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# Exploring the Relationship between AI Tool Language Learning Awareness and Motivation to Learn English: Focusing on the Mediating Role of Adaptability

Abstract

As AI technology becomes more available and accessible to students, there has been a surge of research investigating its impact on how students learn a target language. However, a comprehensive understanding of how these technologies influence the motivational aspects of language learning remains limited. Addressing this gap, this study explores the broader relationship between individual engagement with various AI-based tools and their motivational impact on English learning, moving beyond the focus on specific AI tools. To achieve the research objectives, engagement with AI-based programs was examined in relation to awareness, experience, and interest in the future use of AI-based programs. Then, the relationships between these AI-related elements and motivational variables (such as self-efficacy and ideal L2 self) in language learning were investigated. Finally, the influence of adaptability was explored in these specific relationships.

For this study, convenience sampling was employed to collect data from 180 Korean students who were enrolled in an English course at a university in South Korea. Hierarchical regression and mediation analyses revealed that students' awareness and experience significantly influenced their interest in the future use of AI-based applications. Among the three AI-related elements, awareness and interest in future use were related to language learning motivation, specifically, self-efficacy and ideal L2 self. Notably, adaptability was identified as a mediating factor in the relationship between awareness of AI and the motivational variables. These findings contribute to our understanding of effective language learning in conjunction with AI-based tools.

*Keywords*: adaptability, AI technology, awareness of AI-based programs, ideal L2 self, language learning motivation, self-efficacy

The rapid development of artificial intelligence (AI) technologies is revolutionizing many areas of modern society. AI-powered language tools have become more sophisticated, and their accessibility has significantly increased. For instance, AI-powered tools such as Open AI's ChatGPT and others of a similar nature have emerged, and the number of users has been growing exponentially (Chow, 2023). This development has even been called "a cultural sensation" (Thorp, 2023, p. 313). AI-powered tools equipped with advanced natural language processing and generative AI can now assist users in understanding, generating, and translating text in a variety of languages. This technological evolution has profoundly impacted the field of language learning, transforming traditional methods and markedly altering how students learn a target language (Wei, 2023).

Recent studies have focused on the impact of AI-based programs (AI-BPs) on language learning. They explored diverse modalities such as machine translation (Cancino & Panes, 2021; Chung & Ahn, 2022; Deng & Yu, 2022), chatbots (Deng & Yu, 2023; Jeon, 2024; Shidiq, 2023), and writing assistance tools (Lee, 2022; Kim, 2023). In general, although studies show that these tools enhance the efficiency of individual language learning (Alqahtani et al., 2023; Deng & Yu, 2022, Kuddos, 2022; etc.), the specific reasons behind the effectiveness of AI-based devices in this process, including their motivational role, remain largely unexplored. Such exploration should be continued because understanding the influence of AI-BPs on learning outcomes is fast becoming essential in the quest for deeper insights into the modern ways of language learning (Song & Song, 2023). Findings in this area would provide valuable information to students and teachers at a time of rapid change and development in AI-assisted language learning environments. In addition, student adaptability seems critical in today's rapidly changing environment. The relatively understudied concept of adaptability has been recently revisited by Zarrinabadi (2022). Adaptability is likely to play an important role in the relationships between engagement in AI-BPs and motivation to learn English.

To fill the gaps in the current literature, this study aims to examine the relationships between individuals' engagement in AI-BPs and their motivation to learn English and seeks to explore the role of adaptability in these relationships. This study begins by exploring relevant research that establishes a foundational understanding of artificial intelligence, motivational beliefs, and adaptability related to language learning. It then describes the methodologies employed, followed by a presentation of the results. The discussion section integrates these findings with existing knowledge, and the study concludes with implications for future research and practical applications.

# Literature Review

## Artificial Intelligence and Language Learning

There have been almost three times as many AI-related publications between 2021 and 2022 (Crompton & Burke, 2023), signifying an inevitable ubiquitous transformation, affecting the education sector. Through examining the perceptions of students and scholars toward ChatGPT, Firat (2023, p. 59) identified the most common themes in his study, listed in order of frequency. The themes include changes in the learning and educational system, changes in the role of the teacher as a facilitator, and shifts in assessment and evaluation paradigms. The participants perceived AI-based technologies as having the potential to significantly transform education. Understanding these themes is crucial for anticipating how AI-based programs like ChatGPT can reshape educational practices and outcomes. Despite some challenges and ethical concerns, Firat (2023) and a few other studies (see Barrot, 2023; Thorp, 2023, etc.) found a generally positive attitude toward AI-based technology.

Technologies that fall under the umbrella of AI include natural language processing (NLP) and large language models (LLMs) as key capabilities (Alqahtani et al., 2023). NLP refers to the AI capability that facilitates the interaction between computers and human language users, forming the foundational basis for machine translation (Son et al., 2023). In other words, it allows computers to understand, assess, and produce human language. LLMs are deep learning models that undergo training on massive datasets, followed by reinforcement learning algorithms based on human feedback to generate human-like language and conduct a variety of language processing tasks. Together, these technologies make up what is known as *generative AI*.

For example, ChatGPT developed by OpenAI is designed to interact conversationally with users based on a trained model capable of providing what is touted as human-like answers to questions. It can admit its mistakes, contest inaccurate assumptions, and refuse inappropriate requests (OpenAI, 2023). Fueled by technological progress as well as heightened demand and popularity, tech enterprises have produced and updated AI-based applications similar to ChatGPT following its initial release (Chow, 2023). This may well indicate an impending, significant, and dramatic transformation in the contexts of both current and future research, including the field of education.

The variety of AI-BPs supporting language learning has significantly increased, and their functionality is rapidly advancing. Previous studies have examined the effects of individual AI-BPs on specific language domains. For instance, research has highlighted the advancements in machine translation tools, which have shown improvements in translation accuracy and learning efficiency (Cancino & Panes, 2021; Chung & Ahn, 2022; Deng & Yu, 2022). Similarly, chatbots have been examined for their potential to enhance conversational skills and provide instant feedback, contributing to better engagement and knowledge retention (Deng & Yu, 2023; Jeon, 2024; Shidiq, 2023). For example, Deng and Yu (2023) conducted a 32-study meta-analysis examining the effects of the use of chatbot technologies in learning. Their findings showed a significant impact ranging from mild to substantial irrespective of moderator variables, not only on overall learning outcomes but also on explicit reasoning, knowledge retention, engagement, and motivation. Similarly, Shidiq (2023) examined the influence of AI-based chatbots like ChatGPT on students' creativity in writing, emphasizing both the advantages and the challenges associated with these technologies. Additionally, writing assistance tools have emerged as a significant area of study, demonstrating their utility in aiding students' writing proficiency by offering real-time grammar and style suggestions. For example, Gayed et al. (2023) developed an AI-BP with advanced writing assistance features for organization and revision. They evaluated its effectiveness and found it potentially useful for English learners. The adoption and utilization of AI in learning English can enhance efficiency by providing practical direction and nurturing students' autonomy (Kuddus, 2022).

