employed the blindfolding process to evaluate the predictive usefulness of the model. This study ran bootstrapping using methods built into Smart PLS 3.0. The researcher used 500 samples (resampling) to produce the T-values for the path coefficients, followed by the P-values.

IV. RESULT

A. Measurement Model Assessment

Evaluation was conducted to confirm the empirical rigor of the constructs within the structural framework. The measurement model was assessed for validity and reliability prior to hypothesis testing. The measurement model was evaluated via convergent and discriminant validation as presented below:

1) Convergent validity

There are three criteria for acceptable convergence validity: reliability measured using Cronbach's Alpha (α) and Construct's Internal Consistency Reliability (ρ_A), Composite Reliability (CR), and Average Variance Extracted (AVE). The recommended threshold of Cronbach's Alpha (α) and " ρ_A ", Composite Reliability (CR) is 0.70. as presented in Table 1 Cronbach's Alpha values (α), Construct's Internal Consistency Reliability (ρ_A), and Composite Reliability CR values were consistently above 0.70, α ranging from 0.87 to 0.93, (ρ_A) ranging from 0.77 to 0.92, while The AVE values were also within acceptable limits, ranging from 0.57 to 0.76, all surpassing 0.50. The recommended threshold of indicator and factors loading values were also within acceptable limits as presented in Tables 2 and 3.

Table 1. Criteria for convergent validity

Dimension	Cronbach's Alpha (α)	Consistency Reliability (ρ_A)	Composite Reliability (CR)
R	0.77	0.77	0.87
Un	0.84	0.85	0.91
Ap	0.77	0.77	0.87
An	0.81	0.82	0.89
D-LC	0.81	0.81	0.87
D-LL	0.85	0.86	0.90
D-LI	0.91	0.92	0.93

Table 2. Achievement and dialogue indicator loadings

Dimension	R	Un	Ap	An	D-LC	D-LI	D-LL
R_1	0.78						
R_2	0.86						
R_3	0.84						
Un_1		0.88					
Un_2		0.87					
Un_3		0.86					
Ap_1			0.83				
Ap_2			0.85				
Ap_3			0.81				
An_1				0.84			
An_2				0.88			
An_3				0.85			
D-LC_1					0.81		
D-LC_2					0.72		
D-LC_3					0.68		
D-LC_4					0.78		
D-LC_5					0.79		
D-LI_1						0.79	
D-LI_2						0.89	
D-LI_3						0.84	
D-LI_4						0.89	
D-LI_5						0.81	
D-LI_6						0.80	
D-LL_2							0.83
D-LL_3							0.80
D-LL_4							0.83
D-LL_5							0.83
D-LL_7							0.68

Note: R_1: remembering item number 1, D-LL_7: dialogue between learners' item number 7, etc.

Most of the items displayed strong loadings on their

intended constructs, with several exceeding 0.78. A small number was slightly lower, though still acceptable from a methodological standpoint, while those below the 0.60 threshold were removed to decide on the best-fit model. A few iterations were conducted, creating a revised model. Table A2 in Appendix A reported achievement test removed items for each dimension with their original item numbers. Also, Table A3 in Appendix A details the removed measurement items, loadings, and justifications during measurement model refinement.

Table 3. Significance of achievement and dialogue factor loadings

Achievement	Factor Loadings	Dialogue	Factor Loadings
R	0.61	D-LC	0.79
Un	0.80	D-LL	0.64
Ap	0.75	D-LI	0.82
An	0.70	-	-

Note: R: Remembering, D-LL: Dialogue between learners;' etc.

2) Discriminate validity

There are two criteria for acceptable discriminant validity: Fornell-Larcker Criterion and Heterotrait-Monotrait (HTMT) ratio. Based on the Fornell-Larcker standard, the square root of each construct's AVE was greater than its correlations with other constructs. In simpler terms, each construct shared more variance with its own indicators than with the indicators of any other construct, fulfilling the Fornell-Larcker requirement. As presented in Table 4, the AVE's square root (shown diagonally in bold) is higher than its association with the other constructs.

