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Investigating Korean College EFL Learners' Perceptions and Intentions toward AI-Enabled Language Learning Applications*

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ABSTRACT

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This mixed-methods study investigated Korean college EFL learners' perceptions and behavioral intentions toward AI-enabled language learning applications. A survey based on the Technology Acceptance Model and Theory of Planned Behavior was administered to 196 Korean university students, with model validation using 370 Chinese students. Structural equation modeling revealed a six-factor model with Perceived Usefulness, Attitude toward AI Use, and Subjective Norm significantly predicting behavioral intention, explaining 68% of the variance. The analysis confirmed the importance of social factors and positive attitudes in AI adoption decisions. Qualitative findings revealed a significant attitude-behavior gap. While students expressed favorable views toward AI language tools, their usage focused on basic functions: translation (60.3%) and grammar checking (20.6%), with limited engagement in advanced AI platforms (17.5%). Participants expressed high expectations for real-time feedback, pronunciation support, and personalized guidance. Results suggest Korean EFL learners possess positive attitudes toward AI-enhanced language learning but demonstrate limited utilization of sophisticated AI capabilities. The study highlights the need for targeted interventions to bridge the gap between current basic usage and AI's pedagogical potential, emphasizing the importance of practical training and social support in promoting comprehensive AI adoption in Korean educational contexts.

KEYWORDS

AI, language learning, self-directed learning, behavioral intention, Korean EFL learners, mixed methods, technology acceptance model

1. Introduction

The landscape of language education has been fundamentally transformed by the rapid advancement of artificial intelligence (AI) technologies, particularly with the emergence of large language models and generative AI systems. Since the release of ChatGPT in late 2022, AI-enabled applications have demonstrated unprecedented capabilities in natural language processing, conversation generation, and personalized learning support (Liu and Ma 2024, Song and Song 2023). These technological developments have created new opportunities for self-directed language learning, offering learners access to immediate feedback, adaptive content, and authentic practice opportunities that can complement traditional instruction.

South Korea represents a particularly compelling context for examining AI-enabled language learning adoption. With one of the world's highest smartphone penetration rates and a strong emphasis on English proficiency for academic and professional advancement, Korean learners are strategically positioned to leverage AI-enhanced language learning tools (Go et al. 2025, Kim and Kim 2022). The Korean government's recent initiatives, including AI Digital Textbooks (AIDT) and policies to incorporate AI tools into the national curriculum, reflect a commitment to advancing education through cutting-edge technologies (Kim and Kim 2022, Park 2023, Park et al. 2024).

However, despite the proliferation of AI-enabled language learning applications and positive government support, empirical research examining Korean learners' actual perceptions, usage patterns, and behavioral intentions toward these technologies remains limited. Recent studies have shown mixed findings regarding the relationship between learners' stated intentions and actual usage behaviors, highlighting the need for comprehensive investigations that examine both quantitative relationships and qualitative experiences (Choi 2024, Kim and Choi 2024).

The significance of self-directed learning (SDL) in language acquisition has been well-established, particularly in contexts where formal classroom instruction may be insufficient for achieving communicative competence (Benson 2021, Little 2022). AI-enabled applications have the potential to support SDL by providing immediate feedback, personalized learning paths, and authentic practice opportunities. However, the successful integration of these tools depends largely on learners' acceptance, attitudes, and behavioral intentions toward their use.

This study addresses the gap in understanding how Korean college EFL learners perceive and intend to use AI-enabled applications for language learning. By employing a mixed-methods approach that combines quantitative analysis of learner attitudes with qualitative examination of their actual experiences and expectations, this research provides comprehensive insights into the factors that influence AI adoption in Korean EFL contexts. The findings have important implications for language educators, curriculum designers, and technology developers seeking to enhance the effectiveness of AI-supported language learning environments.

2. Literature Review

2.1 AI-Enabled Language Learning in Korean Higher Education

The integration of AI technologies in Korean language education has gained significant momentum in recent years, driven by both technological advancement and educational policy initiatives. The Korean Ministry of Education has prioritized AI integration into classrooms to modernize language education, with recent research showing that generational differences significantly impact acceptance patterns among educators (Choi 2024, Park et al. 2024).

Recent studies from Korean EFL contexts have demonstrated the potential of AI tools for language learning while also revealing implementation challenges. Kim et al. (2021) investigated the effects of AI chatbots on Korean EFL students' communication skills, finding significant improvements in speaking competence when learners engaged with voice-based AI chatbots over a 10-week period. Similarly, research by Lee et al. (2024) on the use of generative AI in Korean university-level general English courses showed positive effects on affective factors including motivation, interest, and confidence among 89 participants.

However, adoption patterns vary significantly across different user groups. A recent study examining generational differences in Korean EFL classrooms found that preservice Generation Z teachers naturally embrace AI integration, while in-service Generation X and Y teachers approach these technologies with greater caution, viewing them as complements rather than replacements for traditional teaching methods (Choi 2024, Kim and Choi 2024).

2.2 Theoretical Framework: Technology Acceptance and Behavioral Intention in AI Contexts

This study draws on the Technology Acceptance Model (TAM) developed by Davis (1989) and the Theory of Planned Behavior (TPB) by Ajzen (1991) to understand factors influencing learners' adoption of AI-enabled language learning tools. TAM posits that perceived usefulness and perceived ease of use are primary determinants of technology acceptance, while TPB incorporates social factors (subjective norms) and perceived behavioral control into the prediction of behavioral intentions.

