Attitude Toward Computer-Assisted Language Learning of University Students in Regions XI and XII: A Structural Equation Model

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Abstract: The purpose of this quantitative study employing Partial Least Square Structural Equation Modelling (PLS-SEM) is to construct and test a model of Attitude toward Computer-Assisted Language Learning (ACALL) in the context of Language Mindset (LM), Second Language Grit (L2G), and Motivation (M) of University Students. The study was conducted virtually in selected universities in Regions XI and XII and included a total of 373 university students or respondents. The data obtained were analyzed using descriptive statistics and PLS-SEM. The findings of the study revealed that the level of ACALL and LM of the students were moderate, while their L2G and Motivation were high. Further, both the reflective ($\chi 2$ = 45.942, P<0.001) and formative ($\chi 2$ = 0.913, P<0.001) measurement models were reliable, valid, and free from common method bias. Further, it was revealed in the model that LM significantly predicted L2Grit (β=.455, p<.001, f^2=.207, medium effect size), Motivation (β=.229, p<.001, f^2=.099, small effect size), and Attitude toward CALL (β=.175, p<.001, f^2=.059, small effect size), while L2Grit predicted motivation (β=.471, p<.001, f^2=.269, medium effect size) and Attitude toward CALL (β=.163, p<.001, f^2=.061, small effect size), and motivation predicted Attitude toward CALL (β=.226, p<.001, f^2=.087, small effect size). The structural model of attitude toward computer-assisted language learning was the best fit.

Keywords: CALL, Language Mindset, L2 Grit, Motivation, PLS-SEM.

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INTRODUCTION

Computer-Assisted Language Learning (CALL) is a language pedagogy that employs technology or computer-based learning packages, software, applications, and other digital tools designed to assist language acquisition/learning. According to Phan et al. (2016), language teachers can impart knowledge to language learners more readily and effectively by using technology in English language classes. However, language learners have been reported to have a negative attitude toward CALL (Demirdöken, 2019) and other related technology due to a lack of technology literacy (Vasbieva & Saienko, 2018), lack of technical and instructor support (Ahsan et al., 2021; Hussein et al., 2020), intermittent internet connectivity, and limited technology-based instructions (Demirdöken, 2019; Tafazoli et al., 2018, 2019).

Technology-Assisted Language Learning (TALL) has garnered mixed student opinions (Erdem et al., 2018; Jahangard et al., 2020; Tafazoli et al., 2019; Thuy Nguyen & Habók, 2022). Tuncay (2020) evaluated CALL attrition in 79 Turkish English learners. Their attrition has many causes. Inauthentic CALL materials caused 74.3% withdrawals. 65.7% mentioned inadequate education quality and 62.9% stated low motivation. Lack of guidance accounted for 42.9% of attrition. Similarly, Hussein et al. (2020) examined UAE undergraduate students' views on CALL in the context of online learning during the pandemic. The researchers found that students disliked this form of instruction for four main reasons. 53.3% reported that they get easily distracted and have problems focusing. Second, 37.7% of respondents

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felt overburdened. Ahsan et al. (2021) also found that internet access negatively impacts CALL or online learning attitudes in Pakistani students.

Studies in the Philippine context reported instructional, pedagogical, and technical support, technological-related difficulties, individual readiness, and domestic barriers (Aguilar & Torres, 2021; Alvarez, 2020a, 2020b), which may have influenced students' perceptions and attitudes toward technology or computer-assisted learning. Similarly, Barrot et al. (2021), Ignacio (2021), and Lim et al. (2022) reported poor technological competency and literacy, an inconducive learning environment at home, heavy online workloads, and mental health-related issues such as depression and anxiety as reasons why students flaunt online set-up or computer-assisted learning.

Apparently, most of these investigations on attitudes towards CALL revolve around software design, learning tasks and how to structure them for optimal learning conditions, and learners, their interaction with the e-learning environment, and individual differences (Vandewaetere & Desmet, 2009, as cited by Zarrinabadi et al., 2022). Nevertheless, much of these research has paid little attention to the psychological constructs that are deemed influential in language learning. Recent studies by Aparicio et al. (2017) and Zarrinabadi et al. (2022) in educational technology demonstrate that learners' traits relating to their ability to deal with failure and setbacks, as well as their perseverance and motivation in learning, influence their attitude toward CALL and perception of technology-mediated learning.

