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Research Article

A Method of Improving Oral English Teaching Based on PLS-SEM

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To improve the quality of oral English teaching, we must first analyze the factors that affect teaching. Second, it examines the relationship between these factors in order to aid the teaching staff's oral English instruction and improve the learners' oral English pronunciation. As a result, determining how to analyze the relationship between various factors in the process of oral English teaching is a problem that is still being worked on. In response to this issue, this paper proposes a partial least squares-structural equation modeling (PLS-SEM) method for improving oral English teaching. The central idea of this method is to first analyze and summarize all relevant factors affecting oral English teaching as thoroughly as possible. Second, the influencing factors are quantified into specific numerical data, and the data are subjected to a series of preprocessing steps. Third, the PLS-SEM model is trained, and the preprocessed data are fed into the statistical analysis. Finally, the relationship between the factors is summarized based on the statistical analysis results. This paper evaluates the PLS-SEM model in terms of reliability and validity in order to validate the effectiveness of the method used. The PLS-SEM model developed in this paper for improving oral English teaching has high reliability, validity, and explanatory power. This method-based oral English teaching strategy can improve students' oral English levels and has a high practical application value.

1. Introduction

As the importance of English grows, so does the investment of individuals, schools, and governments in English learning. However, students' English listening, speaking, reading, and writing abilities are not uniformly improved, and there is a significant gap in their abilities, particularly their generally low listening and speaking abilities. From a geographical standpoint, students in the central and western regions have generally poor English skills. The following are the primary reasons. The first is that the teaching mode is lagging, and students are deprived of opportunities to exercise. The teacher imparts knowledge in the form of lectures throughout the course of the class in the teacher-based teaching mode. In this mode, students can only passively accept the teacher's information, and rarely can speak, so they cannot improve their speaking ability. Second, there is a lack of a conducive environment for practicing oral English. Most schools do not have adequate oral language training facilities, and there are few organizations dedicated to oral English practice. Even if there are counterpart organizations, there is no effective mechanism in place to promote their growth. In the current oral practice environment, if someone uses English to have a conversation in a public place, the people around them will perceive it as bragging. Third, oral language is unappreciated. Currently, many colleges and universities do not have strict requirements for oral English, resulting in students paying insufficient attention to it. CET-4, for example, is included as one of the requirements for college graduation, which greatly increases students' motivation to study English. Graduation and employment are unaffected by the lack of a speaking certificate. As a result, students generally do not pay attention in public speaking classes. Fourth, there is a significant disparity in the teaching level of English teachers and the teaching staff of schools across the country, resulting in uneven English teaching levels. In response to the issues, current English instruction has shifted from the study of vocabulary and grammar, with a focus on the development of reading and writing skills, to the development of oral language and communication skills. Simultaneously, the state has gradually increased the provision of teacher training in underdeveloped schools, but it will take a long time to improve both the hardware environment and the level of teachers.

Reading, writing, listening, and speaking are the main teaching contents of English, as one of the tools of human communication. The goal is to improve students' listening, speaking, reading, and writing skills. According to linguist statistics from the United States, the proportions of listening, speaking, reading, and writing in language communication activities are as follows: listening 45 percent, speaking 30 percent, reading 16 percent, and writing 9 percent. As can be seen, speaking is crucial in language learning. However, in today's English class, teachers spend most of the time teaching, and students are mostly allowed to write or read on their own after class, leaving students with little time and opportunity to communicate in English. This type of teaching normalcy has resulted in the current situation of Chinese students speaking poor English. Students find it difficult to communicate with foreigners daily despite years of English study in elementary, junior high, high school, and university. Most students can only communicate in a few simple words and are unable to communicate smoothly and completely. As can be seen, oral language has always been a weak link in my country's English learning. The current situation of this type of English teaching cannot meet the needs of my country's economic and social development, and there is a significant gap with the requirements of the times. People have become increasingly interested in learning oral language as educational concepts and modern information technologies have advanced. The development of English-speaking ability necessitates a positive oral communication environment in order to effectively improve students' English levels. Through the integration of teaching content and information technology in English learning, teaching methods will change, displaying new characteristics, making students' learning more interesting and vivid, and the teaching effect will be more obvious.

English teachers should understand the characteristics of oral English learning and focus on cultivating and maintaining students' interest in learning. It is also one of the new curriculum standard's basic requirements to mobilize students' enthusiasm for learning and make them happy and willing to learn. Many computer-aided products have been developed to improve the quality of oral English teaching [1–3]. These products primarily employ artificial intelligence [4, 5], pattern recognition [6, 7], and other related technologies to recognize oral pronunciation and determine whether it is correct. To some extent, timely error detection and correction can aid in the learning of oral language. However, by analyzing the most appropriate pronunciation teaching method for their own situation at the start of learning, people can avoid some mistakes in the process of oral pronunciation learning. To find a way to improve oral English teaching, first examine the factors that influence oral English teaching. Second, by analyzing the relationship between these factors, the teaching staff will be able to assist students in improving their oral English pronunciation. PLS-SEM is a statistical analysis method that can examine the relationship between multiple variables. PLS-SEM [8, 9] performs better when dealing with nonnormal data and small sample problems, and this modeling method has been used in an increasing number of studies in recent years [10, 11]. In terms of theoretical research, some scholars have compared and analyzed household stability using the CB-SEM method based on covariance and the PLS-SEM method based on variance. The experimental results show that PLS-SEM is better suited for data with a low normal distribution [12]. PLS-SEM is widely used in practical applications such as customer satisfaction, strategic management, marketing, and MIS [13–15]. As a result, this paper proposes a PLS-SEM-based method for improving oral English teaching. This method's central concept is as follows: first, analyze and summarize all relevant factors affecting oral English teaching as thoroughly as possible. Second, the influencing factors are quantified into specific numerical data, and the data are subjected to a series of preprocessing steps. Third, the PLS-SEM model is trained and the preprocessed data are fed into the statistical analysis. Finally, the relationship between the factors is summarized based on the statistical analysis results.