Table 4. Discriminant validity analysis: Fornell and Larcker standard

Dimension	R	Un	Ap	An	D-LC	D-LL	D-LI
R	0.83						
Un	0.36	0.87					
Ap	0.30	0.45	0.83				
An	0.22	0.39	0.42	0.85			
D-LC	0.36	0.42	0.28	0.23	0.76		
D-LL	0.19	0.48	0.29	0.26	0.38	0.80	
D-LI	0.30	0.41	0.25	0.28	0.46	0.22	0.84

Note: R: Remembering, D-LL: Dialogue between learners;' etc.

Discriminant validity was further confirmed using the HTMT ratio. The HTMT values stayed well below the 0.90 threshold. As presented in Table 5, all values stay below the 0.90 threshold.

Table 5. Discriminant validity criteria: HTMT ratio

Dimension	An	Ap	D-LC	D-LI	D-LL	R	Un
An							
Ap	0.52						
D-LC	0.27	0.35					
D-LI	0.32	0.30	0.52				
D-LL	0.31	0.35	0.46	0.24			
R	0.27	0.39	0.45	0.36	0.23		
Un	0.46	0.55	0.50	0.47	0.57	0.44	

Note: R: Remembering, D-LL: Dialogue between learners;' etc.

B. Predictive Power of the Model and Common Method Bias

The predictive power of the model was evaluated using three criteria: variance explained (R^2), predictive relevance (F^2), and predictive importance of the endogenous variables (Q^2) as presented in Table 6. The variance explained (R^2) accounts for 62% of the variation in learning achievement. The model also has a strong predictive relevance of the endogenous (F^2) range from 0.60 to 1.98. The model's high

predictive importance of the endogenous variables (Q^2), where all values exceeded 0.0.

Table 6. Predictive power of the model: R^2 , F^2 , and Q^2

Dimensions	R^2	R^2 Adjusted	F^2	Q^2
R	0.37	0.37	0.60	0.37
Un	0.64	0.64	1.77	0.50
Ap	0.57	0.57	1.32	0.37
An	0.50	0.49	0.98	0.44
D-LC	0.63	0.63	1.68	0.36
D-LL	0.41	0.40	0.69	0.45
D-LI	0.66	0.66	1.98	0.30
Dialogue-achievement	0.62	0.62	1.63	0.455

Note: R^2 : variance explained, F^2 : predictive relevance, Q^2 : predictive importance of the endogenous variables.

Confirming predictive relevance through a blindfolding procedure, as recommended by Henseler *et al.* [41], a sample re-use technique that omits data points and uses the model

parameters to predict them. Yielding (Q^2) values between 0.30 and 0.50, well above the zero threshold. Statistical Common Method Bias (CMB) using a proctored final exam as an objective measure; statistical checks confirmed VIF scores below 3.3, and Harman's single factor explained less than 50% of the variance.

C. Assessment of the Inner Model and Hypotheses Testing

Assessment of the structural model shows that the path coefficients are statistically significant. At the 0.001 significance level, results show that dialogue has a significant effect on learning achievements ($\beta = 0.58$, $t = 13.86$, $p < 0.001$). The path model results, and the structure model results displayed in Table 7, Figs. 2 and 3, respectively, provide support for hypotheses H1, H2, and H3. Detailed results are presented in Table 7.

Table 7. Result of the inner structural model

Hypothesis	Relations	Path coefficient	T Statistics	P Values	Decision
H1	Achievement $\rightarrow$ R	0.61	08.41	<0.001	Support
	Achievement $\rightarrow$ Un	0.80	31.68	<0.001	Support
	Achievement $\rightarrow$ Ap	0.75	17.70	<0.001	Support
	Achievement $\rightarrow$ An	0.70	15.40	<0.001	Support
H2	Dialogue $\rightarrow$ D-LC	0.79	28.18	<0.001	Support
	Dialogue $\rightarrow$ D-LL	0.64	11.92	<0.001	Support
	Dialogue $\rightarrow$ D-LI	0.82	28.50	<0.001	Support
H3	Dialogue $\rightarrow$ Achievement	0.58	13.86	<0.001	Support

