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AI-Assisted Learning Systems for Enhancing English as a Foreign Language Outcomes in Lebanese High Schools

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Abstract

The pedagogical efficacy of artificial intelligence (AI) technologies in education heavily depends on cultural, technological, and cognitive contexts. Prior studies examined AI-driven learning outcomes without accounting for cultural variability or sufficiently anchoring their analyses in robust theoretical frameworks. The current study discusses the interconnection between AI technologies, learner competencies, and educational outcomes, in addition to the significance of digital and media literacy in secondary foreign language teaching. It employs Hofstede's cultural dimensions theory, the technology acceptance model, and sociocultural learning theory to examine how AI technologies affect learning outcomes of English as a foreign language among Lebanese high school students. One hundred and eighty high school students in Mount Lebanon were given a 20-item survey using a quantitative research design. The results were analyzed using statistical tests and analyses in SPSS version 27.0.1. The findings indicate that AI technologies significantly enhance student learning outcomes: affective and motivational outcomes (45%), social and collaborative competencies (35%), and English language proficiency (accounting for 43% of variance). Furthermore, these relationships are strongly moderated by digital and media literacy, which increases the beneficial effects of AI on learning outcomes. The findings also show that students' opinions, engagement, and acceptance of AI-supported language learning are influenced by cultural traits.

Keywords: artificial intelligence; English as a foreign language; cultural dimensions; technology acceptance model; digital and media literacy; learning outcome; cognitive load theory; Hofstede's cultural dimensions theory; sociocultural learning theory; multi-theoretical framework

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Academic Editor: Ju-Chuan Huang

Received: 5 February 2026
Revised: 18 March 2026
Accepted: 23 March 2026
Published: 26 March 2026

1. Introduction

Artificial intelligence (AI) technologies have received a lot of interest lately in educational settings, especially in the area of English as a foreign language (EFL). These technologies—such as chatbots, automated writing assessors, translation tools, and speech recognition systems—are becoming more widely acknowledged for their potential to boost student engagement, facilitate personalized learning, and improve language performance (Heil et al., 2020; Liu et al., 2022). Through adaptive learning pathways, learners can practice writing interactively, improve their pronunciation, increase their vocabulary, and receive automated grammatical feedback in AI-assisted environments (Fuchs, 2024; Salloum et al., 2019).

The effects of AI are not always transferable across educational cultures, although this worldwide movement indicates strong instructional potential. The currently available research exhibits significant geographical and cultural gaps. The majority of studies have been carried out in technologically sophisticated cultures or university settings, but secondary-level students in developing regions have not received enough attention (Chou & Ting, 2023). Additionally, very little research takes into account cultural factors as explanations for differences in AI adoption and educational impact, and even less incorporates theoretical viewpoints to illustrate why and how AI influences learning outcomes.

Throughout past years, artificial intelligence (AI) has been widely applied across many fields, including education and language acquisition (Abdulmajeed et al., 2023). Most of the recent research examined the potential of using AI technologies to improve students' proficiency in learning languages, especially English as a foreign language (Fountoulakis, 2024). With the integration of machine learning, natural language processing, and adaptive feedback, AI has progressed from basic language-learning applications to cultured systems (Son et al., 2025). For instance, advanced learning-language systems enhance linguistic competence and provide educational awareness among learners (Kristiawan et al., 2024). This transition in adapting AI technologies in the learning process facilitates individual learning, maintains student engagement in classrooms, and encourages communication skills among individuals from different cultures (Xia et al., 2024). Globally, millions of students are nowadays using AI-driven applications to improve access to learning, boost motivation, and support language attainment (Ismoilovna, 2025).

Despite the rapid advancements in AI, several challenges still stand in the way of effectively using this technology in foreign language education. These challenges include finding the right balance among technological innovation, maintaining cultural sensitivity, and keeping classroom relevance (Aijun, 2024). Many recent studies have highlighted the gap in understanding the application of AI across different cultures and educational backgrounds. Moreover, there is limited evidence on its long-term effect and to what extent school teachers are prepared to integrate these technologies into their teaching strategies (Al-Raimi et al., 2024; Khoudri et al., 2024).

While some researchers highlighted the benefits of using AI technologies in delivering personalized and immersive learning experiences (Abuhussein & Badah, 2025; Cahyono & Rosita, 2023), warned that over-reliance on technology would reduce human interactions and critical thinking. In addition, they argue that, if these technologies are not used wisely and equitably, they will decrease educational quality and limit learners' ability to develop strong intercultural skills (Karakas, 2023).

There are plenty of empirical research, systematic reviews, and theoretical studies that were carried out in Asia, Europe, and North America using qualitative, quantitative, and/or mixed approaches focusing on the integration of AI into learning English as a foreign language (Alhusaiyan, 2025). They showed that AI-integrated systems—including chatbots, machine translation tools, intelligent tutoring systems, and speech recognition software—can significantly improve speaking, writing, and listening skills (Zhang et al., 2023). Additionally, by simulating real-world interactions and facilitating real-time language practice, AI technologies enable international communications, which can enhance learners' confidence and fluency in using English in diverse contexts (AlTwijri & Alghizzi, 2024).

While the accessibility of these systems can accelerate learning, it is essential to clarify how AI-based tools will affect education in the long term across different aspects, such as learning independency, data privacy, and cultural diversity (Wei, 2025). These aspects are critical at the academic level for evaluating the utilization of AI technologies as supplementary instruction tools that could complement the roles of teachers and instructors in class (Ouyang & Jiao, 2021). Consequently, advancing a learner's level is achieved by emphasizing blended learning strategies that integrate technological innovations and human-guided instructions (Kovalenko & Baranivska, 2024).