These findings provide valuable insights and contribute to our understanding of the role of AI in language acquisition, highlighting the potential to improve the performance and learning dynamics of students by transforming the way they learn (Alqahtani et al., 2023). While these programs are becoming more accessible to students, the concrete impact on language learning still requires further investigation. In particular, this study identifies a critical gap in understanding the motivation to learn English in relation to the use of AI-BPs, specifically in the areas of awareness, experience, and interest in future use. Investigating these factors offers a deeper understanding of how individuals' awareness and experience of AI-BPs influence their interest in utilizing them in the future. Such insights can offer valuable information for the effective integration and utilization of AI-BPs in the field of language learning. Awareness of AI-BPs may significantly affect individuals' English learning since it involves knowing the existence of the AI-BPs, their functionality, and their benefits. This study aims to address this gap by investigating the interplay among these elements and their impact on language learning motivation such as self-efficacy and ideal L2 self.

## Motivational Beliefs Related to Language Learning

Many studies have focused on the L2 self-guides and the self-efficacy of EFL students to explore language learning motivation. The findings show that such motivational beliefs are closely related to the learning process and its outcomes.

L2 self-guides are internal standards that L2 learners use to navigate their learning path and motivate themselves toward their future language selves (Dörnyei & Chan, 2013). Dörnyei's L2 self-system theory (2009) served as a foundational framework for research related to L2 future self-guides involving the ideal L2 self and ought-to L2 self. Dörnyei (2009, p. 29) defined the ideal L2 self as "the L2 specific facet of 'ideal self'" considering it "a powerful motivator to learn the L2." On the other hand, ought-to L2 self pertains to the qualities individuals believe they should possess to prevent potential negative outcomes. The notion of the ideal L2 self was developed through the following key studies. While many empirical studies have underscored the profound connection between the ideal L2 self and positive outcomes in language learning processes, the ought-to L2 self is seen as having a less powerful or negligible effect, often failing to predict a substantial motivational drive (Csizér & Kormos, 2009; Papi & Teimouri, 2012; Taguchi et al., 2009; Takahashi & Im, 2020; Teimouri, 2017). Recently, Papi et al. (2019) presented the 2x2 model of L2 self-guides based on two regulation focuses such as promotion/prevention perspectives (aspirations and growth vs. safety and responsibility) and own/other standpoints (personal desires and internal motivations vs. external expectations and obligations). Kim (2023) conducted a study in Korea using this model and found that the ideal L2 self, encompassing its own standpoint and promotion focus, was more strongly related to motivated behavior in English learning. Her findings also support that the ideal L2 self is linked to intrinsic and identified motivation.

Additionally, self-efficacy beliefs are viewed as regulating motivation and emotion, leading to specific behavioristic patterns (Bandura, 1994; Bong & Skaalvik, 2003). Bandura (1997, p. 3) says self-efficacy is the "beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments." He explains that individuals with high levels of academic self-efficacy are inclined to take on specific assigned tasks, exert effort to complete them, and continue to engage in these tasks even when facing challenges. Many studies (e.g., Bai & Wang, 2020; Bandura, 1994; Bong & Skaalvik, 2003; Kim et al., 2015, etc.) have found that self-efficacy plays a crucial role in driving individuals to engage in learning processes persistently and earnestly, which is essential for achieving language learning goals. In the study by Bai and Wang (2020), self-efficacy was categorized as one of the motivational beliefs and found to affect English language learning achievement through the mediator of self-regulated learning strategy use involving monitoring, effort regulation and goal setting, and planning. Likewise, self-efficacy is employed as a motivating and regulating variable that affects language learning.

With these insights in mind, a recent study by Wei (2023) examined the impact of AI technologies on English learning. Using a mixed-methods approach he analyzed data collected from 60 Chinese EFL university students to investigate how AI-mediated language instruction affects L2 motivation, self-regulated learning, and outcomes. The results indicate that those who received AI-mediated instruction outperformed their counterparts in these three areas. The responses of the 14 students in the experimental group revealed that the effect of AI platforms heightened academic involvement and provided tailored learning experiences, thereby enhancing motivation and promoting self-directed learning. However, it remains uncertain how the motivational variables such as ideal L2 self and self-efficacy are impacted by an individual's awareness of and level of engagement with AI technologies for language learning, necessitating the need for further investigation.

## Adaptability

Martin et al. (2012) conceptualized the notion of adaptability which serves as a framework for comprehending an individual's capacity to regulate and adjust psychological and behavioral properties when confronted with challenging situations, including new, changing, and uncertain conditions. They position adaptability as encompassing cognitive, behavioral, and affective adjustments, demonstrated by how an individual manages and regulates their resources in these facets to facilitate positive adjustment. Martin et al. (2013, p. 729) argue that adaptability places greater emphasis on "adjustments and modifications to thought and behavior (and affect)" rather than on the functions of self-regulation (Winne & Hadwin, 2008) such as monitoring, guiding, and orchestrating thought and behavior. They distinguish adaptability from the adversity variables that depict responses to challenges in difficult or adversarial situations such as buoyancy, resilience, and coping. Adaptability has a deliberate focus on psycho-behavioral functions in reaction to novelty and uncertainty.

Based on this notion, Martin et al. (2012) developed and validated the Adaptability Scale with a domain-general nature. A study conducted by Martin et al. (2013) aimed to explore the characteristics of adaptability. Notably, their study indicates that adaptability played significant mediating roles in the influence of neuroticism, conscientiousness, and effort beliefs regarding both academic and non-academic variables. It was shown that adaptable students are more likely to have favorite effort-related beliefs. They tend to not only exhibit high engagement in class and school enjoyment but also show heightened academic motivation and engagement irrespective of academic and non-academic domains. With the data collected from 186 freshmen in a university, Collie et al. (2017) investigated the degree to which adaptability is linked to behavioral involvement at the start of their first year. They also examined how these factors are connected to academic achievement. Their findings indicate that adaptability is greatly associated with persistence and planning, which are categorized under positive behavior involvement, and weakly with disengagement and self-handicapping, which are considered as negative involvement. Negative involvement is found to predict lower academic achievement. Their study implies that adaptability is a vital variable in academic domains. However, while their study contributes to our understanding of adaptability, it has yet to explain its association with motivation in language learning. Recently, Zarrinabadi et al. (2022) revealed that adaptability serves mediating roles in language learning in line with Martin et al. (2013). Their study underscores the importance of adaptability in explaining the influence of language mindsets on emotional factors such as enjoyment and anxiety as well as self-related factors such as self-efficacy and self-concept in the context of language learning.

In the rapidly changing landscape of information and technology, the need for individual adaptability becomes evident as its definition indicates. Given the limited understanding of how adaptability mediates the connection between engagement with available AI-BPs and language learning motivation, this study seeks to explore this relationship with a focus on the mediating influence of adaptability.

Taken together, this study aims to explore how students' engagement with AI-BPs influences their motivation to learn English. It includes a thorough examination of how engagement with AI-BPs, characterized by awareness, experience, and interest in future use, affects key motivational variables such as ideal L2 self, self-efficacy, and motivational intensity. Notably, in response to the rapid advancements in AI technologies within educational environments, the study also investigates how adaptability serves as a mediator in these relationships. To address these issues, this study involves the following research questions (RQs).