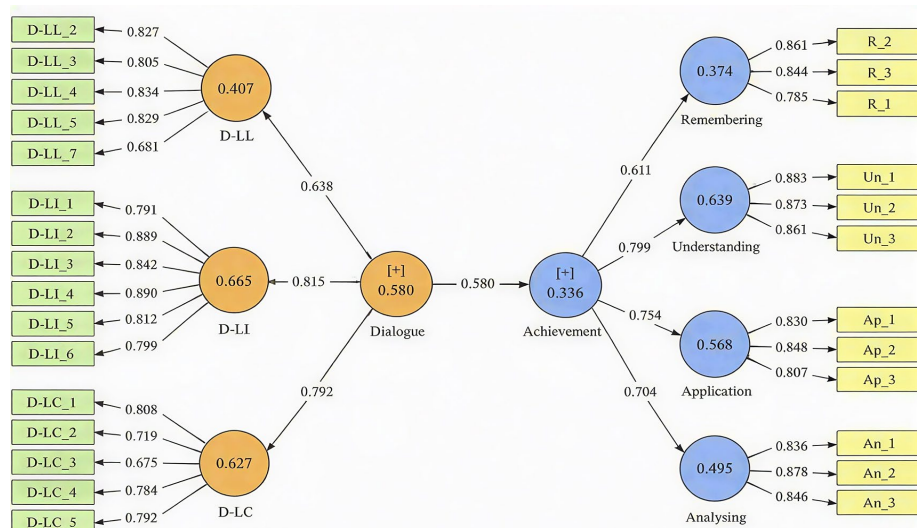


Fig. 2. Path model results.

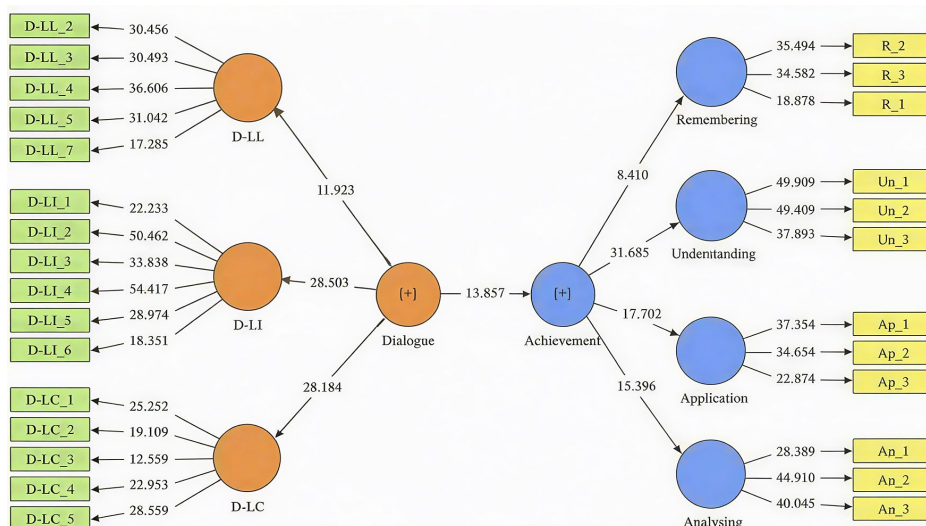


Fig. 3. Structure model results.

V. DISCUSSION

The findings of this research provide strong empirical support for the proposed hypotheses (H1, H2, and H3), confirming the structural validity of the constructs and their interrelationships. The analysis validated a four-dimension model for learning achievement, which represented the dimensions of Remembering (R), Understanding (Un), Applying (Ap), and Analyzing (An), and a three-dimensional model for learning dialogue, including Learner-Content Dialogue (D-LC), Learner-Learner Dialogue (D-LL), and Learner-Instructor Dialogue (D-LI), through both discriminant and convergent indicators. The statistical evaluation of the path coefficients ($\beta = 0.58$, $t = 13.86$, $p < 0.001$) confirms that dialogue is a significant and strong predictor of learning achievement. Besides, these results provide convincing evidence of the model's predictive relevance, confirming that the dialogue mechanisms effectively predict achievement outcomes across all four Bloom's levels, variance explained (R^2) accounts for 62% of the variation in learning achievement, predictive relevance F^2 of the endogenous range from 0.60 to 1.98, and predictive importance of the endogenous variables Q^2 , where all values exceeded 0.0. The results show that when online learning environments are structured to enable meaningful interactions, students prove higher levels of engagement and more effective cognitive processing behaviors.