This study bases cultural interpretation on Hofstede's theory of cultural dimensions, which finds national patterns of uncertainty avoidance, collectivism, and power distance (Hofstede, 2001; Hofstede & Hofstede, 2005). Cultural values in Lebanon are different from those examined elsewhere:

- In Lebanese classroom systems, power distance shapes students' expectations for instruction by positioning instructors as knowledgeable authorities (Dorji & Smet, 2022; Tang, 2023).
- Middle Eastern cultures have collectivist learning orientations that prioritize mutual academic assistance, peer cooperation, and group belonging (Al-Hoorie, 2021; Oyserman et al., 2002).
- Lebanese learners frequently favor structured, rule-driven, predictable teaching styles due to their high degree of uncertainty avoidance (Shane, 2020; Vlachopoulos, 2022).

These factors have a direct impact on how pupils view, trust, and interact with AI systems. For instance, in a high-power-distance setting, substituting algorithmic feedback for instructor authority may feel unsettling or unfamiliar. On the other hand, AI-assisted teamwork might perform better than individualistic learning models in collectivist settings. This study fills a key gap left by earlier research's lack of such cultural framing, particularly in understanding how different cultural contexts influence the effectiveness of AI-assisted learning models.

This research paper investigates the impact of AI technologies as assistants in learning EFL for high school students in Lebanon. Lebanon offers a distinctive example of bilingual education, difficulties with digital instruction, and cultural customs that affect learning habits. Schools are governed by collective classroom structures, teacher-centered traditions, and standardized tests (Abdul-Latif, 2023; Atkinson, 2023). Lebanese students may view AI differently than students in Western environments due to the country's unstable economy and uneven technical infrastructure, which can limit their access to technology and influence their perceptions of its effectiveness in education. This research assesses how AI-powered technologies such as grammar checkers, voice recognition software, language translation tools, and interactive chatbots, can enhance students' expertise, increase their motivation, and build their educational experiences. As a result, the findings of this paper should clarify the role of AI technology in learning EFL within the Lebanese context.

Consequently, to manage the investigation proposed in this research, the following research questions (RQ) have been formulated:

- RQ1: How can AI technologies affect high school students' English proficiency, including vocabulary, grammar, reading comprehension, writing quality, and speaking fluency?
- RQ2: How does the use of AI technologies transform students' affective and motivational outcomes in English language learning, including self-learning, self-efficacy, and self-motivation?

- RQ3: How do AI technologies contribute to improving students' social and collaborative competencies in English language classrooms, including peer interaction, teamwork, and communication?
- RQ4: How does students' level of digital and media literacy moderate the relationship between the use of AI technologies and the development of English language proficiency, motivational outcomes, and social learning skills?

This study provides a conceptually sound and comprehensive study of the interaction of AI technologies, learner skills, and educational impact by introducing the cultural theory and defining digital and media literacy as an essential moderating factor. This highlights the novelty and necessity of research on the possibilities of AI and challenges in teaching foreign languages at the secondary level.

This paper is divided into five sections. Section 2 outlines the use of AI technologies in learning EFL in the literature. Section 3 describes the methodology of this paper, including participants, data collection techniques, and analysis steps that draw the investigation of the learning processes. The experimental results are exposed in Section 4, followed by a clarification of the discoveries in regard to previous studies. Finally, Section 5 concludes this paperwork and highlights future research directions in this area.

2. Literature Review

Digital writing, speaking, and reading tools include a range of interconnected activities: composing on social networking platforms, producing videos, and engaging with articles and other kinds of online communication (El Shazly, 2021; Le et al., 2025; Rad et al., 2024; Xia et al., 2024). Online tools for digital language learning support users in several ways. For example, digital writing tools include lexicographic programs such as online dictionaries and thesauruses, grammar-oriented tools such as QuillBot, conversational tools such as chatbots, and reading supports such as ChatGPT. To justify the connection between AI technologies and student learning outcomes, this research uses a multi-theoretical framework that is based on the following: the cultural dimensions theory of Hofstede, the Technology Acceptance Model (TAM), the sociocultural learning theory, and the cognitive load theory (CLT). The combination of these theories clarifies the effectiveness of AI and why it functions differently in Lebanon. This section discusses recent studies that have been conducted to show the effectiveness of using AI-based systems in language-learning advancements, including speaking, writing, reading, and listening (Wu & Liu, 2025).

2.1. Student Learning Outcomes

This section comprises recent research work on the advantages and limitations of utilizing AI technologies as assistants and collaborators in learning foreign languages in different countries worldwide. In addition, the authors concentrate on highlighting literature studies in terms of English language proficiency, self-learning motivations, and social media interventions.

2.1.1. English Language Skills

AI-enabled writing tools, such as QuillBot and ChatGPT, have demonstrated a remarkable impact on strengthening the writing skills of EFL learners (Suharto et al., 2025). For instance, Grammarly highlighted a statistically significant improvement in writing quality and style among Palestinian EFL learners (Abuhussein & Badah, 2025). Equally, Grammarly demonstrated a substantial increase in overall writing performance among Indonesian university students (Soegiyarto et al., 2022). Moreover, research was conducted to confirm that AI technologies are also valuable in enlightening academic English writing skills in higher education (Dja'far & Hamidah, 2024) and defining the AI role played in

English writing skills among Indonesian students (Ahmad et al., 2024). Likewise, the use of ChatGPT has also considerably improved the writing skills of Chinese university students, specifically in the areas of vocabulary, the organization of ideas, and logical thinking (Song & Song, 2023). It has also been demonstrated that AI-assisted tools, such as Wordtune, encourage students' engagement in English-language discussions and improve assessment performance (Le et al., 2025).