Recent applications of TAM to AI technologies have shown strong predictive validity. Liu and Ma (2024) employed TAM to examine Chinese learners' attitudes toward ChatGPT use in extracurricular EFL activities, finding that perceived ease of use indirectly influenced attitude through perceived usefulness. Similarly, Gupta et al. (2024) demonstrated that perceived usefulness emerged as the most significant predictor of attitude toward AI use, aligning with findings regarding AI usage across various educational contexts.

An extended TAM framework has proven particularly valuable for understanding AI acceptance in educational settings. Recent research by Dahri et al. (2024) investigating ChatGPT acceptance for metacognitive self-regulated learning among 300 preservice teachers found that the extended TAM effectively predicted usage intentions when incorporating factors such as self-efficacy and anxiety. This approach recognizes that AI technologies present unique characteristics that may require additional predictive factors beyond traditional TAM constructs.

2.3 Self-Directed Learning and AI Technology Integration

The concept of learner autonomy and self-directed learning has gained increasing attention in language education, particularly in contexts where learners need to supplement formal instruction with independent study (Benson 2021, Ushioda 2020). AI-enabled applications have demonstrated significant potential to support SDL by providing learners with tools for independent practice, immediate feedback, and personalized learning experiences.

Recent research has shown that AI tools can enhance various aspects of self-directed language learning. Studies have documented positive effects on vocabulary knowledge (Yang 2025), writing performance (Nazli et al. 2025), and overall learning achievement (Xu and Wang 2024). Furthermore, AI-assisted language learning has been shown to contribute to improved self-regulated learning and increased motivation among English language learners (Caldwell 2025).

However, successful SDL requires not only access to appropriate tools but also learners' motivation, self-efficacy, and positive attitudes toward autonomous learning (Little et al. 2017, Oxford, 2016). Recent research by Kim and Su (2024) examining AI chatbot use among Korean EFL learners found that while technology acceptance was generally positive, actual usage patterns often differed from stated intentions, highlighting the importance of understanding both attitudinal and behavioral factors.

2.4 Current State of AI Language Learning Research in Asian Contexts

Recent research in Asian contexts has revealed both opportunities and challenges in AI-enabled language learning adoption. Studies from China have shown that while learners express positive attitudes toward AI language learning tools, actual usage patterns often differ from stated intentions, influenced by cultural factors including preferences for teacher-centered instruction and concerns about technology replacing human interaction (Mavridi 2018, Roca et al. 2024).

A comprehensive meta-analysis of AI education effectiveness in K-12 Korean classrooms, examining 64 studies conducted from 2019 to 2023, revealed generally positive effects of AI integration on learning outcomes (Lee and Kwon 2024). However, the study also highlighted implementation challenges related to teacher preparation, technological infrastructure, and pedagogical integration.

Recent qualitative research has provided deeper insights into learner experiences and expectations. A study of Chinese EFL students' perceptions of AI challenges and opportunities revealed themes of enhanced motivation and personalized learning support, while also highlighting ethical concerns and the need for balanced implementation approaches (Liang et al. 2024). Similar findings have emerged in studies of Korean pre-service teachers and EFL learners, where AI-assisted tools supported engagement and autonomy but also raised concerns regarding over-reliance and ethical transparency (Choi 2024, Song and Song 2023).

Based on the literature review and research gaps identified, this study addresses the following research questions:

RQ1: What is the factor structure of Korean college EFL learners' perceptions toward AI-enabled language learning applications?

RQ2: What factors significantly predict Korean college EFL learners' behavioral intention to use AI-enabled applications for self-directed language learning?

RQ3: What are Korean college EFL learners' current experiences with AI-enabled language learning tools, and what types of applications do they commonly use?

RQ4: What are Korean college EFL learners' expectations for future AI-enabled language learning support, and what specific functionalities do they desire?

RQ5: How do Korean college EFL learners' actual usage patterns relate to their stated attitudes and intentions regarding AI-enabled language learning?

3. Methodology

This study employed a convergent parallel mixed-methods design, collecting quantitative and qualitative data simultaneously to provide a comprehensive understanding of Korean EFL learners' perceptions and intentions toward AI-enabled language learning (Creswell and Clark 2017). The quantitative component examined the factor structure and predictive relationships among key constructs using survey data, while the qualitative component explored learners' actual experiences and future expectations through open-ended responses.

3.1 Participants

A total of 196 Korean university students participated in this study. Participants were recruited through convenience sampling from multiple universities across South Korea. The sample comprised 89 male (45.4%) and 107 female (54.6%) students, with ages ranging from 19 to 26 years (*M* = 21.8, *SD* = 1.7). Participants represented diverse academic majors, including English Education (*n* = 42), Engineering (*n* = 35), Business Administration (*n* = 28), Nursing (*n* = 24), and other fields (*n* = 67). All participants were enrolled in English language courses as mandatory degree requirements at their respective universities.

For the CFA and SEM procedures, a separate dataset of 370 Chinese university students was used for CFA/SEM for cross-validation. These participants were recruited through university English language instructors at a comprehensive university. Among them, 84% were second-year students, with the remainder in their third or fourth year. Approximately 90 students were English language majors, while the rest were from engineering-related departments. Female students made up 44.3% of the sample, and the mean age was 21.5 years (*SD* = 0.89).

This external dataset provided a robust basis for model validation while maintaining the independence of analytic procedures.

For the qualitative component, 63 participants (32.1%) provided responses to open-ended questions. Among qualitative respondents, 44 were female (69.8%) and 19 were male (30.2%), with ages ranging from 16 to 30 years (*M* = 22.8, *SD* = 2.1). English Education majors comprised 35 participants (55.6%), while other majors accounted for 28 participants (44.4%).