Overall, the results suggest that online learning works better when meaningful dialogue is built in and guided by TDT, CLT, and Bloom's Taxonomy. When learners had more opportunities to engage in dialogue, they became more involved in the learning process, which helped them think and process information more effectively. Dialogue between instructors and learners was especially helpful for clearing up misunderstandings and correcting errors. This kind of interaction supported basic learning skills, such as remembering information, understanding ideas, and applying what was learned. When learners are given more opportunities to contribute to dialogue, they show higher levels of engagement in the learning process. Learners' engagement supported deeper thinking and more effective information processing. D-LI performed a key role in clarifying and correcting errors, which supported lower-level cognitive skills, including remembering information, understanding concepts, and applying newly learned information. Within online learning, D-LI bridge transactional gaps by clarifying concepts and providing feedback, in most cases, contributes to the development of trust. While D-LL subjects' learners to diverse perspectives and adopts a sense of community, thereby reducing feelings of isolation. Although D-LI dialogue is important for retention and understanding, D-LL is the specific functional mechanism that facilitates higher-order achievements through responding and argumentations, which improve the analyzing capability of learned content. In addition, interactions with course content, D-LC promotes deeper dialogue with learning materials and enables learners to construct knowledge according to their own pace of learnings. Together, these dialogue patterns highlight the effects of dialogue observed in this foreign English learning context. Consistent with these patterns, dialogue was a strong

predictor of learning achievement.

Theorizing dialogues' cognitive mechanisms in online environments are a theoretical limitation of previous studies. While previous studies reported D-LL in online environments as an effective factor in social context, these studies did not recognize or connect the D-LL with specific cognitive processes. Phillipson and Wegerif [3] proposed a thinking together approach, conceptualizing the D-LL structure as an area for reasoning, elaboration, and argumentation to slightly decrease this gap. However, few empirical studies clearly connect this dialogic framework to classified learning models such as Bloom's Taxonomy. Also, previous studies rely on perception-based instruments to measure learners' achievements, such as satisfaction questionnaires, lacking a cognitive framework for achievement measures. As a result, literature provides inconsistent evidence about which dialogue types are most effective for different learning achievements domains. For instance, Suen and Hung [31] note that instructor presence D-LI is vital for retention and understanding, yet English [42] suggests that higher-order outcomes such as analysis and creation require significantly more intensive dialogue to bridge transactional distance than foundational tasks. By adopting the "Thinking Together" approach described by Phillipson and Wegerif [3], this study shows how D-LL provides the social framework for the "elaboration and argumentation" essential for these higher-order levels.

Previous studies have recognized the importance of dialogue in online learning; however, their theoretical treatments did not account for different cognitive levels. For example, Suen and Hung [31] emphasize the critical role of D-LI in mainly supporting lower-order cognitive processes, namely retention and understanding, with their methodological focus placed on learning achievements. While this emphasis is valuable, it provides limited insight into how dialogue supports more complex learning goals. In contrast, English [42] showed that higher order achievements such as analysis and creation require significantly more interactive dialogue to effectively reduce transactional distance. However, within the TDT framework, English's work considers dialogue as a scalar variable rather than exploring how diverse types of dialogue function cognitively [42].

Based on the research findings of Suen and Hung [31], English [42], and Phillipson and Wegerif [3], this study addresses these limitations throughout conceptualizing the online learning environments factors connecting TDT with CLT. This study uniquely links diverse types of dialogue to the cognitive demands outlined in Bloom's Taxonomy. It also provides empirical support for the validation of second-order reflective structures of both dialogue and learning achievements. Although, the use of an objective proctored final examination strengthens the power of the findings. It theorizes D-LI, D-LL, and D-LC as supporting diverse cognitive processes aligned with Bloom's Taxonomy. It also explains why certain dialogue forms are more effective at specific cognitive demands. This approach ensures that the identified relationship between dialogue and achievement is an exact reflection of actual learning achievements, independent of student perceptions.

