East-West J. of Mathematics: Vol. 25, No 2 (2024) pp. 133-144
https://doi.org/10.36853/ewjm0405

'SECOND DEGREE ENGLISH-MAJOR' AT SAI GON UNIVERSITY: AN ANALYSIS OF RECENT STUDENTS' PERFORMANCE

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Abstract

This study aims to analyze the self-assessment data of students participating in the 'Second-Degree English-Major' (SDEM) program at Sai Gon University (SGU). Using data from a recent survey conducted in October 2023 with a graduating batch of 55 students, this study examines students' perceptions of their improvements in listening, reading, writing, and speaking skills. Data from 37 students (though for some skills it was 38 as well as 39) with complete information were analyzed using the logistic regression model as well as the bootstrap method (to assess the variations in the estimates of the model parameters) to determine whether the level of improvement depended on their background factors (such as - gender, age and the type of job held). The results show no significant impact of background factors on the students' self-assessment, suggesting that improvements were evenly distributed across different student groups (identified by the background factors). The subjective nature of the self-assessment data is recognized as a potential source of bias which needs to be addressed in future studies.

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Keywords: logistic regression model, bootstrap method, self-assessment data, parameter estimation, standard error.
Mathematics Subject Classification (MSC) 2020: 62G09, 62F40, 62E17

1 Introduction

1.1 Background of this study

The 'Second Degree English-Major' (SDEM) program at Sai Gon University (SGU) is pursued by many students to meet their professional requirements and/or improve their English skills. SDEM is a four-semester structured English program designed for existing bachelor's degree holders to enhance their listening, reading, writing, and speaking skills. Upon successful completion, students earn a second bachelor's degree in English.

1.2 The main objectives

This study uses data from a recent survey conducted in October 2023 with a graduating batch of 55 students at SGU to explore their self-assessments of improvements in the aforementioned skills. The goal is to investigate whether the level of improvement depends on their background information, thereby providing insights for program administrators to better support specific student groups.

2 Literature Review

- **Turkey:** Research at Middle East Technical University (METU) (August 2019) on students' self-assessment of English speaking skills showed that students generally rated themselves higher in fluency and pronunciation compared to teacher evaluations. Factors like gender and confidence also influenced self-assessment discrepancies (Frontiers, METU) [5],[6]

- **Thailand:** A study compared teacher assessments with combined teacher-student self-assessments for writing skills. Results indicated that self-assessment significantly enhanced students' writing development, though students tended to overestimate their abilities, likely influenced by confidence levels (SpringerOpen) [7]

- **India:** A study (June 2018) involving management students used Likert scales to assess communication skills, revealing high self-ratings in listening and grammar but challenges with public speaking and vocabulary usage. The research highlighted personal confidence as a key factor in self-assessment outcomes (Semantic Scholar) [8]

- **Vietnam:** At Hue University (June 2024), a study on self-assessment in English writing found that students viewed self-assessment positively, seeing it as a valuable tool for improving idea organization and vocabulary. A mixed-methods approach ensured reliability, suggesting integrating self-assessment practices into writing instruction (Hue University Portal) [9]

3 Materials and Methods

3.1 Description of the self-assessment data

The self-assessment data used in this study were collected through a survey conducted in October 2023, targeting a graduating cohort of 55 students from the SDEM program at SGU. The survey focused on gathering information about the students' perceptions of their progress in four English communication skills: listening, reading, writing, and speaking. Of the 55 invited students, 40 responded, providing self-assessments of their improvement levels in each skill area, rated as 0 (no improvement), 1 (some improvement), or 2 (a lot of improvement). The study analyzed responses from at least 37 students who provided complete information, with a very few responses excluded where students reported no improvement across the skills.

Along with the self-assessment data on their skill development, the survey also collected background information, including age, gender, and job type. The objective of analyzing this data was to investigate existence of any potential relationships between these background factors and the level of improvement reported by the students. To examine these relationships, a logistic regression model was applied, complemented by the bootstrap method to enhance the robustness of the findings. It is important to note that the data reflect students' personal perspectives on their improvement and may contain subjective biases, as the responses were not corroborated by any instructor evaluations.

3.2 A brief review of logistic regression model

We generalize the model to one with more than one independent variable (i.e., the multivariable or multiple logistic regression model). Central to the consideration of the multiple logistic models is estimating the coefficients and testing for their significance.