In the parlance of language learning, mainly when technology-based tools are incorporated, learners' attitude indicates their acceptance of technology. Likewise, Attitude towards CALL has been found to predict success in language learning (Erdem et al., 2018b; Khajavy et al., 2021; Krsmanović, 2021; Obenza-Tanudtanud & Obenza, 2024; Tafazoli et al., 2019) and in developing language skills such as vocabulary (Alamer, 2021; Enayati & Gilakjani, 2020; Sedaghatkar, 2017), oral proficiency (Ratnaningsih et al., 2019; Ulangkaya, 2021), writing skills (Ali Ghufron & Nurdianingsih, 2021; Jahangard et al., 2020). In addition, according to Krsmanović (2021), a positive attitude has synergy towards ease and fun of learning. Thus, it is imperative to pay attention to and develop this construct as it is a relevant element for attaining the goals and objectives of language classes. Moreover, among the numerous variables filtered by the researchers through thorough reading, the following stood out for their relevance and recency: language mindset, second language (L2) grit, and motivation.

The exogenous variables mentioned above, language mindset, L2 grit, and motivation, are found to have associations with students' attitudes. In their study, Zarrinabadi et al. (2022) found that persistence, L2 grit, and a growth mindset predicted the effectiveness of CALL. Various papers have described learners' attitudes or perceptions toward CALL (Afshari et al., 2013a; Jahangard et al., 2020; Krsmanović, 2021; Tafazoli et al., 2018, 2019; Talebinezhad & Abarghoui, 2013; Vasbieva & Saienko, 2018); developed and validated tools to measure attitude towards CALL (Erdem et al., 2018; Thuy Nguyen & Habók, 2022; Vandewaetere & Desmet, 2009); and the effects of CALL and attitude towards CALL in developing language skills, vocabulary, lexicon, reading comprehension, English proficiency, oral/speaking skills, (Enayati & Gilakjani, 2020; Rahnavard & Mashhadi Heidar, 2017; Ratnaningsih et al., 2019; Sedaghatkar, 2017; Suñas & Tulud, 2022; Ulangkaya, 2021; Ysquierdo, 2018). Additionally, most of these studies employ qualitative methods and descriptive and comparative approaches in their investigations. However, there is limited knowledge about studies investigating multiple factors or variables that might predict attitudes toward CALL using Structural Equation Modeling (SEM): language mindset, L2 grit, and motivation. Further, there is a dearth of studies, particularly in the context of the Philippines, that offer a best-fit model of attitude towards CALL. This warrants the need to undertake this investigation to clarify and illuminate such a gap.

The aim of this quantitative study, utilizing Partial Least Square Structural Equation Modeling (PLS-SEM), is to develop and test a model that examines the relationship between attitude toward Computer-Assisted Language Learning (CALL), language mentality, L2 grit, and motivation. This study holds great relevance and importance in the subject of Applied Linguistics, namely in the domain of Language Teaching and Learning. The data may offer a framework for shaping attitudes about CALL.

METHOD

Research Design

This study utilized a quantitative research design, namely Structural Equation Modeling (SEM), to investigate a model on attitude towards Computer-Assisted Language Learning (CALL). The model included variables such as language mindset, L2 grit, and motivation. Therefore, the researchers utilized Structural Equation Modeling (SEM) in this study since the main objective of the research was to develop the best-fit model on attitude toward CALL, taking into account the exogenous variables. The foundation of Quantitative Research design is based on the philosophical assumption or worldview of Postpositivism. Postpositivism, commonly referred to as the scientific method or empirical science, is a deterministic ideology that posits that causes have a direct influence on consequences or results (Creswell, 2009;

Creswell & David Creswell, 2018). Postpositivism posits that knowledge is obtained via meticulous observation and measurement of the objective reality existing in the external world.

PLS-SEM is an approach to structural equation modeling (SEM) that focuses on both prediction and causal explanations. It lays particular emphasis on predicting outcomes while estimating statistical models that are designed to provide causal explanations. This is a crucial aspect of the methodology (Hair et al., 2019, 2021; Sarstedt et al., 2017). Furthermore, PLS-SEM has the ability to overcome three limitations of other statistical modeling techniques, specifically those used in first-generation multivariate data analysis. These limitations include the assumption of a simple model structure, the consideration of all variables as observable, and the assumption that there are no measurement errors in any of the variables (Hair et al., 2021). Similarly, this strategy resolves the apparent division between explanation and prediction, which is crucial for evaluating management consequences, as commonly stressed in academic research (Hair et al., 2019). Additionally, Geng (2014) noted that SEM has a wide variety of possible applications in applied linguistics because it is the only statistical technique capable of doing a thorough analysis of the correlations between multiple variables concurrently, as was done in this study.