Speaking is an important skill for international communications (Madhavi et al., 2023). The ability to speak in a foreign language is a complicated process that requires cognitive and language abilities (Nguyen, 2024). AI-based language learning technologies are better than traditional methods at improving the English-speaking abilities of college students (Cahyono & Rosita, 2023). This is because these platforms include interactive features and provide personalized feedback. Moreover, it has been established that conversational AI chatbots have the potential to reduce the anxiety connected to speaking in foreign languages. Additionally, the combination of chatbots, translation tools, and vocabulary tools leads to better reading comprehension, speaking, and critical thinking (Chea & Xiao, 2024).

Motivation for reading is essential in the acquisition of EFL. Consequently, inadequate reading motivation results in several issues related to learners' reading development. Integrating AI technologies into language instruction is a strategy to sustain and enhance learners' motivation. The research of (Daweli & Moqbel, 2024) investigated EFL learners' perspectives on using AI technologies in their reading lesson development, such as decreased comprehension, lower engagement with texts, and a lack of persistence in reading tasks, assessing the potential influence of these tools on learning outcomes. The results indicated that AI has shown potential in enhancing reading education when effectively integrated with conventional approaches. The research advised EFL teachers to strategically use AI technologies in the classroom to improve reading competence and motivation.

2.1.2. Affective and Motivational Outcomes

AI offers users novel methods to learn foreign languages and has been gradually integrated into the process of learning EFL (Shahid et al., 2024). Nevertheless, it also instills more apprehension and fear; authors studied students' apprehensions regarding AI to assist educators in comprehending students' fears and encourage high school pupils to utilize AI tools in learning EFL (Wen et al., 2024). Furthermore, educators and learners of English must understand the application of AI in the classroom, including the use of intelligent teaching systems, virtual reality, immersive virtual environments, self-regulated learning, and natural language processing (Alhalangy & AbdAlgane, 2023). The use of AI in educational settings enhances the competencies of both students and educators.

2.1.3. Social and Collaborative Competencies

Several measures should be considered when evaluating the use of AI for EFL: the time learners spend using AI technologies, the type of instruction they seek, the required English proficiency level, and the level of interaction with AI (El Shazly, 2021). Although students generally demonstrate a high willingness to accept and use AI technologies for EFL learning, with social influence being the strongest motivation (Wen et al., 2024), successful integration requires addressing technological challenges, ethical considerations, and comprehensive instructors' training (Iqbal et al., 2025).

2.2. Digital and Media Literacy

Digital literacy is a technological skill that students should acquire to utilize AI technologies effectively in their educational pursuits. This literacy is acknowledged by students

https://doi.org/10.3390/educsci16040517

across all degrees for their ability to utilize technology to enhance their learning processes. Digital literacy plays a crucial role in employing AI technologies to enhance language acquisition, as it is defined as the capability to effectively and efficiently utilize technical tools or digital devices to access and disseminate information. Consequently, students' digital literacy is the primary worry for educators about the efficacy of AI technologies as a medium for facilitating hybrid learning, as insufficient digital literacy may hinder students' ability to fully engage with and benefit from these technologies in their educational experiences (Puniatmaja et al., 2024).

2.3. Hofstede's Cultural Dimensions

Hofstede's cultural dimensions theory provides a systematic framework for understanding how cultural values influence behavior, communication, and decision-making across societies. It identifies key dimensions—such as power distance, individualism versus collectivism, and uncertainty avoidance—that help explain differences in learning styles and classroom interactions. In education, this framework is useful for designing inclusive teaching strategies, improving teacher–student communication, and supporting culturally diverse learners. By acknowledging cultural variations, educators can enhance student engagement, equity, and overall learning outcomes.

2.3.1. Power Distance

Students in Lebanese schools, where teachers have historically held absolute authority, may perceive AI as an alternative authority source, rather than a productive dominance, particularly if students view these systems as undermining the traditional authority of their teachers and the established educational hierarchy due to high power distance characteristics (Dorji & Smet, 2022; Hofstede, 2001). Adoption trends and student trust may be impacted by the reluctance to accept AI systems that challenge teacher dominance.

2.3.2. Collectivism

Lebanon's collectivist inclinations suggest a greater response to AI systems that promote group involvement, communication, and shared learning results (Al-Hoorie, 2021; Oyserman et al., 2002). This culturally motivated desire supports the anticipation that AI will have a major impact on social and collaborative competencies.

2.3.3. Uncertainty Avoidance

Rule-based explanations, organized grammatical corrections, and predictable responses are provided by AI feedback systems. These characteristics enhance acceptance and decrease anxiety in high uncertainty avoidance situations (Shane, 2020; Vlachopoulos, 2022). Therefore, Hofstede's model offers a convincing rationale for examining AI outcomes in Lebanon as conceptually different from other regions.

2.4. Technology Acceptance Model

According to TAM, perceived utility and perceived ease of use influence an individual's desire to adopt technology (McCoy et al., 2007). TAM predictors are influenced by cultural differences; Arab learners rely more on trust and social approbation (Tarhini et al., 2014). This research postulates:

- AI acceptance levels are influenced by societal expectations of authority;
- Peer-driven technology adoption is accelerated by collectivism;
- The need for dependable AI output rises when ambiguity is avoided.

2.5. Sociocultural Theory

According to Vygotsky's theory, learning is socially mediated, and AI serves as a tool that lets students work in a zone of proximal development (Cress & Kimmerle, 2023). AI collaborative spaces are anticipated to improve social competencies in collectivist Lebanese schools.

2.6. Cognitive Load Theory

According to CLT, poorly created digital learning environments can hinder learning by increasing extraneous cognitive load and overtaxing students' working memory (Lankshear & Knobel, 2021). Thus, digital literacy turns into a moderating factor:

- Increased literacy lowers unnecessary cognitive stress.
- This impact facilitates the use of AI more effectively.
- Linguistic results are enhanced.

