Enhance Students' Engagement And Proficiency In English Teaching By Incorporating Adaptive Learning Methods

Donghui Guo

Foreign Linguistics and Applied Linguistics, Xi'an Fanyi University, Xi'an 710105, China

Corresponding author. E-mail: Donghuiguo1@outlook.com, G3056391788@163.com

Received: March 03, 2026; Accepted: May 06, 2026

This study examines adaptive learning in English language teaching with a sample of 1,000 students. It is evident that adaptive learning greatly increases student engagement as evident from participation patterns ($p < 0.001$, Cohen's d = 6.937). Yet engagement does not have a significant effect on language proficiency ($r = -0.008$, $p = 0.805$). Rather, skill is heavily predicted by linguistic features such as mean sentence length, lexical density, grammaticality, and overall quality ($R^2 = 0.554$), suggesting that skill-based language learning is more important than just participation. This proposed framework facilitates a deeper comprehension of the correlation between student engagement and language development, while also giving educators relevant insights to create personalized learning strategies. In conclusion, this study makes it clear that adaptive learning technologies have a significant positive effect on engagement, while at the same time emphasizing the importance of linguistic skills development for English proficiency advancement.

Keywords: Adaptive learning; student engagement; English language proficiency; linguistic analysis; personalized education

http://dx.doi.org/10.6180/jase.202610_33.062

1. Introduction

Contemporary education is very much based on the English language for learning [1]. Nevertheless, learners have different levels of proficiency, speed of learning, and learning styles, thus generalized instruction is not sufficient [2]. Standard methodologies tend to ignore learner diversity [3], and more learners are passive in class, and so the class development impedes and the effectiveness of the class drops [4]. For this reason, personalized learning has been increasingly emphasized [5]. Individual learning Adapt content and pace according to the needs of each learner, and the learning experience is enhanced [6]. Prior to better English teaching outcomes, it is critical to comprehend how it affects participation and proficiency [7]. By monitoring learner performance and interactions, adaptive learning technologies increase engagement [8] and present personalized materials based on the specific requirements of the learners [9]. In English learning, they offer focused activities and feedback to learn grammar, vocabulary, reading and writing [10]. Such techniques/technologies are utilized in e-learning solutions and intelligent tutoring systems [11]. They also facilitate teachers in tracking learners' progress and providing efficient assistance to those in need [12], which in turn nurtures a learner-centered learning environment supported by active engagement and autonomy of learning [13]. The use of tools of information and communication technology (ICT) facilitates the effectiveness of the teaching–learning process through the creation of interactive, flexible, and student-centered environments, which in turn increases the students' involvement in the learning process [14]. Despite extensive research on adaptive learning, limited studies have systematically examined the combined impact of engagement metrics and linguistic features on language proficiency outcomes. The study is grounded in constructivist, self-regulated learning, and SLA theories to explain how interaction, feedback, and adaptive learning enhance engagement and language proficiency. The remainder of the paper is organized as follows: Section 2 describes the materials and methods, Section 3 presents the results and discussion, and Section 4 concludes the study.

2. Materials and methods

Rincon-Flores et al [15] showcased a form of adaptive learning with flipped classroom and self-regulated theoretical framework that increased both achievement and engagement [16]. The mixed-methods approach further the findings [17], and the efficacy of the platform was rated as positive [18]. Yaseen et al [19] reported that adaptive tools and AI feedback can boost engagement and that this factor was moderated by the level of computer/digital literacy of participants [20]. Their research incorporated 500 students [21], and underlined the significance of instant feedback [22]. Smyrnova-Trybulska et al [23] identified a degree of in personalization in Moodle-based learning, advocating for learner choice [24]. Strielkowski et al [25] reviewed 3,518 articles, describing the development of adaptive learning. The study adopts an observational design using pre-existing learner data to analyze relationships between participation (time, interaction, feedback) and proficiency (grammar, sentence length, lexical density). Furthermore, aspects of data preprocessing will include the treatment of missing values, normalization of numeric variables, and the elimination of outliers for the purpose of performing statistical and comparative group analyses to test inferred hypotheses, as shown in Fig. 1.