3.2 Instruments

3.2.1 Quantitative survey

The survey instrument was developed based on established scales from previous technology acceptance research, adapted for the AI language learning context. The selection of constructs was grounded in the Technology Acceptance Model (Davis 1989) and Theory of Planned Behavior (Ajzen 1991). The instrument consisted of eight main constructs for the primary analysis:

1. Actual Use (AU): 6 items adapted from Chai et al. (2024) measuring current usage of AI-enabled language learning tools (5-point Likert scale)
2. Knowledge of AI-enabled Language Apps (K): 7 items grounded in Wang and Chuang's (2024) AI self-efficacy framework assessing familiarity with various AI language learning applications (6-point Likert scale)
3. Perceived Usefulness (PU): 4 items adapted from Teo et al. (2018) measuring perceived benefits of AI tools (6-point Likert scale)
4. Perceived Behavioral Control (PBC): 5 items based on Sohn and Kwon (2020) assessing perceived control over AI tool usage (6-point Likert scale)
5. Attitude to Use AI (ATU): 5 items adapted from Teo et al. (2018) measuring attitudes toward AI language learning (6-point Likert scale)
6. Subjective Norm (SN): 4 items based on Sohn and Kwon (2020) assessing social influences (6-point Likert scale)

7. Perceived Ease of Use (PEU): 4 items adapted from Sohn and Kwon (2020) measuring perceived usability (6-point Likert scale)
8. Behavioral Intention to SDL (BI): 5 items adapted from Teo et al. (2018) measuring intention to use AI for self-directed learning (6-point Likert scale)

Two additional constructs (Autonomy Support and Competence Support) were collected but excluded from the final analysis due to poor factor loadings (< 0.50) during exploratory analysis.

3.2.2 Qualitative component

Two open-ended questions were included to gather qualitative data:

OE1: "Please describe your experiences using AI-enabled language learning applications/programs. If possible, please specify the names of the applications you have used."
OE2: "Please describe specifically what kind of help you expect AI technology to provide for your language learning in the future."

3.3 Data Collection

Data were collected online via a secure survey platform at multiple universities in South Korea. Participants were recruited through instructor networks and student organizations. The survey took approximately 15–20 minutes to complete. Participation was voluntary, and informed consent was obtained from all respondents. Ethical approval was granted by the university's institutional review board.

3.4 Data Analysis

3.4.1 Quantitative analysis

To ensure the independence of the exploratory and confirmatory phases of analysis, we utilized a split-sample validation approach. Specifically, a subset of 147 participants from the Korean dataset ($N = 196$) was used for the exploratory factor analysis (EFA). For confirmatory factor analysis (CFA) and structural equation modeling (SEM), an independently collected dataset of 370 Chinese university students was used. These students completed the same survey instrument under equivalent research conditions. This cross-national validation procedure aligns with recommended best practices in scale development and model confirmation (Hair et al. 2017), while allowing the primary focus of the study to remain on the Korean EFL learner context.

The quantitative data analysis followed a multi-step approach:

1. Exploratory Factor Analysis (EFA): Conducted using SPSS 27 with principal axis factoring and oblimin rotation to identify the underlying factor structure.
2. Confirmatory Factor Analysis (CFA): Performed using AMOS 27 to validate the measurement model.
3. Structural Equation Modeling (SEM): Used to test hypothesized relationships between constructs and predict behavioral intention.

Model fit was assessed using multiple indices: χ^2/df ratio, Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR), Goodness of Fit Index (GFI), Tucker-Lewis Index (TLI), and Comparative Fit Index (CFI).

3.4.2 Qualitative analysis

The qualitative data analysis followed a multi-step approach: The qualitative data from open-ended responses were analyzed using thematic analysis following Braun and Clarke's (2006) six-phase approach:

1. Familiarization: Repeated reading of all responses to gain overall understanding
2. Initial coding: Systematic coding of interesting features across the dataset
3. Theme development: Collating codes into potential themes
4. Theme review: Checking themes against coded extracts and entire dataset
5. Theme definition: Ongoing analysis to refine theme definitions
6. Report production: Final analysis and selection of compelling extract examples

Two researchers independently coded a subset of responses to ensure reliability, achieving substantial agreement ($\kappa = 0.84$ for OE1 and $\kappa = 0.81$ for OE2). Frequency counts and demographic patterns were analyzed to understand usage and expectation patterns across different participant groups.

4. Results

4.1 Quantitative Results

4.1.1 Exploratory factor analysis of the measurement model (RQ1)

Table 1 shows a summary of the exploratory factor analysis (EFA) results, including the mean, standardized deviation, factor loadings, and the Alpha reliabilities. The EFA extracted 22 items with factor loadings greater than 0.50 in the final version of the 6-factor measurement model. A factor loading threshold of 0.50 was adopted following Hair et al. (2017), who recommend this criterion for ensuring practical significance and interpretability of factors in educational research contexts with sample sizes over 100. The Kaiser-Meyer-Olkin was 0.897, and Bartlett's Test of Sphericity was 2328.506 ($df = 231$, $p < 0.001$). These results indicated the six factors were favorable for explaining students' behavioral intention to learn English supported by AI.

A total of 77.26% variance was explained by the six factors: Knowledge of AI-enabled language apps (4 items, $\alpha = 0.75$), perceived usefulness (4 items, $\alpha = 0.90$), attitude to use AI (4 items, $\alpha = 0.93$), subjective norm (3 items, $\alpha = 0.89$), perceived ease of use (3 items, $\alpha = 0.89$), and behavioral intention to SDL (4 items, $\alpha = 0.91$). The overall α value was 0.93, which suggested that these constructs had satisfactory reliability for the structure and the internal consistency was sufficient for assessing students' behavioral intention to learn English supported by AI.

