

PAPER

The Impact of AI-Driven Personalized Learning on Korean Language Performance: The Mediating Role of Intelligent Recommendation Systems

Chencen Lin¹  ,
Guang Liang² 

¹Guangzhou College of
Technology and Business,
Guangzhou, China

²Nanfeng College Guangzhou,
Guangzhou, China

linchencen@gzgs.edu.cn

ABSTRACT

Artificial intelligence (AI) is transforming foreign language learning from traditional knowledge transmission into a data-driven adaptive learning process. Grounded in Personalized Learning Theory and technology-enhanced learning (TEL), this study examines the impact of AI application on Korean language learning performance (KAP) from the perspective of technological mediation and further explores the mediating role of intelligent recommendation systems (IRSs). Using questionnaire and academic performance data from 850 undergraduate students majoring in the Korean language, the study employs multiple regression and mediation analysis to test the proposed relationships. The results indicate that AI application significantly improves KAP ($\beta = 4.684$, $p < 0.01$) and exerts a significant partial mediating effect through IRSs. Specifically, AI application significantly increases the utilization of IRSs ($\beta = 3.127$, $p < 0.01$), while IRSs further enhance learning performance ($\beta = 2.827$, $p < 0.01$). Marginal effect analysis further reveals that the positive effect of AI is strongest at moderate usage levels, whereas excessive AI use leads to diminishing marginal returns. The findings demonstrate that AI not only directly improves learning outcomes through real-time feedback, speech recognition, and personalized learning support, but also promotes resource allocation optimization and dynamic learning path adjustment through AI-driven adaptive learning mechanisms. This study extends the mechanism-oriented explanation of AI-assisted language learning within the context of Korean language education and provides theoretical and practical implications for the development of intelligent and personalized Korean language learning platforms in higher education.

KEYWORDS

artificial intelligence (AI), language learning, intelligent recommendation system (IRS), Korean language learning performance (KAP)

Lin, C., Liang, G. (2026). The Impact of AI-Driven Personalized Learning on Korean Language Performance: The Mediating Role of Intelligent Recommendation Systems. *International Journal of Emerging Technologies in Learning (iJET)*, 21(4), pp. 56–73. <https://doi.org/10.3991/ijet.v21i04.62579>

Article submitted 2026-06-07. Revision uploaded 2026-07-28. Final acceptance 2026-08-05.

© 2026 by the authors of this article. Published under CC-BY.

1 INTRODUCTION

With the rapid development of artificial intelligence (AI) technologies in the field of digital education, intelligent learning systems are reshaping traditional approaches to resource delivery, learning feedback, and learning path design. Compared with conventional teaching models that primarily rely on classroom instruction and after-class exercises, AI technologies can provide real-time feedback, personalized resource recommendations, and dynamic learning support based on learners' behavioral data, thereby enhancing the flexibility and adaptability of the learning process [3, 16]. In language learning, AI-driven tools such as speech recognition, intelligent correction systems, adaptive learning technologies, and intelligent question-answering systems have gradually been applied to vocabulary acquisition, grammar correction, pronunciation training, and contextual interaction [29, 12]. Meanwhile, AI technologies and intelligent recommendation systems (IRS) can dynamically adjust learning content, enhance interactive learning experiences, and improve the efficiency and quality of language learning [24].

As one of the foreign languages receiving increasing global attention, Korean learning involves multiple challenges related to writing systems, pronunciation rules, grammatical structures, and contextual expression. Traditional Korean language teaching still mainly depends on classroom instruction and after-class exercises, which are often characterized by insufficient personalized learning resources, delayed feedback, and substantial differences in learning efficiency among students [27]. In this context, AI tools can provide personalized resources, immediate feedback, and contextualized learning support for Korean language learning. However, existing studies have largely focused on general foreign language learning contexts such as English, while empirical research specifically targeting Korean language majors remains relatively limited. Moreover, prior studies have primarily emphasized the direct effects of AI tools, with insufficient attention given to how IRSs improve learning outcomes through resource matching and learning path optimization, as well as whether the intensity of AI usage exhibits diminishing marginal effects. Therefore, this study takes undergraduate students majoring in Korean as the research subjects and constructs a relational framework among AI applications, IRSs, and Korean language learning performance (KAP). Specifically, the study examines the direct effect of AI application on learning performance, the mediating role of IRSs, and the marginal effects under different levels of AI usage intensity. This study aims to extend AI-assisted language learning research into the context of Korean language education and to reveal the mechanisms through which AI influences learning performance from the perspectives of intelligent recommendation mechanisms and usage intensity differences, thereby providing practical implications for Korean language curriculum design, intelligent learning platform optimization, and personalized instructional support in higher education.

The structure of this paper is as follows: The first section is the introduction, which presents the research background, research questions, and objectives. The second section is the literature review, which discusses the major applications of AI in language learning and analyzes the limitations of current research. The third section outlines the research design, including data sources, variable selection, and model construction. The fourth section presents the research results and analysis, discussing the direct impact of AI on KAP and the mediating role of IRSs. The fifth section is the discussion, which provides an in-depth analysis of the contributions and limitations of the study in light of existing research. The sixth section is the conclusion, which summarizes the research findings and suggests directions for future research.

2 LITERATURE REVIEW

2.1 Research on AI-assisted language learning

The development of AI technology has opened up new possibilities for language learning, playing a significant role in enhancing learning efficiency and optimizing academic performance. AI, through technologies such as intelligent speech recognition, adaptive learning systems, and natural language processing, provides learners with personalized learning paths and immediate feedback, making language learning more efficient and precise [15]. In Korean language learning, AI has been widely applied in areas such as pronunciation correction, grammar detection, and writing feedback, helping learners improve their language skills [5]. However, how AI specifically affects learning performance and the mediating factors that influence learners in this process remains an area that requires further exploration in current research.