To conclude, this study offers a coherent conceptual

framework for dialogue contributions to learning achievement in online environments, responding to the theoretical gap in the literature. The validated model supports a conceptual framework for curriculum designers and educators to structure online environments, minimizing transactional distance.

This study had certain limitations. The study was based on one institution and one context, which limits the generalizability of the results; therefore, future studies should examine the model in several institutions. Additionally, the study only measured achievement on four levels of Bloom's taxonomy. The study did not take into consideration other possible influential factors like motivation or digital readiness; thus, future studies should take these factors into consideration. Moreover, it depends on self-reported dialogue measures; consequently, future studies should use a mixed-methods approach that includes interviews, student reflection, and learning analytics to triangulate dialogue behaviors beyond self-report instruments.

VI. CONCLUSION

This study empirically validates that online learning dialogue comprised of learner-instructor, learner-content, and learner-learner interactions function as a significant and positive predictor of learning achievement across the cognitive demands of remembering, understanding, applying, and analyzing. These dialogue mechanisms serve to bridge transactional gaps and enhance learner engagement while helping with more effective information processing within digital environments.

The primary theoretical contribution of this research is the validation of dialogue and learning achievement as reflective second-order constructs. By providing a novel synthesis of TDT and CLT, the study establishes a comprehensive framework for understanding how interaction types drive cognitive outcomes in online English as a Foreign Language (EFL) context. This integration shows that dialogue is a cognitive qualifying condition, where lower-level achievements rely heavily on instructor guidance and content interaction, while higher-level cognitive learning achievements are increasingly dependent on peer-based argumentation and analysis. Furthermore, methodologically, this study enhances the validity of the dialogue-achievement relationship by employing an objective, proctored final

examination, designed to measure remembering, understanding, applying, and analyzing, as a means of measuring achievement, which is independent of subjective self-reports of students' perceptions of dialogue. This offers an exact reflection of achievement outcomes.

The study also offers practical contributions that are used by institutions of higher education to create effective student-centered approaches to online teaching and learning. The study offers insights into effective ways of designing online courses that support positive dialogue between learners and instructors, learners and content, and learners and learners, which can reduce psychological distance, increase cognitive engagement, and improve learners' achievement outcomes. By intentionally aligning dialogue mechanisms with specific cognitive learning achievements, institutions can facilitate a more effective transition towards student-centered learning. These findings underscore the necessity of designing interactive content and peer-based tasks to ensure that dialogue effectively supports the transition from foundational knowledge to higher-order analysis. Furthermore, policymakers and instructional designers seeking ways of creating positive dialogue patterns use this study results for professional development programs, LMS development, and curriculum guidelines. For example, an LMS might be modified by integrating peer-based argumentation tools at the specific stages of a course where analysis is the primary cognitive goal. Moving forward, the next steps in the study will be expanding the study to include several different organizations to figure out the overall stability of the results. Improvements include the addition of moderators to further explore the results. A mixed-methods study could further explore the way that students interact with the dialogue mechanisms. A longitudinal study could further explore the way that dialogue mechanisms affect learning growth. And lastly, the next essential step for validating the model's stability at the highest cognitive demands is to include the final two levels of Bloom's Taxonomy: evaluation and creation.

To conclude, this research provides a conceptual framework for educators, demonstrating that dialogue serves as a cognitive qualifying condition for learning achievement. Both theory and practice can benefit from this model, improving online learning in EFL contexts.

