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Article

A Study of the Mechanisms of Generative AI Mobile Learning App's Impact on Vocational Students' Self-Directed Oral Technical Communication Skills

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Abstract: The rapid development of artificial intelligence (AI) has broken the time and space limitations of traditional classroom learning and provides vocational school students with a convenient and new forms of mobile learning supported by generative AI applications. In order to explore the impact of mobile learning app tools on students' oral technical communication skills, this study adopts a qualitative investigation and research design to analyze the current status of vocational school students' self-directed oral technical communication skills with a questionnaire, builds a controlled experimental process of generative AI mobile learning app-assisted intervention teaching, and synthesizes the survey results, quiz data, and interview transcripts to discuss the students' oral technical communication skills' changes. Considering the mechanism of further quantifying the improvement of the competence, research variables were set up, and logistic regression model was selected as the test tool to test and examine the specific connection between the two. The results indicate that both the experimental and control groups showed imporovements after the intervention; however, the gains in the control group were almost negligible. The independent samples t-test results also revealed that the post-test scores of the experimental group were significantly higher than those of the group ($p<0.01$). Logistic regression analysis further demonstrated that AI simulation realism, AI feedback adaptivity, app course fit, and ease of use of the app had significant positive effects on the learning outcomes. These findings confirm the positive role of generative AI mobile earning in promoting the development of vocational students' oral technical communication skills.

Keywords: generative AI; mobile learning app; logistic regression model; oral technical communication; self-direction

1. Introduction

Vocational school education training goal is mainly for the grassroots, for production, service, management, the first line of practical, skilled professionals, this talent is characterized by strong practical ability, and in these abilities, its oral technical communication skills is the most basic, the most important kind of skills for vocational school students [1-4]. Every industry, every field, from small personal dialog, communication, to large business negotiations, and even the national image of the country, all reflect the role and significance of oral technical communication skills, only to improve this ability of the students, in order to make them better adapted to society [5-8].

The traditional method of cultivating oral technical communication ability is mainly based on teacher guidance to promote students to speak, practice and imitate more, which is inefficient and unsatisfactory, and with the development of artificial intelligence (AI) and the popularization of smart phones and tablet computers, generative AI mobile learning app has become the key to solve the above problems [9-10]. Generative AI mobile learning apps are able to generate specific practice scenarios based on students' needs [11]. Many apps are equipped with multilingual support, speech recognition, and instant translation capabilities, allowing students to learn collaboratively in situations that would otherwise require overcoming communication barriers [12-14]. By communicating with classmates, and even with partners from different linguistic backgrounds, students learn to put complex ideas into clear and simple language, while also learning to respect and understand the different ways of expression of others [15-17]. This self-directed interactive learning helps develop empathy, contextual understanding, and social sensitivity, which are important components of social competence [18-19]. The role of generative AI mobile learning apps in this regard is not to replace interpersonal contact, but to lower the barriers so that more students can try to express themselves, correct their mistakes and receive positive feedback in a safe practice environment thereby improving oral technical communication skills [20-21].

Oral technical communication ability is an important skill in the career development of students in vocational colleges and universities, and this paper, in order to clarify whether the generative AI m-learning app can promote the development of this ability, launched a study from the two aspects of controlled teaching and regression empirical test. On the one hand, the current development level of vocational school students' self-directed oral technical communication ability was clarified through the front-side questionnaire, 91 vocational school students were selected to enter the teaching experiment of generative AI mobile learning app, and the teaching programs of experimental group and control group were designed to ensure that there was no interference from other factors. On the other hand, six important features of the mobile learning app, such as the degree of realism of AI simulation, adaptability of AI feedback, and app course fit, were used as explanatory variables, and five dimensions of oral technical communication skills, such as the use of technical terms and logical organization, were used as explanatory variables for the empirical test, and the test tool was a logistic regression model. The results of the two empirical studies are combined to explore the effectiveness of the application of generative AI mobile learning apps. This study aims to answer the following research questions:

(1) Does a generative AI mobile learning app improve vocational school students' self-directed oral technical communication skills?

(2) What specific aspects of these skills can be enhanced by the use of generative AI mobile learning apps?"

2. Research Design and Methodology

This study adopts a survey research design to investigate the current status of vocational school students' self-directed oral technical communication abilities. Data were collected through instruments such as questionnaires and semi-structured interviews, supplemented by pre-and post-course experiments using a generative AI mobile learning App. The research subjects are students from major vocational colleges in G City. By analyzing the quantitative data from the questionnaires and the qualitative content from the interviews, this study determines the effectiveness of the generative AI app in enhancing students' communication skills.