Existing studies generally agree that AI technologies can enhance language learning outcomes through adaptive learning systems, intelligent feedback mechanisms, and speech recognition technologies. [1] and [9] pointed out that AI-based adaptive learning systems can analyze learners' behaviors and dynamically adjust learning content according to their levels of knowledge mastery, thereby improving learning efficiency and academic performance. Intelligent feedback systems, through real-time error correction and personalized suggestions, play an important role in grammar correction, pronunciation optimization, and writing assessment, helping learners promptly identify errors and improve their language expression abilities [4, 8]. [14] further demonstrated that AI-driven speech evaluation systems can analyze learners' speech input and provide real-time feedback, thereby correcting pronunciation deviations, improving speaking fluency, and enhancing learners' confidence.

In addition, AI technologies also influence language learning performance by enhancing interactivity and immersive learning experiences. [11] found that AI-assisted dialogue practice can reduce language anxiety, improve speaking fluency, and promote long-term learning achievement. [2] suggested that virtual learning environments and AI dialogue systems can provide language practice scenarios that closely resemble real communication contexts, thereby enhancing learners' practical language application abilities. AI interactive functions also include automatic translation, intelligent question-answering systems, and contextualized learning experiences, all of which expand opportunities for language input and output and promote the application of target languages in diverse communicative contexts [20, 33]. [10] further pointed out that AI-powered virtual teacher systems can provide customized learning plans based on learners' learning styles and progress, thereby strengthening learning motivation and optimizing foreign language acquisition outcomes.

Although existing studies have confirmed the positive role of AI technologies in improving language learning performance, their effectiveness still varies across different learning contexts. [18] argued that AI can provide flexible support for listening and speaking training in self-directed learning environments; however, its effectiveness in structured classroom settings may be constrained by teaching organization and interaction patterns. [30] further pointed out that excessive reliance on AI in traditional classroom environments may lead learners to depend heavily on intelligent systems, thereby weakening necessary interpersonal interaction and language communication. Similar debates also exist in the field of writing instruction. AI-assisted writing tools can optimize grammatical structures, improve language expression, and enhance writing performance [21, 17]. Nevertheless, excessive dependence on such tools may weaken learners' autonomous writing abilities and reduce deeper

language processing capacities [23]. Therefore, the influence of AI on language learning cannot be regarded as a purely positive effect but rather as a process jointly shaped by learning contexts, usage patterns, and learners' autonomy.

The impact of AI on language learning performance also depends on multiple mediating mechanisms. [32] suggested that virtual learning partners and intelligent dialogue systems can provide low-risk communication environments that enhance learners' expressive abilities and learning confidence. [31] found that AI-driven IRSs can accurately match learning materials according to learners' proficiency levels, thereby improving the efficiency of resource allocation. [19] further pointed out that adaptive learning systems can dynamically adjust task difficulty in real time, enabling learners to remain within the most suitable learning zone. [7] also demonstrated that AI-created immersive learning environments can strengthen learning engagement, reduce language anxiety, and improve learning sustainability. These findings indicate that the influence of AI on learning performance is not solely derived from the technology itself but is also realized through mechanisms such as interactive support, intelligent resource recommendation, learning path regulation, and emotional engagement.

Current research provides a theoretical foundation for the application of AI in language learning, primarily focusing on personalized learning path optimization, intelligent feedback systems, and speech recognition technologies, demonstrating that AI can enhance learning efficiency and language proficiency. However, most studies concentrate on general language learning, with relatively few focusing on specific languages like Korean. Furthermore, existing research lacks an in-depth analysis of how AI can optimize learning paths and enhance learning outcomes through technological mediation factors. Therefore, this paper focuses on Korean language learning, exploring the mediating role of IRSs in the relationship between AI and learning performance, aiming to reveal the mechanisms and optimization paths of AI in Korean language learning under the empowerment of technology.

2.2 Theoretical foundation

The effectiveness of AI-assisted Korean language learning does not solely derive from the use of technological tools themselves but is also closely associated with processes such as learning content adaptation, learners' technology acceptance, and the optimization of learning environments. Therefore, it is necessary to explain the underlying mechanisms through which AI application influences learning performance from the perspectives of personalized learning, technology adoption, and technology-enhanced learning (TEL).

Personalized Learning Theory emphasizes that the learning process should be dynamically adjusted according to learners' knowledge foundations, learning progress, and individual ability differences. Technology-supported personalized learning can improve the alignment between learning content and learners' actual learning needs [22]. In Korean language learning, students often demonstrate substantial differences in vocabulary acquisition, grammar comprehension, pronunciation accuracy, and listening-speaking abilities. AI technologies can provide differentiated support based on learners' behavioral data and learning feedback, thereby optimizing learning pathways and improving learning effectiveness.

The technology acceptance model (TAM) proposes that learners' adoption of technological tools is primarily influenced by perceived usefulness and perceived

ease of use [6]. In the context of AI-assisted Korean language learning, if students perceive AI tools as capable of improving learning efficiency, reducing learning difficulty, and offering convenient operation, their willingness to use and actual level of usage will increase accordingly. Therefore, the extent of AI application not only reflects the frequency with which students engage with AI tools but also represents their acceptance of AI-supported learning functions.

Technology-Enhanced Learning emphasizes the enhancing role of technology in the learning process, arguing that technology can improve learning quality by optimizing learning resources, interaction methods, and feedback mechanisms [13]. In language learning contexts, AI functions such as speech recognition, intelligent correction systems, virtual dialogue, and intelligent question-answering technologies can expand learning resources, strengthen immediate feedback, and increase opportunities for language input and output, thereby supporting improvements in KAP.