Research Respondents

This study included a total of three-hundred seventy-three (373) university students from various universities in Regions XI and XII of the Philippines. They were identified using stratified random sampling. Using the WarpPLS 8.0 software, the suggested number of samples was computed using the Inverse Square Root and Gamma-Exponential Methods as suggested by Hair et al., 2019 Kock & Hadaya, 2018 Sarstedt et al., 2017 when using PLS-SEM. Based on the Inverse Square Root results, the recommended sample is two-hundred thirty-three (233), while based on the Gamma-Exponential Methods, the recommended sample is two-hundred twenty (220). Thus, the actual sample in the study exceeds the recommended sample sizes.

The respondents were selected based on the study's inclusion criteria. The inclusion criteria for this study are as follows: the student must be currently enrolled in a higher education institution with university status in either the Davao Region or SOCCSKSARGEN; the student must be enrolled in an English Major Program, such as BA English, BSE English, or a similar program; the student must be in their second to fourth year of study; the student must be willing to participate in the study; and the student must have at least one year of experience learning the English language through CALL.

Research Instruments

The researchers utilized adopted questionnaires. These questionnaires were submitted to three experts for validation with a basic qualification of at least a PhD degree holder. Moreover, the researchers used the attitude toward Computer Assisted Language Learning (CALL) scale developed by Vandewaetere and Desmet (2009), the Language Mindset scale of Lou and Noels (2017), the second language grit (L2 Grit) scale developed by (Teimouri et al., 2022), and the Motivation scale of Gardner (2004).

Data Gathering Procedure

The researchers submitted the manuscript to a Research Ethics Committee (REC) for evaluation and approval in order to proceed with the data collection process. After obtaining certification from the REC, the researchers sent letters of request and approval to the school presidents of the five universities selected for the study. After obtaining approval, a Google form link was utilized to distribute the survey to eligible respondents who expressed willingness to engage in the study, with the assistance of gatekeepers. The Google form was structured into five distinct sections: the informed consent form, attitude towards CALL scale, language mindset scale, L2 grit scale, and motivation scale sections. These components were designed to ensure that students would react to or complete the survey with genuine attention and seriousness. The informed consent form was included in the initial section of the online survey to notify the intended participants about the nature and objective of the study. Furthermore, the participants were queried on their willingness to collaborate and fully engage in the study.

The privacy and security of the respondents' identity and other personal information were maintained by rigorously complying to RA 10173 or the Data Privacy Act of 2012 and other ethical principles. Upon collecting the data, the dataset was cleaned, organized, and prepared for statistical analyses.

Statistical Tools

This research employed both descriptive and inferential statistics to analyze the data involved. Using the Jamovi 2.0 software, descriptive statistics such as mean and standard deviation were used to describe the level and variability of attitude towards CALL, language mindset, L2 grit, and motivation. Moreover, the Partial Least Squares Structural Equation Modeling (PLS-SEM) was used through the WarpPLS 8.0 software to test and establish the best-fit model of the attitude towards CALL of university students.

RESULTS AND DISCUSSION

Descriptive Level of ACALL, Language Mindset, L2 Grit, and Motivation

Table 1 shows the levels of exogenous variables as manifested by the University students in Regions XI and XII. The data is presented using descriptive statistics, specifically the measure of variability, represented by the standard deviation and measure of central tendency, as indicated by the mean. The standard deviation values for the four variables range from 0.85-0.53, indicating a consistent and homogeneous pattern in the results.

The university students showed a moderate Attitude toward Computer-Assisted Language Learning (ACALL), as indicated in the grand mean of 3.18. This shows that they hold a generally favorable attitude toward learning the English language with the aid of computers or technology. Like Afshari et al. (2013), who indicated that students' ACALL were moderate.

The Language Mindset (LM) of university students appeared to be moderate, as manifested in the grand mean score of 3.35. This suggests that the respondents possess an average level of growth language mindset, indicating a belief in the potential for language development and improvement through effort and practice. Ciaccio (2019) found in his study that students with a fixed mindset lack success in language exercises due to their lack of effort. Additionally, he believed that students with a growth mindset worked diligently to finish their assignments effectively. Moreover, Mrazek et al. (2018) discovered that students with a growth mindset could self-regulate their thoughts and emotions more.