RQ1. How are the three elements that consist of engagement with AI-BPs related?

RQ2. How are these underlying factors related to motivational variables?

RQ3. How does adaptability mediate these underlying factors and motivational variables?

# Methods

## Participants

Korean university students (180) studying at a university in Seoul, Korea, with various majors voluntarily joined the study in the spring semester (June) of 2023. They were in one of the English courses such as conversation ($n$ = 110), reading ($n$ = 30), and basic writing ($n$ = 40). English conversation was one of the compulsory general education courses, mostly taken by first-year students while reading and writing were electives available to all students. Those in the English conversation course were placed in the Basic English Level based on the results of the placement test before starting the English course. Those in reading and writing courses had varying levels of English. The participants responded to questions involving their perceived proficiency and experience using AI-BPs as well as a series of questionnaires. Before data collection, the participants were provided with the aims of this study and informed that they could quit answering the questions whenever they wanted. Those who were willing to join the study were given the link to the online survey.

Their average age was 20.22 years ($SD$ = 2.07), with 107 female and 73 male students. Considering the mean scores of perceived English proficiencies marked by the participants in the four domains of reading ($Mean$ = 3.54, $SD$ = 1.08), writing ($Mean$ = 2.95, $SD$ = 1.09), listening ($Mean$ = 3.41, $SD$ = 1.20), and speaking ($Mean$ = 2.93, $SD$ = 1.13) on a 6-point Likert scale (1 = not at all proficient, 6 = very proficient), it was found that they considered their speaking and writing to be moderately low while reading and listening was average.

Among the total participants ($n$ = 180), 75% ($n$ = 135) reported having used AI-BPs for English learning. When asked about the tools used (with multiple responses allowed), the most common were translation tools (78.12%, $n$ = 250) (e.g., Google Translator, Papago, etc.), followed by AI-based Chatbots (15.94%, $n$ = 51) (e.g., ChatGPT, etc.), online editing tools (4.96%, $n$ = 15) (e.g., Grammarly, etc.), and AI-based speaking services (1.25%, $n$ = 4). The lower reported usage of services like ChatGPT may be due to the fact that data collection took place in June 2023 while they were relatively new. Among the students who have experience using AI-BPs for English learning (with multiple responses allowed), the predominant reason stated was for English assignments (51.11%, $n$ = 138), followed by personal improvement in English skills (25.56%, $n$ = 69), studying English for their academic majors (18.52%, $n$ = 50), and others (4.81%, $n$ = 13).

## Instruments

This study aims to explore the relationship between students' engagement with AI-BPs and their motivation to learn English. It also investigates how adaptability mediates these relationships. To achieve these objectives, the following instruments were used.

### *Engagement with AI-BPs in English Learning (EL-AI)*

To capture participants' engagement with AI-BPs, 14 items were proposed. This instrument measures three key aspects of AI-BP engagement and the three underlying factors of EL-AI were identified through exploratory factor analysis. As shown in Table 1, "experience with AI-BPs" indicates the actual usage or interaction that individuals have had with AI-BPs. "Awareness of AI-BPs" describes the knowledge of the existence of these programs, understanding how they function, and recognizing their potential benefits in language learning. "Future-driven interest in AI-BPs" reflects a student's eagerness to stay updated on new AI programs, understand their applications, and seek guidance for their use in English learning, as well as their readiness to incorporate them into their language studies.

Participants responded to survey items on a Likert scale ranging from 1 (completely disagree) to 6 (completely agree). The average scores of the three underlying factors of EL-AI, identified through exploratory factor analysis, were used for achieving the research aims.

To examine motivation in language learning, this study investigated three key motivational variables: self-efficacy, ideal L2 self, and motivational intensity. The participants also responded to the motivational items in the same manner as they did for those on EL-AI. The results of exploratory factor analysis (Table 2) and the coefficients of internal consistency are provided in the Data Analysis section. Average scores for each variable were used in subsequent analyses to explore their relationships with EL-AI.

### *Self-Efficacy (SE)*

To measure students' self-efficacy beliefs, five self-efficacy items were adapted from the study by Bong (2001). As already hinted, according to Bandura's (1997) definition, self-efficacy is focusing on an individual's perception of their capabilities when facing difficulties. Therefore, the wording of a few items was modified based on this. The five items are as follows: "I can master even the hardest material in English if I try. I can do almost all the work in English if I don't give up. I can do an excellent job on the problems and tasks assigned for English class. I can learn the material for English class. I can receive a good grade in English this semester."

### *Ideal L2 Self (IL2S)*

This study employed the concept of the ideal L2 self, encompassing both "own standpoint" and "promotional perspective," following the categorization by Papi et al. (2019). Their L2 self-guides consist of two regulation focuses: ideal L2 self (promotion) vs. ought-to L2 self (prevention), and two standpoints: own vs. other. IL2S in this study refers to "the L2 attributes that the learner (own standpoint) would ideally hope (promotion focus) to possess in future" (Papi et al., 2019, p. 346). This model identified IL2S as the only significant predictor of intended effort, which is measured by "eager L2 use." This involves strategies employed by an individual to enhance positive outcomes and performance among the other L2 self-guides. This suggests that IL2S is one of the more powerful motivational drives for target language learning. It includes four items.

### *Motivational Intensity (MI)*

The five-item scale that measures motivational intensity in L2 learning was adapted from the study by Feng and Papi (2020). According to them, motivational intensity is one dimension that can help understand and describe students' motivation when individuals learn a target language, similar to motivational effort, but distinct from persistence. This variable represents the degree of cognitive and behavioral engagement held by individuals in their L2 learning.

### *Perceived L2 Competence (L2C)*

Participants were asked to rate their subjective competence in four English skills – reading, listening, writing, and speaking – on a six-point Likert scale (1 = not at all proficient, 6 = very proficient). As Du (2015) points out, individuals' perceptions of their competence are true in and of themselves, and often serve as a driving force for their behavior, even if it may have a weak correlation with actual proficiency. In the study of Tanaka (2024), L2C was found to be more closely related to the development of intrinsic motivation than actual achievement, thereby serving as an indicator of an individual's motivation. Exploratory factor analysis consolidated the four skills into one factor, and the high internal consistency was observed and shown in the Data Analysis section. Consequently, the average score of these four skills was used as the value for perceived L2 competence.

### *Adaptability*

This variable refers to the capacity to adjust and respond appropriately and effectively to uncertainty and novelty such as changes in either situations or people. The Adaptability Scale constructed by Marin et al. (2013) was employed to capture adaptability (see the survey items and the result of exploratory factor analysis in Appendix 1). Nine items were identified as a single factor, and the average score of all items was used for the analysis.

The average scores of all the factors employed in this study to achieve the research aims can be found in Table 3, under Descriptive Statistics.