Within the context of CLT, DML offers a crucial explanatory mechanism for comprehending how students engage with AI-assisted educational systems. Through automated feedback, structured explanations, and adaptive guidance, AI tools can make language learning easier, but these advantages rely on students' proficiency with digital environments.

Learners who have developed greater levels of digital literacy are better equipped to assess AI-generated responses, manage multiple digital interfaces, and incorporate technological feedback into their learning processes. By focusing their cognitive resources on language processing instead of technology navigation, this decreases unnecessary cognitive load and boosts learning efficiency (Falloon, 2020).

On the other hand, when interacting with AI technologies, students who lack digital literacy may find it more difficult to think clearly. Challenges with interpreting AI outputs, choosing suitable prompts, or critically analyzing generated content may necessitate extra mental effort unrelated to the language learning task itself (Kirschner & De Bruyckere, 2017). AI technologies may become sources of unnecessary cognitive load in such circumstances instead of serving as learning facilitators. As a result, digital and media literacy functions as a moderating variable that establishes whether AI technologies improve language learning or inadvertently impede it.

2.7. Research Gaps and Motivation

The use of AI technologies in EFL instruction has been the subject of more recent research; nonetheless, a thorough understanding of their pedagogical impact is limited by a number of important and connected gaps in the literature. Previous research had a tendency to narrowly concentrate on discrete language abilities, most notably writing, while paying little attention to speaking fluency, listening comprehension, pronunciation, and integrated language use. This leads to inconsistent findings about learning effects.

Additionally, digital and media literacy is often considered a background or demographic variable, rather than being theorized as a moderating construct. However, how well students can benefit from AI-supported learning environments depends directly on their capacity to critically assess digital content, decipher AI-generated responses, and operate technological interfaces. While students with low digital literacy may find it difficult to understand outputs or confirm the accuracy of AI responses, students with higher digital literacy are better able to incorporate AI-generated feedback into their language learning strategies. As a result, learners' digital competencies are just as important to the pedagogical efficacy of AI technologies as the tools themselves.

There is considerable evidence indicating that cultural factors, as outlined in Hofstede's framework, significantly influence learning practices and technological adoption. However, no research has yet examined the effect of AI on EFL learning in Lebanon from a cultural perspective. The literature's emphasis on higher education contexts further limits its empirical scope, leaving high school populations—especially those in understudied areas like Lebanon—largely non-analyzed.

To fill these gaps, the current study examines how AI technologies, such ChatGPT (GPT-4o–based models with updates including GPT-4.5), Grammarly (extension version 8.935.0), and QuillBot (Web-based AI paraphrasing tool with no fixed version), support EFL learning among Mount Lebanon high school students in three interconnected domains: affective and motivational outcomes (autonomy, self-efficacy, and confidence), social and collaborative competencies (peer interaction and communication skills), and English language skills (writing, reading, speaking, and listening). This research provides a more theoretically grounded and comprehensive account of the interaction between AI technologies, learner capabilities, and educational outcomes by integrating cultural theory and placing digital and media literacy as a crucial moderating factor. This highlights the novelty and necessity of investigating AI's pedagogical potential and challenges in secondary foreign language education.

3. Methodology

This section outlines the study's design, detailing the conceptual framework that guides this research. Then, the approach to data collection is described, including the methods and instruments used to gather information. Finally, the data analysis techniques employed to interpret the collected data are explained in detail.

3.1. Research Design

To investigate the connections between AI technologies and student learning outcomes in a culturally unique EFL setting, this study uses a theory-driven quantitative research approach. Four complementary theoretical viewpoints inform the design:

- To provide contextual specificity, Hofstede's cultural dimensions theory is employed.
- AI adoption behavior is explained by TAM.
- Sociocultural learning theory is applied to analyze the results of cooperative learning, and digital and media literacy is justified as a moderating variable by CLT.

The use of a quantitative method is consistent with other AI-EFL research that aimed to quantify impact sizes, variance explanation, and learning variable interaction effects (Chou & Ting, 2023). The study focuses on high school students, a group that has not received much attention in previous empirical studies on AI-EFL.

3.2. Conceptual Framework

This study is guided by a conceptual framework that includes a quantitative model to examine the relationship between the following key variables: the independent variable (artificial intelligence technologies) and the dependent variable (student learning outcomes (SLOs)) (see Figure 1), which is composed of three indicators listed below:

- English language skills (ELSs): Based on theories of cognitive and sociocultural learning theories.
- Affective and motivational outcomes (AMOs) based on TAM and self-determination principles.
- Social and collaborative competencies (SCCs) based on Hofstede's collectivism dimension and sociocultural theory.

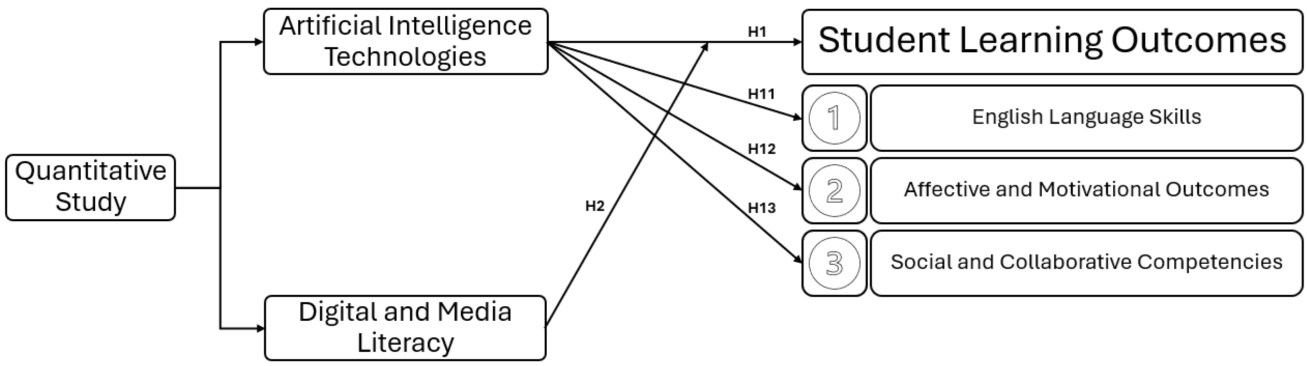

Figure 1. The conceptual framework adopted in this research, consisting of quantitative data collection through a questionnaire distributed to high school students.