The exogenous variable, Second Language Grit (L2G), obtained a grand mean of 3.55. This indicates that university students manifested a high level of L2G. Duckworth et al. (2007) and Duckworth and Quinn (2009) were the ones who came up with the idea that eventually became known as "grit." They viewed grit as a higher-order construct that consisted of two parts: perseverance of efforts (PE) and consistency of interest (CI). The findings of this study revealed that university students have high levels of Second Language Grit. According to Teimouri et al. (2020), students with a higher level of grit are more likely to participate in class discussions than students with a lower level of grit.

University students were found to be highly motivated in the context of this investigation, as revealed by the grand mean score of 4.04. Students who are highly motivated and believe that their work using CALL is relevant to their needs are more likely to regard CALL as an essential component of the course. Furthermore, according to Moè and Katz (2020) and Salmee and Arif (2019), L2 learners' motivation, self-regulation, and positive learning dispositions are critical for success in online education, computer-assisted learning, and achieving language learning goals.

Table 1. Descriptive Level of Attitude towards Computer Assisted Language Learning (A-CALL), Language Mindset, Second Language Grit, and Motivation.

Latent Variables / Observed Variables	Standard Deviation	Mean	Descriptive Level
ACALL	0.85	3.18	Moderate
Language Mindset	0.92	3.35	Moderate
Second Language Grit	0.93	3.55	High
Motivation	0.92	4.04	High

Assessing the Reflective and Formative Measurement Models

Prior to testing the structural model, the researchers first assessed the measurement model of the study, as suggested by Hair et al. (2017). According to Hair et al. (2017), in the event that the measurement models satisfy the prerequisite criteria or indices, the researchers will need to evaluate the structural model.

Using the WarpPLS software, the reflective measurement model was assessed based on the following indices: Composite Reliability (CR) and Cronbach's Alpha (α) to measure the reliability of the measurement model; indicator/factor loading and Average Variance Extracted (AVE) to measure the convergent validity, square root of Average Variance Extracted (AVE) to measure the discriminant validity, and the Full Collinearity Variance Inflation Factor (Ful. Collin. VIF) to measure the common method bias.

Fornell and Larcker (1981) and Nunnally and Bernstein (1994) recommended that Composite Reliability and Cronbach's Alpha value is ideally .70 and above or at least .60 or higher. Moreover, Amora (2021) recommended that each item should have a ≥ .50 indicator loading, low cross-loadings relative to indicator loadings, and should be statistically significant ($p<0.05$). Additionally, Fornell and Larcker (1981) asserted that the AVE of each latent variable should be ≥ .50 to establish convergent validity. Further, Fornell and Larcker (1981) and Roemer et al. (2021) suggested that each construct's square root of AVE should be greater than its correlations with other constructs, and their Heterotrait-Monotrait Ratio of Correlations (HTMT2) should be less than .90 or .85 to establish discriminant validity. Finally, in terms of the Full Collinearity Variance Inflation Factor (Ful. Collin. VIF), Kock (2021) asserted that latent variables with Ful. Collin. VIF value of ≤ 3.3 implies the non-existence of common method bias.

As shown in Table 2, the latent variables which qualified to be included in the measurement model and to proceed to the structural equation model based on the criteria of indices mentioned were the Effectiveness of CALL (EC), the Surplus value of CALL (SVC), and Teacher influence (TI) for the Attitude toward Computer-Assisted Language Learning (ACALL) construct; Second language aptitude beliefs (L2B), and Age-Sensitivity beliefs about language learning (ASB) for the Language Mindset (LM) construct; Perseverance of Effort (PE) and Consistency of interest (CI) for the Second Language Grit (L2G) construct; and Motivational Intensity (MI) and Attitudes toward Learning English (ATLE) for the Motivation (M) construct. Moreover, the Goodness-of-Fit indices implied a better fit of the reflective measurement model and were confirmed by the significant chi-square value ($\chi2 = 45.942$, $P<0.001$).

In establishing the reliability and validity of the reflective measurement model, several items were removed. Items 1, 2, and 3 under Second language aptitude beliefs (L2B), items 1, 2, and 3 under Age-Sensitivity beliefs about language learning (ASB), item 2 under Perseverance of Effort (PE), item 2 under Desire to Learn English (DLE), items 1 to 5 under Motivational Intensity (MI), item 1 under Exhibition to CALL (2EC), and item 5 under Surplus value of CALL (SVC) were removed from the reflective measurement model as they have not met the satisfactory values of indices necessary to establish the reliability, convergent validity, discriminant validity, and common method bias.