2.1. Data collection and analysis

2.1.1. Questionnaire

The questionnaire focused on the students of major vocational colleges in G City. The questionnaire included how often and how long the vocational students used the generative AI m-learning app, whether or not it helped oral technical communication, and what aspects of oral technical communication skills were improved.

2.1.2. Learning App Application Quiz

This experiment is based on the development of course learning strategies for generative AI mobile learning apps. Positioned as a holistic approach, it attempts to extend other teaching strategies, techniques, and construct diverse learning environments to accommodate students with different intellectual developmental strengths and guide them to optimal developmental opportunities. This experiment began in September 2024 and ended in September 2025.

Phase 1: 91 vocational school students participating in the course passed the pre-oral technical communication test before entering the teaching session, and according to the students' performance in the oral test, corresponding corpus collection and comparative analysis were done for the obstacles and problems encountered by the students in the process of oral technical communication.

Phase 2: Students were grouped at different levels and randomly divided into an experimental group (46 students) and a control group (45 students). In the experimental group, the classroom activities were organized based on the concept of student-centered teaching, and reasonable teaching activities were designed according to the students' own characteristics and problems, as well as their problems in oral technical communication, and the teaching process was centered on how to improve the students' ability in oral technical communication as an important dimension of measurement. The teaching activities are centered on how to improve students' oral technical communication skills as an important dimension. The results were tracked dynamically by means of follow-up tests and classroom presentations, and the test scores of the two groups in two semesters were used as the main source of comparative data. And the two control groups were taught in traditional classrooms with traditional classroom organization.

Phase 3: Effectiveness Testing and Comparison. At the end of the course learning stage, the study participants were tested on their oral technical communication skills accordingly, and the dimensions of the students' oral technical communication skills at different stages were compared and analyzed.

2.2. Analytical Framework and Modeling

2.2.1. Construction of Logistic Regression Models

Because of the inappropriateness of conventional least squares models, nonlinear functions are generally used for the analysis of dichotomous dependent variables. The nonlinear relationship between the conditional probability of an event, $P(Y_i=1\mid x_i)$, and x_i is usually a monotonic function, i.e., as x_i increases or decreases, $P(Y_i=1\mid x_i)$ also monotonically increases or monotonically decreases. A natural choice is to have a curve with a S shape between $(0,1)$, such that $E(Y_i)$ tends to 0 as x_i approaches negative infinity, and $E(Y_i)$ tends to 1 as x_i approaches positive infinity, which is analogous to the cumulative distribution of a random variable, the most commonly used function being the Logistic distribution.

Suppose there is a theoretically existing continuous response variable Y_i^* representing the likelihood of an event occurring, with a range of values from negative infinity to positive infinity. When the value of this variable crosses a threshold c leading to an event, there is:

When $Y_i^* > \mathrm{c}$, $Y_i = 1$.

$Y_i = 0$ for all other cases.

Here, Y_i is the actual observed response variable, with $Y_i = 1$ indicating that the event occurred and $Y_i = 0$ indicating that the event did not occur. If a linear relationship is assumed to exist between the response variable Y_i^* and the independent variable x_i, i.e:

$$Y_i^* = \alpha + \beta x_i + \varepsilon_i \tag{1}$$

is obtained from the above equation:

$$P(Y_i = 1\mid x_i) = P[(\alpha+\beta x_i+\varepsilon_i) > \mathrm{c}] = P[\varepsilon_i > (\mathrm{c}-\alpha-\beta x_i)] \tag{2}$$

Assuming that the error term ε_i in Eq. (1) is a Logistic distribution, the distribution function of the Logistic distribution is $F(x)=\frac{1}{1+e^{-x}}$ and the Logistic distribution is a symmetric distribution, such that $\alpha = \alpha_1 - \mathrm{c}$ then we have:

$$P\left(Y_i=1\middle|x_i\right) = P\left[\varepsilon_i > -(\alpha+\beta x_i)\right] = P\left[-\varepsilon_i \le (\alpha+\beta x_i)\right] = \frac{1}{1+e^{-(\alpha+\beta x_i)}} \tag{3}$$

This function is called the Logistic function and it has a distribution of type S.