Fig. 1 presents the study workflow, where adaptive learning is treated as the independent variable and participation and proficiency as dependent variables, analyzed using secondary data from the Reflective English Learning Dataset [26]. The anonymized dataset includes demographic, engagement, and linguistic features to analyze learner behavior and proficiency in adaptive learning contexts. The dataset contains 1000 anonymous learner records consisting of demographical, engagement and linguistic features to be utilized for studying patterns of participation and for assessing the evolution of the language proficiency in an AL environment. Adaptive learning is treated as the independent variable inferred from interaction patterns, while participation and proficiency are the dependent variables representing engagement and performance. Adaptive learning is conceptualized as a variable that accounts for learner behavior rather than being manipulated in an ex-

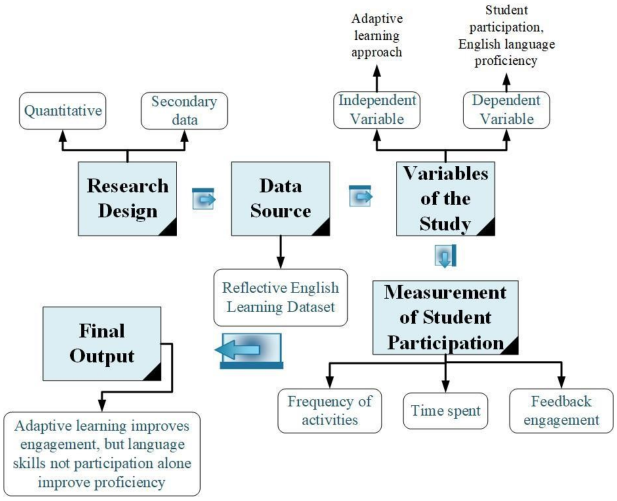

Fig. 1. Research Methodology Flow Diagram for Adaptive Learning and English Proficiency Study.

periment. The proficiency distribution within the dataset is skewed with very few advanced learners and more beginners and intermediate users. Although small, the advanced group is included and analysed for completeness to allow cross-proficiency comparisons to be valid, and keep the statistical treatment consistent across all learner levels. Participation is measured using time spent, interaction frequency, and feedback, combined into a normalized composite score. All the variables are systematically coded and non-engagement is converted in a composite participation score via Z-score normalization. The missing values were treated by mean imputation and outlier were capped to mitigate the effect of outlier. Linguistic features are derived by way of rule-based approaches. The data set is inspected for outliers, normalized to bring all the features into the same scale, and subjected to test for distributional assumptions using moments i.e. skewness and kurtosis. The assumptions for regression, including linearity, independence, homoscedasticity, and multicollinearity were all checked to confirm the quality and stability of the data as well as to confirm the appropriateness of the data for good statistical analysis. The preprocessing steps applied in this study are mathematically represented as follows in Eq. (1):

$$\bar{X} = \frac{1}{n} \sum_{i=1}^{n} X_i, \tag{1}$$

where $\bar{X}$ is the mean of the variable, n is the total number of observations, and X_i represents individual data points.

$$X_i = \bar{X} \tag{2}$$

In Eq. (2), where missing values X_i are replaced with

Table 1. Demographic-engagement-analysis.

Analysis	Test	F-statistic	p-value	Significance
Engagement by Age Group	One-way ANOVA	2.155	0.1164	NOT SIGNIFICANT
Engagement by Education Level	One-way ANOVA	0.524	0.5926	NOT SIGNIFICANT

Table 2. Demographic-summary.

Variable	N	Mean	Std. Deviation	Minimum	Maximum
Age	1000	26.7	7.85	14	39
Education-level	1000	0.99	0.82	0	2
Native-language	1000	1.94	1.45	0	4

Table 3. Frequency-engagement-level

Category	Frequency	Percent
Low	353	35.3
High	325	32.5
Medium	322	32.2

the mean value $\bar{X}$ of the respective variable.

$$Z = \frac{x-\mu}{\sigma} \tag{3}$$

In Eq. (3), where Z is the standardized value, X is the observed value, μ is the mean, and σ is the standard deviation.

$$X_{\text{capped}} = \begin{cases} L, & X < L \\ X, & L \le X \le U \\ U, & X > U \end{cases} \tag{4}$$

In Eq. (4), where L and U represent the lower and upper threshold values used to limit extreme observations. Behavioural indicators were standardized into a composite participation metric, with missing data handled using listwise deletion (<5%) and mean imputation, and outliers managed by retaining engagement variability while capping extreme linguistic values. The assumptions of normality of distribution were tested by the skewness and kurtosis to determine the shape of distribution, to ensure the variables satisfied the assumption of applying valid parametric correlation and regression analyses. Skewness is given as follows in Eq. (5):

$$\text{skewness} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{X_i-\mu}{\sigma}\right)^3 \tag{5}$$

where X_i represents individual observations, μ is the mean, σ is the standard deviation, and n is the total number of observations. Skewness measures the degree of asymmetry in the data distribution, where values close to zero indicate a symmetrical distribution, while positive and negative values indicate right and left skewness, respectively.