Table 2. Reliability, Validity, and Common Method Bias of Reflective Measurement Model.

	ACALL-EC	ACALL-SVC	ACALL-TI	LM-L2B	LM-ASB	L2G-PE	L2G-CI	M-MI	M-ATLE
CR	0.866	0.913	0.923	0.859	0.923	0.846	0.813	0.869	0.915
(α)	0.793	0.893	0.875	0.747	0.874	0.756	0.693	0.811	0.896
AVE	0.618	0.541	0.801	0.675	0.799	0.582	0.521	0.572	0.518
Ful. Collin. VIF	1.202	1.647	1.647	1.766	1.526	2.379	2.077	1.458	1.694
sq. rts. of AVEs	0.786	0.735	0.895	0.822	0.849	0.763	0.722	0.756	0.720

$\chi2 = 45.942$, $P<0.001$

After assessing the reflective measurement model, the researchers proceeded to test the higher-order latent variables or the formative measurement model. Using the same software, convergent validity, indicator collinearity, and statistical significance and relevance of the indicator weights were used to evaluate formative measurement models, as Hair et al. (2021) and Sarstedt et al. (2017) suggested. As suggested by Fornell and Larcker (1981), the AVE of each latent variable should be ≥ .50 to establish convergent validity. Moreover, the Variance Inflation Factor (VIF) should be ≤ 2.5 with statistically significant formative indicator weights ($p < .05$) and a small Effect Size (ES) of .02 or higher. Any formative indicator with an effect size less than .02, even if statistically significant, should be considered for removal. Additionally, Amora (2021) and Kock (2021) asserted that the indicator weight-loading sign (WLS) should be positive, as a negative WLS indicates the presence of Simpson's paradox instance.

Table 3 presents the latent variables or constructs that met the mentioned criteria and were included in the formative measurement model and structural model. Moreover, the Goodness-of-Fit indices implied a better fit of the formative measurement model and were confirmed by the significant chi-square value ($\chi2 = 0.913$, $P<0.001$). The latent variables General Language intelligence Beliefs (GLB) under Language Mindset (LM), Desire to Learn English (DLE) under Motivation (M), and Exhibition to CALL (2EC) under Attitude toward Computer-Assisted Language learning (ACALL) were omitted as they have not satisfied the indices in assessing formative measurement model which are the AVE, VIF, Indicator Weights, WLS, and ES.

Table 3. Reliability, Validity, and Common Method Bias of Formative Measurement Model.

	ACALL	LM	L2G	M	Type	SE	P Value	VIF	WLS	ES
AVE	0.781	0.772	0.843	0.721	-	-	-	-	-	-
ACALL-SVC	(0.566)	0.000	0.000	0.000	Formative	0.048	<0.001	1.460	1	0.500
ACALL-TI	(0.566)	0.000	0.000	0.000	Formative	0.048	<0.001	1.460	1	0.500
LM-L2B	0.000	(0.569)	0.000	0.000	Formative	0.048	<0.001	1.420	1	0.500
LM-ASB	0.000	(0.569)	0.000	0.000	Formative	0.048	<0.001	1.420	1	0.500
L2G-PE	0.000	0.000	(0.545)	0.000	Formative	0.048	<0.001	1.885	1	0.500
L2G-CI	0.000	0.000	(0.545)	0.000	Formative	0.048	<0.001	1.885	1	0.500
M-MI	0.000	0.000	0.000	(0.589)	Formative	0.048	<0.001	1.242	1	0.500
M-ATLE	0.000	0.000	0.000	(0.589)	Formative	0.048	<0.001	1.242	1	0.500

$\chi 2 = 0.913$, $P<0.001$

Best Fit Structural Model of Attitude toward Computer-Assisted Language Learning.

The hypothesized structural equation model was tested to determine the best-fit model for the attitude of University students in Region XI and Region XII toward computer-assisted language learning (ACALL).