Additionally, TAM and CLT support the inclusion of DML as a moderating variable. The latter affects students' capacity to effectively navigate AI systems, decipher feedback produced by AI, and incorporate technological outputs into their learning strategies. Higher digital literacy allows students to concentrate their cognitive resources on language learning activities and reduce the unnecessary cognitive load that comes with using technology (Falloon, 2020). On the other hand, when using AI technologies, students with lower levels of digital literacy might encounter more cognitive demands, which could limit these technologies' efficacy. As a result, DML moderates the connection between student learning outcomes and AI technologies.

The conceptual model is built based on multiple theoretical frameworks to assess how AI systems impact student achievement results. Students adopt and maintain their use of AI technologies through TAM, as they find them useful and easy to use. The sociocultural learning theory recognizes these technologies as mediational agents, which assist children in learning language through dialogues and structured learning processes. The theory of CLT points out how AI systems enhance language abilities and student interest through their ability to minimize unnecessary mental effort by providing customized feedback and organized explanations and individualized assistance. The cultural dimensions theory of Hofstede provides additional context to the framework by explaining how cultural elements influence students' self-directed learning abilities, technological acceptance, and communication methods, all of which affect their outcomes from AI-based learning systems in Lebanon.

The framework unites AI systems with digital and media literacy (DML) education and various learning targets to create an entire system that illustrates how AI functions in language education. The framework unites cognitive, sociocultural, and technological and cultural approaches to create a theoretically based method for testing hypotheses about ChatGPT and other conversational AI technologies that support English language learning, social learning, and motivation development.

The framework outlines the hypotheses that connect the independent, dependent, and moderating variables. This framework serves as the foundation for designing the survey instruments, which included a questionnaire with closed-ended statements. Moreover, it helps explore the interaction of all variables among each other. The suggested hypotheses in this study are introduced as follows:

- Based on the primary dependent variable, SLO, the primary hypothesis is constructed as follows.

  H1: There is a significant impact of AI technologies on student learning outcomes.

Consequently, the secondary hypotheses that can be deduced for the three indicators of the dependent variable are as follows.

- H11: There is a significant impact of AI technologies on English language skills.
- H12: There is a significant impact of AI technologies on affective and motivational outcomes.
- H13: There is a significant impact of AI technologies on social and collaborative competencies.

- Based on the moderate variable, DML, the following hypothesis is formulated.
  H2: Digital and Media Literacy will strengthen the impact of AI technologies on student learning outcomes.

3.3. Data Collection

The quantitative data collection involves gathering data through a survey designed using Google Forms, which is then shared via social media platforms such as WhatsApp communities, LinkedIn posts, and Facebook groups, targeting high school students in the Mount Lebanon region. This target represents Lebanese secondary education, which is characterized by teacher-centered instruction, collectivist classroom norms, and regulated curriculum requirements (Abdul-Latif, 2023). This situation is consistent with Hofstede's dimensions of high-power distance, high uncertainty avoidance, and moderate collectivism, all of which are predicted to have an impact on AI acceptance, motivation, and teamwork.

The data collection phase ensured confidentiality because no personal information, such as names, IDs, or emails, was requested from the survey respondents. Also, this phase was adopted to answer the research questions elaborated in Section 1 and prove hypotheses in Section 3.2.

As the survey consists of closed-ended statements, a five-point Likert scale was adopted during the data collection process, where the answers could range from 1 to 5. The value "1" represents strong disagreement with the given statement, whereas the value "5" illustrates strong agreement. Later, the data was cleaned and prepared for the process phase to ensure accuracy, consistency, completeness, and clearance.

3.4. Data Analysis

The data collected from the quantitative survey was analyzed using statistical methods to identify patterns, relationships, and significant differences among the variables. The strategy applied in this study was elaborated using SPSS version 27.0.1 software and pursued as follows:

- Descriptive statistics are calculated for each variable to determine the central tendency and variability of the data (Nassereddine & Nassreddine, 2024). Skewness and kurtosis statistics are calculated to examine the normality of data distribution. A skewness value close to zero shows symmetry. Kurtosis values near zero indicate a mesokurtic distribution. Deviations from these values are investigated to identify non-normality. For the mean value representation, three different categories are adopted: "Bad," "Moderate," and "Good" classes, starting with the value "1" and ending at the value "5," identified using the below formula:

$$Category\ Width = \frac{Max - Min}{Number\ of\ category} = \frac{5-1}{3} = 1.33 \quad (1)$$

where the variables *Max* and *Min* are the maximum and minimum values of the five-point Likert scale for some categories equals to the value "3". Accordingly, the

category window is calculated as: a "Bad" category ($1 \leq mean < 2.33$), a "Moderate" category ($2.33 \leq mean < 3.66$), and a "Good" category ($mean \geq 3.66$).
- Quantile–quantile (Q–Q) plots are created to assess the normality supposition visually by comparing the observed data distribution to a theoretical normal distribution (Hawkins & Esquivel, 2024).
- Participant responses were assessed for internal consistency using Cronbach's alpha and the Kaiser–Meyer–Olkin (KMO) test to represent sampling adequacy and determine the convenience of the data for indicator analysis (Hussein et al., 2023).
- A multivariate analysis of variance (MANOVA) is performed to investigate whether there is a statistically significant impact of the independent variable on the three indicators of the dependent variable, while controlling for inter-correlations among them (Noor et al., 2023).