Consider a collection of p independent random variables denoted by the vector $\boldsymbol{X} =$
$(X_1, X_2, \ldots, X_p)'$. Let the conditional probability that the outcome is present be denoted by $\Pr(Y = 1|\boldsymbol{X}) = \pi(\boldsymbol{X})$. The logit of the multiple logistic regres-

sion model is given by the equation

$$g(\boldsymbol{X}) = \ln\left(\frac{\pi(\boldsymbol{X})}{1-\pi(\boldsymbol{X})}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p,$$

where, for the multiple logistic regression model,

$$\pi(\boldsymbol{X}) = \frac{\exp\{g(\boldsymbol{X})\}}{1+\exp\{g(\boldsymbol{X})\}} \tag{3.1}$$

Assume that we have a sample of n independent observations $(\boldsymbol{X}_j, Y_j), j = 1, 2, \ldots, n$. As in the univariable case, fitting the model requires that we obtain estimates of the vector $\boldsymbol{\beta} = (\beta_0, \beta_1, \ldots, \beta_p)'$. We have used the maximum likelihood method to estimate $\boldsymbol{\beta}$. There will be $(p+1)$ normal equations that are obtained by differentiating the log-likelihood function with respect to the $(p+1)$ coefficients which result into the following system of equations:

$$\sum_{j=1}^{n}[Y_j - \pi(\boldsymbol{X}_j)] = 0, \text{and}$$

$$\sum_{j=1}^{n} X_{ji}[Y_j - \pi(\boldsymbol{X}_j)] = 0 \quad \text{for} \quad i = 1, 2, \ldots, p.$$

The solution of the above normal equations requires software that is available in virtually every statistical software package. Let $\hat{\boldsymbol{\beta}}$ denote the solution to these equations. Thus, the fitted values for the multiple logistic regression model are $\hat{\pi}(\boldsymbol{X}_i)$ the value of the expression in equation (3.1) computed using $\hat{\boldsymbol{\beta}}$ and $\boldsymbol{X}_i$.

The main objective of logistic regression is to estimate the probability of a binary dependent variable based on the values of the independent variables and to assess the impact of each independent variable on this probability. Specifically, logistic regression helps to: (i) Identify the important predictors for the binary outcome; (ii) Estimate the probability of the binary outcome based on the predictors; and (iii) Test the statistical significance of the independent variables.

In this study, logistic regression is used to analyze whether the level of improvement in English skills (1 = some improvement = "failure"; 2 = a lot of improvement = "success") depends on the background information such as age, gender, and job type.

In this study we have used data from $n = 37$ students with independent variables as Age, Gender, and JobType; and the dependent variable being the '(skill) Improvement level'. Also, those one or two responses with outcome 0 have been ignored to keep the model easy to comprehend.

3.3 Coding the qualitative variables and the full model

The general logistic regression hypothesizes that the response variable Y takes only two possible values as

$$Y = \begin{cases} 2 \text{ with probability } \pi(\boldsymbol{X}) \\ 1 \text{ with probability } (1 - \pi(\boldsymbol{X})) \end{cases}$$

In our problem: 2 = Success, and 1 = Failure. Therefore, from (3.1),

$$\ln\left(\frac{\pi(\boldsymbol{X})}{1-\pi(\boldsymbol{X})}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p.$$

In our study our independent variables are as follows:

X_1 = Age = quantitative (standardized) = {(actual - mean)/standard deviation}.

X_2 = Gender = qualitative with 2 levels = $\begin{cases} 1 \text{ female} \\ 0 \text{ male} \end{cases}$

X_3 = Job type = qualitative with 4 levels. Create three binary variables as follows: $X_{31} = \begin{cases} 1 \text{ if Teaching} \\ 0 \text{ if not} \end{cases}$ $X_{32} = \begin{cases} 1 \text{ if State Agencies} \\ 0 \text{ if not} \end{cases}$ $X_{33} = \begin{cases} 1 \text{ if Private Company} \\ 0 \text{ if not} \end{cases}$