Kurtosis is given as follows in Eq. (6):

$$\text{Kurtosis} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{X_i-\mu}{\sigma}\right)^4 \tag{6}$$

where X_i, μ, σ, and n represent the observed values, mean, standard deviation, and number of observations, respectively. Kurtosis measures the peakedness of the distribution, where values close to zero indicate a normal distribution, while higher or lower values indicate heavier or lighter tails.

Z-score normalization standardizes variables for unbiased analysis with assumption checks, while average sentence length serves as a measure of syntactic complexity alongside grammar accuracy.

$$\text{Average Sentence Length} = \frac{\text{Total Number of Words}}{\text{Total Number of Sentences}} \tag{7}$$

Average sentence length is computed as total words divided by total sentences, where higher values indicate greater structural complexity. This metric serves as a proxy for syntactic development as shown inEq. (7). Lexical density is the ratio of content words to total words. Content words are nouns, verbs, adjectives, and adverbs.

$$\text{Lexical Density} = \frac{\text{Number of Content Words}}{\text{Total Number of Words}} \times 100 \tag{8}$$

Lexical density Eq. (8) is calculated as the percentage of content words in total words, and grammar accuracy derived from error detection reflects syntactic correctness, both serving as key indicators of language proficiency.

$$\text{Grammar Accuracy} = \frac{\text{Number of Grammatically Correct Sentences}}{\text{Total Number of Sentences}} \times 100 \tag{9}$$

Grammatically correct sentences refer to error-free constructions. Total sentences represent all written responses.

Table 4. Hypothesis-h1-results.

Hypothesis	Test	Group-1	Group-2	N1	N2	Mean1	Mean2	SD1
H1	Independent ttest	High Engagement	Low Engagement	325	353	83.28	17.29	9.82
	SD2	tstatistic	df	pvalue	Cohens-d	EffectSize	Significant	
	9.22	90.235	676	0.000	6.937	Large	Significant	

Table 5. Hypothesis-h2-results.

Hypothesis	Test	Groups	MeanLow	MeanMedium	MeanHigh	SDLow
H2	One-way NOVA	Low, Medium, High Engagement	0.79	0.76	0.78	0.42
	SD-Medium	SDHigh	F-statistic	p-value	Etasquared	Significance
	0.45	0.43	0.581	0.5593	0.001	Not Significant

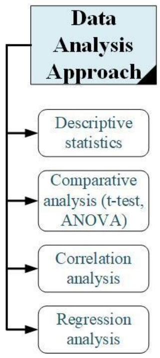

Fig. 2. Structured Framework of the Data Analysis Approach.

The ratio measures structural correctness proportion. Multiplying by 100 expresses the value as a percentage. Higher percentages indicate stronger grammatical competence as shown in Eq. (9). Linguistic features were extracted using rule-based methods and dataset annotations, ensuring consistent and reproducible computation of sentence length, lexical density, and grammar accuracy. Rule-based approaches are designed to analyze linguistic features to quantify language proficiency. Mean sentence length is taken to reflect syntactic complexity; lexical density is the proportion of content words and grammar accuracy is the degree of correctness. The two features are combined to calculate the overall linguistic quality, which corresponds to coherence and fluency. All features are calculated uniformly over the dataset.

Grammatically correct sentences refer to error-free constructions. Total sentences represent all written responses. The ratio measures structural correctness proportion. Multiplying by 100 expresses the value as a percentage. Higher percentages indicate stronger grammatical competence as shown in Eq. (9). Linguistic features were extracted using rule-based methods and dataset annotations, ensuring consistent and reproducible computation of sentence length, lexical density, and grammar accuracy. Rule-based approaches are designed to analyze linguistic features to quantify language proficiency. Mean sentence length is taken to reflect syntactic complexity; lexical density is the proportion of content words and grammar accuracy is the degree of correctness. The two features are combined to calculate the overall linguistic quality, which corresponds to coherence and fluency. All features are calculated uniformly over the dataset.