4. Results and Discussion

In this section, the authors present the findings derived from the collected data and offer a significant investigation of the results in the context of this study. By examining the numerical trends and the underlying insights, the discussion aims to connect the results back to the research questions and the conceptual framework. Through this analysis, the authors explore not only what the data reveal but also how these outcomes contribute to a more profound understanding of the topic and its implications.

4.1. Research Participants and Settings

The survey was distributed among high school students during the third semester of the academic year 2024–2025 through social media. To ensure transparency, the researchers organized and verified the responses received from the survey based on the timing and patterns of the answers. A total of 180 responses were collected with the following personal information.

- Gender: 94 males (52.20%) and 86 females (47.80%)
- Number of students: 52 in Grade 10 (28.89%), 46 in Grade 11 (25.56%), and 82 in Grade 12 (45.55%)

To ensure the quality and trustworthiness of the data, responses were carefully reviewed by checking when they were submitted and how participants answered. At the same time, the survey remained fully anonymous. This approach helped us confirm that the responses were consistent and genuinely provided by the intended participants.

4.2. Survey Structure

Table 1 depicts the survey structure to detect students' engagement with AI technologies, showing the codes associated for AI background information (AIB), the independent variable (AIT), the dependent variable's indicators (ELS, AMO, and SCC), and moderate variable (MV) statements. The questionnaire encompasses a primary question asking participants to list the major AI technologies they use for studying English (AIB2).

Table 1. The survey's statements distributed among Lebanese high school students in Mount Lebanon.

Code	Statement
	AI Background Information
AIB1	What kinds of smart devices do you use to study English? Options: Laptop, Tablet, or Desktop PC.
AIB2	What AI tools do you use to learn English? Options: ChatGPT, Gemini, Grammarly, and/or Other).
AIB3	Are there workshops on using AI tools at your school? Options: Yes or No.
AIB4	What kind of AI tool user are you? Options: Beginner, Intermediate, or Advanced.
	Independent Variable (AIT)
AIT1	My school allows me to use AI technologies under a determined policy.
AIT2	AI technologies are made to fit my goals and the way I learn.
AIT3	I understand how to use AI technologies well.
AIT4	AI technologies should be taught in high schools as part of the curriculum.
AIT5	I will keep using AI technologies in the future.
	Dependent Variable: First Indicator (ELS)
ELS1	AI technologies help me improve my writing skills in English.
ELS2	AI technologies help me speak English fluently and confidently.
ELS3	AI technologies help me read text in English.
ELS4	AI technologies help me build a stronger English vocabulary.
ELS5	AI technologies help me improve my listening skills in English.
	Dependent Variable: Second Indicator (AMO)
AMO1	I feel confident learning English when I use AI technologies.
AMO2	I feel joyful learning English when I use AI technologies.
AMO3	I feel motivated to explore English when I use AI technologies.
	Dependent Variable: Third Indicator (Social and Collaborative Competencies—SCC)
SCC1	I can easily use AI technologies that help me practicing and learning English.
SCC2	AI technologies help me prepare better for group activities in English classes.
SCC3	AI technologies help me share more ideas freely in English classes.
SCC4	AI technologies help me collaborate easily with my classmates in English classes.
SCC5	AI technologies support me when working on shared English-language tasks.
	Moderate Variable (Digital and Media Literacy—DML)
DML1	I can effectively use AI technologies to organize, analyze, and present academic work in a professional manner.
DML2	I am skilled at integrating AI-generated content with my own ideas to produce original and high-quality assignments.
DML3	I use AI systems responsibly by respecting data privacy, citation requirements, and ethical guidelines.

4.3. Descriptive Statistics

Table 2 represents the descriptive statistics' results of the independent variable and the three indicators of the dependent variable with a statistically minimum value of 1.00 (total disagreement) and a maximum value of 5.00 (total agreement).

https://doi.org/10.3390/educsci16040517

Table 2. Descriptive statistics for mean, standard deviation, skewness, and kurtosis values for the independent variable and the dependent variable's indicators.

	Code	Mean	Standard Deviation	Skewness [a]	Kurtosis [b]
Independent Variable (AIT)	AIT1	3.13	1.088	−0.388	−0.435
	AIT2	3.70	0.997	−0.840	0.626
	AIT3	3.78	0.925	−0.914	1.137
	AIT4	3.92	1.126	−1.128	0.785
	AIT5	4.06	1.071	−1.242	1.099
	Average AIT	3.72	1.0414	−0.9024	0.6424
Dependent Variable First Indicator (ELS)	ELS1	3.79	0.997	−1.035	1.137
	ELS2	3.51	1.070	−0.665	−0.049
	ELS3	3.66	1.044	−0.851	0.284
	ELS4	3.83	1.051	−1.081	1.056
	ELS5	3.49	1.131	−0.665	−0.215
	Average ELS	3.65	1.056	−0.859	0.4426
Dependent Variable 2 Second Indicator (AMO)	AMO1	3.59	1.007	−0.794	0.669
	AMO2	3.52	1.000	−0.621	0.393
	AMO3	3.64	1.017	−0.978	0.948
	Average AMO	3.613	1.008	−0.797	0.670
Dependent Variable 3 Third Indicator (SCC)	SCC1	3.79	0.955	−1.054	1.411
	SCC2	3.72	1.031	−0.969	0.771
	SCC3	3.77	1.024	−1.077	1.047
	SCC4	3.61	0.989	−0.613	0.224
	SCC5	3.84	0.908	−1.089	1.879
	Average SCC	3.746	0.9814	−0.9604	1.0664

[a] Standard error for skewness is 0.181. [b] Standard error for kurtosis is 0.360.