Through the above coding, we have Job1 = Teaching, Job2 = State Agencies, Job3 = Private Companies, and Job4 = Other/Self employed.
So, our full model is going to look like (with a quadratic effect of age)

$$\begin{aligned}\ln\left(\frac{\pi(\boldsymbol{X})}{1-\pi(\boldsymbol{X})}\right) =& \beta_0 + \beta_1 X_1 + \beta_{11} X_1^2 + \beta_2 X_2 + \beta_{12}(X_1 X_2) + \beta_{112}(X_1^2 X_2) \\ &+ \beta_{31} X_{31} + \beta_{32} X_{32} + \beta_{33} X_{33} + \beta_{131}(X_1 X_{31}) + \beta_{132}(X_1 X_{32}) \\ &+ \beta_{133}(X_1 X_{33}) + \beta_{1131}(X_1^2 X_{31}) + \beta_{1132}(X_1^2 X_{32}) + \beta_{1133}(X_1^2 X_{33}) \\ &+ \beta_{231}(X_2 X_{31}) + \beta_{232}(X_2 X_{32}) + \beta_{233}(X_2 X_{33}) + \beta_{1231}(X_1 X_2 X_{31}) \\ &+ \beta_{1232}(X_1 X_2 X_{32}) + \beta_{1233}(X_1 X_2 X_{33}) + \beta_{11231}(X_1^2 X_2 X_{31}) \\ &+ \beta_{11232}(X_1^2 X_2 X_{32}) + \beta_{11233}(X_1^2 X_2 X_{33}) \\ \\ =& \beta_0^* + \beta_1^* X_1^* + \beta_2^* X_2^* + \beta_3^* X_3^* + \cdots + \beta_{24}^* X_{24}^*\end{aligned}$$

Where the variables X_i^* have been redefined, for example, as
$X_{24}^* = (X_1^2 X_2 X_{33}); X_{23}^* = (X_1^2 X_2 X_{32}); \cdots ; X_1^* = X_1$

4 The dataset used and the results

The following Table 4.1 presents the survey data followed by an analysis using the software R. It was noted that the quadratic term of age was insignificant along with its interactions with other factors.

Table 4.1: Survey Data

ID	Age (months)	Gender	JobType	Listening Skill	Speaking Skill	Reading Skill	Writing Skill
1	585	Male	Teaching	1	2	1	2
2	427	Male	Teaching	2	1	2	1
3	277	Female	Teaching	1	1	2	1
4	484	Male	Teaching	1	1	1	1
5	343	Female	Teaching	1	1	1	1
6	481	Male	Teaching	1	1	1	1
7	410	Female	State Agencies	1	1	1	1
8	351	Female	Teaching	1	1	1	1
9	442	Male	State Agencies	1	1	1	1
10	428	Male	State Agencies	1	1	1	1
11	388	Male	Other	1	1	1	1
12	316	Female	Teaching	1	1	1	1
13	326	Female	Teaching	1	1	1	2
14	403	Male	Teaching	0	1	1	1
15	477	Female	Teaching	1	1	1	1
16	439	Female	Private Company	1	1	1	1
17	403	Female	Teaching	1	1	1	1
18	364	Male	Teaching	1	1	1	1
19	388	Male	Other	1	1	1	1
20	522	Female	Teaching	1	2	2	2
21	504	Female	Teaching	1	1	2	1
22	332	Female	Teaching	1	1	1	1
23	419	Female	State Agencies	1	1	1	1
24	417	Male	Other	2	NA	NA	NA
25	439	Female	Teaching	1	1	1	1
26	428	Male	Private Company	1	1	1	1
27	412	Male	Teaching	1	1	1	1
28	423	Male	State Agencies	1	1	1	1
29	516	Male	Teaching	1	1	1	1
30	312	Male	Teaching	1	1	1	2
31	354	Female	Teaching	1	1	1	1
32	352	Male	Teaching	1	1	1	1
33	399	Female	State Agencies	1	0	1	0
34	346	Female	Private Company	2	1	2	2
35	414	Female	Other	0	0	1	1
36	323	Male	Private Company	1	1	1	1
37	468	Female	Teaching	1	1	1	1
38	500	Female	State Agencies	0	1	2	1
39	597	Male	Teaching	1	1	2	2
40	363	Female	State Agencies	1	1	1	1

Table 4.2. Logistic regression results for **listening skill** ($n = 37$)

term	**estimate**	**std.error**	**statistic**	**p.value**
(Intercept)	-3.4307	1.5399	-2.2278	0.0259
Gender(Femal	-0.7903	2.2160	-0.3566	0.7214
Age	0.4693	0.9836	0.4771	0.6333
Age*Gender	-1.8042	2.1884	-0.8244	0.4097
Job2	-15.9466	4020.8389	-0.0040	0.9968
Job3	2.5638	1.8512	1.3849	0.1661
Job4	3.4922	2.1437	1.6291	0.1033