Table 1. The EFA for Students' Behavioral Intention to Learn English Supported by AI (n = 147)

Items	Factor loading
Knowledge of AI-enabled language apps (α = 0.75, M = 3.89, SD = 1.23)	
K6 I know how to interact with chatbots to gain more experiences in communication using the language I am learning.	0.76
K5 I know how to subscribe to language learning applications that can help me to practice using the language.	0.71
K7 I am able to use text generator to create ideas for writing.	0.68
K3 I am able to use voice recognition software to check my pronunciations.	0.66
Perceived usefulness (α = 0.90, M = 4.57, SD = 0.93)	
PU3 Using AI technology increases my productivity in language outputs.	0.89
PU4 Using AI technology enhances my effectiveness in using language.	0.86
PU2 Using AI technology improves my performance in language learning.	0.71
PU1 Using AI technology enables me to accomplish the language learning tasks more quickly.	0.67
Attitude to use AI (α = 0.93, M = 4.57, SD = 0.93)	
A4 I find that using AI technology to learn language is enjoyable.	0.76
A3 I have fun using language-related AI technology.	0.71
A5 I like using AI technology to learn language.	0.68
A2 Using AI-enabled applications to learn language is pleasant.	0.66
Subjective norm (α = 0.89, M = 4.27, SD = 0.93)	
SN2 People who are important to me would think that I should use the AI product to learn language.	0.96
SN1 People who influence my behavior would think that I should use the AI product that supports language learning.	0.90
SN3 People around me will take a positive view of me using the AI technology to improve my language skills.	0.78
Perceived ease of use (α = 0.82, M = 4.24, SD = 0.93)	
PEU2 Interaction with the AI product would be clear and understandable.	0.86
PEU4 I would find it easy to get the AI product to do what I want it to do.	0.85
PEU1 Using the AI product would be easy.	0.64
Behavioral intention to SDL (α = 0.91, M = 4.59, SD = 0.94)	
BI2 I plan to pay attention to emerging AI applications that can be used for language learning.	0.83
BI5 I will be using the feedback generated by the intelligent systems to check my language learning progress.	0.82
BI4 I plan to use different types of AI technology in the future to help me learn language.	0.81
BI3 I expect that I would be choosing appropriate AI technologies to support my language development in the future.	0.74

4.1.2 Correlations among the factors (RQ2)

Pearson correlation coefficients were calculated to examine the relationships between the six factors. These factors were significantly and positively correlated (r from 0.21 to 0.41), with weak to moderate correlations among factors, as indicated by Table 2, except for the correlation between knowledge of AI-enabled language apps and attitude to use AI, which was very weak (r = 0.03). Discriminant validity was assessed using the average variance extracted (AVE) criterion (Fornell & Larcker, 1981). The square roots of the AVE values exceeded the inter-construct correlation coefficients, confirming discriminant validity.

Table 2. Correlations in the Measured Model (*n* = 147)

	1	2	3	4	5	6
1. Knowledge of AI-enabled language apps	(0.72)	0.30***	0.03***	0.21***	0.28***	0.22***
2. Perceived usefulness		(0.83)	0.38***	0.39***	0.33***	0.41***
3. Attitude to use AI			(0.89)	0.29***	0.35***	0.33***
4. Subjective norm				(0.84)	0.28***	0.40***
5. Perceived ease of use					(0.81)	0.35***
6. Behavioral intention to SDL						(0.86)

Note: *** $p < 0.001$
The items on the diagonal represent the square roots of the AVE; off-diagonal elements are the correlation estimates.

4.1.3 Confirmatory factor analysis of the measurement model

Confirmatory factor analysis (CFA) confirmed the construct validity and structure of the measurement model. All item parameters were significant, as shown in Table 3. The goodness-of-fit indices of the survey indicated satisfactory model fit: $\chi 2/df$ = 1.97 (< 5.0), root-mean-square error of approximation (RMSEA) = 0.051 (< 0.08), standardized root-mean-square residual (SRMR) = 0.04 (<0.05), goodness-of-fit index (GFI) = 0.914 (>0.90), Tucker–Lewis index (TLI) = 0.963 (>0.90), and comparative fit index (CFI) = 0.969 (>0.90, Hair et al. 2017). The results demonstrated that the survey items had high construct validity.

Moreover, the composite reliability (CR) of each sub-scale was higher than 0.70, and the average variance extracted (AVE) was higher than 0.50. The scales for knowledge of AI-enabled language apps (CR = 0.81, AVE = 0.52), perceived usefulness (CR = 0.90, AVE = 0.69), attitude to use AI (CR = 0.94, AVE = 0.80), subjective norm (CR = 0.88, AVE = 0.71), perceived ease of use (CR = 0.85, AVE = 0.66), and behavioral intention to SDL (CR = 0.92, AVE = 0.74) displayed satisfactory reliability and convergent validity (Hair et al. 2017).