2. PLS-SEM

Because of the widespread use of the structural equation modeling (SEM) method in scientific research, market research, customer satisfaction, and other fields, people began to pay attention to the specific SEM implementation method. AMOS, SmartPLS, LISREL, and other commonly used implementation software are currently in use. However, each software will be unique. Because it is difficult to collect more than 200 samples in some studies, particularly management studies, and because the model estimated using the maximum likelihood method is unstable when the sample size is small, researchers developed the partial least squares method (PLS) to estimate the SEM model for small samples. As a result, the primary distinction between LISREL, AMOS, and PLS is one of the algorithms. LISREL or AMOS can be used when the study sample is relatively large. PLS should be used when the research sample is small, less than 200, or even less than 100. A complete SEM model consists of a measurement model and a structural model [16]. The measurement model represents the relationship between the measurement variable and its associated latent variable, while the structural model represents the relationship between the latent variables. This is where SEM has an advantage over traditional statistical analysis. The SEM model is shown in Figure 1.

In general, structural equation modeling [17] entails the following steps, specifically as shown in Figure 2.

The first is the model configuration. Using a path diagram, describe the model to be built, the relationship between latent variables and measured variables, and the relationship between latent variables. Second, there is model fitting. This stage is primarily concerned with attempting to obtain the model's solution, that is, the estimated value of each model parameter. The third step is to evaluate the model. Each evaluation index tested the model's and data's fitting degree, as well as the model's reliability and validity. Finally, there is a model correction. The model's path is

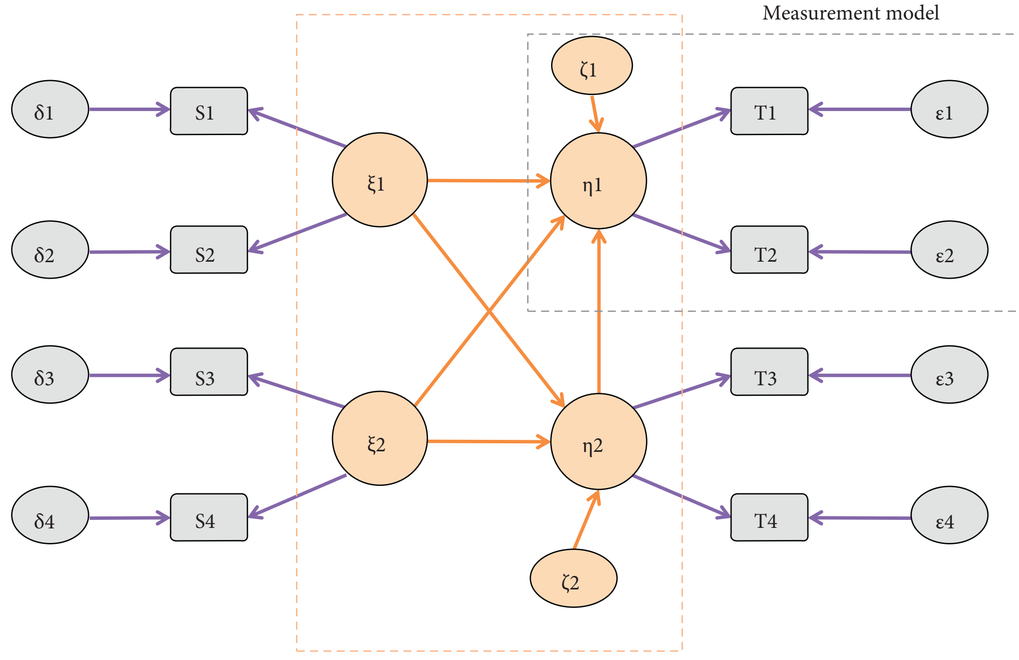

Figure 1: SEM model.