APPENDIX A: PARTICIPANT DEMOGRAPHIC CHARACTERISTICS

Table A1. Participant demographic characteristics (N = 261)

Characteristic	Category	No.	%
Gender	Female	149	57%
	Male	112	43%
Academic Year	First Year	261	100%
Faculty	Engineering	17	6.5%
	IT	28	10.7%
	Nursing	24	9.2%
	Science	27	10.4%
	Earth and Environment Sciences	8	3%
	Arts and Humanities	54	20.7 %
	Foreign Languages	14	5.4%
	Law	11	4.2
	Political Science and International Studies	2	0.8
	Shari'a	23	8.8
	Educational Sciences	53	20.3
Age	Range	18–19 years	100%

APPENDIX B: ACHIEVEMENT TEST REMOVED ITEMS

Table A2. Achievement test removed items

Construct instruments	Dimensions	Original No. of items	item	Removed item	No. of items after removal
Achievement Test	R	4	R-1		3
			R-2		
			R-3		
			R-4	X	
	Un	3	Un-1		3
			Un-2		
			Un-3		
	Ap	4	AP-1		3
			AP-2		
			AP-3		
			AP-4	X	
	An	3	An-1		3
			An-2		
			An-3		
Dialogue Questionnaire	D-LC	5	D-LC-1		5
			D-LC-2		
			D-LC-3		
			D-LC-4		
			D-LC-5		
	D-LL	8	D-LL-1	X	5
			D-LL-2		
			D-LL-3		
			D-LL-4		
			D-LL-5		
			D-LL-6	X	
			D-LL-7		
			D-LL-8	X	
	D-LI	8	D-LI-1		6
			D-LI-2		
			D-LI-3		
			D-LI-4		
			D-LI-5		
			D-LI-6		
			D-LI-7	X	
			D-LI-8	X	

APPENDIX C: JUSTIFICATION OF THE ACHIEVEMENT TEST REMOVED ITEMS

Table A3. Removed measurement items, loadings, and justifications

Construct	Item	Original Loading	Construct	Reason for Removal	Justification
D-LL	D-LL_1	0.54	Dialogue	Weak indicator	It did not contribute meaningfully to construct reliability or validity.
	D-LL_6	0.54		Weak indicator	It did not contribute meaningfully to construct reliability or validity.
	D-LL_8	0.54		Weak indicator	It did not contribute meaningfully to construct reliability or validity.
D-LI	D-LI_7	0.57		Conceptually redundant + low loading	Removal improved AVE and internal consistency.
	D-LI_8	0.57		Conceptually redundant + low loading	Removal improved AVE and internal consistency.
R	R_4	0.55	Learning Achievement	Below threshold	Dropped to preserve convergent validity of the dimension.
Ap	Ap_4	0.58		Below threshold	Dropped to preserve convergent validity of the dimension.

CONFLICT OF INTEREST

The author declares no conflict of interest.

AUTHOR CONTRIBUTIONS

The contributions of the individual authors are as follows: Atef F. Al Mashakbh was responsible for conceptualization, design, data analysis, and drafting the original version of the manuscript. Rania A. Bataineh was responsible for implementation, reviewing language, and editing. Mamon S. Alzboun contributed methodological guidance. Hmoud M. Olaimat and AbdelKarim H. Makhadmeh contributed to

validation, expert supervision, and Rehab Tharwat contributed to the review of didactic and pedagogical aspects. Fares A. Mohammad participated in the research organization. All authors approved the definitive version of the manuscript.

REFERENCES

- [1] C. Lubbe, P. Marais, and D. Kruger, "Collaborative learning and dialogue in cognitive development: A constructivist approach," *Journal of Educational Psychology and Practice*, vol. 18, no. 2, pp. 134–149, 2025.
- [2] M. G. Moore, "Theory of transactional distance," in *Theoretical Principles of Distance Education*, D. Keegan, Ed. Routledge, 1997, pp. 22–38.