## Data Analysis

Before the analysis was aimed at the research questions, several exploratory factor analyses (EFA) were performed to ensure the validity of the instruments used in this study. The participants' responses to the survey items were computed using SPSS (version 24.0). Principal axis factoring was employed with a direct oblimin rotation. Factors with eigenvalues greater than 1.0 and loading values greater than .05 were retained.

First, the 14 EL-AI items were examined with factor analysis to identify the structure of this instrument. EFA resulted in a three-factor solution which accounted for 59.46% of the total variance. The first factor ($n$ = 6) explained 40.37% of the total variance and was labeled as "English learning experience with AI-BPs" (AI-EX) because it deals with the effectiveness of English learning experiences and tasks with the help of AI-BPs. The second factor ($n$ = 4) explained 10.28% of the total variance. It was labeled "awareness of AI-BPs" (AI-AW) because it addresses an individual's understanding of AI implementation and of how to use AI-BP, awareness of their benefits, and identification of effective learning areas for them. The third factor ($n$ = 4) explained 8.81% of the total variance. It was named "a future-driven interest in AI-BPs" (AI-FI). This factor represents an individual's willingness for timely updates on newly released AI-BPs, acquiring information on their use, desiring guidance on incorporating them in English classes, and willingness to use them for English learning purposes (see Table 1). The internal consistencies for the three AI factors were high (α = .86, .86, and .87, respectively), ensuring the reliability of this scale. To answer the research questions, the mean scores of the factors were used.

**Table 1**
*Factor Analysis for EL-AI*

| Items | | Factor 1 | Factor 2 | Factor 3 |
|---|---|---|---|---|
| Factor 1 | English learning experience with AI-BPs (AI-EX) | | | |
| AI-EX4 | I have used an AI-BP to help me learn to speak English. | .79 | | |
| AI-EX3 | I have used an AI-BP to help me read and understand English texts related to my major or liberal arts. | .73 | | |
| AI-EX6 | I have used an AI-BP to help me learn to listen to English. | .73 | | |
| AI-EX1 | I use an AI-BP to help me with my English assignments. | .72 | | |
| AI-EX5 | I have used an AI-BP to help me learn to write English. | .64 | | |
| AI-EX2 | I think it is efficient to use an AI-BP for English assignments. | .60 | | |
| Factor 2 | Awareness of AI-BPs (AI-AW) | | | |
| AI-AW3 | I understand how AI-BPs will benefit me. | | .87 | |
| AI-AW2 | I know how to use the AI-BPs I am aware of. | | .84 | |
| AI-AW4 | I know which learning domains AI-BPs are effective in. | | .74 | |
| AI-AW1 | I know how AI-BPs are designed and implemented. | | .59 | |
| Factor 3 | Future-driven interest in AI-BPs (AI-FI) | | | |
| AI-FI3 | I want guidance on how to use AI-BPs in my English class. | | | –.83 |
| AI-FI2 | I want to learn how to use AI-BPs in the future. | | | –.80 |
| AI-FI4 | I would like to use AI-BPs for English-related learning activities in the future. | | | –.74 |
| AI-FI1 | I want to be informed about new AI-based programs as they become available. | | | –.68 |

Second, motivation-related survey items pertaining to MI, SE, and IL2S were analyzed in SPSS. EFA yielded a three-factor solution, which accounted for 71.68% of the total variance. Except for one SE item ("I can receive a good grade in English this semester") due to an insufficient loading value (greater than .50), all the items were classified into their respective categories. The primary factor identified as MI accounted for 48.85% of the variance, followed by IL2S explaining 16.94%, and SE explaining 5.89% of the total variance (see Table 2). These distinct factors indicate that they reflect different facets of motivation. The internal consistencies were high (α = .92, .96, and .86, respectively). Lastly, all nine items of adaptability resulted in a one-factor solution, explaining 58.51% of the total variance based on EFA. Its internal consistency was also high (α = .92). The mean scores of each variable were used for further analyses. The descriptive statistics for the variables used in this study are shown in Table 3.

**Table 2**

*Factor Analysis for Motivational Variables*

| Items | | Factor | | |
|---|---|---|---|---|
| | | 1 | 2 | 3 |
| Factor 1 | Motivational intensity (MI) | | | |
| MI1 | I spend lots of time studying English. | .90 | | |
| MI2 | I am a diligent English language learner. | .87 | | |
| MI3 | I concentrate on studying English more than any other topic. | .85 | | |
| MI5 | I put much time and effort into improving my English language weaknesses. | .79 | | |
| MI4 | I can break through any distractions when having important English assignments to do immediately. | .62 | | |
| SE5 | | | | |
| Factor 2 | Ideal L2 self (IL2S) | | | |
| IL2S2 | I can imagine a day when I speak English fluently with international friends/colleagues. | | .93 | |
| IL2S4 | I can imagine a day when I use English effectively to communicate with people from all around the world. | | .93 | |
| IL2S1 | I can imagine a day when I speak English like a native speaker of English. | | .90 | |
| IL2S3 | I can imagine a day when I write effectively and read fluently in English. | | .88 | |
| Factor 3 | Self-efficacy (SE) | | | |
| SE1 | I can master even the hardest material in English if I try. | | | .79 |
| SE4 | I can learn the material for English class. | | | .76 |
| SE2 | I can do almost all the work in English if I don't give up. | | | .73 |
| SE3 | I can do an excellent job on the problems and tasks assigned for English class. | | | .72 |

To address the first research question, a hierarchical regression analysis was conducted to examine the interactive relationship between these factors. AI-FI was input as a dependent variable (DV, and AI-AW and AI-EX were independent variables (IV). Secondly, to examine how these AI-related factors are related to the motivational variables, a bivariate correlation was performed. Lastly, several mediating analyses were performed following the suggestions of Baron and Kenny (1986) to examine the role of adaptability as a mediator between AI-related factors and language learning motivational variables.

**Table 3**

*Descriptive Statistics (n = 180)*

| Variables | Number of Items | Minimum | Maximum | Mean | Std. Deviation | Internal consistency (α) |
|---|---|---|---|---|---|---|
| AI-AW | 4 | 1.00 | 6.00 | 3.59 | 1.14 | .87 |
| AI-EX | 6 | 1.00 | 6.00 | 3.65 | 1.13 | .86 |
| AI-FI | 4 | 1.00 | 6.00 | 4.13 | 1.05 | .86 |
| L2C | 4 | 1.00 | 5.50 | 3.21 | .95 | .85 |
| SE | 4 | 1.00 | 6.00 | 4.05 | 1.07 | .86 |
| IL2S | 4 | 1.00 | 6.00 | 4.28 | 1.25 | .96 |
| MI | 5 | 1.00 | 6.00 | 3.50 | 1.14 | .92 |
| Adapt | 9 | 1.00 | 6.00 | 4.27 | .90 | .92 |

*Note*. AI-AW = Awareness of AI-BPs; AI-EX = English learning experience with AI-BPs; AI-FI = Future-driven interest in AI-BPs; L2C = Perceived L2 competence; SE = Self-efficacy; IL2S = Ideal L2 self; MI = Motivational intensity; Adapt = Adaptability.