To move from the Logistic function to the Logistic regression model, equation (3) is rewritten as:

$$P\left(Y_i=1\middle|x_i\right) = \frac{1}{1+e^{-(\alpha+\beta x_i)}} \tag{4}$$

The logistic regression model is obtained by labeling the conditional probability of an event as $P\left(Y_i=1\middle|x_i\right)=p_i$:

$$p_i = \frac{1}{1+e^{-(\alpha+\beta x_i)}} = \frac{e^{\alpha+\beta x_i}}{1+e^{\alpha+\beta x_i}} \tag{5}$$

where p_i is the probability of the i th event occurring, which is a nonlinear function consisting of the explanatory variables x_i, but it can be transformed into a linear function.

First, define the conditional probability of the non-occurrence event as:

$$1-p_i = 1-\left(\frac{e^{\alpha+\beta x_i}}{1+e^{\alpha+\beta x_i}}\right) = \frac{1}{1+e^{\alpha+\beta x_i}} \tag{6}$$

Then the ratio of the probability of the event occurring to the probability of the event not occurring is:

$$\frac{p_i}{1-p_i} = e^{(\alpha+\beta x_i)} \tag{7}$$

This ratio is called the incidence ratio of the event and is abbreviated as odds. odds is a positive value and has no upper bound. A linear function is obtained by taking the natural logarithm of odds:

$$\ln\left(\frac{p_i}{1-p_i}\right) = \alpha + \beta x_i \tag{8}$$

Eq. (8) transforms the logistic function into a natural logarithmic transformation called the logit form, also known as the logit transformation of Y, i.e., $\log it\left(Y\right)$.

When there are k independent variables, equation (5) expands to:

$$p_i = \frac{e^{\alpha+\sum_{k=1}^{k}\beta_k x_{ki}}}{1+e^{\sum_{k=1}^{k}\beta_k x_{ki}}} \tag{9}$$

Let $\beta_0 = \alpha$ and $x_{0i} = 1$, then the above equation can be transformed as:

$$p_i = \frac{e^{\sum_{k=0}^{k}\beta_k x_{ki}}}{1+e^{\sum_{k=0}^{k}\beta_k x_{ki}}} \tag{10}$$

The corresponding logistic regression model is of the following form [22]:

$$\ln\left(\frac{p_i}{1-p_i}\right) = \sum_{k=0}^{k}\beta_k x_{ki} \tag{11}$$

where $p_i = P\left(Y_i = 1 \middle| x_{1i}, x_{2i}, \cdots, x_{ki}\right)$ is the probability of the event occurring given the value of the series independent variable $x_{1i}, x_{2i}, \cdots, x_{ki}$.

Once we have samples of the independent variables x_1 to x_k into which each event is formed, along with observations of whether or not its event occurs, we are able to use this information to analyze and characterize the ratio of occurrences of the event to its probability of occurrence under specific conditions.

2.2.2. Parameter Estimation Procedures

From the binary logistic regression model: the likelihood function for the parameter $\beta = (\beta_1, \beta_2, \cdots, \beta_p)'$ is

$$L(\beta) = \prod_{i=1}^{n} p_i^{y_i}(1-p_i)^{1-y_i} \tag{12}$$

where $y_i = 0$ or 1 and $p_i = \frac{e^{x_i'\beta}}{1+e^{x_i'\beta}}$, obtained by taking the logarithm of the likelihood function:

$$\begin{aligned} \ell(\beta) = \log L(\beta) &= \sum_{i=1}^{n} \log\left[p_i^{y_i}(1-p_i)^{1-y_i}\right] \\ &= \sum_{i=1}^{n} \log\left[\left(\frac{p_i}{1-p_i}\right)^{y_i}(1-p_i)\right] \\ &= \sum_{i=1}^{n}\left[y_i \log\left(\frac{p_i}{1-p_i}\right) + \log(1-p_i)\right] \\ &= \sum_{i=1}^{n}\left[y_i(x_{i'}\beta) - \log(1+e^{x_{i'}\beta})\right] \end{aligned} \tag{13}$$