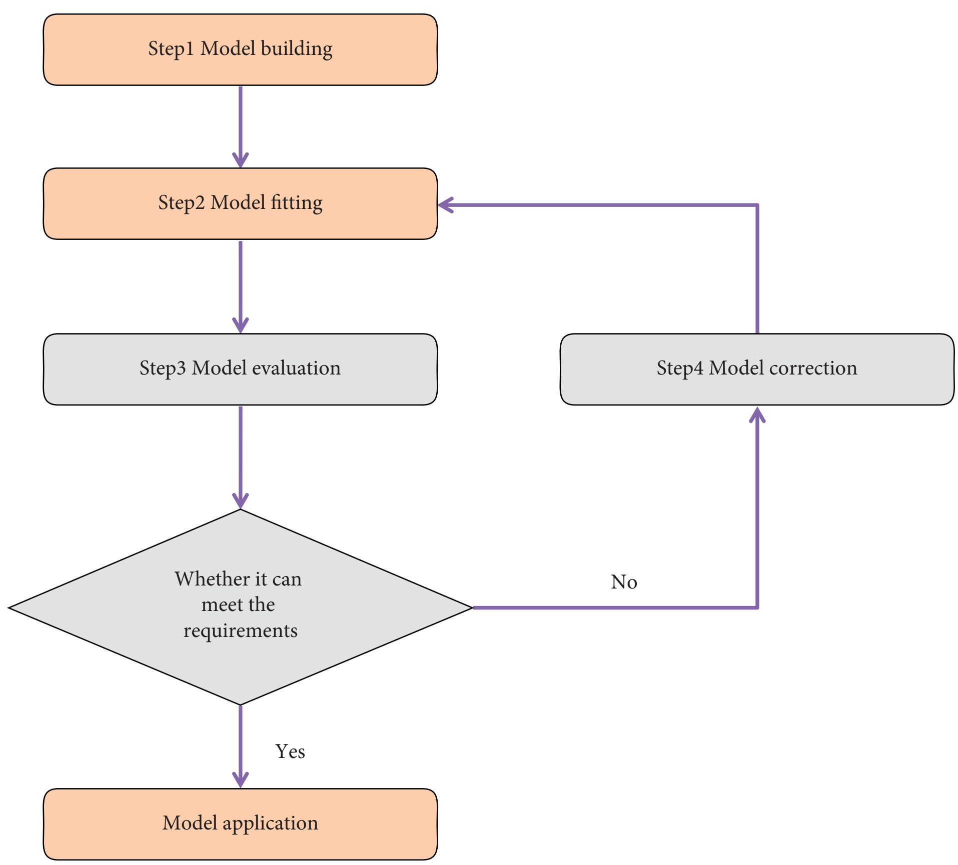

Figure 2: Schematic diagram of SEM modeling process.

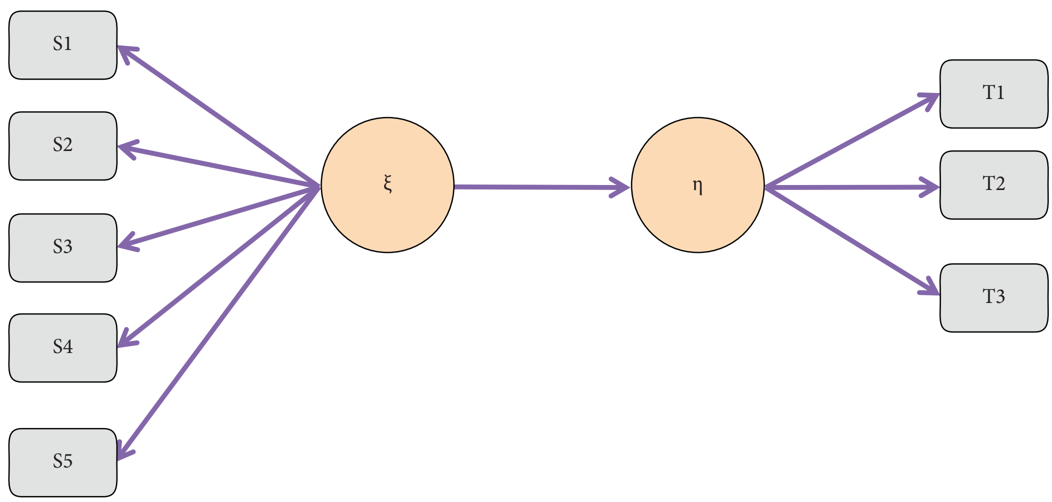

Figure 3: Structural equation model of two latent variables.

adjusted using evaluation metrics. After the model has been corrected, the cycle is repeated until the model meets the requirements.

PLS-SEM is primarily used to investigate the relationship between several variables. Two latent variables are described as examples to demonstrate its working principle. The fundamental principle of PLS is as follows: the information from each group of observation variables is assumed to be transmitted via latent variables, and the estimated values of the latent variables are all centered. The model's correlations are all set to be linear. Assume the structural equation model of the two latent variable models is depicted in the figure below, with the latent variable having 5 observed variables and the latent variable having 3 observed variables. This is a representation of the two latent variables' structural equation model in Figure 3.

Conditional probability is the causality principle in statistics. If the probability of event s_i determines the probability of event t_j, the conditional probability is as follows:

Its expected form can be expressed as

$$P\{T = t_j | S = s_i\}, \tag{1}$$

$$E\{T = t_j | S = s_i\}. \tag{2}$$

Conditional expectations can represent the causal relationship between events S and T. Polynomials of any degree can be used to approximate the computation of conditional expectations. The expression is as follows:

$$E\{T|S\} = \alpha_0 + \alpha_1 s + \alpha_2 s + \cdots \approx \alpha_0 + \alpha_1 s. \tag{3}$$