Table 3. CFA of Students' Behavioral Intention to Learn English Supported by AI (*n* = 370)

Scale	Item	Mean	SD	Standardized estimate	t-value
Knowledge of AI-enabled language apps (K)	K3	4.11	1.24	0.69	12.92***
	K5	4.04	1.26	0.71	13.18***
	K6	3.57	1.19	0.82	-
	K7	3.83	1.24	0.66	12.21***
Perceived usefulness (PU)	PU1	4.66	0.84	0.83	19.15***
	PU2	4.54	0.93	0.88	21.17***
	PU3	4.48	0.96	0.76	16.90***
	PU4	4.60	0.97	0.85	-
Attitude to use AI (A)	A2	4.63	0.92	0.87	25.24***
	A3	4.64	0.94	0.89	26.26***
	A4	4.45	0.97	0.92	28.90***
	A5	4.57	0.91	0.91	-
Subjective norm	SN1	4.25	0.92	0.85	-
	SN2	4.12	1.01	0.87	19.55***
	SN3	4.44	0.87	0.82	18.28***
Perceived ease of use	PEU1	4.55	0.89	0.82	14.62***
	PEU2	4.14	0.96	0.89	15.37***
	PEU4	4.01	0.95	0.71	-
Behavioral intention to SDL	BI2	4.59	0.91	0.87	-
	BI3	4.69	0.90	0.87	22.50***
	BI4	4.52	0.98	0.89	23.45***
	BI5	4.56	0.976	0.80	19.27***

The final structural model, illustrated in Figure 1, shows the significant paths predicting behavioral intention to use AI for self-directed language learning.

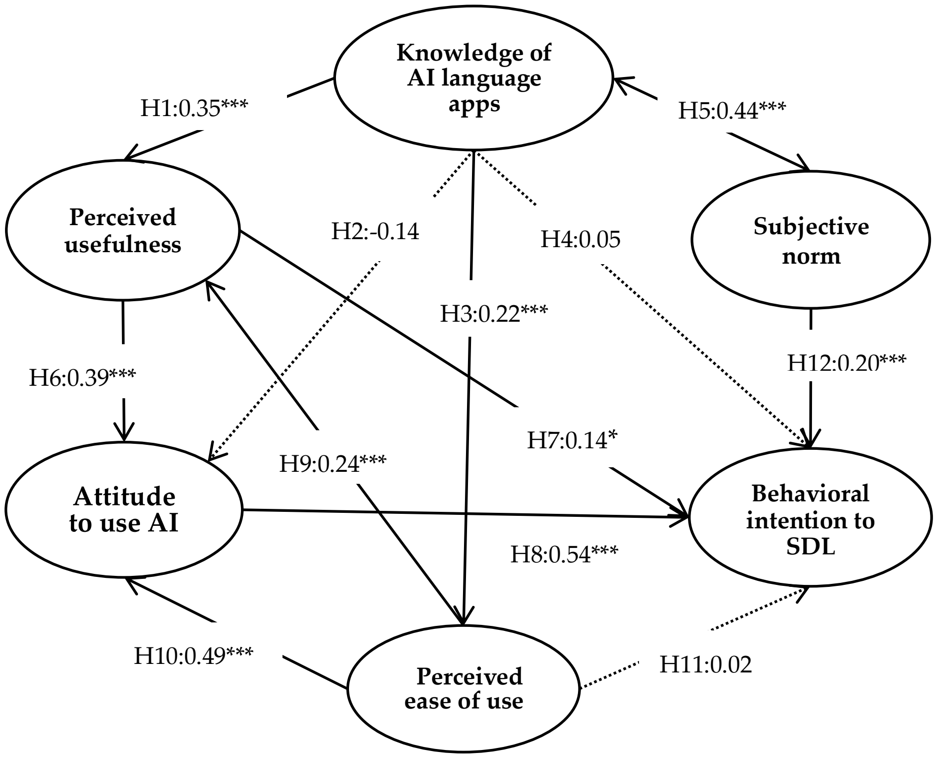

Figure 1. Structural Model of the Measured Factors

Note: Standardized path coefficients are shown; ***$p < 0.001$,* $p < 0.05$

The structural paths depicted in Figure 1 were specified a priori based on the Technology Acceptance Model (TAM, Davis 1989) and the Theory of Planned Behavior (TPB, Ajzen 1991), rather than derived post hoc from the data. According to TAM, perceived usefulness was hypothesized to influence both attitude toward AI use and behavioral intention, reflecting its central role in technology acceptance. TPB further informed the paths from attitude and subjective norm to behavioral intention, emphasizing the impact of social influences and personal evaluations on behavioral decisions. These theoretical foundations justify the directional relationships in the model and are consistent with recent applications of TAM and TPB to AI adoption in educational contexts (e.g., Liu and Ma 2024, Dahri et al. 2024).

Figure 1 presents a conceptual structural model focused on the latent-level relationships that directly address the study's research questions. This representation highlights the theoretically driven pathways predicting behavioral intention among Korean EFL learners. The measurement model was rigorously evaluated through exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and structural equation modeling (SEM). CFA results, based on an independent cross-validation sample of 370 Chinese university students, confirmed construct validity and model fit (see Table 3). The full item-level specifications are reported in Table 3, ensuring transparency and replicability of the measurement properties.

4.2 Qualitative Results

The qualitative analysis revealed rich insights into Korean EFL learners' actual experiences with AI-enabled language learning tools and their future expectations. Out of 196 participants, 63 provided responses to both open-ended questions (32.1% response rate).