The analysis uses descriptive statistics, t-tests, ANOVA, correlation, and regression to evaluate engagement-proficiency relationships as in Figure 2. Pearson correlation was used to assess the strength and direction of the linear relationship between participation and language proficiency. Pearson correlation was used for continuous variables under linear assumptions with verified normality, eliminating the need for Spearman correlation. Multiple linear regression analysis was used to examine the predictive value of linguistic variables on proficiency outcomes. Prior to the regression, assumptions are checked to make sure the results will be reliable: linearity is for the relationships, independence to make sure there is no bias, multicollinearity to assure there is no redundancy and homoscedasticity regarding a constant residual variance, to allow for valid interpretations and not misleading model results. A multiple linear regression model was used with linguistic features as predictors of English proficiency, focusing on direct linear relationships without hierarchical or generalized models. Sentence length, lexical density, and grammar accuracy were used as predictors in regression to assess their individual and combined effects on proficiency. Variables were normalized for standardized interpretation, while stratified grouping and ANOVA controlled demographic heterogeneity for reliable analysis of proficiency and engagement. Cohen's d was used alongside p-values to evaluate both sta-

Table 6. Hypothesis-h3-results.

Hypothesis	Test	Variable-1	Variable-2	N	r
H3	Pearson Correlation	Participation Score	Language Proficiency	1000	-0.008
	r-squared	p-value	CorrelationStrength	Direction	Significance
	0.000	0.805	Negligible	Negative	Not Significant