When $S = s$,

$$t|_{S=s} = E\{T|S\} = \alpha_0 + \alpha_1 s + \alpha_2 s + \delta, \tag{4}$$

where α_0 and α_1 are polynomial coefficients and δ is a residual term. The preceding model can be expressed as follows:

$$\begin{aligned} s_i &= \alpha_{i0} + \alpha_i \xi + \delta_i, \\ t_m &= \alpha_{m0} + \alpha_m \eta + \delta_m, \end{aligned} \tag{5}$$

where α_{i0} and α_{m0} are the intercepts, α_i and α_m are the load factors, and δ_i and δ_m are the residuals. To overcome the uncertainty caused by variable dimensions, consider the following:

$$\begin{aligned} E(\xi) &= 0, \\ E(\eta) &= 0, \\ \operatorname{Var}(\xi) &= 1, \\ \operatorname{Var}(\eta) &= 1. \end{aligned} \tag{6}$$

They satisfy the relationship:

$$\begin{aligned} E\{s_i|\xi\} &= \alpha_{i0} + \alpha_i \xi, \\ E\{t_m|\eta\} &= \alpha_{m0} + \alpha_m \eta, \\ r(\xi, \delta_i) &= r(\eta, \delta_m) \\ &= r(\xi, \delta_m) \\ &= r(\eta, \delta_i) \\ &= r(\delta_m, \delta_i) \\ &= 0. \end{aligned} \tag{7}$$

The structural model can be represented as follows:

$$\eta = \beta_0 + \beta_1 \xi + \varepsilon, \tag{8}$$

where β_0 is the intercept, β_1 is the path coefficient, and ε is the residual term.

$$\begin{aligned} E\{\eta|\xi\} &= \beta_0 + \beta_1 \xi, \\ r(\xi, \varepsilon) &= 0. \end{aligned} \tag{9}$$

Assume the sample size is N, and the sample observations for indicators x_i and t_j are x_{in} and t_{jn}, respectively. Because the two measurement models discussed above are both reflective, the weight relationship between and is as follows:

$$\begin{aligned} \tilde{\xi} &= \sum_m (w_m t_{mn}) + \delta_{mn}, \\ \tilde{\eta} &= \sum_i (w_i s_{in}) + \delta_{in}, \end{aligned} \tag{10}$$

where w_i and w_m represent the weights and δ_{mn} and δ_{jkn} represent the residuals.

The PLS algorithm's execution steps are as follows:

(1) Calculate the estimated value of the latent variable iteratively. The weighted sum of the latent variable's measurement indicators is the estimated value of the latent variable in each sample in PLS, and the expression is as follows:

$$\tilde{\xi} = f_1 \sum_i (w_i s_{in}), \tag{11}$$

$$\tilde{\eta} = f_2 \sum_m (w_m t_{mn}), \tag{12}$$

where z_1 and z_2 are normalization operators whose expressions are

$$z_1 = \pm \left\{ \frac{1}{N} \sum_n \left[\sum_i (w_i x_{\text{in}}) \right]^2 \right\}^{1/2}, \tag{13}$$

$$z_2 = \pm \left\{ \frac{1}{N} \sum_n \left[\sum_m (w_m y_{mn}) \right]^2 \right\}^{1/2}. \tag{14}$$

The estimated values of the latent variables are obtained using equations (11)–(14). The following is the specific implementation process for obtaining the estimated value of the latent variable Algorithm 1.

(2) The latent variable estimates are used to estimate the normalized load and path coefficients of the measurement model and the structural model. Regress the measurement variables using $\tilde{\xi}$ and $\tilde{\eta}$ from (1), and the load coefficients and residuals for each measurement variable are as follows:

$$\begin{aligned} s_{in} &= p_{in}\tilde{\xi} + \mu_{in}, \\ t_{mn} &= p_{mn}\tilde{\eta} + \mu_{mn}, \end{aligned} \tag{15}$$

where p_{in} and p_{mn} denote load factors and μ_{in} and μ_{mn} denote residual terms. According to the formula of the resulting model, the path coefficients and residuals of the latent variables can be obtained:

$$\tilde{\eta} = \beta_0 + \beta_1 \tilde{\xi} + \varepsilon. \tag{16}$$

(3) Using the original data, calculate the model's unstandardized load coefficient and unstandardized path coefficient.

$$\begin{aligned} \overline{\xi} &= f_1 \sum_i (w_i \overline{x}_i), \\ \overline{\eta} &= f_2 \sum_m (w_m \overline{y}_m). \end{aligned} \tag{17}$$

(4) Other parameters in the structural equation can be estimated using the estimated value of latent variables and ordinary least squares regression. Each parameter estimate of the model can be obtained using (1)–(4).

The situation of multiple latent variables becomes clear once the model principle of two latent variables is clarified. Assuming G $(G > 1)$ latent variables exist and the measurement index corresponding to each latent variable is S_{gk}, where k represents the kth measurement index, the measurement model can be expressed as follows:

$$s_{gk} = \alpha_{gk0} + \alpha_{gk}\xi_g + \delta_{gk}, \tag{18}$$

where α_{gk0} and α_{gm0} are intercepts, α_{gk} and α_{gm} are load factors, and δ_{gk} and δ_{gm} are residuals and satisfy the following:

$$\begin{aligned} &E\{s_{gk}|\xi\} = \alpha_{gk0} + \alpha_{gk}\xi_g, \\ &\text{s.t. } r(\xi_g, \delta_{gk}) = r(\xi_i, \delta_{gk}) = r(\xi_g, \xi_i) = r(\delta_{gk}, \delta_{ik}) = 0, \quad i \neq g. \end{aligned} \tag{19}$$