Table 4.3. Logistic regression results for **speaking skill** ($n = 37$)

term	**estimate**	**std.error**	**statistic**	**p.value**
(Intercept)	-7.0011	6.9314	-1.0101	0.3125
Gender(Femal	-204.3094	74376.8252	-0.0027	0.9978
Age	2.9576	3.1405	0.9418	0.3463
Age*Gender	160.7149	58240.6191	0.0028	0.9978
Job2	-17.1139	42838.1231	-0.0004	0.9997
Job3	-16.2079	50855.4093	-0.0003	0.9997
Job4	-17.5295	216000.1244	-0.0001	0.9999

Table 4.4. Logistic regression results for **reading skill** ($n = 39$)

term	**estimate**	**std.error**	**statistic**	**p.value**
(Intercept)	-2.7574	1.2181	-2.2636	0.0236
Gender(Femal	1.7555	1.2812	1.3702	0.1706
Age	1.0674	0.7703	1.3858	0.1658
Age*Gender	-0.3559	0.9679	-0.3677	0.7131
Job2	-0.6447	1.2616	-0.5110	0.6093
Job3	0.8154	1.4219	0.5734	0.5664
Job4	-15.8346	2600.0216	-0.0061	0.9951

Table 4.5. Logistic regression results for **writing skill** ($n = 38$)

term	**estimate**	**std.error**	**statistic**	**p.value**
(Intercept)	-1.9146	0.9278	-2.0637	0.0391
Gender(Femal	0.4318	1.1025	0.3916	0.6953
Age	0.9287	0.6529	1.4225	0.1549
Age*Gender	-0.8400	0.9332	-0.9000	0.3681
Job2	-16.9943	2457.6440	-0.0069	0.9945
Job3	0.7523	1.3350	0.5635	0.5731
Job4	-16.7493	4558.1515	-0.0037	0.9971

Remark 4.1. It is seen from the above tables that none of the factors and interactions have any effect on the skill improvement. But these are based on the p -values provided by the software package which relies on the asymptotic theory and may not be accurate due to non-large sample size.

5 Further analysis using bootstrap method

5.1 Bootstrap Method to Calculate Revised P-values

Consider a particular response variable Y, say the listening skill (LS), which is being fitted by a suitable logit function. Y is a binary response variable which can be either Success ("S") or Failure ("F") where $\pi = P(Y = \text{"}S\text{"})$. We fit the model

$$\ln\left(\frac{\pi(\boldsymbol{X})}{1-\pi(\boldsymbol{X})}\right) = \boldsymbol{X}'\boldsymbol{\beta} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p$$

where $\boldsymbol{\beta} = (\beta_0, \beta_1, \ldots, \beta_p)'$. Based on the responses $Y_1, Y_2, \ldots, Y_n$ from n individuals, with corresponding $\boldsymbol{X}_j$ $(1 \le j \le n)$ values, we obtain $\hat{\boldsymbol{\beta}}$ by maximizing the likelihood function. In other words, $\hat{\boldsymbol{\beta}}$ is the MLE of $\boldsymbol{\beta}$. Under standard assumptions (which are valid for the logistic model) the MLE $\hat{\boldsymbol{\beta}}$ is a consistent estimator of $\boldsymbol{\beta}$ (i.e., $\hat{\boldsymbol{\beta}} \to \boldsymbol{\beta}$ in probability as $n \to \infty$). Further, as $n \to \infty$, $\hat{\boldsymbol{\beta}} \to N(\boldsymbol{\beta}, \Sigma) =$ the $(p+1)$ -dimensional (multivariate) normal distribution with mean vector $\boldsymbol{\beta}$ and dispersion (or variance - covariance) matrix Σ, with $\Sigma = I^{-1}$, I being the $(p+1) \times (p+1)$-dimensional Fisher Information matrix. All the p-value computations related to hypothesis testing (involving either an individual coefficient β_i or the whole vector $\boldsymbol{\beta} = (\beta_0, \ldots, \beta_p)'$) uses this asymptotic normal distribution. However, this asymptotic normal distribution is fairly accurate only when the sample size n is sufficiently large relative to the number of parameters which is $(p+1)$. Usually, the p-values generated by the standard statistical packages are reliable if $(n-p) > 30$. But for the current dataset with $n = 37$, we do not have that luxury when $(p+1) \ge 7$.