The likelihood equation is obtained by taking the log-likelihood function to be partial for $\beta_1, \beta_2, \cdots, \beta_p$ and letting the partial derivatives go to zero. From $\frac{\partial \ell(\beta)}{\partial \beta} = 0$, we have:

$$\begin{aligned} \frac{\partial \ell(\beta)}{\partial \beta} &= \frac{\partial \sum_{i=1}^{n}\left[y_i(x_{i'}\beta) - \log(1+e^{x_{i'}\beta})\right]}{\partial \beta} \\ &= \sum_{i=1}^{n} \frac{\partial\left[y_i(x_{i'}\beta) - \log(1+e^{x_{i'}\beta})\right]}{\partial \beta} \\ &= \sum_{i=1}^{n}\left[y_i x_i - \frac{x_i e^{x_{i'}\beta}}{1+e^{x_{i'}\beta}}\right] = \sum_{i=1}^{n}\left[x_i(y_i - p_i)\right] \end{aligned} \tag{14}$$

From there, there is:

$$\sum_{i=1}^{n}\left[x_i(y_i - p_i)\right] = 0 \tag{15}$$

To wit:

$$\sum_{i=1}^{n}\left[x_i y_i - \frac{x_i e^{x_{i'}\beta}}{1+e^{x_{i'}\beta}}\right] = 0 \tag{16}$$

The above equation is a system of nonlinear equations about β . For this purpose, Newton's iterative method can be used to solve it. The solution of the resulting likelihood equation $\hat{\beta} = \left(\hat{\beta}_1, \hat{\beta}_2, \cdots, \hat{\beta}_p\right)'$ is the regression parameter $\beta = \left(\beta_1, \beta_2, \cdots, \beta_p\right)'$ as the great likelihood estimate of the regression parameter [23].

Let $v_i = y_i - p_i$, $s_i = p_i(1-p_i)$, take $V = (v_1, \cdots, v_n)'$ and $S = diag(s_i)$. Thus, we have:

$$\frac{\partial \ell(\beta)}{\partial \beta} = \sum_{i=1}^{n} x_i(y_i - p_i) = \sum_{i=1}^{n} x_i v_i = X'V \tag{17}$$

$$\begin{aligned} -\frac{\partial^2 \ell(\beta)}{\partial \beta \partial \beta'} &= -\frac{\partial}{\partial \beta}\sum_{i=1}^{n} x_i(y_i - p_i) \\ &= -\frac{\partial}{\partial \beta}\left(\sum_{i=1}^{n} x_i\left(y_i - \frac{e^{x_i'\beta}}{1+e^{x_i'\beta}}\right)\right) \\ &= \sum_{i=1}^{n} p_i(1-p_i)x_i x_i' = X'SX \end{aligned} \tag{18}$$

Among them:

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1p} \\ x_{21} & \cdots & x_{2p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix} \tag{19}$$

The order of X is $n \times p$, the order of β is $p \times 1$, the order of V is $n \times 1$, and the order of S is $n \times n$.

Assuming the number of iterations is k, the great likelihood estimate of the regression parameter β is:

$$\begin{aligned} \hat{\beta}^k &= \hat{\beta}^{k-1} - \left[\left(\frac{\partial^2 \ell(\beta)}{\partial\beta\partial\beta'} \right)^{-1} \frac{\partial \ell(\beta)}{\partial\beta} \right]_{\beta=\hat{\beta}^{k-1}} \\ &= \hat{\beta}^{k-1} + \left[(X'SX)^{-1}(X'V) \right]_{\beta=\hat{\beta}^{k-1}} \end{aligned} \tag{20}$$

The basic method of binary logistic regression parameter estimation is the great likelihood method, and its premise is a large sample. However, when the sample size is relatively small and the data structure is biased, the results can be unreliable or even unsolvable.

3. Results

3.1. Analysis of Capacity Enhancement for Oral Technical Communication

Both pre- and post-test oral technical communication scores were investigated and examined in the experimental and control groups by means of a test questionnaire, which was based on a percentage system, with a total of 20 objective multiple-choice questions, each of which was worth 5 points (scored according to the standardized answer, with 5 points for a correct answer and 0 points for an incorrect one).

The data from the pre- and post-tests of the experimental group's oral technical communication skills were analyzed and their oral technical communication skills scores were calculated separately, and the pre- and post-tests obtained are shown in Figure 1. The average score of oral technical communication ability of the students in the experimental group increased from 63.6 to 78.4 after app learning, and the assisting effect of generative AI mobile learning app is obvious.

The paired-sample t-test of the pre-test and post-test scores of the oral technical communication ability of the experimental group can be concluded that the probability of significance between the pre and post-test scores of the experimental group is p=0.005, so it can be considered that there is a significant difference between the results of the two measurements before and after. After using the generative AI mobile learning app as an aid in the learning process, there was a very significant improvement in oral technical communication skills.