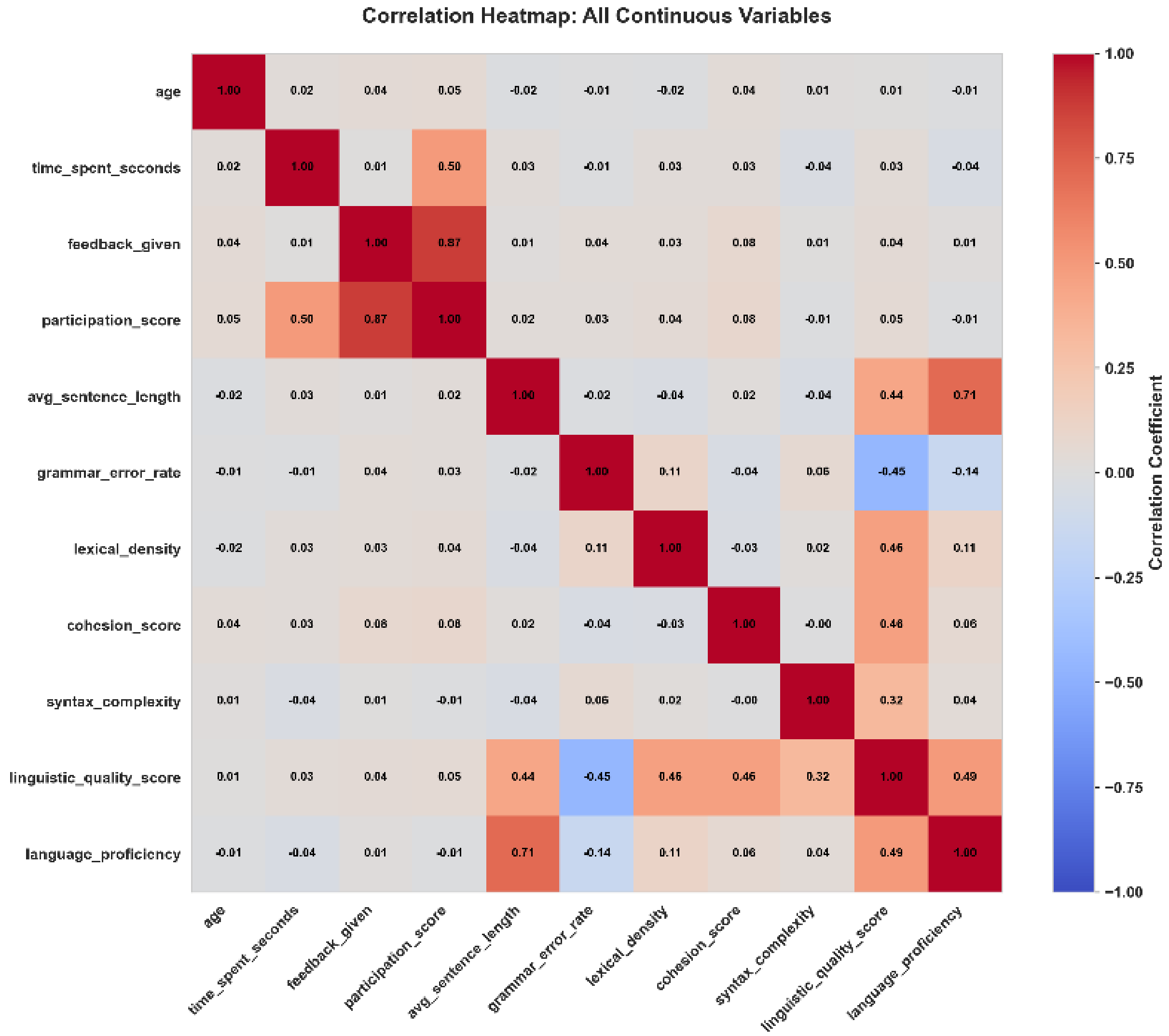

Fig. 3. Correlation Heatmap. All Continuous Variables.

Table 7. Participation-statistics.

Metric	Value
R^2	0.5538
Adjusted R^2	0.5502
F-statistic	153.743
df1	8
df2	991
p-value	0
N	1000

tistical significance and practical effect size. While p-values indicate significance, they do not reflect the magnitude of differences. Cohen's d measures the strength of differences in standard units. It was applied to compare participation across low, medium, and high engagement groups.

3. Results and discussion

The findings indicate adaptive learning is most effective for early-stage learners, with beginners showing higher engagement variation and greater linguistic gains than ad-

Table 8. Proficiency-statistics.

Variable	N	Mean	Std. Deviation	Minimum	Maximum	Skewness	Kurtosis
Language-proficiency	1000	0.78	0.43	0	2	-1.075	-0.093
Linguistic-qualityscore	1000	55.09	7.67	33.47	79.53	-0.02	-0.123
Avg-sentence-length	1000	11.95	2.93	3.29	20.31	0.07	-0.167
Grammar-error-rate	1000	0.28	0.17	0	0.88	0.605	-0.264
Lexical-density	1000	0.51	0.19	0.05	0.95	-0.094	-0.602
Cohesion-score	1000	0.6	0.1	0.31	0.89	0.001	-0.221
Syntax-complexity	1000	0.51	0.15	-0.11	1	-0.112	0.356

Table 9. Regression-model-summary.

Feature	F-statistic	p-value	Significance
Avg-sentence-length	510.556	0	SIGNIFICANT
Grammar-error-rate	10.773	0	SIGNIFICANT
Lexical-density	6.235	0.002	SIGNIFICANT
Cohesion-score	1.945	0.1435	NOT SIGNIFICANT
Syntax-complexity	0.818	0.4418	NOT SIGNIFICANT
Linguistic-quality-score	161.342	0	SIGNIFICANT

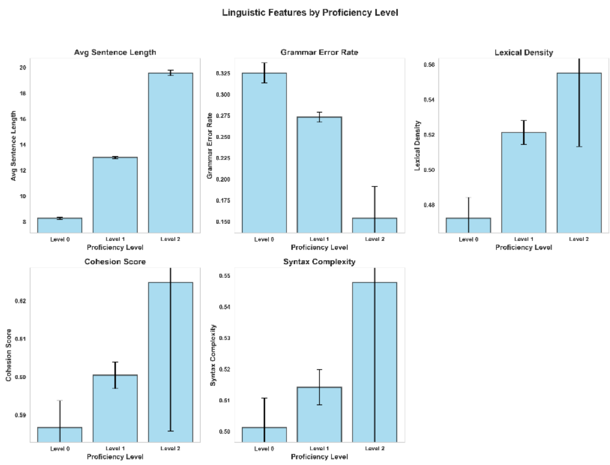

Fig. 4. Linguistic Features by Proficiency Level.

vanced learners.