Note that our full model has the total number of parameters $= (p+1) = 24$. Therefore, we need an alternative mechanism to validate the p-values, and this is done by the bootstrap method.

For the n subjects, say $S_1, S_2, \ldots, S_n$ (with $n = 37$). We have the following data structure

Subject	Y - variable	$\boldsymbol{X}$ - variable vector
S_1	Y_1	$\boldsymbol{X}_1 = (\boldsymbol{X}_{11}, \ldots, \boldsymbol{X}_{1p})$
S_2	Y_2	$\boldsymbol{X}_2 = (\boldsymbol{X}_{21}, \ldots, \boldsymbol{X}_{2p})$
$\vdots$	$\vdots$	$\vdots$
S_n	Y_n	$\boldsymbol{X}_n = (\boldsymbol{X}_{n1}, \ldots, \boldsymbol{X}_{np})$

From the original sample $\{S_1, S_2, \ldots, S_n\}$ we draw a random sample of size n with replacement and let this new sample, called the bootstrap sample, be $\{S_1^*, S_2^*, \ldots, S_n^*\}$ with the corresponding variables $\{(Y_j^*, \boldsymbol{X}_j^*), 1 \le j \le n\}$. Using this bootstrap data, we then carry out the original logistic regression fitting, and let the estimate of $\boldsymbol{\beta}$ be $\hat{\boldsymbol{\beta}}^*$. We now repeat this resampling mechanism a large number (say, B) times. This gives B copies of $\hat{\boldsymbol{\beta}}^*$ values, say $\hat{\boldsymbol{\beta}}^{*(b)}, 1 \le b \le B$. These bootstrap estimates of $\boldsymbol{\beta}$, i.e., $\hat{\boldsymbol{\beta}}^{*(1)}, \hat{\boldsymbol{\beta}}^{*(2)}, \ldots, \hat{\boldsymbol{\beta}}^{*(B)}$ help us understand the amount of variability involved in the original estimate (MLE) $\hat{\boldsymbol{\beta}}$.

If we are interested in testing whether a particular coefficient β_i $(0 \le i \le p)$ ought to be 0 or not, then we approximate the standard error (SE) of $\hat{\boldsymbol{\beta}}_i$ by looking at $\hat{\boldsymbol{\beta}}_i^{*(b)}, 1 \le b \le B$.

$$SE(\hat{\boldsymbol{\beta}}_i) \approx SE_{\text{boot}}(\hat{\boldsymbol{\beta}}_i) = \left(\sum_{b=1}^{B} \left(\hat{\boldsymbol{\beta}}_i^{*(b)} - \bar{\boldsymbol{\beta}}_i^* \right)^2 / B \right)^{1/2}$$

Where $\bar{\boldsymbol{\beta}}_i^* = \sum_{b=1}^{B} \hat{\boldsymbol{\beta}}_i^{*(b)}/B$. The above $SE_{\text{boot}}(\hat{\boldsymbol{\beta}}_i)$ is then used to see the test statistic value $\hat{\Delta}_i^* = \hat{\boldsymbol{\beta}}_i / SE_{\text{boot}}(\hat{\boldsymbol{\beta}}_i)$ to test $H_i^0 : \beta_i = 0$ vs $H_i^a : \beta_i \neq 0$ by comparing it against a t-distribution cut-off point with $(n-p-1)$ df.

Alternatively, a better approach is to compute the p-value as

$$p_{\text{boot}}(\beta_i) = \{\text{Number of } |\hat{\boldsymbol{\beta}}_i^{*(b)}| > |\hat{\boldsymbol{\beta}}_i|\}/B$$

If we want to perform a hypothesis testing for the whole vector $\boldsymbol{\beta}$ as $H_0 : \boldsymbol{\beta} = 0$ vs $H_A : \boldsymbol{\beta} \neq 0$, then we first need to compute the approximate variance-covariance matrix of $\hat{\boldsymbol{\beta}}$ as

$$\hat{\Sigma}_{\text{boot}}^* = \sum_{b=1}^{B} (\hat{\boldsymbol{\beta}}^{*(b)} - \bar{\boldsymbol{\beta}}^*)(\hat{\boldsymbol{\beta}}^{*(b)} - \bar{\boldsymbol{\beta}}^*)'/B$$

Where $\bar{\boldsymbol{\beta}}^* = \sum_{b=1}^{B} \hat{\boldsymbol{\beta}}^{*(b)}/B$. The test statistic to be used is $\hat{\Delta}^* = \hat{\boldsymbol{\beta}}'(\hat{\Sigma}_{\text{boot}}^*)^{-1}\hat{\boldsymbol{\beta}}$.