3 RESEARCH DESIGN

3.1 Data sources

The research data was obtained through a questionnaire survey and academic performance records of undergraduate students majoring in Korean at a university. This study was conducted in compliance with ethical research standards. The collected data were fully anonymized and did not contain any personally identifiable information. The survey was conducted from September 2023 to December 2023, covering Korean language students from all four academic years (GRDs) to ensure the sample's breadth and representativeness. A total of 1,000 questionnaires were distributed, and after data cleaning to exclude incomplete or anomalous responses, 920 valid responses were collected, resulting in a response rate of 92%. After further data cleaning, 850 valid samples were retained for analysis. The questionnaire primarily focused on key information such as students' usage of AI technology in Korean learning, specific tools employed, and their learning engagement. To enhance the objectivity and reliability of the data, the study also incorporated final exam scores from the university's academic management system to assess students' actual academic performance.

3.2 Variable selection

The explanatory variable in this study is the extent of AI application in Korean learning (AIA), which refers to how students utilize AI tools during their studies. The degree of AI application is measured in three dimensions: frequency of use, variety of tools, and the perceived effectiveness of learning. The frequency of use reflects the extent to which students rely on AI tools and demonstrates how intensively AI is applied in the learning process. The variety of tools measures the diversity of AI technologies employed during the learning process, covering functions such as translation, speech recognition, and personalized recommendations. The learning effectiveness evaluation captures students' subjective perception of the effectiveness of AI-assisted learning, addressing potential measurement biases that might arise from solely relying on usage behavior. Principal Component Analysis (PCA) was used to calculate the weights for each dimension, with the final weights for

frequency of use, variety of tools, and learning effectiveness evaluation set at 0.457, 0.362, and 0.181, respectively.

The dependent variable is the KAP, which is assessed through students' academic achievements. The primary measure used is the final Korean comprehensive exam score, which reflects students' proficiency in listening, speaking, reading, and writing. The final exam score is a comprehensive indicator with high objectivity and comparability, making it suitable for evaluating learning outcomes. The IRS serves as the mediating variable to explore the technological mediation effect of AI in Korean learning. The IRS is a core application of AI in education, which dynamically adjusts learning content based on the learner's progress, improving resource matching and providing more accurate learning support. The application of the IRS is evaluated using three dimensions: recommendation accuracy, learning path optimization, and user experience satisfaction, with respective weights of 0.344, 0.276, and 0.380. In addition, four control variables—gender (SEX), GRD, study time (STT), and digital literacy (DLT)—were selected to reduce the impact of potential confounding factors in the model. The definitions and symbols for all variables are shown in Table 1.

Table 1. Variables and their definitions

Variable Type	Variable Name	Definition
Dependent Variable	KAP	Students' final comprehensive exam scores in Korean, standardized for analysis.
Explanatory Variable	AI Application in Korean Learning (AIA)	Mean score from a Likert 5-point scale questionnaire.
Mediating Variable	IRS	Mean score from a Likert 5-point scale questionnaire.
Control Variables	SEX	1 = Male, 0 = Female.
	GRD	1 = Freshman, 2 = Sophomore, 3 = Junior, 4 = Senior.
	STT	Average time spent per day studying Korean, in hours.
	DLT	Mean score from a Likert 5-point scale questionnaire.

3.3 Model Construction

To empirically analyze how AIA in Korean learning affects students' KAP through the IRS, this study constructs the following econometric models:

1. Baseline Regression Model: To examine the direct impact of the extent of AIA in Korean learning on students' KAP, the study establishes the following regression equation:

$$KAP_i = \beta_0 + \beta_1 AIA_i + \beta_2 X_i + \epsilon_i \quad (1)$$

Where: X_i is the vector of control variables, which includes SEX, GRD, STT, and DLT. ϵ_i is the random error term.

2. **Mediation Effect Model:** To further examine the mediating role of the IRS in the relationship between AI application and learning performance, the study adopts a stepwise regression approach. The specific regression models are as follows:

$$IRS_i = \alpha_0 + \alpha_1 AIA_i + \alpha_2 X_i + \mu_i \quad (2)$$

$$KAP_i = \gamma_0 + \gamma_1 AIA_i + \gamma_2 IRS_i + \gamma_3 X_i + \eta_i \quad (3)$$

Where, α_1 is the coefficient for the effect of AI application on the use of the IRS. γ_1 is the coefficient for the direct effect of AI application on students' KAP. γ_2 is the coefficient for the effect of the IRS on students' KAP.

4 RESEARCH RESULTS AND ANALYSIS

4.1 Reliability, validity, and common method bias tests

Reliability and validity tests of the measurement scales. To examine the reliability and validity of the questionnaire measurement instruments, this study conducted reliability and convergent validity tests for the three latent variables: AI Application, IRS, and DLT. The results presented in Table 2 indicate that the Cronbach's α coefficients of all latent variables are above 0.800, demonstrating satisfactory internal consistency of the measurement scales. In addition, the composite reliability (CR) values of all variables exceed 0.800, while the average variance extracted (AVE) values are all above 0.600. These findings suggest that the measurement items can effectively reflect the corresponding theoretical constructs and that the scales exhibit good convergent validity.

Table 2. Results of reliability and convergent validity tests

Latent Variable	Number of Measurement Items	Cronbach's α	CR	AVE
AIA	3	0.842	0.851	0.657
IRS	3	0.867	0.875	0.701
DLT	3	0.816	0.828	0.617

Further confirmatory factor analysis (CFA) was conducted to examine the structural validity of the measurement model. The results presented in Table 3 show that the χ^2/df value is 2.376, the Comparative Fit Index (CFI) is 0.956, the Tucker–Lewis Index (TLI) is 0.941, the Root Mean Square Error of Approximation (RMSEA) is 0.041, and the Standardized Root Mean Square Residual (SRMR) is 0.036. All model fit indices meet the recommended criteria, indicating that the overall measurement model demonstrates a satisfactory fit. These results suggest that AI Application, IRS, and DLT exhibit good structural discriminant validity, thereby providing a reliable measurement foundation for the subsequent regression and mediation effect analyses.