## Results

The first RQ was to investigate the impact of AI-AW and AI-EX on AI-FI. With AI-AW and AI-EX as IVs and AI-FI as DV, a hierarchical regression analysis was performed. As described in Table 4, the first model with only AI-AW as a single predictor for AI-FI accounted for 17% ($r$ = .42). However, the second model with AI-AW and AI-EX as the combined predictors accounted for 30%, an increase of 13%. Examining the impact of the two predictors, AI-EX ($r$ = .40) had a higher impact than AI-AW ($r$ = .25). It can be inferred that an individual's inclination to adopt AI-based programs in the future is more likely to be influenced by their familiarity with rather than their knowledge or awareness of such programs.

**Table 4**

*The Effect of AI-AW and AI-EX on AI-FI*

| | Model | Unstandardized Coefficients | | Standardized Coefficients | *t* | *R2* |
|---|---|---|---|---|---|---|
| | | *B* | *SE* | *ß* | | |
| 1 | (Constant) | 2.74 | .24 | | 11.57*** | .17 |
| | AI-AW | .39 | .06 | .42 | 6.13*** | |
| 2 | (Constant) | 1.96 | .26 | | 7.61*** | .30 |
| | AI-AW | .23 | .06 | .25 | 3.55*** | |
| | AI-EX | .37 | .06 | .40 | 5.72*** | |

*Note.* **p* < .05, ***p* < .01, ****p* < .001; AI-AW = Awareness of AI-BPs; AI-EX = English learning experience with AI-BPs; AI-FI = Future-driven interest in AI-BPs.

The second RQ examined the relationship between AI factors and motivational variables. The results in Table 5 indicate that AI-AW and AI-FI were positively related to all motivational variables ($.23 \leqslant r \leqslant .41$, $p <.001$), although the correlation between AI-FI and L2C was weak ($r = .18$, $p <.05$). Unlike AI-AW and AI-FI, AI-EX did not have any significant correlations with motivational variables.

Among motivational variables, SE had the highest correlation with MI ($r = .63$), followed by L2C ($r = .55$) and IL2S ($r = .46$). It was notable that adaptability was correlated with all motivational variables and was highly correlated with SE ($r = .51$) and IL2S ($r = .50$).

**Table 5**

*Bivariate Correlations between Variables*

| Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1. AI-AW | 1 | | | | | | | |
| 2. AI-EX | .43*** | 1 | | | | | | |
| 3. AI-FI | .42*** | .50*** | 1 | | | | | |
| 4. L2C | .32*** | .03 | .18* | 1 | | | | |
| 5. SE | .32*** | .13 | .41*** | .55*** | 1 | | | |
| 6. IL2S | .24*** | .10 | .30*** | .27*** | .46*** | 1 | | |
| 7. MI | .26*** | .07 | .23*** | .46*** | .63*** | .36*** | 1 | |
| 8. Adapt | .36*** | .15* | .30*** | .27*** | .51*** | .50*** | .43*** | 1 |

*Note.* **p* < .05, ***p* < .01, ****p* < .001; AI-AW = Awareness of AI-BPs; AI-EX = English learning experience with AI-BPs; AI-FI = Future-driven interest in AI-BPs; L2C = Perceived L2 competence; SE = Self-efficacy; IL2S = Ideal L2 self; MI = Motivational intensity; Adapt = Adaptability.

Lastly, the mediating roles of adaptability between AI factors and motivational variables were explored. As shown in Table 4, with the two AI-related predictors, AI-EX was found not to have any associations with the motivational variables. Therefore, it was investigated how AI-AW affected the motivational variables through adaptability. To investigate the mediation of adaptability between AI-AW and the motivational variables, this study followed Baron and Kenny's (1986) step-by-step approach. First, the analysis revealed a significant relationship where AI-AW (IV) predicted adaptability (a mediating variable, MV) as shown in Table 6. Second, AI-AW (IV) was found to have significant relationships with the motivational variables (DVs), that is, L2C, SE, IL2S, and MI as observed in Models 4, 5, 8, and 10 in Table 7. Third, both AI-AW and adaptability exhibited significant relationships with the motivational variables (DVs). The direct effects of AI-AW on the motivational variables (DV) in Models 4, 6, 8, and 10 were greater than the effects of AI-AW (IV) on the DVs in Models 5, 7, 9, and 11. In other words, adaptability serves as an MA in the way AI-AW affects all motivational variables. Particularly, when adaptability was combined with AI-AW, the effects of AI-AW on IL2S and MI lost significance as seen in Models 9 and 11. This indicates that adaptability completely mediates the relationships between AI-AW and IL2S, as well as between AI-AW and MI. The summaries of the analyses are illustrated in Figure 1.

**Table 6**

*The Effect of AI-AW on Adaptability*

| Model (DV = L2C) | | Unstandardized Coefficients | | Standardized Coefficients | *t* |
|---|---|---|---|---|---|
| | | *B* | *SE* | *ß* | |
| 3 | (Constant) | 3.27 | .21 | | 15.78*** |
| | AI-AW | .28 | .06 | .35 | 5.06*** |

*Note*. *$p < .05$, **$p < .01$, ***$p < .001$; AI-AW = Awareness of AI-BPs; L2C = Perceived L2 competence.

The strongest indirect effect coefficient was observed for adaptability with a value of .17 ($z = 4.07$, $p < .001$)[1], indicating its mediating role in the relationship between AI-AW and IL2S. This was followed by the coefficient of .16 ($z = 4.02$, $p < .001$) for the relationship between AI-AW and SE, .14 ($z = 3.70$, $p < .001$) for AI-AW and MI, and .06 ($z = 2.13$, $p < .05$) for AI-AW

[1] Sobel test was computed to examine if a mediator carries the mediating effects of an IV on a DV. It provides information about the significance and strength of the indirect effect.

and L2C. According to the results presented in Table 7, the models with the IVs with both AI-AW and adaptability exhibited significantly higher accountability compared to when AI-AW alone served as the single IV in predicting the motivational variables. For example, the largest improvement, of 19%, was observed in Models with IL2S as a DV, increasing from 6% (Model 8) to 25% (Model 9). The next largest improvement was 18% in Models with SE, increasing from 10% (Model 6) to 28% (Model 7), followed by a 13% increase in Models with MI, advancing from 7% (Model 10) to 20% (Model 11). The smallest increase of 3% was observed in Models with L2C, going from 10% (Model 4) to 13% (Model 5).