Fig. 3 illustrates participation is positively associated with both feedback and time, competence is associated with linguistic quality and sentence length, and both performance and number of errors in grammar are negatively associated.

With higher levels of ability, sentence length, lexical density, cohesion and complexity increase and the number of grammar errors decreases significantly. Based on the visual results of these graphs, there is significant support for the English language proficiency model as shown in Fig. 4.

A random scatter with an almost flat regression line is displayed in Fig. 5; correlation (r = - 0.008, p = 0.805) is non-significant, suggesting that participation is not a predictor of proficiency outcomes.

Fig. 6 indicates that proficiency was comparable at different engagement levels, with slightly more variability and greater spread in the middle group.

Most of the learners (76.4%) are intermediate level, followed by the beginners 22.9% and a small percentage of learners are at advanced level (0.7%), which can be observed as imbalance from Fig. 7; Table 1 presents that age and education have no significant effect on engagement.

Table 2 depicts the average age of learners (26.7 years), limited diversity in educational backgrounds but substantial variation in native languages.

Most students reported low engagement (35.3%), and a similar proportion reported high (32.5%) and medium (32.2%) engagement, as presented in Table 3.

As can be seen in Table 4, high engagement activity (M= 83.28) was much higher than low level activity (M= 17.29), t = 90.235, p < 0.001, d = 6.937, supporting RQ1.

Table 5 reveals that there are no significant differences in proficiency between engagement groups (F=0.581, p=0.5593), and in this respect, H2 is not supported.

Participation and proficiency were not significantly correlated according to Table 6 (r=-0.008, p=0.805), which was contrary to the H3 expectation.

The regression shown in Table 7 is significant (F=153.743, p<0.001), which explains 55.38% variance (R^2=0.5538) that suggests the strong predictors of proficiency.

The linguistic feature, predicted proficiency, but not engagement, is shown in Table 8 to have small variance and the mean of proficiency is 0.78.

Sentence length, grammar error rate, lexical density and quality are significantly different as shown in Table 9, but cohesion and syntactic complexity are not.

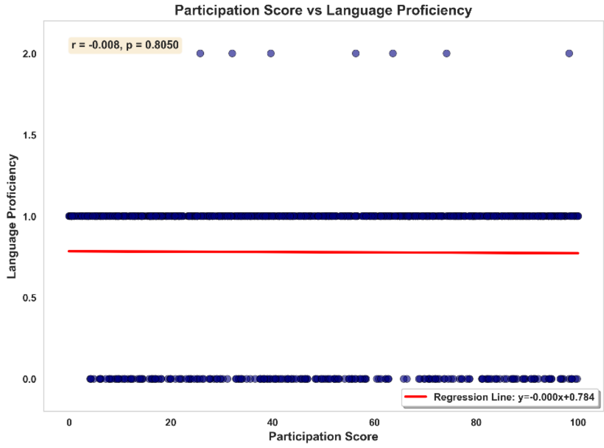

Fig. 5. Relationship Between Participation Score and Language Proficiency.

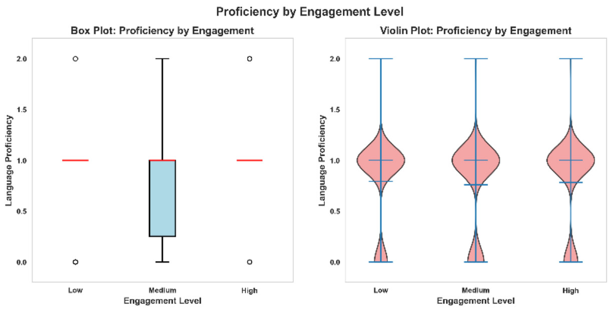

Fig. 6. Proficiency by Engagement Level.

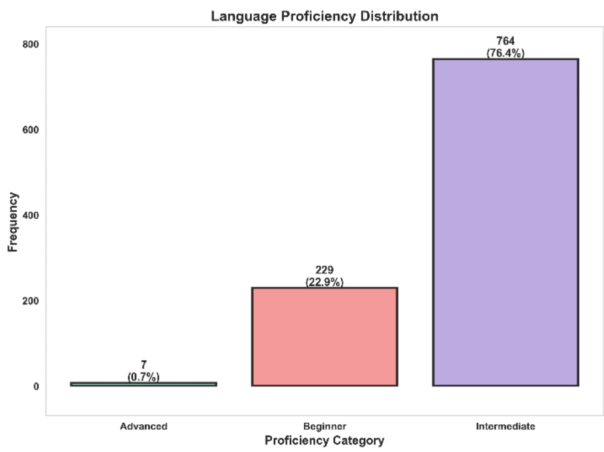

Fig. 7. Language Proficiency Distribution.