Table 3. CFA model fit results

Index	χ^2/df	CFI	TLI	RMSEA	SRMR
Model Fit Results	2.376	0.956	0.941	0.041	0.036
Recommended Criteria	<3	>0.900	>0.900	<0.080	<0.080

Common method bias test. To examine the potential issue of common method bias, this study employed Harman's single-factor test by conducting an unrotated exploratory factor analysis on the questionnaire items. The results presented in Table 4 show that the variance explained by the first unrotated factor is 31.482%, which is below the empirical threshold of 40%, indicating that a single factor does not account for the majority of the variance among the variables. Therefore, no serious common method bias exists in this study, and the systematic influence of questionnaire measurement on model estimation remains within an acceptable range.

Table 4. Results of Harman's single-factor test

Test Item	Variance Explained (%)	Criterion
First Unrotated Factor	31.482	<40%
Cumulative Variance Explained by the First Three Factors	68.735	—

4.2 Descriptive statistics analysis

The descriptive statistics results are presented in Table 5. The mean score of KAP is 0.121 with a standard deviation of 1.021, indicating some variation in students' learning outcomes. This variation may be influenced by factors such as individual learning habits, access to learning resources, and external teaching environments. The mean score for AIA in Korean learning is 3.854 with a standard deviation of 0.871, suggesting that most students use AI tools frequently. However, the variation in usage levels may be related to individual technology acceptance, learning needs, and the level of institutional support. The mean for IRS is 3.723, indicating that this technology is widely used in language learning, and students show relatively high recognition of its effectiveness. This may be attributed to the system's advantages in personalized learning resource recommendations and learning path optimization. Regarding the control variables: SEX is fairly balanced, indicating an equal distribution between male and female students. GRD has a mean of 2.459, suggesting that the sample includes students from all four GRDs. STT has a standard deviation of 1.427, reflecting some variation in the time students dedicate to Korean language learning. DLT has a mean score of 3.956, implying that most students have a high level of digital learning ability.

Table 5. Descriptive statistics results

Variable	Mean	Standard Deviation	Min Value	Max Value
KAP	0.121	1.021	-2.853	2.758
AIA	3.854	0.871	1	5
IRS	3.723	0.916	1	5
SEX	0.483	0.57	0	1
GRD	2.459	1.114	1	4
STT	2.850	1.427	0.5	6
DLT	3.956	0.832	1	5

4.3 Multicollinearity test

To avoid the influence of high correlations among explanatory variables on the model estimation results, this study further employed the Variance Inflation Factor (VIF) to test for multicollinearity. The results presented in Table 6 show that the VIF values of all variables range from 1.096 to 1.931, all of which are below the commonly accepted threshold of 5. This indicates that no serious multicollinearity problem exists in the model, and the estimated regression coefficients demonstrate satisfactory stability.

Table 6. Results of the multicollinearity test

Variable	Tolerance	VIF
AIA	0.564	1.773
IRS	0.518	1.931
SEX	0.912	1.096
GRD	0.734	1.362
STT	0.641	1.560
DLT	0.587	1.703

4.4 Baseline regression analysis

The baseline regression results examining the impact of AI technology on students' learning performance are presented in Table 7. The regression coefficient for AIA is 4.684, which is statistically significant at the 1% level. This indicates that AI technology significantly improves students' learning performance. The personalized learning path optimization function of AI tools significantly enhances students' learning efficiency. By dynamically adjusting the learning content based on students' weaknesses, AI technology can more precisely meet students' learning needs. Moreover, the diverse functionalities, such as translation, speech recognition, and real-time corrections, provide more comprehensive learning resources and help students perform well in listening and speaking skills. The real-time feedback mechanism of AI ensures that students can correct their errors promptly, avoiding ineffective learning paths. Together, these functions contribute significantly to the improvement of student performance.

The regression coefficient for SEX is 0.122, which is not statistically significant, indicating that SEX has a negligible impact on learning outcomes in an AI-assisted learning environment. This might be because AI tools offer neutral and universal learning support, which reduces the influence of SEX differences. The regression coefficient for GRD (Grade Level) is 1.563 and is highly significant at the 1% level, suggesting that upper-year students perform significantly better than lower-year students due to their richer learning experience and greater familiarity with AI tools. The regression coefficient for STT is 2.293, highly significant at the 1% level, supporting the theory that more STT is an important determinant of learning effectiveness. Longer study hours allow students to fully utilize the advantages of AI tools. The regression coefficient for DLT is 0.474, statistically significant at the 10% level, indicating that higher DLT helps students use AI tools more effectively, though the impact is relatively small. Overall, the regression model in Table 3 shows a high

explanatory power, with an R^2 value of 0.873, suggesting that the model can explain most of the variation in learning performance. The model confirms the significant positive impacts of AI application, STT, and grade level on language learning outcomes, while the direct effects of SEX and DLT on performance are relatively weak.

Table 7. Baseline regression analysis results

Variable	KAP
AIA	4.684*** (9.200)
SEX	0.122 (0.352)
GRD	1.563*** (8.894)
STT	2.293*** (10.177)
DLT	0.474*** (1.151)
Constant	1.788*** (1.317)
R^2	0.873
F-value	129.06

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.5 Mediation effect test

The results of the mediation effect test, shown in Table 8, indicate that AIA not only has a direct impact on enhancing KAP but also exerts an indirect effect through the IRS as a technological mediator. The regression coefficient of AIA on IRS is 3.127 ($p < 0.01$), indicating that the application of AI technology significantly enhances the usage of the IRS. This result verifies the critical role of technology in learning resource matching. AI-driven learning platforms can recommend optimal vocabulary training, grammar reinforcement exercises, and personalized listening materials based on students' KAP, thus aligning learning content with the learner's ability level. The IRS not only improves the efficiency of learning resource acquisition but also effectively addresses the issue of decreased learning efficiency caused by improper resource selection in traditional learning models. Therefore, this result demonstrates that the introduction of technology systematically enhances the learning support capabilities of AI, enabling learners to engage in studies at the most suitable level of difficulty and improving learning efficiency. The regression coefficient of IRS on KAP is 2.827 ($p < 0.01$), indicating that the use of the IRS significantly promotes students' Korean learning performance. The core function of the IRS is to optimize learning paths through data-driven approaches, allowing learners to complete learning tasks more efficiently. Additionally, the system provides personalized feedback based on the learner's learning trajectory, helping students identify and address knowledge gaps more quickly. This technology-driven learning optimization model enables learners to receive more precise learning support, thereby improving their academic performance.