**Figure 1**

*A Causal Chain Including Adaptability as a Mediator on the Relationships between AI-AW and the Motivational Variables*

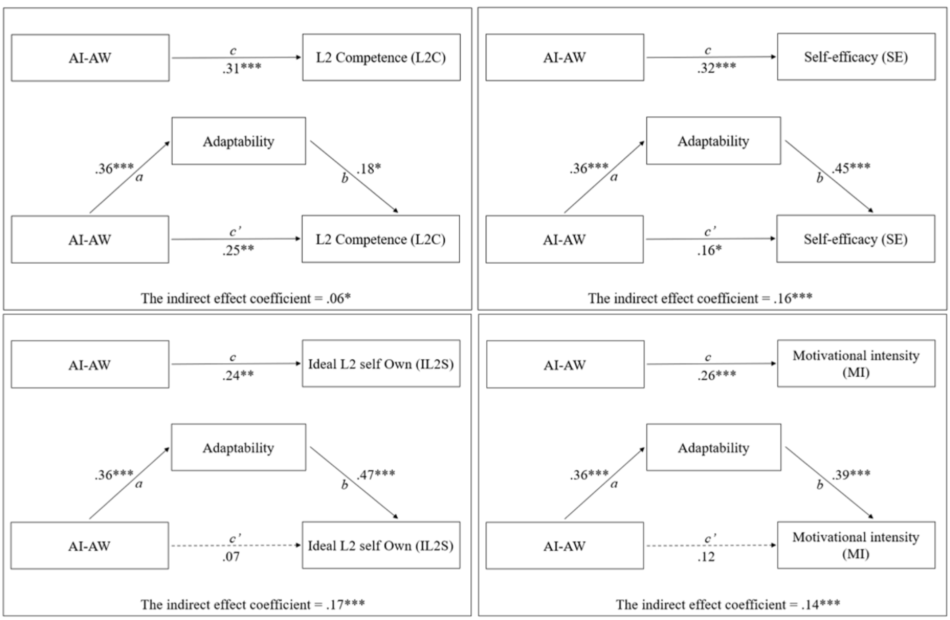

**Table 7**

*The Effects of AI-AW and Adaptability on L2C, SE, IL2S, and MI*

| Model (DV = L2C) | | Unstandardized Coefficients | | Standardized Coefficients | *t* | *R2* | Model (DV = SE) | | Unstandardized Coefficients | | Standardized Coefficients | *t* | *R2* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *B* | *S.E.* | *ß* | | | | | *B* | *S.E.* | *ß* | | |
| 4 | (Constant) | 2.28 | .22 | | 10.38*** | .10 | 6 | (Constant) | 2.98 | .25 | | 11.83*** | .10 |
| | AI-AW | .26 | .06 | .31 | 4.42*** | | | AI-AW | .30 | .07 | .32 | 4.45*** | |
| 5 | (Constant) | 1.68 | .34 | | 4.99*** | .13 | 7 | (Constant) | 1.21 | .35 | | 3.46** | .28 |
| | AI-AW | .21 | .06 | .25 | 3.35** | | | AI-AW | .15 | .06 | .16 | 2.29* | |
| | Adapt | .18 | .08 | .18 | 2.35* | | | Adapt | .54 | .08 | .45 | 6.60*** | |
| Model (DV =IL2S) | | Unstandardized Coefficients | | Standardized Coefficients | *t* | *R2* | Model (DV = MI) | | Unstandardized Coefficients | | Standardized Coefficients | *t* | *R2* |
| | | *B* | *S.E.* | *ß* | | | | | *B* | *S.E.* | *ß* | | |
| 8 | (Constant) | 3.34 | .30 | | 11.08*** | .06 | 10 | (Constant) | 2.56 | .27 | | 9.43*** | .07 |
| | AI-AW | .26 | .08 | .24 | 3.27** | | | AI-AW | .26 | .07 | .26 | 3.60*** | |
| 9 | (Constant) | 1.16 | .42 | | 2.80** | .25 | 11 | (Constant) | .94 | .39 | | 2.41* | .20 |
| | AI-AW | .08 | .08 | .07 | 1.01 | | | AI-AW | .12 | .07 | .12 | 1.70 | |
| | Adapt | .66 | .10 | .47 | 6.84*** | | | Adapt | .49 | .09 | .39 | 5.42*** | |

*Note*. * $p < .05$, ** $p < .01$, *** $p < .001$; AI-AW = Awareness of AI-BPs; L2C = Perceived L2 competence; SE = Self-efficacy; IL2S = Ideal L2 self-own; MI = Motivational intensity; Adapt = Adaptability.

## Discussion

This study aimed to explore how engagement with AI-based programs—specifically through awareness of these programs, experience with them, and anticipation of future use—affects motivation in English language learning. To support this investigation, exploratory factor analyses and internal consistency assessments were conducted to validate scales measuring engagement with AI-based programs and motivational variables (see Tables 1, 2, and 3).

First, three factors that indicate engagement with AI-based programs were explored: awareness, experience, and future interest. The analysis showed that both awareness of and experience with AI-based programs were significant predictors of interest in their future use. This highlights that to foster interest in utilizing AI-based programs to aid English learning, not only awareness of these programs but also exposure and experience with them are crucial. This is emphasized by the model incorporating both awareness and experience as predictors exhibiting higher accountability for future interest, improving from predicting 17% to 30 % of the total variance than when awareness was a single predictor (see Table 4). It is worth noting that when experience was included along with awareness, the impact of awareness decreased. This suggests that while both awareness of and experience with AI-based programs are influential, it is the effect of practical experience using these tools that more robustly drives future interest in utilizing them. Taken together, fostering sustained interest in the future use of AI-based programs may be more effectively achieved not just through enhancing awareness and knowledge but by providing hands-on experience with these tools.

Second, the findings regarding the correlations between the three AI-related factors and the motivational variables showed that awareness of AI-based programs and interest in future use were positively related to all motivation variables. This indicates that awareness of the benefits and potential of AI-based programs as well as individuals' interest in future use may play substantial roles in motivating students to study English with AI assistance. However, experience with AI-based programs did not show a significant correlation with any of the motivation variables. Notably, the relevant survey items primarily quantified the participants' experiences with AI-based programs, without necessarily capturing the quality or depth of their engagement with these tools (e.g., "I *have used* an AI-BP to help me learn to speak English"). Thus, this quantitative approach may not have reflected a significant correlation with the motivational variables. This highlights the need for further research that provides a more qualitative or nuanced understanding. Similarly, the novelty of AI-based programs may have had an impact. The participants who have utilized them might not have fully recognized the extensive possibilities of incorporating new and advanced forms of these programs into language learning. Students might have used AI-based programs, but their experience may not have been meaningful enough or had a positive enough impact on the participants' self-efficacy or their ideal goals in language learning. In this case, its impact on motivation could have been minimal.

Finally, the results of this study revealed the mediating role of adaptability between awareness of AI-based programs and the motivational variables, in line with how Zarrinabadi et al. (2022) identified the mediating role of adaptability. This study suggests that awareness and knowledge about AI may enhance adaptability, which in turn predicts several motivational variables in language learning. By serving as a mechanism, adaptability provides a pathway to explain the relationship between awareness of AI-based programs and language learning motivation.