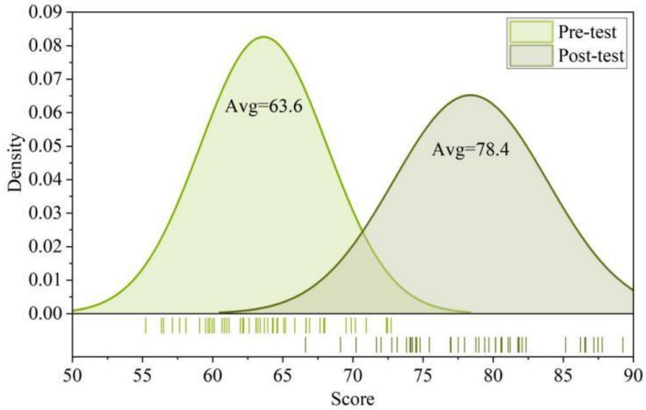

Figure 1. Pre- and post-test data of the experimental group

According to the data from the pre- and post-tests of the control group's oral technical communication ability, their oral technical communication ability scores were analyzed and calculated separately, and the obtained pre- and post-tests are shown in Figure 2. The average score of oral technical communication ability of the control group students after the traditional way changed from 63.2 to 64.1, and the level difference was not obvious.

In order to test the difference between the oral technical communication ability of the control group before and after traditional teaching, a paired-sample t-test was conducted based on the pre-test scores and post-test scores of the control group's oral technical communication ability, and the probability of significance was p=0.742>0.05, which indicates that there is really no significant difference between the control group's oral technical communication ability before and after the experimental study. So there was no significant improvement in the control group's oral technical communication skills, which remained at a similar level overall.

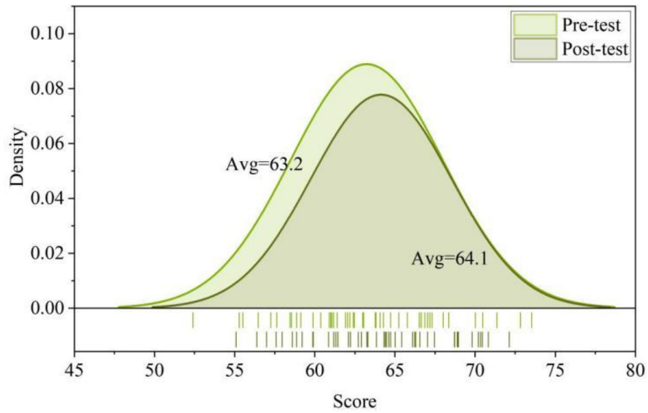

Figure 2. Pre- and post-test data of the control group

According to the data of the post-test of oral technical communication ability of the experimental group and the control group were analyzed, and their scores of oral technical communication ability were calculated respectively, and the obtained post-test data were compared as shown in Figure 3. After the experiment, the average score of the experimental group improved by 22.31% compared with that of the control group, and in terms of absolute scores, the overall students' oral technical communication ability of the experimental group was at a good level after the experiment, while the control group was still at a qualified level.

In order to test the difference between the two classes after the experiment, an independent samples t-test was conducted on the post-test scores of oral technical communication skills of the two classes. Regardless of whether the hypothesized variance holds or does not hold, the probability of significance between the pre-test scores of the experimental and control groups was obtained as p=0.0025<0.01, which is extremely significant, and there is a significant difference between the oral technical communication skills of the experimental group and the control group after the experiment. Therefore, it can be concluded that the average score of oral technical communication ability of the experimental group after a period of generative AI mobile learning app-assisted learning is higher than that of the control group that carries out traditional teaching, which indicates that the oral technical communication ability of the experimental group has been well improved.