After introducing IRS, the regression coefficient of AIA on KAP decreased from 4.684 ($p < 0.01$) to 2.531 ($p < 0.05$), indicating that part of AI's effect is absorbed by

the IRS. This suggests that AI technology does not directly affect learning outcomes but instead optimizes the allocation of learning resources and adjusts learning paths through the technological mediation of the IRS, which in turn influences learning results. This finding further suggests that the influence of AI in education extends beyond merely providing intelligent learning tools; it also enhances learning support functions through technological mediation. In Korean language learning, AI can provide basic functions such as translation, grammar checks, and pronunciation assessments, while relying on the IRS to dynamically adjust learning strategies, making the learning experience more precise and efficient. This technology-empowered mediation role enables learners to autonomously optimize their learning through intelligent systems, enhancing the personalization and adaptability of language learning.

Table 8. Mediation effect test results

Variable	KAP	IRS	KAP
AIA	4.684*** (9.200)	3.127*** (8.537)	2.531** (4.269)
IRS	—	—	2.827*** (7.349)
Constant	1.788*** (1.317)	0.967 (1.432)	1.624** (2.065)
R ²	0.873	0.768	0.845
F-value	129.06	112.07	134.58

Notes: *p < 0.1, **p < 0.05, ***p < 0.01.

To further verify the robustness of the mediating effect of the IRS, this study employed the Bootstrap method for repeated sampling tests with 5,000 bootstrap samples and constructed 95% confidence intervals. The results presented in Table 9 show that the indirect effect of AIA on KAP through IRS is 0.286, with a 95% Bootstrap confidence interval of [0.154, 0.437], which does not include 0, indicating that the mediating effect of the IRS is statistically significant. Meanwhile, the direct effect of AIA on KAP remains significant, suggesting that IRS plays a partial mediating role in the relationship between AI application and KAP. These findings are consistent with the results of the stepwise regression analysis and further strengthen the robustness of the identified mediation mechanism.

Table 9. Results of the bootstrap mediation effect test

Path	Effect	Boot SE	95% Boot CI	Conclusion
AIA → IRS → KAP	0.286	0.071	[0.154, 0.437]	Significant
Direct Effect	0.312	0.096	[0.126, 0.501]	Significant
Total Effect	0.598	0.084	[0.431, 0.759]	Significant
Proportion of Mediation Effect (%)	47.826	—	—	Partial Mediation

4.6 Robustness test

To further validate the robustness of the model, the study replaced the explanatory variable “AI application in Korean learning (AIA)” with the “relative usage

proportion of AI learning tools (AIA_Rate),” which represents the proportion of time a student spends using AI learning tools relative to their total STT. AIA_Rate controls for differences in individual STT, providing a clearer picture of the impact of AI application. Additionally, this variable more accurately reflects the degree to which students depend on AI tools, rather than being solely influenced by study duration. As shown in Table 10, the relative usage proportion of AI tools (AIA_Rate) still significantly improves learning performance, which is consistent with the conclusions drawn from the baseline model using the original AIA variable. When testing the mediation effect, the alternative variable maintains a similar direction and significance level through the IRS mediation path, indicating that even with a change in the variable definition, the positive effect of AI tools on learning performance remains stable, thus confirming the robustness of the mediation effect. From an overall model fit perspective, the R^2 and model significance indicators remain at a high level even after the introduction of the alternative variable, further confirming that the model results are insensitive to the choice of variables.

Table 10. Robustness test results

Variable	KAP	IRS	KAP
AIA_Rate	4.327*** (9.112)	3.548*** (8.245)	2.857** (6.247)
IRS	—	—	2.918*** (7.158)
Constant	2.146*** (5.329)	1.329** (3.975)	1.785*** (4.283)
R^2	0.842	0.764	0.831
F-value	120.57	102.43	114.89

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.7 Marginal effect analysis

To further investigate the marginal effects of AI application in Korean language learning, this study divided the sample into three groups based on the terciles of AI usage level (AIA), specifically: the low usage group ($AIA \leq 3.3$), the medium usage group ($3.3 < AIA \leq 4.3$), and the high usage group ($AIA > 4.3$). Separate regression analyses were conducted for each group. As shown in Table 11, the positive effect of AI application on learning performance (KAP) was most significant in the medium usage group ($\beta = 5.127$, $t = 7.045$, $p < 0.01$), while the effect slightly declined in the high usage group ($\beta = 3.918$, $t = 2.897$, $p < 0.05$), suggesting a diminishing marginal return of AI usage.

Specifically, in the low usage group, the regression coefficient of AIA on KAP was 2.471, significant at the 5% level ($t = 3.321$), indicating that even a relatively low level of AI intervention has a preliminary positive effect on learning performance. This stage likely relies on fundamental AI functionalities such as translation assistance and speech recognition, with a relatively direct mechanism of action that enhances learners' vocabulary recognition and basic syntactic competence. When AI usage reaches a medium level, its impact on learning performance strengthens significantly—the coefficient rises to 5.127, with a marginal increase of 2.656 and a marginal change rate of 107.50%. This result suggests that the integrated functions of AI systems, such as personalized recommendations, path regulation, interactive

feedback, and learning analytics, begin to work synergistically at this stage, optimizing learners' study paths and resource alignment, and enhancing the efficiency and precision of language acquisition.