The values in Table 2 demonstrate that AI technologies are effective for assisting students in their English learning journeys, as proven by mean scores (above 3.66) and standard deviation values, which are considered very low, with an average value of around 1.00 across all questionnaire statements, as described below:

- AIT5, which demonstrates how students will continue to use AI technologies in their future endeavors, scores a mean value of 4.06, which is considered high. Furthermore, AIT4, emphasizing the necessity of incorporating AI technologies into the high school curriculum, achieves a score of 3.92, indicating its significance.
- Students considered AI technologies as good assistants for building vocabulary (ELS4), writing (ELS1), and reading (ELS3) with mean values of 3.83, 3.79, and 3.66, respectively. However, although speaking (ELS2) and listening (ELS5) have moderate mean values of around 3.5, they are less effective than the other factors.
- AMO has an average mean value of around 3.59, indicating that motivation, confidence, and enjoyment have a considerably positive influence on students while studying English using AI technologies.
- The average mean value of SCC is considered satisfactory for students while using AI technologies with an acceptable value of 3.75.

Moreover, as the skewness is negative and the kurtosis is positive, it means that the results for independent and dependent variable's indicators are logically grouped together. Most of the time, students believe that AI is supportive, especially when it comes to reading, writing, and collaborating. They are aware, though, that they need to improve their spoken and listening language skills.

For ELS, the mean scores for individual questions are also consistently high (see Table 2—ELS). These results demonstrate that the use of AI technologies is associated with a strong level of English language skills for students across various aspects. Thus, these results answer RQ1, as the AI technologies positively affect high school students' level of English language skills, including vocabulary, grammar, reading comprehension, writing quality, and speaking fluency. For AMO, the mean scores for individual questions are also consistently high. The mean scores for the sub-questions are all in the positive range (see Table 2—AMO). These findings demonstrate that AI technologies lead to positive outcomes in students' self-learning, self-efficacy, and overall motivation. Thus, these results answer RQ2. Indeed, AI technologies positively affect students' engagement and motivational outcomes in English language learning, such as self-learning, self-efficacy, and motivation. For SCC, the mean scores for individual questions are also consistently high. The mean scores for the sub-questions are all in the positive range (see Table 2—SCC). These results answer RQ3 and demonstrate that AI technologies are highly effective in contributing to students' peer interaction, teamwork, and communication skills within English language classrooms.

4.4. Quantile-Quantile Plots

Figure 2 illustrates the Normal Quantile-Quantile (Q-Q) plot, which is used to establish whether the dependent variable encompasses a normal distribution.

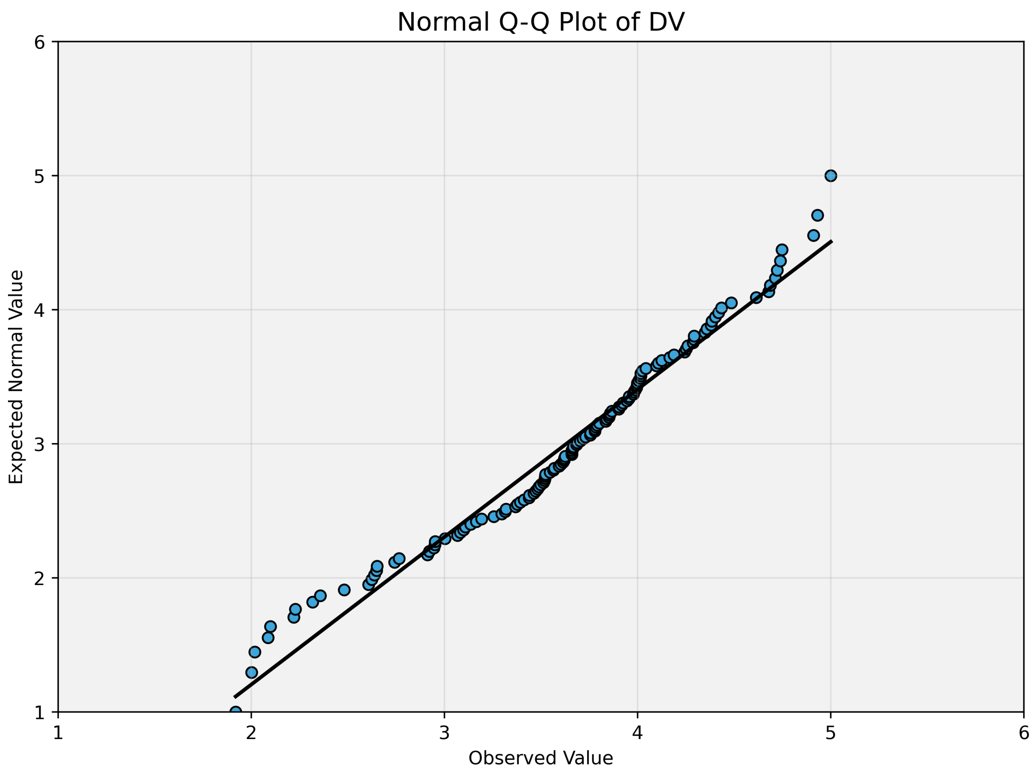

Figure 2. The Q-Q plot of the dependent variable that comprises the three indicators, showing a normal distribution of data collected.

The plot of Figure 2 indicates that almost all data points are close to the diagonal reference line. This suggests that the dependent variable's distribution is roughly normal. However, there is a small break in the line at the ends, especially at the lower end (between Observed Value 1.0 and 2.0). These data points are not near to the reference line, indicating that the lower end of the distribution is not perfectly normally distributed. The overall pattern indicates that the assumption of normality is mostly met for this dataset. Thus, parametric statistical tests that depend on this assumption are suitable for additional analysis.