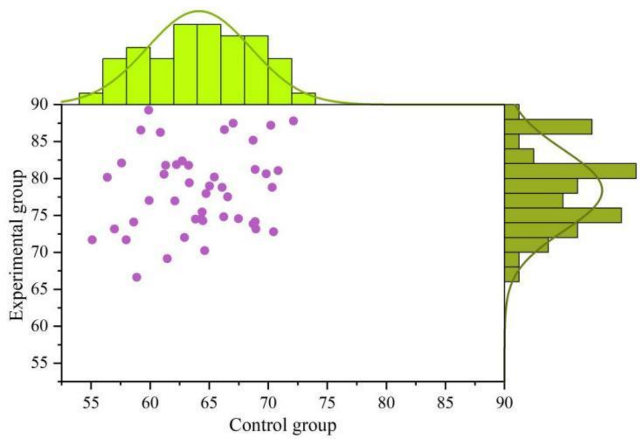

Figure 3. Post-test data comparison

3.2. Logistic model validation of oral communication skills improvement

The logistic regression model was validated through a combination of questionnaire survey and interview data. Before conducting the logistic regression analysis, the research variables were clarified. This study explores the impact of a generative AI mobile learning app on vocational school students' oral technical communication skills. The independent variables (X) include six dimensions: AI simulation (X1), AI feedback adaptability (X2), app course fit (X3), app ease of use (X4), the dialog task rationality (X5), and communication training (X6). The explanatory variables (Y) were set to 5 dimensions of technical terminology use (Y1), logical organization (Y2), expressive fluency (Y3), interaction and response (Y4), and self-directed communication strategies (Y5). Variable assignments were made using a five-level Likert scale. All variables range from 1 to 5.

The results of the descriptive statistical analysis of the explanatory variable Y are given in Table 1, where Sk and Ku denote the skewness and kurtosis of the sample, respectively. Most of the mean values of the observed variables ranged from 2.25 to 3.77 for the experimental group, and the standard deviation values ranged from 0.752 to 1.233. Skewness is characterized by the degree of asymmetry in the distribution of statistical data expressed in terms of numerical experimental groups, the direction of skewness and the degree of skewness in the experimental groups of data distribution. Kurtosis reflects the sharpness of the peak, the experimental group is the distribution curve at the average peak height of the characteristic number. The data samples of the experimental group were basically normally distributed, and the absolute values of kurtosis and data skewness did not have an experimental group exceeding 2.0, indicating that further data analysis and research can be conducted.

The means in descending order are: Logical Organization (Y2=3.77), Interaction and Response (Y4=3.57), Self-Directed Communication Strategies (Y5=3.37), and Technical Terminology Usage (Y1=2.77), expressive fluency (Y3=2.25). The greater the degree of dispersion indicates the less representative the centralized trend measure is, and the degree of dispersion of these five factors indicates the lowest level of stability for Logical Organization and the highest level of stability for Self-Directed Communication Strategies.

Table 1. Descriptive statistics of the explained variable

Variable	min	max	mean	std	Sk	Ku
Y1	1	5	2.77	0.893	-0.569	-0.118
Y2	1	5	3.77	1.233	-0.857	-0.5
Y3	1	5	2.25	1.032	-0.614	-0.337
Y4	1	5	3.57	0.925	-0.942	-1.88
Y5	1	5	3.37	0.752	-0.256	1.931

Before entering the logistic regression test, a Pearson correlation analysis was conducted among the variables. The results are shown in Figure 4, where the lower triangular matrix displays the Pearson correlation coefficients, and the upper triangular matrix shows the significance levels (** for $p<0.01$, * for $p<0.05$, and × for significant correlation). As illustrated, the four dimensions of AI simulation realism, AI feedback adaptability, app course fit, and app ease of use were all significantly and positively correlated with oral technical communication skills (Y). In contrast, dialog task rationality (X5, $r=0.009$, $p>0.05$) and communication training (X6, $r=0.015$, $p>0.05$) showed no significant correlation with Y; therefore, these two variables were excluded from the subsequent logistic regression analysis.

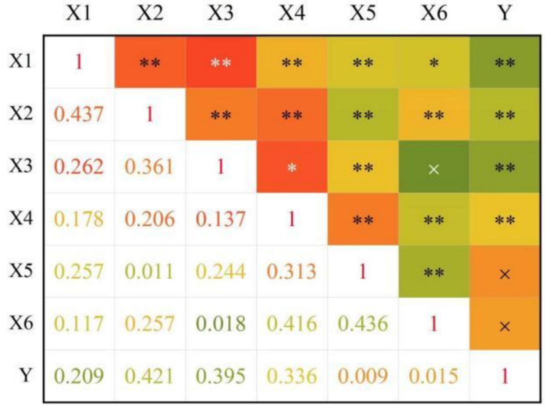

Figure 4. Result of variable correlation test

Further logistic regression analysis was conducted and the results are presented in Table 2. The logistic regression coefficients for AI simulation realism (X1), the adaptability of the AI feedback (X2), app course fit (X3), and app ease of use (X4) were 0.242, 0.172, 0.247, and 0.151, respectively. All four variables positively predicted the improvement of vocational students' oral technical communication skills.