Adaptability refers to an individual's capacity to effectively regulate and adjust to psychological and emotional challenges that arise in the presence of novelty and uncertainty (Martin et al., 2012). This capacity signifies the readiness for learning and growth, as its definition implies the ability to cope with change and embrace innovation. This study reported that awareness of AI-based programs was correlated with adaptability to a moderate degree ($r = .36$, $p < .001$). When adaptability was included in the relationships between awareness of AI-based programs and motivational variables, the direct influence of awareness on the dependent variables decreased (partial mediation) or disappeared (complete mediation), indicating that adaptability serves as a mediator. Specifically, the significance of the direct influence between awareness of AI-based programs and ideal L2 self, as well as between awareness and motivational intensity, was lost when adaptability was included. Adaptability fully mediated these relationships with significant indirect effects, showing its critical role in using their knowledge about AI-based programs to shape ideal L2 self-images and enhance motivational intensity for language learning goals. The largest indirect adaptability effect was .17 in the awareness and the ideal L2 self model, then .14 in the awareness and motivational intensity model. Partial mediation was noted in the awareness's links to self-efficacy and perceived L2 competence, with indirect effects of .16 and .06, respectively. Even with a smaller effect (.06) in awareness and perceived L2 competence, it was still observed that adaptability played a significant and partial mediating role.

In addition, adaptability significantly improved the accountability of the models, resulting in an 18% increase in the model with awareness of AI-based programs and self-efficacy and a 3% increase in the model with awareness of AI-based programs and perceived L2 competence. While the accountability of the models for the direct impact of awareness of AI-based programs on self-efficacy or perceived L2 competence was identical at 10% (Model 4 and 6 in Table 6), the increase in model accountability when adaptability was included varied greatly. This reveals dynamic interplay among the variables. For example, adaptability may contribute to the way awareness of AI-based programs influences individuals' judgments on whether they can successfully conduct language-related tasks, leading to a larger impact on self-efficacy. On the other hand, the impact of adaptability on perceived L2 competence may be less closely related, resulting in a smaller increase in model accountability for perceived L2 competence.

The inclusion of adaptability significantly enhanced the accountability of models including perceived L2 competence, self-efficacy, ideal L2 self, and motivational intensity. Notably, marked increases were observed in the models encompassing motivational variables, namely ideal L2 self, self-efficacy, and motivational intensity, with improvements of 19%, 18%, and 13% respectively. This improvement highlights adaptability's crucial role in the connection between awareness of AI-based programs and essential motivational variables in language learning. Students with a high awareness of AI-based programs can adapt to new tools and technologies more readily, and this adaptability or flexibility can positively influence the development of language learning motivation.

To sum up, the findings of the study show that individuals who possess higher levels of awareness and knowledge of AI-based programs are more likely to exhibit greater adaptability, which in turn leads to higher motivation. This highlights the importance of adaptability as a key factor that helps account for the relationships between awareness of AI-based programs and the levels of motivational variables in their language learning processes. In other words, when considering the relationship between students' awareness of AI-based programs and the motivational variables related to their English learning, it is essential to also consider adaptability.

## Conclusion

This study aimed to investigate the impact of increasingly sophisticated AI-based programs on students' motivation in English learning. The findings reveal that students' awareness of and experience with AI-based programs influence their interest in future use. Among the three AI-related variables, only awareness of such programs and future interest in utilizing them were found to be associated with motivational variables. The study also found that awareness directly influences language learning motivation. Notably, adaptability emerged as a crucial mediating factor, fully or partially mediating the relationship between awareness of AI-based programs and all motivational variables. This mediation significantly enhanced the model accountability. This insight into the role of adaptability not only underscores its importance but also fills crucial gaps in the existing literature, offering a deeper perspective on the dynamics of AI in language learning motivation.

This study has a few limitations to mention. First, while participants were drawn from three different English courses, the majority were categorized as being part of the Basic English Level, based on a placement test. However, the proficiency levels in the other two courses were not identified. Varying levels of English proficiency may yield different insights into the relationship between awareness of AI-based programs and language learning motivation. In addition, for future research, it is recommended to employ an analytical approach such as structural equation modeling to provide a more holistic view of the mechanisms involving all variables. This could enhance the understanding of the complex interactions between awareness of AI-based programs, English proficiency levels, and language learning motivation. One of the results shows that experience with AI-based programs did not have any significant correlation with the motivational variables. This calls for a reassessment of the results using a method that not only considers whether AI tools were used but also examines the quality and depth of their use. Such an approach could provide more accurate information about the influence of experience with AI-based programs.

The present study suggests that it is important for teachers to guide students towards options in AI-BPs that can effectively assist in English learning. It underscores the need for understanding and experiencing how these tools can be utilized to make the language learning processes more efficient and easier. It also informs us that when considering the relationship between students' awareness of AI-based programs and language learning motivation, adaptability must also be considered. In other words, students' AI-related knowledge can further strengthen its impact on motivation if adaptability is enhanced. It is recommended to conduct further research in this area for deeper insight.

## Reference

Alqahtani, T., Badreldin, H. A., Alrashed, M., Alshaya, A. I., Alghamdi, S. S., bin Saleh, K., Alowais, S. A., Alshaya, O. A., Rahman, I., Al Yami, M. S., & Albekairy, A. M. (2023). The emergent role of artificial intelligence, natural learning processing, and large language models in higher education and research. *Research in Social and Administrative Pharmacy, 19*, 1236–1242.

Bai, B., & Wang, J. (2020). The role of growth mindset, self-efficacy and intrinsic value in self-regulated learning and English language learning achievements. *Language Teaching Research, 27*(1), 207–228.

Bandura, A. (1994). Self-efficacy. In V. S. Ramachaudran (Ed.), *Encyclopedia of human behavior* (Vol. 4, pp. 71–81). Academic Press (Reprinted from *Encyclopedia of mental health* by H. Friedman, Ed., 1998, Academic Press).

Bandura, A. (1997). *Self-efficacy: The exercise of control.* Freeman.

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173–1182.

Barrot, J. S. (2023). Using ChatGPT for second language writing: Pitfalls and potentials. *Assessing Writing, 57*, 100745.

Bong, M. (2001). Between- and within-domain relations of academic motivation among middle and high school students: Self-efficacy, task value, and achievement goals. *Journal of Educational Psychology, 93*(1), 23–34.

Bong, M., & Skaalvik, E. M. (2003). Academic self-concept and self-efficacy: How different are they really? *Educational Psychology Review, 15*(1), 1–40.

Cancino, M., & Panes, J. (2021). The impact of Google Translate on L2 writing quality measures: Evidence from Chilean EFL high school learners. *System, 98,* 102464.

Chow, A. R. (2023). How ChatGPT managed to grow faster than TikTok or Instagram. *Time.* Retrieved from https://time.com/6253615/chatgpt-fastest-growing/

Chung, E. S., & Ahn, S. (2022). The effect of using machine translation on linguistic features in L2 writing across proficiency levels and text genres. *Computer Assisted Language Learning, 35*(9), 2239–2264.

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education, 20*(22), 1–22. Open Access.

Csizér, K., & Kormos, J. (2009). Learning experiences, selves and motivated learning behaviour: A comparative analysis of structural models for Hungarian secondary and university learners of English. In Z. Dörnyei & E. Ushioda (Eds.), *Motivation, language identity and the L2 self* (pp. 98–119). Multilingual Matters.