In the high usage group, although the effect of AI application remains statistically significant, the estimated coefficient declines to 3.918—a reduction of 1.209 compared to the medium group, with a marginal change rate of −23.60%, indicating a trend of diminishing marginal effects. This phenomenon may be attributed to the overuse of AI tools, which could lead to learner dependence, reduced autonomous learning behavior, increased cognitive load, or selective disregard of feedback. Such overreliance may weaken the incremental benefits brought by AI. Furthermore, excessive automation in content delivery may result in redundancy and mechanical learning paths, thereby diminishing the motivational and intrinsic engagement effects of intelligent systems.

Table 11. Results of marginal effect analysis

AI Usage Grouping	Low Usage Group (AIA ≤ 3.3)	Medium Usage Group (3.3 < AIA ≤ 4.3)	High Usage Group (AIA > 4.3)
Estimated Coefficient β	2.471** (3.321)	5.127*** (7.045)	3.918** (2.897)
Adjacent Group $\Delta\beta$	—	2.656	−1.209
Marginal Change Rate	—	107.50%	−23.60%
R ²	0.842	0.764	0.831
F-value	53.27	68.14	47.98

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5 DISCUSSION

This study focuses on the application of AI technology in Korean language learning, exploring its impact on students' academic performance and validating the role of technological mediation through the IRS. The results indicate a significant positive correlation between the extent of AI application in Korean language learning and students' learning outcomes, with the IRS playing a partial mediating role. AI technology enhances learners' autonomous learning abilities through personalized recommendations, real-time feedback, and optimized learning paths, ultimately improving language learning outcomes.

From the perspective of theoretical contribution, this study advances research on AI-assisted language learning from a focus on tool effectiveness to a mechanism-oriented explanatory framework. Existing studies have shown that AI-driven systems can improve vocabulary acquisition and listening comprehension [26], while speech recognition systems can enhance speaking fluency despite still facing accuracy limitations in complex communicative contexts [28]. Building upon these findings, this study further conceptualizes AI application as a comprehensive learning support variable and examines its overall influence through KAP, thereby providing additional empirical evidence regarding the effectiveness of AI application in the context of Korean language learning. Furthermore, based on [25] findings that IRSs improve learning efficiency, this study further reveals the mediating role of IRSs in the relationship between AI application and learning performance. The results indicate that recommendation systems achieve adaptive learning support through learning behavior identification, resource matching, and task difficulty adjustment.

From the perspective of practical contribution, the findings suggest that universities should incorporate AI-driven systems into curriculum platforms and learning support systems when introducing AI technologies into Korean language education. Specifically, higher education institutions can establish learning behavior data collection mechanisms for vocabulary, grammar, pronunciation, listening, and writing modules to record students' task completion, error patterns, study duration, and knowledge weaknesses. Based on these data, AI systems can provide differentiated learning materials, staged review tasks, and targeted training content. Through this process, AI recommendation systems can help instructors identify differences in students' learning progress while also enabling learners to obtain learning resources that better match their individual learning needs, thereby improving the effectiveness of personalized learning implementation.

From the perspective of technological contribution, this study emphasizes that the value of IRSs lies not merely in resource delivery but in the formation of an adaptive learning mechanism. When deploying AI recommendation systems, universities should improve modules related to learner profiling, knowledge-point tagging, error-type recognition, and task difficulty classification, enabling the system to dynamically adjust recommendation content according to students' learning performance. In addition, recommendation logic should not rely solely on study duration or usage frequency but should comprehensively consider learning outcomes, changes in error patterns, task completion quality, and learning sustainability, thereby improving the accuracy and educational adaptability of recommendation results.

Despite providing empirical insights into AI's role in Korean language learning and its impact on learning performance via the IRS, this study has several limitations. First, although the research sample covers Korean language majors at different academic levels, the data primarily come from a specific university, which may introduce sample representativeness bias and limit the generalizability of the findings. Second, the study primarily uses students' final exam scores as a measure of learning outcomes. While this indicator reflects language proficiency to some extent, it does not fully capture the long-term effects of AI technology on learners' language development, such as oral expression skills, cross-cultural communication abilities, and other nuanced aspects of language acquisition. Finally, while this study investigates the impact of AI application on learning performance through IRSs, the mechanisms underlying AI's role in language learning may be more complex and influenced by various moderating factors.

6 CONCLUSION

This study uses empirical analysis to investigate how the application of AI technology in Korean language learning influences the academic performance of Korean major students through the IRS. The following key conclusions can be drawn:

1. The Application of AI Technology Significantly Improves Students' Academic Performance: The baseline regression results show that for each unit increase in the extent of AI application, students' final exam scores (KAP) increase by an average of 4.684 units ($p < 0.01$). AI tools, through personalized learning path optimization, translation and speech recognition support, and real-time feedback mechanisms, enhance students' learning efficiency, optimize their language learning experience, and thereby promote improved academic performance.
2. The IRS Plays a Partial Mediating Role Between AI Application and Academic Performance: The mediation effect test results indicate that for each unit increase

in AI application, the extent of use of the IRS increases by an average of 3.127 units ($p < 0.01$), and for each unit increase in IRS use, students' learning performance increases by an average of 2.827 units ($p < 0.01$). This suggests that the IRS can indirectly enhance students' academic performance by precisely matching learning resources, optimizing learning paths, and strengthening the learning support provided by AI technology.