Table 2. Logistic regression test

Variable	β	Standard error	Sig.	95% confidence interval	
				Upper limit	Lower limit
X1	0.242	0.058	0.005	0.242	0.3544
X2	0.172	0.044	0.021	0.17	0.4705
X3	0.247	0.052	0.014	0.247	0.4951
X4	0.151	0.078	0.038	0.151	0.284

4. Discussion

The significant improvement observed in the experimental group (score increasing from 63.6 to 78.4) aligns with previous research emphasizing the potential of AI-driven tools in language and communication acquisition [24]. Like earlier studies on the technology acceptance model (TAM) [25], our regression results also confirm that app ease of use (β = 0.151) positively influences learning outcomes.

However, this study extends beyond prior literature by identifying app course fit (β = 0.247) and AI simulation realism (β = 0.242) as the strongest predictors of improvement. While general-purpose AI tools may support basic language fluency, our findings suggest that in vocational education—where industry-specific technical jargon and practical precision are essential—the alignment between the app's content and the specific technical curriculum plays a critical role in skill enhancement. The results highlights a shift from merely focusing on technological availability to pedagogical contextualization in educational technology design.

The positive regression coefficients for AI simulation realism and app course fit may be explained by a reinforcement mechanism: when students perceive the simulated scenarios and feedback as realistic and relevant to their professional courses, they are more likely to integrate app practice with knowledge learned in the classroom taught by teachers. This increased engagement provides more opportunities for authentic oral technical communication practice, leading to further improvement and sustained motivation.

It is also important to acknowledge the study's limitations. First, the sample was drawn exclusively from vocational colleges in G City, which may limit the generalizability of the findings to other regions, educational or cultural contexts. Second, the 15-minute interviews provided valuable qualitative insights, but a larger qualitative sample or mix-methods design could provide richer understanding. Future research should explore longitudinal effects and compare different types of generative AI models to optimize vocational training curricula.

5. Conclusion

This study empirically validates the effectiveness of generative AI mobile learning apps in enhancing the oral technical communication skills of vocational students. The findings demonstrate a clear distinction in skill acquisition between students using the app and those who do not, with the alignment of app content to vocational curricula emerging as a pivotal factor.

Based on these empirical validations, the following actionable conclusions are drawn:

(1) For Educational Practice: Vocational institutions should integrate generative AI tools as a standard supplementary resource to simulate workplace technical scenarios. It serves as a low-cost, high-efficiency solution to bridge the communication gap between classroom instruction and industry requirements.

(2) For app Development: Developers must prioritize domain-specific customization. Instead of focusing solely on general language functions, future iterations of educational AI should emphasize the accuracy of technical terminology and the realism of industry-specific simulations.

While this study is confined to G City, the framework established here is scalable. Future research should focus on longitudinal tracking to assess the sustainability of these skill improvements and expand the scope to diverse vocational disciplines.