The structural equation is as follows:

$$\xi_i = \beta_{i0} + \sum_{g<i} (\beta_{ig}\xi_g) + \varepsilon_i, \quad i = 1, 2, \ldots, G. \tag{20}$$

and satisfy the following:

$$\begin{aligned} &E(\xi_g|\xi_1, \ldots, \xi_{g-1}) = \beta_{g0} + \sum_{g<i} (\beta_{gi}\xi_i), \\ &\text{s.t. } r(\xi_g, \varepsilon_i) = 0, \quad i < g,\ g = 1, 2, \ldots, G. \end{aligned} \tag{21}$$

As can be seen from the above, the measurement model for multiple latent variables is similar to the representation of two latent variables. But the weight relationship of multiple latent variables is more complicated. In the PLS iteration of multiple latent variables, the estimated value of the latent variable itself is not used, but the signed weighted sum of the latent variable is used, denoted by A_g.

$$A_g = \sum_m (Sg_{gm} Es_m), \tag{22}$$

where Es_m is the estimated value of the latent variable ξ_m located adjacent to latent variable ξ_j and Sg_{gm} is the signed correlation coefficient between ξ_m and ξ_g.

$$\begin{aligned} &\xi_m = Es_m = f_g \sum\nolimits_k (w_{gk} x_{gkn}), \\ &f_g = \pm \left\{ \frac{1}{N} \sum_k \left[\sum_k (w_{gk} x_{gkn}) \right]^2 \right\}^{1/2}, \\ &Sg_{gm} = r(\xi_g, \xi_m). \end{aligned} \tag{23}$$

The above formula is used to compute the estimated value of each latent variable. Regression is used to derive each model parameter from the estimated value of the latent variables and the matching measurement index variables. The calculating procedure can be divided into two parts for the execution of latent variables.

3. Model Training

This article presents the overall foundation for developing an oral English analysis model based on the current state of oral

Input: Strategy indicators s_{in} and t_{in}
Output: Estimated value of latent variable
Initialization: When $m = m_0$, $w_m^{(1)} = 1$, otherwise $w_m^{(1)} = 0$
  Step 1: $w_m^{(1)}$ is used to obtain $z_2^{(2)}$ and $\tilde{\eta}^{(2)}$
  Step 2: $w_i^{(2)}$ is obtained through multiple regression.
  Step 3: $w_i^{(2)}$ is used to obtain $z_1^{(2)}$ and $\tilde{\xi}^{(2)}$
  Step 4: $w_m^{(2)}$ is obtained through multiple regression.
  Steps 1–4 should be repeated in a loop until the iteration accuracy is met.

Algorithm 1: Obtaining latent variable estimates.

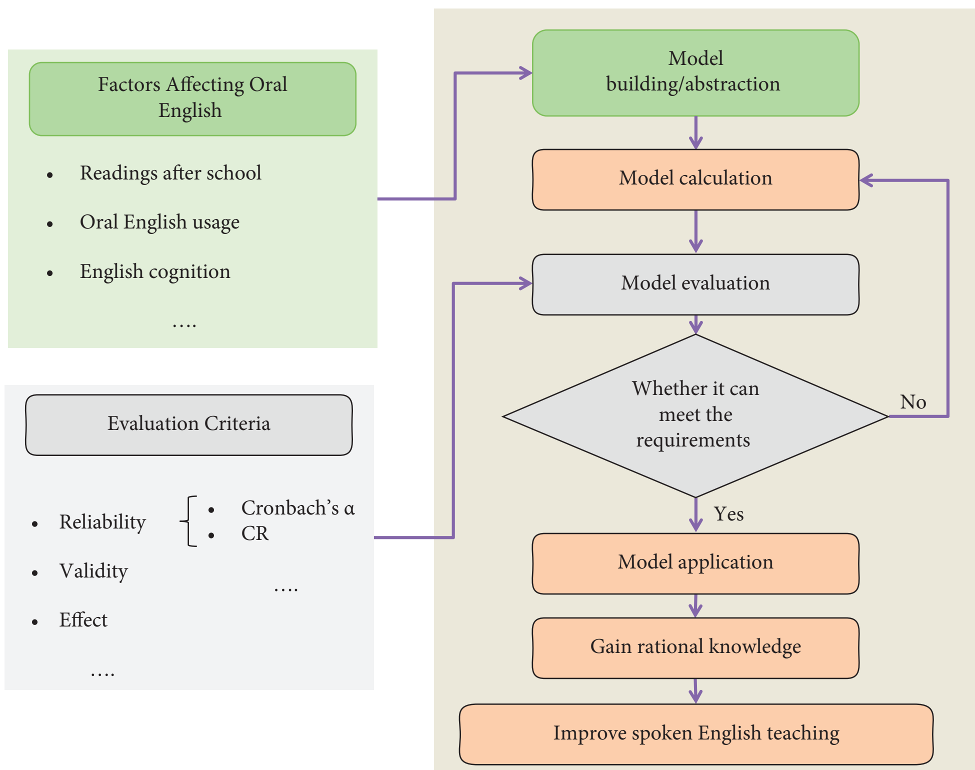

Figure 4: Analysis framework of oral English based on PLS-SEM.