Limitations of the Study

This study uses a secondary dataset of 1,000 learners from an online adaptive environment, which may limit generalizability across diverse contexts. Therefore, findings should be interpreted cautiously, with further studies needed for broader validation.

4. Conclusion

This study integrates behavioural and linguistic features to provide empirical insights into participation and proficiency in adaptive learning. Adaptive learning is significantly associated with student engagement, while no significant differences in proficiency are observed across engagement levels. Linguistic features such as sentence length, grammar accuracy, and lexical density are strong predictors of proficiency, whereas participation metrics show no direct effect. Additionally, demographic factors do not significantly influence engagement or proficiency outcomes. Future research should examine the long-term impact of adaptive learning on language proficiency and explore advanced adaptive feedback mechanisms that incorporate linguistic errors and learning behavior for improved outcomes. In the future, it is recommended that studies employ more balanced datasets containing more advanced learners to increase the strength and generalizability of the comparison analyses at different proficiency levels.

Acknowledgment

This research received no external funding and was conducted as part of academic research activities at Xi'an Fanyi University.

References

[1] H. A. El-Sabagh, (2021) *"Adaptive e-learning environment based on learning styles and its impact on development students' engagement"* **International Journal of Educational Technology in Higher Education** *18*(1): 53. DOI: 10.1186/s41239-021-00289-4.

[2] M. Mejeh and M. Rehm, (2024) *"Taking adaptive learning in educational settings to the next level: leveraging natural language processing for improved personalization"* **Educational Technology Research and Development** *72*(3): 1597–1621. DOI: 10.1007/s11423-024-10345-1.

[3] L. Lim, S. H. Lim, and W. Y. R. Lim, (2023) *"Efficacy of an adaptive learning system on course scores"* **Systems** *11*(1): 31. DOI: 10.3390/systems11010031.

[4] J. Yiling, M. Omar, and F. M. Kamaruzaman, (2025) *"Exploring the AI-Enhanced Project-Based Learning for English Language Acquisition: A Systematic Review of the Key Elements and Emerging Technology Trends"* **International Journal of Learning, Teaching and Educational Research** *24*(2): 636–652. DOI: 10.26803/ijlter.24.2.31.

[5] T.-T. Wu, H.-Y. Lee, W.-S. Wang, C.-J. Lin, and Y.-M. Huang, (2023) *"Leveraging computer vision for adaptive learning in STEM education: effect of engagement and self-efficacy"* **International Journal of Educational Technology in Higher Education *20***(1): 53. DOI: 10.1186/s41239-023-00422-5.

[6] R. Sajja, Y. Sermet, M. Cikmaz, D. Cwiertny, and I. Demir, (2024) *"Artificial Intelligence-Enabled Intelligent Assistant for Personalized and Adaptive Learning in Higher Education"* **Information *15***(10): 596. DOI: 10.3390/info15100596.

[7] H.-C. Yeh, (2025) *"The synergy of generative AI and inquiry-based learning: transforming the landscape of English teaching and learning"* **Interactive Learning Environments *33***(1): 88–102. DOI: 10.1080/10494820.2024.2335491.

[8] Y. Xia, S.-Y. Shin, and J.-C. Kim, (2024) *"Cross-Cultural Intelligent Language Learning System (CILS): Leveraging AI to Facilitate Language Learning Strategies in Cross-Cultural Communication"* **Applied Sciences *14***(13): 5651. DOI: 10.3390/app14135651.

[9] R. Tiwari, (2023) *"The integration of AI and machine learning in education and its potential to personalize and improve student learning experiences"* **International Journal of Scientific Research in Engineering and Management *7***(2): DOI: 10.55041/IJSREM17645.

[10] R. Fitas, (2025) *"Inclusive education with AI: supporting special needs and tackling language barriers"* **AI and Ethics *5***(6): 5729–5757. DOI: 10.1007/s43681-025-00824-3.