- [3] N. Phillipson and R. Wegerif, "The Thinking Together approach to dialogic teaching," in *Deeper Learning, Dialogic Learning, and Critical Thinking*, Routledge, 2019, pp. 32–47. doi: 10.4324/9780429323058-3
- [4] B. S. Bloom, J. T. Hastings, and G. F. Madaus, *Handbook on Formative and Summative Evaluation of Student Learning*, McGraw-Hill, 1971.
- [5] J. L. F. Choy and C. L. Quek, "Modelling relationships between students' academic achievement and community of inquiry in an online learning environment for a blended course," *Australasian Journal of Educational Technology*, vol. 32, no. 4, pp. 106–124, 2016. doi: 10.14742/ajet.2500
- [6] C. M. Chişiu, "Extracurricular activities, an alternative for interdisciplinary learning," *Postmodern Openings*, vol. 4, no. 4, pp. 67–79, 2013.
- [7] V. Wang and L. Farmer, "Adult teaching methods in China and Bloom's taxonomy," *International Journal for the Scholarship of Teaching and Learning*, vol. 2, no. 2, 13, 2008. doi: 10.20429/ijstl.2008.020213
- [8] E. B. Goldring, A. C. Porter, J. F. Murphy, S. N. Elliott, and X. C. Cravens, *A Framework for the Assessment of Learning-Centered Leadership*, 2007.
- [9] H. Abuhassna, N. Yahaya, M. Hashem, and A. Alsaqqaf, "Development of a new model on utilizing online learning platforms to improve students' academic achievements and satisfaction," *International Journal of Educational Technology in Higher Education*, vol. 17, no. 1, pp. 1–23, 2020. doi: 10.1186/s41239-020-00216-1
- [10] J. Murphy, S. N. Elliott, E. Goldring, and A. C. Porter, "Leadership for learning: A research-based model and taxonomy," *School Leadership & Management*, vol. 27, no. 2, pp. 179–201, 2007. doi: 10.1080/13632430701237420
- [11] S. S. S. Hassan and H. Dzakiria, "Attitude towards the use of learning management system among university students: A case study," *International Journal of Information Systems and Engineering*, vol. 1, no. 1, pp. 1–17, 2013.
- [12] M. Letsapa, "Bridging gaps in open distance e-learning: Applying Moore's transactional distance theory to support Early Childhood Care and Education students," *International Journal of Educational Development in Africa*, 2025.
- [13] M. G. Moore, "Theory of transactional distance," in *Theoretical Principles of Distance Education*, D. Keegan, Ed. Routledge, 1993, pp. 22–29.
- [14] Y. Tong and Y. Ding, "Productive classroom dialogue and its association with student achievement in knowledge-building environments," *Language and Education*, vol. 39, no. 1, pp. 232–251, 2025. doi: 10.1080/09500782.2024.2323207
- [15] M. Aziz, D. S. Napitupulu, and F. A. Parapat, "The influence of teacher communication patterns in aqidah akhlak education on students' academic achievement," *Attadrib: Jurnal Pendidikan Guru Madrasah Ibtidaiyah*, vol. 8, no. 1, pp. 71–86, 2025. doi: 10.54069/attadrib.v8i1.840
- [16] J. A. R. Comingking, M. C. Labos, E. M. Rebucas, and C. Caritativo, "Regression analysis of communication gap in teaching-learning process among BTVTED students," *Asian Journal of Education and Social Studies*, vol. 50, no. 8, pp. 393–410, 2024. doi: 10.9734/ajess/2024/v50i81538
- [17] H. Labib, "Learning communication strategies and their effect on students' learning quality during the pandemic," *Jurnal Ilmu Manajemen (JIMMU)*, vol. 7, no. 1, pp. 93–104, 2022. doi: 10.33474/jimmu.v7i1.14835
- [18] Ö. Uzun, "Factors affecting transactional distance perception in online learning environments," Master's thesis, Anadolu University, National Thesis Center, 2019.
- [19] M. G. Moore, "Three types of interaction," *The American Journal of Distance Education*, vol. 3, no. 2, pp. 1–6, 1989. doi: 10.1080/08923648909526659
- [20] A. R. Leach, "A study of the interaction patterns of online learners: Highlighting the usefulness of linking social network analysis and qualitative research," Doctoral dissertation, University of Arizona, 2024.
- [21] I. Kožuh, P. Jeretič, and M. Debevc, "Dimensions of transactional distance in online learning environments: A student perspective," *Computers in Human Behavior*, vol. 48, pp. 113–125, 2015. doi: 10.1016/j.chb.2015.01.041