References

1. Yuan, W., & Wang, Y. (2021, June). The development of vocational education and training in China. In 1st International Conference on Education: Current Issues and Digital Technologies (ICECIDT 2021) (pp. 375-383). Atlantis Press.
2. Mulder, R. H., Messmann, G., & König, C. (2015). Vocational education and training: Researching the relationship between school and work. European Journal of Education, 50(4), 497-512.
3. Jamaludin, K. A., Alias, N., DeWitt, D., & Razzaq, A. R. (2019). Framework for technical communication skills content development for students in malaysian vocational colleges: A fuzzy delphi study. Journal of Technical Education and Training, 11(4).
4. Taneo, A. S., & Candilas, K. S. (2024). Remediating Technical Vocational Livelihood (TVL) Students' Oral Communication Skills Using Active and Didactic Learning Approaches. BRU ELT JOURNAL, 2(2), 130-141.
5. Masduki, M., & Zakaria, N. (2020). Fulfilling the demand for workplace communication skills in the civil engineering industry. Pertanika Journal of Social Sciences & Humanities, 28(4), 3069-3087.
6. Verzella, M., Macià, E. A., & Maylath, B. (2021). Engineers taking a stance on technical communication: Peer review of oral presentations via the Trans-Atlantic and Pacific Project. IEEE transactions on professional communication, 64(1), 66-83.
7. Soto, J. D., Calle, M. G., Oliveros, I., Ripoll, L., Lopez, L., & Rueda-Delgado, D. (2024, July). Improving Students' Oral Communication Skills in Electrical Engineering. In 2024 IEEE Technology and Engineering Management Society (TEMSCON LATAM) (pp. 1-5). IEEE.
8. Asih, N. F., & Ellianawati, E. (2019). The enhancement of verbal communication skills for vocational students through project-based learning physics. Jurnal Penelitian & Pengembangan Pendidikan Fisika, 5(1), 21-28.
9. Lai, C. L., & Tu, Y. F. (2024). Roles, strategies, and research issues of generative AI in the mobile learning era. International Journal of Mobile Learning and Organisation, 18(4), 516-537.
10. Kittredge, A. K., Hopman, E. W., Reuveni, B., Dionne, D., Freeman, C., & Jiang, X. (2025, February). Mobile language app learners' self-efficacy increases after using generative AI. In Frontiers in Education (Vol. 10, p. 1499497). Frontiers.
11. Suvankulova, A. (2024). How AI and mobile apps can enhance student' communicative competencies. Science and innovation, 3(B10), 106-116.
12. Gaspard-Richards, D. (2023). Reflections on the use of Generative AI, Technology Tools, Mobile Applications and Sharing Perspectives from Educators and Stakeholders in the Teaching and Learning process. International Journal of Education and Development using Information and Communication Technology, 19(3), 3-8.
13. Kanoksilapatham, B., & Takrudkaew, T. (2025). Integrating ChatGPT to Enhance University Students 'Communication Skills: Pedagogical Considerations. World Journal of English Language, 15(6), 173-183.
14. Liu, Z. L. (2025). Generative AI and Mobile Learning in Higher Education: Comparing Student and Faculty Perspectives on Employability Impact. International Journal of Interactive Mobile Technologies, 19(1).
15. Pesovski, I., Santos, R., Henriques, R., & Trajkovik, V. (2024). Generative AI for customizable learning experiences. Sustainability, 16(7), 3034.
16. Elkot, M. A., Youssif, E., Elmahdi, O. E. H., AbdAlgane, M., & Ali, R. (2025). Generative Conversational AI: Active Practices for Fostering Students with Mild Intellectual Disabilities to Improve English Communication Skills. Contemporary Educational Technology, 17(1).
17. Tu, Y. F., & Lu, Y. C. (2025). Trends of generative AI applications in educational settings. International Journal of Mobile Learning and Organisation, 19(4), 442-467.

18. Milana, M., Brandi, U., Hodge, S., & Hoggan-Kloubert, T. (2024). Artificial intelligence (AI), conversational agents, and generative AI: implications for adult education practice and research. International Journal of Lifelong Education, 43(1), 1-7.
19. Kanont, K., Pingmuang, P., Simasathien, T., Wisnuwong, S., Wiwatsiripong, B., Poonpirome, K., & Khlaisang, J. (2024). Generative-AI, a learning assistant? Factors influencing higher-ed students' technology acceptance. Electronic journal of e-Learning, 22(6), 18-33.
20. Lee, A. V. Y., Tan, S. C., & Teo, C. L. (2023). Designs and practices using generative AI for sustainable student discourse and knowledge creation. Smart Learning Environments, 10(1), 59.
21. Wijayati, T., Hayatie, M. N., & Safitri, Y. D. (2024). Enhancing Business Communication Skills in Vocational Education: A Generative Ai Approach for Personalized Learning. Frontier Management Science, 1(2), 53-60.
22. Dey, D., Haque, M. S., Islam, M. M., Aishi, U. I., Shammy, S. S., Mayen, M. S. A., & Uddin, M. J. (2025). The proper application of logistic regression model in complex survey data: a systematic review. BMC Medical Research Methodology, 25(1), 15.
23. Kapoor, S., Wills, A. G., Hendriks, J., & Blackhall, L. (2025). Maximum Likelihood Estimation for Line Parameters in Distribution Grids Based on Expectation Maximization Algorithm. Journal of Modern Power Systems and Clean Energy.
24. Vashishth, T. K., Sharma, V., Sharma, K. K., Kumar, B., Panwar, R., & Chaudhary, S. (2024). AI-driven learning analytics for personalized feedback and assessment in higher education. In Using traditional design methods to enhance AI-driven decision making (pp. 206-230). IGI Global Scientific Publishing.
25. Alshammari, M. M., & Al-Mamary, Y. H. (2025). User acceptance of AI-powered training: extending the technology acceptance model (TAM). Future Business Journal, 11(1), 239.