The above $\hat{\Delta}^*$ can be compared against $\chi^2_{(p+1),\alpha}$, which is the right tail α-probability cut-off point of $\chi^2_{(p+1)}$ distribution. Note that $(p+1)$ is the dimension of the coefficient vector $\boldsymbol{\beta} = (\beta_0, \beta_1, \ldots, \beta_p)'$.

5.2 The results from Bootstrap Method

The following Tables 5.1 − 5.4 provide the bootstrap p-values as well as the (asymptotic) p-values generate by the software package R under the logistic regression model. Note that these two types of p-values can be quite different.

Table 5.1. Listening Skills

	Intercept	Gender(Fer	Age	Age*Gender	Job2	Job3	Job4
P(logistic)	0.0259	0.7214	0.6333	0.4097	0.9968	0.1661	0.1033
P(bootstra	0.4929	0.8093	0.5328	0.5046	0.6479	0.7322	0.7395

Table 5.2. Speaking Skills

	Intercept	Gender(Femal	Age	Age*Gen	Job2	Job3	Job4
P(logistic)	0.312	0.998	0.346	0.998	1	1	1
P(bootstrap	0.7234	0.132	0.3946	0.2579	0.3457	0.358	0.371

Table 5.3. Reading Skills

	Intercept	Gender(Fema	Age	Age*Gende	Job2	Job3	Job4
P(logistic)	0.0236	0.1706	0.1658	0.7131	0.6093	0.5664	0.9951
P(bootstrap	0.5553	0.6518	0.5223	0.8452	0.7342	0.8412	0.7928

Table 5.4. Writing Skills

	Intercept	Gender(Fer	Age	Age*Ge	Job2	Job3	Job4
P(logistic)	0.0391	0.6953	0.1549	0.3681	0.9945	0.5731	0.9971
P(bootstrap	0.5807	0.8724	0.583	0.7362	0.8126	0.8673	0.8191

Note that most of the time the p - values are of similar nature (except for the intercept), i.e., if one is "large" then the other is also so. However, this is about testing each coefficient individually. We also test $H_0^c : \boldsymbol{\beta} = 0$ vs $H_A^c : \boldsymbol{\beta} \neq 0$, where $\boldsymbol{\beta}$ is the whole vector of the coefficients. From the given data, we can get $\hat{\boldsymbol{\beta}}$, followed by the bootstrap replications $\hat{\boldsymbol{\beta}}^{*(b)}, 1 \leq b \leq B = 10^4$.

If $\hat{\Delta}^* > \chi^2_{7,(1-\alpha)}$ then we reject H_0^c; Otherwise, we retain H_0^c. With our study, we use the short-hand notations as follows: LS = Listening Skill, SS = Speaking Skill, RS = Reading Skill, WS = Writing Skill.

We have:

$$\hat{\boldsymbol{\beta}}_{\text{LS}} = \hat{\boldsymbol{\beta}} = \begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \hat{\beta}_2 \\ \hat{\beta}_{12} \\ \hat{\beta}_{31} \\ \hat{\beta}_{32} \\ \hat{\beta}_{33} \end{pmatrix} = \begin{pmatrix} -3.4307 \\ -0.7903 \\ 0.4693 \\ -1.8042 \\ -15.9466 \\ 2.5638 \\ 3.4922 \end{pmatrix}; \quad \hat{\boldsymbol{\beta}}_{\text{SS}} = \hat{\boldsymbol{\beta}} = \begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \hat{\beta}_2 \\ \hat{\beta}_{12} \\ \hat{\beta}_{31} \\ \hat{\beta}_{32} \\ \hat{\beta}_{33} \end{pmatrix} = \begin{pmatrix} -7.0011 \\ -204.3094 \\ 2.9576 \\ 160.7149 \\ -17.1139 \\ -16.2079 \\ -17.5295 \end{pmatrix}$$