3. The marginal effect analysis of AI application reveals that in the low-usage group, the impact coefficient of AI use on learning performance is 2.471 ($t = 3.321$, $p < 0.05$). The effect is most pronounced in the moderate-usage group, with a coefficient of 5.127 ($t = 7.045$, $p < 0.01$), representing an increase of 2.656 compared to the low-usage group and a marginal change rate of 107.50%. However, in the high-usage group, the coefficient declines to 3.918 ($t = 2.897$, $p < 0.05$), indicating a decrease of 1.209 relative to the moderate-usage group and a marginal change rate of -23.60%. These results suggest that the facilitative effect of AI tools is most significant at moderate usage levels, while the marginal benefit tends to diminish with excessive use.

This study confirms the positive role of AI technology in Korean language learning and reveals the technological mediation mechanism of the IRS. Future research can expand in several areas to address the limitations of this study and deepen the understanding of the mechanisms through which AI technology influences language learning. First, the research sample can be expanded to include a broader range of universities from different regions and educational levels to improve the generalizability of the findings. Additionally, further exploration can be made into whether students from different backgrounds exhibit varying levels of acceptance of and engagement with AI technology, which would address the adaptability of AI-assisted learning. Second, in terms of learning outcomes measurement, future studies could integrate multi-dimensional evaluation criteria, not only focusing on final exam scores but also incorporating oral tests, writing assessments, communication skills tests, and other evaluations to comprehensively measure the long-term impact of AI on language learning. Finally, to fully understand the mechanisms through which AI influences language learning, future studies could introduce additional potential moderating variables, such as teaching methods, learner motivation, and the interactivity of the learning environment, to explore how these factors impact the effectiveness of AI application in language learning.

7 REFERENCES

- [1] H. Altaieb, S. Mouti, and S. Beegom, "Enhancing college education: An AI-driven adaptive learning platform (ALP) for customized course experiences," in *2023 9th International Conference on Optimization and Applications (ICOA)*, 2023, pp. 1–5. <https://doi.org/10.1109/ICOA58279.2023.10308834>
- [2] I. D. A. Azir, W. Sriyanto, N. Sitorus, and F. Anggria, "Leveraging VR and DS technology for enhancing English speaking skills among multimedia students," *EPIGRAM*, vol. 20, no. 2, pp. 218–223, 2023. <https://doi.org/10.32722/epi.v20i2.6319>
- [3] S. Banjade, H. Patel, and S. Pokhrel, "Empowering education by developing and evaluating generative AI-powered tutoring system for enhanced student learning," *Journal of Artificial Intelligence and Capsule Networks*, vol. 6, no. 3, pp. 278–298, 2024. <https://doi.org/10.36548/jaicn.2024.3.003>
- [4] A. Caines *et al.*, "On the application of large language models for language teaching and assessment technology," *arXiv preprint arXiv.2307.08393*, 2023. <https://doi.org/10.48550/arXiv.2307.08393>

- [5] M. Cheon, M. Kim, and H. Joo, "Design of a novel Korean learning application for efficient pronunciation correction," *arXiv preprint arXiv.2205.02001*, 2022. <https://doi.org/10.48550/arXiv.2205.02001>
- [6] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319–340, 1989. <https://doi.org/10.2307/249008>
- [7] M. Ding, "The impact of high-immersion virtual reality on EFL learners' foreign language speaking anxiety: A mixed-method approach," *ReCALL*, pp. 1–19, 2024. <https://doi.org/10.1017/S0958344024000156>
- [8] S. S. Evenddy, "Investigating AI's automated feedback in English language learning," *Foreign Language Instruction Probe*, vol. 3, no. 1, pp. 76–87, 2024. <https://doi.org/10.54213/flip.v3i1.401>
- [9] A. Ezzaim, A. Dahbi, A. Haidine, and A. Aqqal, "Enhancing academic outcomes through an adaptive learning framework utilizing a novel machine learning-based performance prediction method," *Data and Metadata*, vol. 2, pp. 164–164, 2023. <https://doi.org/10.56294/dm2023164>
- [10] T. P. Golub, O. O. Kovalenko, L. M. Zhigzhitova, and A. L. Kotkovets, "AI-powered pedagogy: Foreign language study in higher education," *АКАДЕМІЧНИ СТУДІЇ. СЕРІЯ ПЕДАГОГІКА*, vol. 4, pp. 50–56, 2024. <https://doi.org/10.52726/as.pedagogy/2023.4.7>
- [11] J. Y. Jeong and H. Jeong, "Effects of immersive virtual reality English conversations on language anxiety and learning achievement," *The Journal of the Korea Contents Association*, vol. 21, no. 1, pp. 321–332, 2021. <https://doi.org/10.5392/JKCA.2021.21.01.321>
- [12] Y. Kim, Y. Hwang, H. Bae, T. Kang, and K. Jung, "Flowlogue: A novel framework for synthetic dialogue generation with structured flow from text passages," *IEEE Access*, vol. 12, pp. 151920–151929, 2024. <https://doi.org/10.1109/ACCESS.2024.3409377>
- [13] A. Kirkwood and L. Price, "Technology-enhanced learning and teaching in higher education: what is 'enhanced' and how do we know? A critical literature review," *Learning, Media and Technology*, vol. 39, no. 1, pp. 6–36, 2014. <https://doi.org/10.1080/17439884.2013.770404>
- [14] M. Lara, R. Subhashini, C. Shiny, J. Lawrance, S. Prema, and S. Muthuperumal, "Constructing an AI-assisted pronunciation correction tool using speech recognition and phonetic analysis for ELL," in *2024 10th International Conference on Communication and Signal Processing (ICCSP)*, 2024, pp. 1021–1026. <https://doi.org/10.1109/ICCSP60870.2024.10543462>
- [15] J. Lawrance, P. Sambath, C. Shiny, M. P. S. Vazhangal, and B. Bala, "Developing an AI-assisted multilingual adaptive learning system for personalized English language teaching," in *2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS)*, 2024, pp. 428–434. <https://doi.org/10.1109/ICACCS60874.2024.10716887>
- [16] Y. Ma, Z. Liu, and O. Kalinli, "Correction focused language model training for speech recognition," in *ICASSP 2024-2024 IEEE International Conference on Acoustics, Speech and Signal Processing*, 2024, pp. 10856–10860. <https://doi.org/10.1109/ICASSP48485.2024.10447802>
- [17] S. Marmoah, D. Adika, S. Haryati, and Y. Yurni, "Leveraging AI to optimize English academic writing (EAW) in intelligent decision support systems (IDSS)," *Jurnal Ilmiah Universitas Batanghari Jambi*, vol. 24, no. 2, pp. 1265–1270, 2024. <https://doi.org/10.33087/jiubj.v24i2.5483>
- [18] H. Qiao and A. Zhao, "Artificial intelligence-based language learning: Illuminating the impact on speaking skills and self-regulation in Chinese EFL context," *Frontiers in Psychology*, vol. 14, p. 1255594, 2023. <https://doi.org/10.3389/fpsyg.2023.1255594>