Table 4. Summary of Qualitative Themes

Themes	Frequency	Percentage
Current Usage Patterns (RQ3)		
Translation-focused tools	38	60.3%
Limited or no experience	14	22.2%
Grammar and writing support tools	13	20.6%
Comprehensive language platforms	11	17.5%
Pronunciation/voice recognition	5	7.9%
Future Expectations (RQ4)		
Real-time error correction	19	30.2%
Convenience and accessibility	16	25.4%
Pronunciation and speaking support	11	17.5%
Contextual language support	11	17.5%
Personalized learning support	8	12.7%
Skepticism and limitations	5	7.9%

4.2.1 Current AI language learning tool usage (RQ3)

The thematic analysis of participants' reported experiences with AI language learning tools revealed five primary themes:

Theme 1: Translation-Focused Tools (*n* = 38, 60.3%)

The majority of participants reported using translation applications, with Papago (Naver's translation service) being the most frequently mentioned, followed by Google Translate. Representative responses included:

"*I frequently use Papago for translation functions and to check the meaning of texts I want to read*" (P2)

"*I mainly use Grammarly, an English grammar checker, and Papago or Google Translate when I want to express something through translation*" (P42)

Several participants demonstrated awareness of translation tools' AI nature while expressing some uncertainty:

"*I'm not sure if translation tools are AI-based... but if so, I have used Google Translate and Papago*" (P6)

Theme 2: Grammar and Writing Support Tools (*n* = 13, 20.6%)

A substantial number of participants reported using AI-powered grammar checking and writing assistance tools, with Grammarly being the most commonly mentioned:

"*I use AI-based Grammarly.com to finally check and correct typos and grammatical errors in English essays and assignments. I also frequently use Google Docs' automatic grammar error correction feature*" (P91)

Theme 3: Comprehensive Language Learning Platforms (*n* = 11, 17.5%)

A smaller group of participants reported experience with dedicated language learning applications:

"*I have experience using Duolingo's personalized program for language learning*" (P84)

"*I used the Tutor app (free version). I didn't think it was very efficient so I stopped using it. It seems more suitable for younger students or beginner learners*" (P89)

Theme 4: Pronunciation and Voice Recognition Tools (*n* = 5, 7.9%)

Some participants mentioned emerging AI applications like voice recognition and pronunciation tools:

"*I use Cambridge or Google Translate's 'listen to pronunciation' function quite frequently to learn the correct pronunciation of words*" (P72)

Theme 5: Limited or No Experience (*n* = 14, 22.2%)

A notable portion of participants reported minimal or no experience with AI language learning tools:

"*I haven't used AI-based language learning apps or programs much*" (P17)

4.2.2 Future expectations for AI language learning support (RQ4)

The analysis of participants' expectations for future AI language learning support revealed six main themes:

Theme 1: Real-Time Error Correction and Feedback (*n* = 19, 30.2%)

The most frequently expressed expectation was for AI systems to provide immediate, accurate feedback on language errors:

"*I expect AI to correct expressions I'm curious about or wrong expressions, provide feedback, and help me correct them into natural expressions*" (P1)

"*I hope there will be programs that can quickly provide feedback on linguistic errors that may occur not only in writing but also in other areas*" (P43)

Theme 2: Pronunciation and Speaking Support (n = 11, 17.5%)

Many participants expressed strong interest in AI-powered pronunciation correction and speaking practice:

"*I expect AI to help with pronunciation and stress, which are difficult to check without native speakers*" (P77, P97)

"*I hope it helps me check whether I'm pronouncing correctly*" (P89)

Theme 3: Contextual and Authentic Language Support (n = 11, 17.5%)

Participants desired AI tools that could provide contextually appropriate and naturally used expressions:

"*I want AI to accurately tell me expressions that actual foreigners use. Also, I'd like expressions to be categorized by situation, such as everyday conversation and business conversation*" (P119)

"*I hope AI can provide various practical materials so that I can acquire language that is practically needed for communication*" (P94, P109)

Theme 4: Personalized and Adaptive Learning Support (n = 8, 12.7%)

Several participants expressed expectations for AI systems that could adapt to individual learning needs:

"*I hope diverse programs will be developed that match individual learners' abilities and needs*" (P84)

"*I expect AI to help me focus on my weak areas by identifying what I lack and allowing me to learn those areas intensively*" (P118)

Theme 5: Convenience and Accessibility (n = 16, 25.4%)

Participants valued the potential for AI tools to make language learning more convenient and accessible:

"*I think I can learn much more easily with immediate feedback*" (P39)

"*It can help when I want to know something I don't know quickly and easily*" (P174)

Theme 6: Skepticism and Limitations (n = 5, 7.9%)

Some participants expressed caution about over-reliance on AI for language learning:

"*If AI technology becomes more advanced, it will help in using language more accurately. However, I don't think learning language by relying only on AI technology is meaningful learning*" (P79, P107)

4.2.3 Integration of quantitative and qualitative findings (RQ5)

The qualitative analysis revealed a significant gap between the availability of sophisticated AI language learning tools and Korean learners' actual usage patterns. While participants demonstrated positive attitudes toward AI language learning (M = 4.57 on a 6-point scale), their reported experiences were dominated by basic translation tools (60.3% of responses) and grammar checkers (20.6% of responses), with limited engagement with comprehensive AI-powered language learning platforms (17.5% of responses). The integration of quantitative and qualitative results revealed several important patterns:

1. Attitude-Behavior Gap: While quantitative results showed high mean scores for attitude toward AI use (M = 4.57 on a 6-point scale) and behavioral intention (M = 4.59), qualitative findings revealed that actual usage remained limited to basic tools, with 60.3% primarily using translation tools.
2. Knowledge-Usage Discrepancy: Despite positive scores on AI knowledge (M = 3.89), many participants demonstrated limited awareness of sophisticated AI language learning capabilities, with 22.2% reporting minimal or no experience with AI tools.
3. Expectation-Reality Mismatch: Participants' future expectations for real-time feedback, pronunciation support, and personalized learning contrasted sharply with their current reliance on basic translation and grammar checking tools.
4. Social Influence Confirmation: The significant role of subjective norms (β = 0.20) in predicting behavioral intention was supported by qualitative evidence of social factors influencing technology adoption decisions in Korean educational contexts.