- [22] L. S. Vygotsky, *Mind in Society: The Development of Higher Psychological Processes*, Harvard University Press, 1978.
- [23] F. S. A. Halim, T. A. Buhari, N. H. Rahmat, and S. S. Lee, "Investigating student strategy in online learning: The role of student interaction and engagement in online distance learning among UiTM students," *International Journal of Research and Innovation in Social Science*, vol. 8, no. 8, pp. 4104–4118, 2024. doi: 10.47772/IJRIS.2024.8080310
- [24] A. Sher, "Assessing the relationship of student-instructor and student-student interaction to student learning and satisfaction in Web-based online learning environment," *Journal of Interactive Online Learning*, vol. 8, no. 2, pp. 102–120, 2009.
- [25] H. Abuhassna and S. Alnawajha, "The transactional distance theory and distance learning contexts: Theory integration, research gaps, and future agenda," *Education Sciences*, vol. 13, no. 2, 112, 2023. doi: 10.3390/educsci13020112
- [26] M. M. Walsh and M. C. Lovett, "The cognitive science approach to learning and memory," in *The Oxford Handbook of Cognitive Science*, S. E. F. Chipman, Ed. Oxford University Press, 2017, pp. 211–230.
- [27] R. E. Mayer, "Information processing," in *APA Educational Psychology Handbook*, K. R. Harris et al., Eds. American Psychological Association, 2012, vol. 1, pp. 85–99. doi: 10.1037/13273-004
- [28] R. E. Mayer, *Multimedia Learning*, 2nd ed., Cambridge University Press, 2009.
- [29] X. Fan and M. Chen, "Parental involvement and students' academic achievement: A meta-analysis," *Educational Psychology Review*, vol. 13, no. 1, pp. 1–22, 2001. doi: 10.1023/A:1009048817385
- [30] D. R. Krathwohl, "A revision of Bloom's taxonomy: An overview," *Theory into Practice*, vol. 41, no. 4, pp. 212–218, 2002. doi: 10.1207/s15430421tip4104_2
- [31] H. K. Suen and Y. H. Hung, "Instructor presence and expressiveness in asynchronous learning: Impacts on learner engagement and retention," *Journal of Online Learning Research*, vol. 11, no. 1, pp. 45–62, 2025.
- [32] A. F. Mashakhb, "Online individualized multimedia instructional model for engineering communication skills," Thesis, University Kebangsaan Malaysia, 2016.
- [33] J. F. Hair, M. Sarstedt, T. M. Pieper, and C. M. Ringle, "The use of partial least squares structural equation modeling in strategic management research: A review of past practices and recommendations for future applications," *Long Range Planning*, vol. 45, nos. 5–6, pp. 320–340, 2012. doi: 10.1016/j.lrp.2012.09.008
- [34] R. B. Kline, *Principles and Practice of Structural Equation Modeling*, 4th ed. Guilford Press, 2015.
- [35] J. F. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, *Multivariate Data Analysis*, 7th ed. Pearson Prentice Hall, 2009.
- [36] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *Journal of Marketing Research*, vol. 18, no. 1, pp. 39–50, 1981. doi: 10.2307/3151312
- [37] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *Journal of the Academy of Marketing Science*, vol. 43, no. 1, pp. 115–135, 2015. doi: 10.1007/s11747-014-0403-8
- [38] J. Cohen, *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed. Routledge, 1988. doi: 10.4324/9780203771587
- [39] J. D. Smith, J. J. Couchman, and M. J. Beran, "The highs and lows of theoretical interpretation in animal-metacognition research," *Philosophical Transactions of the Royal Society B: Biological Sciences*, vol. 369, no. 1655, 20140176, 2014. doi: 10.1098/rstb.2014.0176
- [40] J. F. Hair, M. Sarstedt, L. Hopkins, and V. G. Kuppelwieser, "Partial Least Squares Structural Equation Modeling (PLS-SEM): An emerging tool in business research," *European Business Review*, vol. 26, pp. 106–121, 2014.
- [41] J. Henseler, C. M. Ringle, and R. R. Sinkovics, "The use of partial least squares path modeling in international marketing," *Advances in International Marketing*, vol. 20, pp. 277–319, 2009.
- [42] P. S. English, "A comparative case study of online learning and Bloom's taxonomy," Doctoral dissertation, Indiana State University, 2016.

Copyright © 2026 by the authors. This is an open access article distributed under the Creative Commons Attribution License which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited (CC BY 4.0).