English learning. This framework is ubiquitous, and it may also be applied to the oral language learning of other languages, provided that the model composition is adjusted to the specific scenario, as illustrated in Figure 4.

The following is the precise meaning of the entire modeling framework:

Abstraction of data from models: complete the abstract description of the oral English analysis model starting with a specific course, taking into account the amount of extracurricular reading, daily oral English usage, current English level, English knowledge, and class satisfaction. This abstract procedure necessitates an awareness of the oral English knowledge system and a general grasp of the degree of oral English assessment in order for the abstract model to be reasonable.

Composition of an abstract model: the abstract model is composed of two components. A portion of it is due to the elements that influence or define oral English. The elements that are currently being considered in this paper include the amount of extracurricular reading, daily oral English usage, current English level, English knowledge, and class satisfaction. Additionally, it can be expanded to fit the circumstances. Additionally, there is an evaluation factor.

Model calculation: after creating a new model, we must feed it actual data and attempt to solve the model, specifically, the model's parameters, that is, the factors indicated previously that affect oral English. The algorithm for calculating the model varies according to the modeling method used. The PLS-SEM model is used in this article.

Model evaluation: when reviewing a newly constructed model, it is vital to determine whether the model's solution is adequate. Including whether the model's iteration converges and whether the model's estimated parameter values are consistent with reality. Within a suitable range, it is also required to assess the consistency of the relationship between the elements and the model's relationship. Simultaneously, it is vital to be vigilant for model overfitting in order to avoid the model fitting well to known data but performing poorly when predicting unknown data. Model evaluation is a time-consuming process that should be reviewed model by model.

Model correction: the purpose of revising the model is to alter the number of elements and their relationships in light of the model evaluation results. Gradually tweak the regions that require adjustment first and then analyze the model and make any corrections based on the results. The model revision process is iterative, and the amended model evolves into a new theoretical model. Repeat the abstract model composition, model computation, and model evaluation procedures to obtain a complete model.

4. Experiment

4.1. Experimental Data. This study examines English majors at a university from 2016 to 2018. The purpose of this paper is to examine the elements that influence the acquisition of oral English pronunciation through a questionnaire survey. Throughout the experiment, 500 questionnaires were sent and 465 were recovered, resulting in a 93 percent recovery rate. There are 460 valid questionnaires in circulation, with an effective rate of 98.92 percent. 300 questionnaires are randomly chosen from the 460 total as training samples for the teaching analysis model, and the remaining 160 data are utilized to evaluate the model. The questionnaire developed in this article contains a total of 12 items over five dimensions, including extracurricular reading, everyday oral English usage, current English level, English knowledge, and class satisfaction as shown in Table 1.

Extracurricular reading can assist the user in producing correct sentence patterns in oral English and can help enhance speech fluency. Students who frequently watch English-language television programs or listen to English music will not have a problem with their English listening abilities. If their listening skill improves, it is inevitable that their speaking ability will improve as well. This study splits the English reading volume into annual volumes of English original books and annual volumes of English television programs. The amount of reading outside of class also has an effect on students' satisfaction with the class. Establish the model path as follows: extracurricular reading volume ⟶ class satisfaction.

The cognitive environment of English learning reflects the students' enthusiasm to study this subject. According to expectation value theory, References [18, 19] believe that students' perceptions of the importance or utility of a course will influence their level of engagement with learning. According to Reference [20], in a study on undergraduates' learning techniques and effects, the students' subjective impression of the subject's relevance affects their learning behavior, which in turn affects their learning effect. Additionally, numerous academics' relevant teaching research has demonstrated that courses with a high perceived value and relevance to future goals affect students' behavioral intention to learn positively [21]. As a result, this article splits English cognition into two dimensions: interest and utility. Simultaneously, three model routes are established: English cognitive situation ⟶ extracurricular reading volume, English cognitive situation ⟶daily oral English usage, and English cognitive situation ⟶ class satisfaction.

The extent to which oral English is used is primarily determined by two factors: oral practice time and oral practice strategy. In the 1980s, Reference [22] introduced the hypothesis that students' learning styles and practices can have a significant impact on learning results. According to References [23, 24], students' learning styles and practices have an effect on their academic achievement. Thus, the duration of students' oral practice time and the number of modalities in which they practice oral language directly represent the students' oral language learning. Determine the following path based on the analysis above: English usage in conversation ⟶ present English level.

The learning effect is measured using the present English level and Reference [25] taxonomy of learning levels. In general, students' present English proficiency is classified as CET, IELTS, or TOEFL. Different levels can be used to approximate a student's English-speaking competence. Given that students' existing English proficiency has an effect on their happiness with the class, the path is set: Current English Level ⟶ Level of Satisfaction in the Class.

The term "class satisfaction" refers to the philosophy of customer satisfaction [26]. Satisfaction evaluation from the student's perspective: the disparity between students' subjective perceptions of educational quality prior to and following oral English instruction reflects their satisfaction with class instruction in oral English. On this basis, the satisfaction with teaching topic, teaching manner, and instructor level are formulated to reflect class satisfaction.