Kock (2021) recommends that the p-values for the average path coefficient (APC), average R-squared (ARS), and average adjusted R-squared (AARS) be equal to or less than 0.05, showing statistical significance at the 0.05 level. Additionally, the ideal values of average block variance inflation factor (AVIF) and average full collinearity VIF (AFVIF) are ≤3.3, particularly in models where two or more indicators measure most variables. Regarding the Tenenhaus GoF (GoF), which measures a model's explanatory power, Kock (2021) recommended that the ideal value is ≥ 0.36. Moreover, according to Kock (2015), Kock and Gaskins (2016), Pearl (2011), and Wagner (1982), the Simpson's paradox ratio (SPR) index assesses the absence of Simpson's paradox instances in a model. Simpson's paradox occurs when the path coefficient and correlation associated with a pair of linked variables have opposite signatures. Ideally, the SPR should equal 1, indicating that the model contains no instances of Simpson's paradox.

Kock (2015), Kock and Gaskins (2016), Pearl (2011), and Wagner (1982) asserted that the R-squared contribution ratio (RSCR) index quantifies the absence of negative R-squared contributions, frequently occurring in instances of Simpson's paradox. Ideally, the RSCR should be equal to 1, indicating that the model has no negative R-squared contributions. According to Kock and Gaskins (2016), the statistical suppression ratio (SSR) index assesses a model's absence of statistical suppression instances. Acceptable SSR values are equal to or greater than 0.7, indicating that at least 70% of the model's paths are free of statistical suppression. Further, the nonlinear bivariate causality direction ratio (NLBCDR) index quantifies the degree to which bivariate nonlinear coefficients of the association support the model's hypothesized causal links. Acceptable values for NLBCDR are equal to or greater than 0.7, indicating that at least 70% of path-related instances in the model exhibit minimal or no support for the reversed hypothesized direction of causality.

The weights of the path coefficients, as reflected in Table 5, were estimated to determine the effects of exogenous variables on the endogenous variables. As shown in the model and as presented in the said table, all exogenous variables, Language Mindset, Second Language Grit, and Motivation, have significant direct effects ($p<0.05$) with beta coefficients of 0.175, 0.163, and 0.226, respectively, on the attitude of University students in Region XI toward computer-based language learning. In addition, the indirect effects of language mindset through L2 grit ($\beta=0.455$) and through motivation ($\beta=0.229$) are all significant ($p<.05$). Likewise, the indirect effect of L2 grit through motivation ($\beta=0.471$) is also significant ($p<.05$).

In its entirety, the model having satisfied the model fit indices, as shown in Table 4, is considered the best-fit model. Over and above the indices shown in the table, the average path coefficient (0.287) and the average adjusted R-squared (0.260) of the model are all significant ($p<0.05$), not to mention its ideal average full collinearity of 1.382, which is much lesser than the ideal range of less than 3.3. As reflected in the table, the GoF is 0.450, which is ideal since this index should be greater than 0.36. The SPR and RSCR are both 1.000, the ideal range for these indices. For the SSR and NLBCDR, the ideal range is greater than 0.7, and the model registered a 1.000 value for both indices.

Table 4. Summary of Goodness-of-Fit of the Structural Equation Model

Indices	Ideal Range	Value
APC	<0.05	0.287, <0.001
ARS	<0.05	0.260, <0.001
AARS	<0.05	0.256, <0.001
AVIF	<3.3	1.382
AFVIF	<3.3	1.406
GoF	>0.36	0.450
SPR	1.000	1.000
RSCR	1.000	1.000
SSR	>0.70	1.000
NLBCDR	>0.70	1.000

The results from the Partial Least Square Structural Equation Modelling (PLS-SEM) regarding the exogenous variables revealed that Language Mindset influenced L2 Grit (β=.455,$p<$ .001, f^2=.207, medium effect size), motivation (β=.229,$p<$ .001, f^2=.099, small effect size), and Attitude toward CALL (β=.175,$p<$ .001, f^2=.059, small effect size). This implies that every unit increase in university students' Language Mindset complements a .455, .229, and .175 increase in their L2 Grit, Motivation, and Attitude toward CALL, respectively.

Moreover, L2 Grit was found to have also predicted Motivation (β=.471,$p<$ .001, f^2=.269, medium effect size) and Attitude toward CALL (β=.163,$p<$ .001, f^2=.061, small effect size). This suggests that in every unit, an increase in the university students' L2 Grit corresponds to a .471 and .163 increase in their Motivation and Attitude toward CALL, respectively. Furthermore, motivation predicted Attitude toward CALL (β=.226,$p<$ .001, f^2=.087, small effect size). This can be inferred as every unit increase in the university students' motivation results in a .226 increase in their Attitude toward CALL.