[11] W. Liu and Y. Wang, (2024) *"The Effects of Using AI Tools on Critical Thinking in English Literature Classes Among EFL Learners: An Intervention Study"* **European Journal of Education *59***(4): e12804. DOI: 10.1111/ejed.12804.

[12] C. A. Eden, O. N. Chisom, and I. S. Adeniyi, (2024) *"Harnessing technology integration in education: Strategies for enhancing learning outcomes and equity"* **World Journal of Advanced Engineering Technology and Sciences *11***(2): 001–008. DOI: 10.30574/wjaets.2024.11.2.0071.

[13] L. Zhang and W. Zhang, (2025) *"Integrating large language models into project-based learning based on self-determination theory"* **Interactive Learning Environments *33***(5): 3580–3592. DOI: 10.1080/10494820.2024.2446535.

[14] D. Ramya and O. T. Poongodi, (2021) *"A study on the usage of information communication technology tools in the teaching–learning process of engineering education"* **Journal of Applied Science and Engineering *25***(2): 321–326. DOI: 10.6180/jase.202204_25(2).0017.

[15] E. G. e. a. Rincon-Flores, (2024) *"Improving the learning-teaching process through adaptive learning strategy"* **Smart Learning Environments *11***(1): 27. DOI: 10.1186/s40561-024-00314-9.

[16] J.-C. Liang, G.-J. Hwang, M.-R. A. Chen, and D. Darmawansah, (2023) *"Roles and research foci of artificial intelligence in language education: an integrated bibliographic analysis and systematic review approach"* **Interactive Learning Environments *31***(7): 4270–4296. DOI: 10.1080/10494820.2021.1958348.

[17] O. O. Adeleye, C. A. Eden, and I. S. Adeniyi, (2024) *"Innovative teaching methodologies in the era of artificial intelligence: A review of inclusive educational practices"* **World Journal of Advanced Engineering Technology and Sciences *11***(2): 069–079. DOI: 10.30574/wjaets.2024.11.2.0091.

[18] J. Belda-Medina and V. Kokošková, (2023) *"Integrating chatbots in education: insights from the Chatbot-Human Interaction Satisfaction Model (CHISM)"* **International Journal of Educational Technology in Higher Education *20***(1): 62. DOI: 10.1186/s41239-023-00432-3.

[19] H. e. a. Yaseen, (2025) *"The Impact of Adaptive Learning Technologies, Personalized Feedback, and Interactive AI Tools on Student Engagement: The Moderating Role of Digital Literacy"* **Sustainability *17***(3): 1133. DOI: 10.3390/su17031133.

[20] R. Rebolledo Font De La Vall and F. González Araya, (2023) *"Exploring the Benefits and Challenges of AI-Language Learning Tools"* **International Journal of Social Science and Humanity Invention *10***(1): 7569–7576. DOI: 10.18535/ijsshi/v10i01.02.

[21] M. Alenezi, S. Wardat, and M. Akour, (2023) *"The Need of Integrating Digital Education in Higher Education: Challenges and Opportunities"* **Sustainability *15***(6): 4782. DOI: 10.3390/su15064782.

[22] R. Daher, (2025) *"Integrating AI literacy into teacher education: a critical perspective paper"* **Discover Artificial Intelligence *5***(1): 217. DOI: 10.1007/s44163-025-00475-7.

[**23**] E. Smyrnova-Trybulska, N. Morze, and L. Varchenko-Trotsenko, (2022) *"Adaptive learning in university students' opinions: Cross-border research"* **Education and Information Technologies** ***27***(5): 6787–6818. DOI: 10.1007/s10639-021-10830-7.

[**24**] S. M. Chandrakant, (2023) *"Gamified learning and NLP: Enhancing student engagement through AI-driven interactive education models"* **International Journal of Science Research Archive** ***9***(1): 813–824. DOI: 10.30574/ijsra.2023.9.1.0496.

[**25**] W. e. a. Strielkowski, (2025) *"AI-driven adaptive learning for sustainable educational transformation"* **Sustainable Development** ***33***(2): 1921–1947. DOI: 10.1002/sd.3221.

[**26**] Kaggle. *Reflective English Learning Dataset*. https://www.kaggle.com/datasets/ziya07/reflective-english-learning-dataset. 2026.