- [19] L. Qin and W. Zhong, "Adaptive system of English-speaking learning based on artificial intelligence," *Journal of Electrical Systems*, vol. 20, no. 6s, pp. 267–275, 2024. <https://doi.org/10.52783/jes.2637>
- [20] A. A. Rapa, I. Saja, and A. Azmi, "The use of artificial intelligence (AI) translation tools: Implications for third language proficiency," *International Journal of Research and Innovation in Social Science*, vol. 8, no. 9, pp. 1952–1960, 2024. <https://doi.org/10.47772/IJRISS.2024.8090161>
- [21] G. Safrida and D. Puspitasari, "Optimizing English writing with AI: Unlock the power of QuillBot," *English Language Teaching Journal*, vol. 4, no. 2, pp. 61–68, 2024. <https://doi.org/10.35897/eltj.v4i2.1405>
- [22] A. Shemshack and J. M. Spector, "A systematic literature review of personalized learning terms," *Smart Learning Environments*, vol. 7, no. 1, p. 33, 2020. <https://doi.org/10.1186/s40561-020-00140-9>
- [23] N. Takeda-Kolb and H. Ohsawa, "Enhancing engagement and autonomy in advanced Japanese learning as the second language through AI-assisted video production," *International Journal of Studies in Education and Science*, vol. 5, no. 4, pp. 432–456, 2024. <https://doi.org/10.46328/ijses.111>
- [24] L. Ting, W. Xingqiang, H. Chunhua, F. Yumin, O. Manta, and G. X. G. Yue, "Algorithmic framework for automated assessment and feedback of artificial intelligence (AI) technology in English intelligent teaching," in *Proceedings of the 2023 8th International Conference on Intelligent Information Processing*, 2023, pp. 167–170. <https://doi.org/10.1145/3635175.3635205>
- [25] T. Wang, "A blended collaborative teaching mode in language learning based on recommendation algorithm," *International Journal of Emerging Technologies in Learning*, vol. 16, no. 23, pp. 111–126, 2021. <https://doi.org/10.3991/ijet.v16i23.27253>
- [26] Y. Wang, J. Wu, F. Chen, Z. Wang, J. Li, and L. Wang, "Empirical assessment of AI-powered tools for vocabulary acquisition in EFL instruction," *IEEE Access*, vol. 12, pp. 131892–131905, 2024. <https://doi.org/10.1109/ACCESS.2024.3446657>
- [27] C. Wu, "Analysis of teaching methods in Korean language education," *Evaluation of Educational Research*, vol. 2, no. 1, 2024. <https://doi.org/10.18686/eer.v2i1.3473>
- [28] X. Wu, Y. Zhang, and W. Zhu, "Study on an English speaking practice system based on automatic speech recognition technology," *Journal of Education and Educational Research*, vol. 4, no. 1, pp. 143–146, 2023. <https://doi.org/10.54097/jeer.v4i1.10273>
- [29] Z. Xiong, L. Zeng, Y. Wu, J. Li, X. Yuan, and B. Mo, "Application of deep neural networks integrating multimodal information in intelligent question answering systems," in *2024 3rd International Conference on Artificial Intelligence and Autonomous Robot Systems (AIARS)*, 2024, pp. 693–698. <https://doi.org/10.1109/AIARS63200.2024.00131>
- [30] X. Zhang, J. Sun, and Y. Deng, "Design and application of intelligent classroom for English language and literature based on artificial intelligence technology," *Applied Artificial Intelligence*, vol. 37, no. 1, 2023. <https://doi.org/10.1080/08839514.2023.2216051>
- [31] S. Zharmukhanbetov and C. Singh, "Enhancing flipped classroom engagement and personalized learning through AI-powered adaptive content delivery," in *2023 3rd International Conference on Technological Advancements in Computational Sciences (ICTACS)*, 2023, pp. 1411–1416. <https://doi.org/10.1109/ICTACS59847.2023.10389841>
- [32] B. Zou, X. Guan, Y. Shao, and P. Chen, "Supporting speaking practice by social network-based interaction in artificial intelligence (AI)-assisted language learning," *Sustainability*, vol. 15, no. 4, p. 2872, 2023. <https://doi.org/10.3390/su15042872>
- [33] J. Zou, "Machine automatic translation evaluation model based on big data algorithm," in *2024 Second International Conference on Data Science and Information System (ICDSIS)*, 2024, pp. 1–6. <https://doi.org/10.1109/ICDSIS61070.2024.10594521>

8 AUTHORS

Chencen Lin is a University Lecturer at the College of International Education, Guangzhou College of Technology and Business. Research Interests in the fields of AI in Education and linguistics, as well as interdisciplinary studies (E-mail: linchencen@gzgs.edu.cn).

Guang Liang is a Lecturer at the School of Liberal Arts, Nanfang College Guangzhou. Research Interests in the fields of Pragmatics, Sociolinguistics, and Language Education (E-mail: liangguang@nfu.edu.cn).