Table 5. Estimate of Beta Weights in the Best Fit Model

Hypothesis	Path Coefficient (β)	SE.	P-value	Effect Size (f^2)	Remark
H1: LM → L2G	0.455	0.049	<0.001	0.207	H1 is supported
H2: LM → M	0.229	0.050	<0.001	0.099	H2 is supported
H3: LM → ACALL	0.175	0.051	<0.001	0.059	H3 is supported
H4: L2G→ M	0.471	0.048	<0.001	0.269	H4 is supported
H5: L2G→ ACALL	0.163	0.051	<0.001	0.061	H5 is supported
H6: M→ ACALL	0.226	0.050	<0.001	0.087	H6 is supported

Effect size: f^2 =.02 (Small); f^2=.15 (Medium); f^2=.35 (Large) (Cohen, 1988).

Dweck's (1999) Mindsets Theory provides a theoretical framework for comprehending fundamental beliefs or mental states. The fixed mindset is the belief that an individual's intellect level is fixed and unchangeable. In contrast, the growth mindset is the belief that intelligence is malleable and can be improved through consistent and deliberate effort. Based on the model, the language mindset was a significant predictor of university students' attitudes toward computer-assisted language learning. This finding is consistent with the hypothesis advanced by Zarrinabadi et al. (2022), who argued that a growth mindset is associated with a favorable attitude toward CALL, whereas a fixed mindset is associated with aversion to CALL.

In addition, the results revealed that second language grit predicted attitudes toward CALL. This result is consistent with the findings of Aparicio et al. (2017), who discovered that grit positively affected individuals' satisfaction with e-learning experiences and their perceptions of the quality of such experiences.

Tafazoli et al. (2018) asserted that the affective component of the multi-component model of attitude refers to an individual's emotional sentiments and emotions toward an object of attitude. In accordance with this, the findings of this study corroborate the hypothesis proposed by Zarrinabadi et al. (2022), who hypothesized that effort persistence is a reliable predictor of both the perceived value of CALL and the influence of teachers on CALL. Moreover, Zarrinabadi et al. (2022) hypothesized that the persistence of interest predicts the extent of exposure to CALL. This could be attributed to the fact that individuals who consistently study a second language value computer-assisted activities to enhance their language skills.

As defined by Tafazoli et al. (2018), attitude refers to an individual's expression of favor or disfavor toward something or someone. The structural model employed in this study revealed that motivation significantly predicts individuals' attitudes toward CALL. This finding is consistent with prior research demonstrating a positive link between higher motivation and a preference for using CALL, as well as a positive attitude toward CALL. Pinner (2012) reported that individuals with greater motivation tend to prefer CALL, and Nasri and Sepehri (2021) corroborated this finding by demonstrating a correlation between motivation and a positive attitude toward CALL.

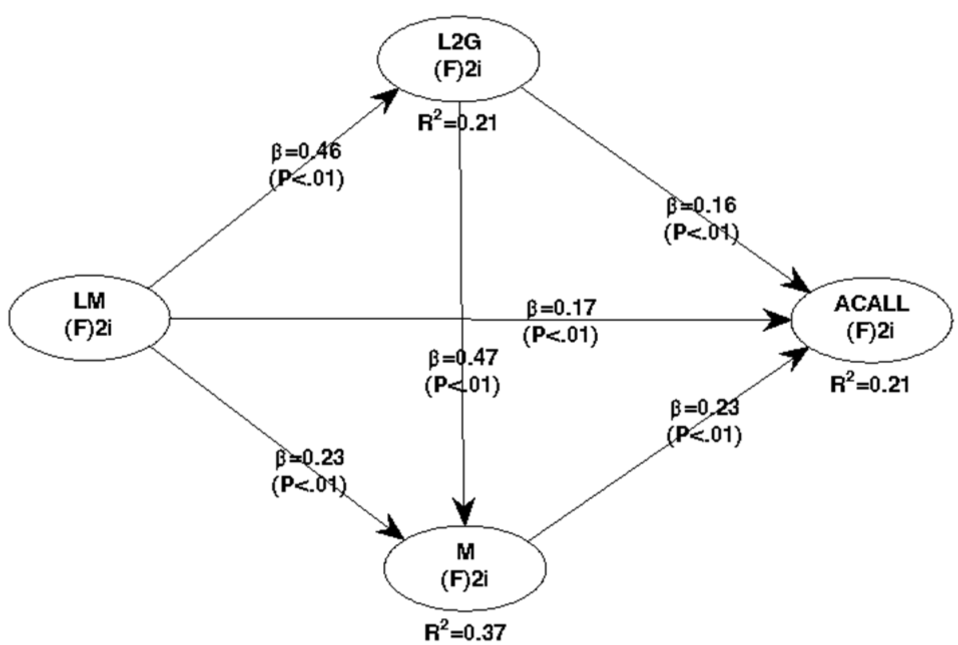
Moreover, this study revealed that Language Mindset predicted L2 Grit. This finding is consistent with previous research of Dweck and Leggett (1986), indicating that growth-minded individuals believe that attributes can be developed through effort and hard work. Dweck et al. (2014) found that students with a growth mindset regarding intelligence demonstrate greater academic grit. In addition, the findings of this study are consistent with the previous empirical studies of Ingebrigtsen (2018), Teimouri et al. (2020), and West et al. (2016), who reported a positive effect of a growth mindset on overall grit.