$$\hat{\boldsymbol{\beta}}_{\text{RS}} = \hat{\boldsymbol{\beta}} = \begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \hat{\beta}_2 \\ \hat{\beta}_{12} \\ \hat{\beta}_{31} \\ \hat{\beta}_{32} \\ \hat{\beta}_{33} \end{pmatrix} = \begin{pmatrix} -2.7574 \\ 1.7555 \\ 1.0674 \\ -0.3559 \\ -0.6447 \\ 0.8154 \\ -15.8346 \end{pmatrix}; \quad \hat{\boldsymbol{\beta}}_{\text{WS}} = \hat{\boldsymbol{\beta}} = \begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \hat{\beta}_2 \\ \hat{\beta}_{12} \\ \hat{\beta}_{31} \\ \hat{\beta}_{32} \\ \hat{\beta}_{33} \end{pmatrix} = \begin{pmatrix} -1.9146 \\ 0.4318 \\ 0.9287 \\ -0.8400 \\ -16.9943 \\ 0.7523 \\ -16.7493 \end{pmatrix}$$

And the results from the software:
Listening Skills: $\hat{\Delta}^* = 1.2212079$; Writing Skills: $\hat{\Delta}^* = 0$
Speaking Skills: $\hat{\Delta}^* = 0$; Reading Skills: $\hat{\Delta}^* = 0$

We have: (i) $\hat{\Delta}^*_{LS} < \chi^2_{7,(1-\alpha)}(1.2212079 < 14.067)$, so, we retain H_0^c; (ii) $\hat{\Delta}^*_{SS} < \chi^2_{7,(1-\alpha)}(1.04032444e^{-10} < 14.067)$, so, we retain H_0^c;(iii) $\hat{\Delta}^*_{RS} < \chi^2_{7,(1-\alpha)}(8.96726253e^{-26} < 14.067)$, so, we retain H_0^c; (iv) $\hat{\Delta}^*_{WS} < \chi^2_{7,(1-\alpha)}(1.9096034e^{-14} < 14.067)$, so, we retain H_0^c.

The analysis shows no significant impact of background factors (age, gender, job type) on students' self-assessment of improvements in listening, reading, writing, and speaking skills. Both logistic regression model and bootstrap analysis support this conclusion. This finding suggests that the reported improvements by students are evenly distributed among different groups, indicating that the SDEM program benefits all students regardless of their background.

6 Discussion

A logistic regression model for the data has been used to see if it revealed any interesting patterns. The statistical package (R) output may not reveal the full extent of the inferences, and hence a bootstrap method has been resorted to for a deeper analysis. Finally, the analysis shows that there is no impact of the background factors (i.e., age, gender, job held) on the students' reported self-assessment. The results show that although students report varying levels of improvement, these differences are not significantly dependent on their background information. This suggests that the SDEM program is effective in providing equal improvement in English skills for all students. The use of both logistic regression models and the bootstrap method provided a comprehensive analysis, ensuring the robustness of the results. The subjective nature of the self-assessment data is acknowledged as a limitation, which may introduce bias and mask the true impact of the SDEM program. Future research should incorporate objective evaluations and consider longitudinal studies to validate and expand these findings.

7 Conclusion

This study provides insights into students' self-assessment in the SDEM program at SGU. The results emphasize that background factors do not significantly affect the reported improvement, suggesting that the program offers equal benefits. Recommendations for program administrators include maintaining the current structure while exploring additional support mechanisms for all students. Further research is suggested to address the limitations and explore additional factors influencing students' learning outcomes.

Acknowledgments

We would like to express our deepest gratitude to the organizers of the International Conference on Mathematical Research, Education and Applications 2024 (ICMREA – NTTU & DThU 2024) from July 15 – 18, 2024 at Nguyen Tat Thanh University and Dong Thap University for providing us with the opportunity to present this research by the first author at the conference.

We sincerely thank the Vietnam Institute for Advanced Study in Mathematics (VIASM) for providing us with the opportunity to work there and for facilitating the first author's participation in the conference during her visit at the Institute in summer of 2024. Additionally, the first author would like to express her sincere gratitude to the teachers and classmates of SDEM at SGU for supporting her in conducting this survey.

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