Collie, R. C., Holliman, A. J, & Martin, A. (2017). Adaptability, engagement and academic achievement at university. *Educational Psychology, 37*(5), 632–647.

Deng, X., & Yu, Z. (2022). A systematic review of machine-translation-assisted language learning for sustainable education. *Sustainability, 14*, 7598.

Deng, X., & Yu, Z. (2023). A meta-analysis and systematic review of the effect of chatbot technology use in sustainable education. *Sustainability, 15(4)*, 2940.

Dörnyei, Z. (2009). The L2 motivational self-system. In Z. Dörnyei & E. Ushioda (Eds.), *Motivation, language identity and the L2 self* (pp. 9–42). Multilingual Matters.

Dörnyei, Z., & Chan, L. (2013). Motivation and vision: An analysis of future L2 self image, sensory styles, and imagery capacity across two target languages. *Language Learning, 63*(3), 437–462.

Du, A. (2015). American college students studying abroad in China: Language, identity, and self-presentation. *Foreign Language Annals, 48*(2), 250–266.

Feng, L., & Papi, M. (2020). Persistence in language learning: The role of grit and future self-guides. *Learning and Individual Differences, 81*, 101904.

Firat, M. (2023). What ChatGPT means for universities: Perceptions of scholars and students. *Journal of Applied Learning & Teaching, 6*(1), 57–63.

Gayed, J. M., Carlon, M. K. J., Oriola, A. M., & Cross, J. S. (2023). Exploring an AI-based writing assistant's impact on English language learners. *Computers and Education: Artificial Intelligence, 3*, 100055.

Kim, D. H., Wang, C., Bong, M., & Ahn, H. S. (2015). English language learners' self-efficacy profiles and relationship with self-regulated learning strategies. *Learning and Individual Differences, 38*, 136–142.

Kim, H.-I. (2023). The effect of L2 self-guides and autonomous motivation on L2 motivated behavior. *SAGE Open, October-December,* 1–14.

Jeon, J. (2024). Exploring AI chatbot affordances in the EFL classroom: young learners' experiences and perspectives. *Computer Assisted Language Learning, 37*(1–2), 1–26.

Kuddus, K. (2022). Artificial intelligence in language learning: Practices and prospects. *Advanced Analytics and Deep Learning Models*, 1–17.

Lee, D., Kim, H.-H., & Sung, S.-H. (2023). Development research on an AI English learning support system to facilitate learner-generated-context-based learning. *Education Tech Research Dev, 71*(1), 629–666.

Martin, A. J., Nejad, H., Colmar, S., & Liem, G. A. D. (2012). Adaptability: Conceptual and empirical perspectives on responses to change, novelty and uncertainty. *Australian Journal of Guidance and Counselling, 22*, 58–81.

Martin, A. J., Nejad, H. G., Colmar, S., & Liem, G. A. D. (2013). Adaptability: How students' responses to uncertainty and novelty predict their academic and non-academic outcomes. *Journal of Educational Psychology, 105*(3), 728–746.

OpenAI. (2023). *Introducing ChatGPT.* Retrieved from https://openai.com/blog/chatgpt.

Papi, M., & Teimouri, Y. (2012). Dynamics of selves and motivation: A cross-sectional study in the EFL context of Iran. *International Journal of Applied Linguistics, 22*(3), 287–309.

Papi, M., Bondarenko, A. V., Mansouri, S., Feng, L., & Jiang, C. (2019). Rethinking L2 motivation research: The 2 X 2 model of L2 self-guides. *Studies in Second Language Acquisition, 41*(2), 337–361.

Shidiq, M. (2023). The use of artificial intelligence-based ChatGPT and its challenges for the world of education; from the viewpoint of the development of creative writing skills. In *Proceedings of the International Conference on Education, Society, and Humanity, 1*(1), 353–357.

Son, J.-B., Ružić, N. K., & Philpott, A. (2023). Artificial intelligence technologies and applications for language learning and teaching. *Journal of China Computer-Assisted Language Learning, 5*(1), 94–112.

Song, C., & Song, Y. (2023). Enhancing academic writing skills and motivation: Assessing the efficacy of ChatGPT in AI-assisted language learning for EFL students. *Frontiers in Psychology, 14*, 1260843.

Taguchi, T., Magid, M., & Papi, M. (2009). The L2 motivational self system amongst Chinese, Japanese, and Iranian learners of English: A comparative study. In Z. Döornyei & E. Ushioda (Eds.), *Motivation, language identity and the L2 self* (pp. 66–97). Multilingual Matters.

Takahashi, C., & Im, S. (2020). Comparing self-determination theory and the L2 motivational self system and their relationships to L2 proficiency. *Studies in Second Language Learning and Teaching, 10*(4), 673–696.

Tanaka, M. (2023). Motivation and growth in kanji proficiency: a longitudinal study using latent growth curve modeling. *International Review of Applied Linguistics in Language Teaching, 62*(4), 1459–1483. https://doi.org/10.1515/iral-2022-0210

Teimouri, Y. (2017). L2 selves, emotions, and motivated behaviors. *Studies in Second Language Acquisition, 39*(4), 681–709.

Thorp, H. H. (2023). ChatGPT is fun, but not an author. *Science, 379*(6630), 313.

Winne, P. H., & Hadwin, A. F. (2008). The weave of motivation and self-regulated learning. In D. H. Schunk & B. J. Zimmerman (Eds.), *Motivation and self-regulated learning: Theory, research, and application* (pp. 297–314). Routledge.

Wei, L. (2023) Artificial intelligence in language instruction: Impact on English learning achievement, L2 motivation, and self-regulated learning. *Frontiers in Psychology, 14*, 1261955.

Zarrinabadi, N., Rezazadeh, M., Karimi, M., & Lou, N. M. (2022). Why do growth mindsets make you feel better about learning and your selves? The mediating role of adaptability. *Innovation in Language Learning and Teaching*, 1962888.

Appendix 1

## The Result of Exploratory Factor Analysis for Adaptability

| Items | Factor (Adaptability) | 1 |
| --- | --- | --- |
| Adap6 | To assist me in a new situation, I am able to change the way I do things if necessary. | .85 |
| Adap3 | I am able to adjust my thinking or expectations to assist me in a new situation if necessary. | .84 |
| Adap2 | I am able to revise the way I think about a new situation to help me through it. | .83 |
| Adap5 | In uncertain situations, I am able to develop new ways of going about things (eg. a different way of asking questions or finding information) to help me through. | .81 |
| Adap4 | I am able to seek out new information, helpful people, or useful resources to effectively deal with new situations. | .79 |
| Adap1 | I am able to think through a number of possible options to assist me in a new situation. | .74 |
| Adap7 | I am able to reduce negative emotions (eg. fear) to help me deal with uncertain situations. | .70 |
| Adap8 | When uncertainty arises, I am able to minimize frustration or irritation so I can deal with it best. | .66 |
| Adap9 | To help me through new situations, I am able to draw on positive feelings and emotions (eg. enjoyment, satisfaction) | .64 |

*Note.* Extraction Method: Principal Axis Factoring.