Language mindset was also found to have a significant influence on motivation. This finding is consistent with the mindsets theory proposed by Dweck (2014) and the Language-Mindset Meaning System (LMMS) framework developed by Lou and Noels (2020), which both emphasize the significance of the effect of mindset on motivation. Additionally, prior research has demonstrated the influence of mindset on numerous motivation-related psychological constructs. Specifically, Waller and Papi (2017) discovered that mindset substantially predicts writing motivation.

This study also uncovered that L2 Grit significantly predicted university students' motivation. This discovery is consistent with the findings of Teimouri et al. (2022), who also discovered a positive effect of students' L2 grit and domain-general grit on motivation levels and language learning performance. According to Ryan and Deci (2000), grit entails the time and effort students devote to academic development as well as their intrinsic motivation. The findings of Duckworth et al. (2007) demonstrate a correlation between grit, perseverance, and achievement, indicating that students with higher levels of grit tend to demonstrate greater motivation, determination, and efficacy in school contexts.

In addition, Gyamfi and Lai's (2020) study highlighted the influence of grit, resilience, and self-efficacy on motivation. Together, these psychological factors influence students' motivation levels, highlighting the significance of cultivating grit to boost motivation in educational settings. Moreover, Changlek and Palanukulwong (2015) postulated a positive influence of grit on motivation, which is consistent with the findings of this study. The link between these two constructs suggests that individuals with higher levels of grit are more likely to manifest increased goal-directed motivation. These findings highlight the significance of cultivating grit as a key trait in language education to improve students' motivation and language learning outcomes.

Figure 1. Best Fit Structural Model



RECOMMENDATIONS

In light of the findings of the study, the following are hereby recommended:

1. Given that the mean scores for attitude toward computer-assisted language learning were moderate, it is suggested that university students be made aware of the advantages and potential of CALL. Targeted interventions such as training programs, awareness campaigns, and seminars & workshops may be provided by universities to enhance students' understanding, appreciation, and utilization of technology in language learning. Additionally, language teachers should consider maximizing the use of computers and optimizing technology in language classes. This will increase students' exposure to CALL and enhance their attitudes toward it. By effectively integrating technology into language instruction, teachers can cultivate positive attitudes and encourage students to embrace and use CALL throughout their learning journey.
2. Language mindset, second language grit, and motivation were found to influence attitudes toward computer-assisted language learning substantially; therefore, it is essential to develop language pedagogical strategies to foster these factors. This may entail incorporating activities that promote a growth mindset, grit, and intrinsic motivation into language learning contexts. Providing students with interactive and engaging learning experiences, incorporating real-world applications and individualized feedback, can also boost their motivation and perseverance. In addition, strategies such as promoting self-reflection, goal-setting, and providing feedback and support can aid in cultivating a positive language mindset and enhancing students' perseverance in their language learning journeys.
3. The best-fit structural model of attitude toward computer-assisted language learning that lies within acceptable and ideal ranges can serve as a foundation for future research. It is recommended to continue refining the model by investigating additional variables and relationships that may significantly affect attitudes toward CALL. Extending the research to other regions or populations will also contribute to a deeper understanding of the factors that influence attitudes toward computer-assisted language learning.
4. Future researchers who may have a shared interest in investigating factors influencing attitudes toward CALL may continue the study by employing other research methodologies such as but not limited to mixed-methods approaches, exploratory structural equation modeling, systematic reviews, and meta-analyses.

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The author reports that there are no competing interests to declare.

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