In summary, the qualitative analysis revealed a significant disconnect between Korean EFL learners' positive attitudes toward AI and their current limited usage patterns. While participants demonstrated sophisticated expectations for AI support, particularly in real-time feedback and pronunciation training, their actual usage remained concentrated on basic translation and grammar checking tools. This finding suggests untapped potential for more comprehensive AI integration in Korean language learning contexts.

5. Discussion

5.1 Theoretical Implications

The findings of this study contribute to the theoretical understanding of technology acceptance in AI-enabled language learning contexts by demonstrating the applicability of combined TAM and TPB models for predicting AI tool adoption among Korean EFL learners. The structural equation modeling results revealed that behavioral intention to use AI for self-directed learning was significantly predicted by attitude toward AI use (β = 0.54), subjective norm (β = 0.20), and perceived usefulness (β = 0.14), explaining 68% of the variance in behavioral intention.

These findings align with recent research on AI acceptance in educational contexts (Dahri et al. 2024, Liu and Ma 2024) while providing new insights specific to Korean EFL learners. The strong predictive power of attitude toward AI use suggests that emotional and evaluative responses to AI technology play a crucial role in adoption decisions, consistent with recent research on AI acceptance in educational settings.

The significant role of subjective norms in predicting behavioral intention highlights the importance of social factors in Korean educational contexts, where peer influence and social approval often play crucial roles in learning decisions. This finding extends previous research on collectivistic cultural influences on technology adoption and suggests that interventions targeting social aspects of AI tool adoption may be particularly effective in Korean contexts.

5.2 Current Usage Patterns and the AI Underutilization Phenomenon

This pattern suggests what we term "AI underutilization" — a phenomenon where learners have access to advanced AI capabilities but primarily use them for basic, instrumental tasks rather than comprehensive language learning support. The predominance of basic tool usage indicates that Korean learners may view AI tools primarily as problem-solving utilities rather than comprehensive learning systems. The concentration on translation and grammar checking tools, despite positive attitudes toward AI (M = 4.57), suggests a gap between attitudinal acceptance and behavioral implementation. This finding challenges traditional technology acceptance models, which typically assume that positive attitudes predict corresponding usage sophistication.

The finding that 22.2% of participants reported minimal AI experience indicates that awareness and familiarity barriers may limit comprehensive AI adoption, even in technologically advanced contexts like Korea. This suggests that positive attitudes alone may be insufficient for realizing AI's full pedagogical potential. The preference for accuracy-focused tools (translation and grammar checking) over experimental learning platforms may reflect risk-averse learning preferences observed in formal educational settings. The limited skepticism expressed by some participants (7.9%) suggests that most learners are receptive to AI integration when properly introduced.

These findings suggest that bridging the utilization gap may require targeted interventions that introduce learners to AI's diverse capabilities while building on their existing positive attitudes. The strong role of social factors (β = 0.20 for subjective norms) indicates that peer-supported approaches may be particularly effective.

5.3 Cultural and Contextual Considerations

The findings reveal several culturally specific aspects of AI language learning adoption in Korean contexts. The high mean scores for subjective norms (M = 4.27) and their significant predictive power suggest that social approval and peer influence play important roles in technology adoption decisions. This finding is consistent with collectivistic cultural values prevalent in Korean society, where group harmony and social consensus are highly valued.

The emphasis on error correction and accuracy in participants' expectations reflects the accuracy-focused nature of Korean English education, where grammatical correctness is often prioritized over communicative fluency. While this focus on accuracy can benefit from AI-powered error detection and correction tools, it may also limit learners' willingness to engage in more experimental, fluency-building activities that AI conversation partners could support.

The skepticism expressed by some participants about over-reliance on AI (7.9% of responses) may reflect Korean educational values that emphasize human guidance and structured learning. This finding suggests that AI integration in Korean language learning contexts should emphasize AI as a supplement to, rather than replacement for, human instruction.

6. Conclusions

This mixed-methods study provides comprehensive insights into Korean college EFL learners' perceptions, experiences, and behavioral intentions toward AI-enabled language learning applications. The quantitative analysis revealed that attitude toward AI use, subjective norms, and perceived usefulness significantly predict behavioral intention to use AI for self-directed learning, with the combined model explaining 68% of the variance in behavioral intention.

The qualitative analysis revealed a significant gap between learners' positive attitudes toward AI and their current usage patterns, which remain dominated by basic translation and grammar checking tools. However, learners demonstrated sophisticated expectations for future AI support, particularly in areas of real-time feedback, pronunciation training, and contextual language guidance.

The findings suggest that while Korean EFL learners are well-positioned to benefit from AI-enhanced language learning, realizing this potential requires targeted interventions to bridge the gap between current usage and AI capabilities. Language educators should focus on raising awareness of advanced AI functionalities while providing guidance on effective integration of AI tools with traditional learning approaches.

For technology developers, the findings highlight the importance of designing AI language learning tools that respect cultural learning preferences while gradually introducing learners to more sophisticated AI capabilities. The emphasis on social factors suggests that collaborative and socially-integrated AI tools may be particularly effective in Korean contexts. As AI technology continues to evolve rapidly, ongoing research is needed to understand how these developments influence language learning practices and outcomes. The framework and findings presented in this study provide a foundation for future research on AI adoption in language learning contexts and offer practical guidance for educators and developers seeking to enhance AI-supported language learning environments.