To summarize, a model for analyzing oral English instruction is created using five latent variables. Figure 5 depicts the association between the factors. The comprehensive teaching effect is evident in the student's current English proficiency and teacher satisfaction. The amount of extracurricular reading, the frequency of everyday oral English use, and the students' English cognition all influence the quality of oral English. Specifically, the volume of reading and the frequency of use are impacted. The cognitive context has an indirect effect on knowledge mastery. Course satisfaction is influenced by student acceptance of the course material, teacher satisfaction with the teaching approach, and teacher level, where course satisfaction is directly related to content acceptance and teaching mode satisfaction. The teacher's level has an indirect effect on student satisfaction with the course.

4.2. Experiment Evaluation Index. Table 2 displays the selected model evaluation indicators for verifying the effectiveness of the trained PLS-SEM model.

Table 1: Variable description.

Latent variable	Observed variable
Extracurricular reading volume (S1)	Annual reading volume of English original works (S11) Annual viewing volume of English programs (S12)
Cognitive situation of English learning (S2)	Interest degree (S21) Instrumentality (S22)
Daily oral English usage (S3)	Oral practice time (S31) Number of ways of speaking practice (S32)
Current English level (S4)	CET (S41) IELTS (S42) TOEFL (S43)
Class teaching satisfaction (S5)	Acceptance of course content (S51) Satisfaction with teaching mode (S52) Teacher level grade (S53)

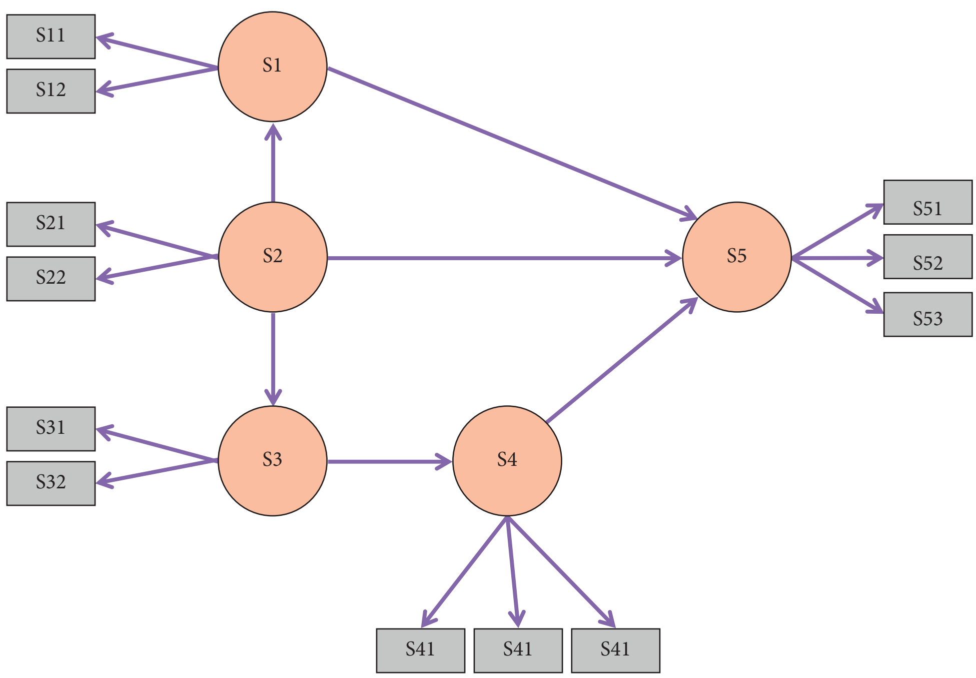

Figure 5: Relationship between variables.

Table 2: Evaluation indicators.

First-level indicator	Secondary indicators	Details
Reliability	Cronbach's α Composite reliability (CR)	Cronbach's α >0.7 CR > 0.7
Validity	Convergent validity [27]	Convergent validity is characterized by average variance extracted (AVE) and factor loadings. It is required that AVE >0.5, factor loading>0.7.
	Discriminant validity [27]	Discriminant validity is indicated by the correlation coefficient between the square root of AVE and latent variables. The model has excellent discriminant validity when the AVE square root value exceeds the latent variable minus the correlation coefficient between latent variables.
Effect	Fit [28]	Reflected by goodness of fit (GOF), when GOF >0.36, the overall fit of the model is considered to be better.
	Explanatory [28]	Characterized by R^2, it is generally required that all latent variables have an R^2 value greater than 0.2.
	Predictive [29]	Redundancy is used to quantify the predictive potential of variables' internal and external linkages. In general, the redundancy value must be more than 0.33, and the inspection level must be greater than 0.052.

Table 3: Fitting of the model.

Extracurricular reading volume (S1)	S1	S2	S3	S4	S5	R^2	Cronbach's α	CR	AVE	Redundancy
Cognitive situation of English learning (S2)	0.825	0.667	0.723	0.609	0.712	0.232	0.753	0.853	0.681	0.320
Daily oral English usage (S3)	0.667	0.773	0.769	0.736	0.562	0.228	0.712	0.836	0.598	0.362
Current English level (S4)	0.723	0.769	0.802	0.635	0.523	0.425	0.760	0.812	0.643	0.413
Class teaching satisfaction (S5)	0.609	0.706	0.635	0.725	0.635	0.605	0.882	0.842	0.526	0.452
Extracurricular reading volume (S1)	0.712	0.562	0.523	0.635	0.912	0.237	0.812	0.867	0.832	0.379

4.3. Experimental Results. Tables 3 and 4 exhibit the questionnaire's reliability, validity, and model evaluation results. The GOF was 0.507 during the experiment.

The questionnaire set's total Cronbach's α value was 0.869, and the split-half reliability was 0.711. Cronbach's α for each latent variable is greater than 0.7, and the overall reliability is greater than 0.8, indicating that the data are very reliable. Cronbach's α and reliability values for the model built this time were both above the 0.70 minimal criterion, indicating that the model is very reliable [30]. The model's GOF value is 0.507, indicating that the model's overall fit is satisfactory. Each latent variable has an R^2 value greater than 0.2. Latent variable path coefficients, latent variable external weights, and external factor loads are all statistically significant, according to the bootstrapping approach used in this study. This demonstrates the model's explanatory capacity and establishes the causal relationship between variables. Each latent variable in Table 3 has an AVE greater than 0.5, indicating that it has good convergent validity. All latent variables have correlation coefficients less than the square root of AVE, indicating that the model has strong discriminant validity [31].

Reference [27] proposes that factor loadings should be no less than 0.70. References [32, 33] believe that the minimum acceptable value of factor loading is 0.4. Reference [34] argues that greater than 0.30 can be considered significant when determining the relative importance and significance of each factor loading. Factor loadings above 0.50 were considered very important. The factor loading of the PLS-SEM model constructed in this study is above 0.5, as shown in Table 4. According to the above theory, it can be considered that the model has good convergent validity.

English proficiency level, course satisfaction, and students' oral English level were positively correlated, and the differences were statistically significant. The redundancy value of daily oral English usage (S3) and current English level (S4) is greater than 0.4, which has good predictive ability. However, the redundancy value of extracurricular reading is small, and the predictive ability is slightly weaker. Based on the model's robustness and validity, as well as the findings of the evaluation, the PLS-SEM model suggested in this research can be deemed feasible for improving oral English education. R^2 is a measure of how dependent the latent variable is on the other variables in the model, and it is used to estimate the model's predictive power [35]. According to reference [36], the value of R^2 should not be lower than 0.2. All latent variables studied in this paper have R^2 values above this criterion.

By closely examining the external factor loadings in Table 4, it is clear that first, reading authentic English literature is more important for extracurricular reading. Second, students perceive that instrumentality has a lower weight than interest driven in terms of English learning cognition, which is congruent with the popular view of interest driven. Thirdly, when it comes to oral language usage, the variety of ways to practice is more significant than the amount of time spent practicing, which indicates the value of implementing what you've learned. In comparison to obsessive and utilitarian activities, actively using oral English in a variety of ways can help enhance oral English proficiency. Thus, for instructional purposes, follow-up activity should be enhanced in two critical areas: assisting students in improving their grade of English reading materials and their interest in English learning and use. As seen in Table 4, the external load factor increases with the level of English proficiency evaluation. This demonstrates that elevating students' study objectives can help them improve their oral English.

Table 4: Analysis results of external weights and factor loadings of the model.

	External factor loadings	t value
S11 ≤ S1	0.851	40.714
S12 ≤ S1	0.655	12.176
S21 ≤ S2	0.848	46.463
S22 ≤ S2	0.648	17.499
S31 ≤ S3	0.626	9.829
S32 ≤ S3	0.796	12.554
S41 ≤ S4	0.792	30.802
S42 ≤ S4	0.830	23.664
S43 ≤ S4	0.876	17.583
S51 ≤ S5	0.802	41.541
S52 ≤ S5	0.639	29.263
S53 ≤ S5	0.554	27.486

5. Conclusion

While oral English is critical, the results of its instruction are less than ideal. To help teachers improve their oral English instruction, this study applies the PLS-SEM model to a statistical analysis of the elements that influence oral English and determines the relationship between the numerous components that affect the level of oral English. The techniques for improving oral English education are summarized in light of the experimental findings. This article compares and analyzes the questionnaire's reliability and validity, the model's evaluation results, and other factors. The experimental results validate the PLS-SEM model's effectiveness. While the PLS-SEM model is capable of analyzing the correlations between numerous influencing elements in oral

English education, it does have certain limitations. One is that during the iterative procedure, the parameter estimations do not converge. Nonconvergence is typically caused by the model or the data itself, including the model being too complex, the relationship between parameters being too constrained, the data being in conflict with one another, and the data being of low quality. Additionally, increasing the number of iterations or supplying an initial value does not guarantee that the nonconvergence problem will be resolved. This is also one of the areas that requires additional research in the paper's follow-up. Second, in structural equation analysis, in order to uncover the properties of latent variables and their relationships, a measurement model must be established. In structural equation analysis, validation is used to determine which models are incorrect and should be deleted or rectified. Models that better suit the data can only be considered models. The study of structural equations is based on correlation coefficients, which only indicate linear correlations. Thus, even if the structural equation analysis results indicate that there is no relationship between the two variables, this may be accurate or it may be because the relationship is not linear. Other factors may also effect structural equation modeling in actual analysis work. That is, if this model is ported to different application settings, it will require additional research to determine whether it is suitable.

Data Availability

The labeled data sets used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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