This study has several limitations. First, its reliance on self-reported data may not accurately capture actual behavior. Longitudinal research is needed to track real-world AI tool use and assess the alignment between intentions and actions. Second, the use of convenience sampling and a university student sample limits generalizability; future studies should include diverse age groups, proficiency levels, and educational settings. Third, given the fast-paced evolution of AI, learner perceptions and available tools may have shifted since data collection—prior to the widespread use of advanced models like ChatGPT. Future research should explore how such developments have shaped learner experiences and adoption patterns.

The implications of this research extend beyond the Korean context, offering insights relevant to other educational systems where technology acceptance is influenced by cultural values and educational traditions. As AI becomes increasingly integrated into language education globally, understanding learner perceptions, experiences, and expectations becomes crucial for designing effective and culturally-sensitive AI-enhanced learning environments.

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Examples in: English
Applicable Languages: English
Applicable Level: Tertiary

Appendix A
Intention to Learn Artificial Intelligence Survey

Directions: Artificial Intelligence (AI) is currently widely used in search engines, online translation, email automated responses and voice assistant etc. This is a survey of your intention to learn about topics related to AI and the psychological factors contributing to your intention to learn about AI. It takes about 20 minutes to complete the questionnaire. All the data you fill in the questionnaire will be treated confidentially and used for academic research purposes only. The data will not be disclosed to the school, any institution or individual. This survey is voluntary and you can leave this survey at any time. If you agree to participate in this survey, please answer the following questions and click the "Submit" button to send your response. Sincerely thank you for your participation!

※Please read the items from the various section carefully and choose the number that represents your view.

1: Strongly disagree 2: Disagree 3: Slightly disagree 4: Slightly agree 5: Agree 6: Strongly agree

		1	2	3	4	5	6
Optimism							
OP1	I am hopeful about my future in a world where AI is commonly used.						
OP2	I always look on the positive side of things in the emerging AI world.						
OP3	I expect the best during uncertain times in an AI infused world.						
OP4	Overall, I expect more good things than bad things to happen to me in the AI enabled world.						
Basic AI Knowledge							
L1	I understand why machine learning needs big data.						
L2	I know the processes through which deep learning enables AI to perform voice recognition tasks.						
L3	I understand how AI technology optimizes the translation output for online translation.						
L4	I understand how AI assistant such as SIRI or Hello Google handles human-computer interaction.						
L5	I know how AI can be used to predict possible outcomes through statistics.						
L6	I understand how computers process image to produce visual recognition.						
Perceived Usefulness							
PU1	Using AI technology enables me to accomplish tasks more quickly						
PU2	Using AI technology improves my performance						
PU3	Using AI technology increases my productivity						
PU4	Using AI technology enhances my effectiveness						
Cognitive Engagement							
CE1	I think through the work for my AI lessons and make sure that it's right						
CE2	I think about different ways to solve the problems in my AI lessons.						
CE3	I try to connect what I am learning to things I have learned before in the AI lessons						
CE4	I try to analyze my mistakes when I get something wrong in the AI class.						
CE5	I would rather be told the answer than have to do the thinking work in the AI class						
Confidence in Learning AI (ARCS & MSLQ)							
C1	I feel confident that I will do well in the AI classes.						
C2	As I am taking the AI classes, I believe that I can succeed if I try hard enough.						
C3	I'm certain I can understand the most difficult material presented in the AI classes						
C4	I'm confident I can learn the basic concepts about AI taught in the lessons.						
C5	I'm confident I can understand the most complex material presented by the instructor in AI classes.						

Subjective Norm							
SN1	My teachers have emphasized the necessity to learn about AI technology						
SN2	My parents support me to learn about AI technology.						
SN3	My classmates feel that it is necessary to learn about AI technology.						
SN4	Most people I know think that I should learn about AI technology.						
Behavioral Engagement							
BE1	I try hard to do well in AI courses.						
BE2	In AI courses, I work as hard as I can.						
BE3	When I'm in AI class, I participate in class discussions.						
BE4	I pay attention in AI class.						
BE5	When I'm in AI class, I listen very carefully.						
Serving Others with AI							
SG1	I can serve others better if I learn more about AI technology.						
SG2	I am motivated to learn more about AI so that I can help others.						
SG3	AI technology should be designed to promote human well-being.						
SG4	AI can enhance my ability to help others.						
SG5	The use of AI should be directed to common good.						
SG6	I believe in using AI technology to make the world a better place.						
AI Attitude to Use							
ATU1	I look forward to those aspects of my life that use of AI technology.						
ATU2	Using AI technology is pleasant.						
ATU3	I have fun using AI technology.						
ATU4	I find using AI technology to be enjoyable.						
ATU5	I like using AI.						
AI Anxiety (MSLQ)							
A1	When I think about AI, I cannot answer many questions about my future.						
A2	When I consider the capabilities of AI, I think about how difficult my future will be.						
A3	When I imagine the future world with AI, I think of the consequences of failing in my life.						
A4	I have an uneasy, upset feeling when I think about AI.						
A5	I feel my heart sinking when I hear about AI advancement.						
Emotional Engagement							
EE1	When I'm in AI class, I feel good.						
EE2	When we work on something in AI class, I feel interested.						
EE3	AI Class is fun.						
EE4	I enjoy learning new things in AI class.						
EE5	When we work on something in AI class, I get involved.						
Behavioral Intention to Learn AI							
BI1	I will continue to learn about AI technology in the future.						
BI2	I will pay attention to emerging AI application.						
BI3	I expect that I would be concerned about AI development in the future.						
BI4	I plan to spend time in learning AI technology in the future.						