4.5. Cronbach Alpha and Kaiser–Meyer–Olkin

Table 3 shows the Cronbach's alpha and KMO values. Values for Cronbach's alpha were grouped as low scores between 0 and 1.7 inclusive, moderate scores between 1.7 and 3.4 inclusive, and high scores between 3.5 and 5.0 inclusive. While a KMO value greater than 0.6 is acceptable, higher values indicate greater adequacy.

Table 3. Cronbach's alpha and KMO values.

Construct	AIT	ELS	AMO	SCC
Cronbach's Alpha	0.88	0.88	0.85	0.87
Kaiser–Meyer–Olkin	0.812	0.925	0.937	0.920

The reliability analysis indicates that all of the constructs used in this study are consistent with each other. Cronbach's alpha values range from 0.85 to 0.88, higher than 0.70. Thus, the survey statements reliably measure their respective constructs (AIT, ELS, AMO, and SCC).

The KMO test supports the construct validity of the scales. The values for all constructs are high, between 0.812 and 0.937. Thus, each set of statements accurately reflects a single underlying dimension. These results indicate that the constructs are both reliable and valid; thus, they can be used for further statistical analyses, including Pearson correlation and multivariate ANOVA to check the existence of differences among the variables.

4.6. Pearson Correlation

Pearson correlation analysis is applied to assess the relationships between the dependent variables from one side and the independent variable on the other side (see Table 4).

Table 4. Pearson correlation values between the dependent variable indicators and the independent variable.

		AIT	ELS	AMO	SCC
AIT	Pearson Correlation	1	0.625 **	0.673 **	0.660 **
	Sig. (2-tailed) (p)		0.000	0.000	0.000
	N	180	180	180	180

** Correlation is significant at the 0.01 level (2-tailed).

The findings of Table 4 demonstrate positive correlations among all indicators with AIT; all bi-variate correlations are statistically significant with a p value smaller than 0.001, meaning that when one indicator's score rises, the others' scores usually rise too. However, the strength of these connections is different, as explained below:

- The highest correlation was between ELS and AMO ($r = 0.862$, $p < 0.001$), which indicates a substantial positive relationship.
- The weakest significant correlation is illustrated between AIT and ELS ($r = 0.625$, $p < 0.001$), showing a moderately strong positive relationship.

4.7. Multivariate ANOVA Test

The principal aim of a MANOVA is to ascertain whether the means of the dependent variable's indicators significantly differ between groups, considering the inter-relationships among them (see Table 5).

All p-values in Table 5 are below the threshold of 0.05, demonstrating that the independent variable has a statistically significant effect on the dependent variable. Therefore, any changes in the independent variable correlate with significant changes in the dependent variable (SLO), with the three indicators combined together.

The partial eta squared values range from 0.255 to 0.522, demonstrating that the independent variable shows a moderate-to-large proportion of the variance in the dependent variable (SLO), with the three indicators combined together.

Table 5. The effects of the multivariate ANOVA tests of the independent variable AIT.

Effect	Pillai's Trace	Wilks' Lambda	Hoteling's Trace	Roy's Largest Root
Value	0.765	0.369	1.370	1.093
F	2.557	2.911	3.321	8.164 [a]
Hypothesis df	51.000	51.000	51.000	17.000
Error df	381.000	372.951	371.000	127.000
Sig.	0.000	0.000	0.000	0.000
Partial Eta Squared	0.255	0.283	0.313	0.522

[a] The statistic is an upper bound on F that yields a lower bound on the significance level.

Indeed, Roy's largest root reaches a value of 0.522 and focuses on the largest eigenvalue, which shows the strongest effect in any one linear combination of the dependent variable's indicators. This value suggests that, for at least one linear combination, the independent variable accounts for more than half of the observed variance.

The multivariate ANOVA tests illustrate that AIT has a statistically significant impact on SLO, combining all indicators. In addition, the effect sizes suggest that AIT explains a moderate to large proportion of variance across the indicators, proving the primary hypothesis H1 of this study.

However, for additional insights, Levene's test is studied afterward to confirm whether the assumption of the homogeneity of variances is met across the groups, in addition to the test of between-subjects effects to identify whether the independent variable produces significant differences in the dependent variable.

4.8. Levene's Test

Levene's test is illustrated in Table 6 to evaluate the homogeneity of error variances for each indicator of the dependent variable (Emerson, 2022).

Table 6. Levene's test of equality of error variances (design: intercept + independent variable).

Indicator	Measure	Levene's Statistic	df1	df2	Sig. (p)
ELS	Based on Mean	1.569	14	127	0.097
	Based on Median	0.915	14	127	0.544
	Based on Median with adjusted df	0.915	14	62.865	0.547
	Based on trimmed mean	1.475	14	127	0.130
AMO	Based on Mean	2.745	14	127	0.001
	Based on Median	1.723	14	127	0.059
	Based on Median with adjusted df	1.723	14	54.016	0.078
	Based on trimmed mean	2.704	14	127	0.002
SCC	Based on Mean	1.410	14	127	0.157
	Based on Median	0.873	14	127	0.589
	Based on Median with adjusted df	0.873	14	78.446	0.590
	Based on trimmed mean	1.327	14	127	0.201

All Levene's statistics in Table 6 are non-significant ($p > 0.05$), suggesting that the homogeneity of variance is met for ELS. However, some tests (mean and trimmed mean) are significant with p values of 0.001 and 0.002, respectively, for AMO, suggesting the violation of the equal variance assumption. However, in alternative tests based on median and adjusted df, they are non-significant with p values greater than 0.05. Thus, the violation may be limited and can be handled with robust methods or adjusted degrees of freedom. For SCC, all tests are non-significant with all p values greater than 0.05, supporting the assumption of equal variances.

4.9. Between-Subjects Effects

The tests of between-subjects effects (Schroeder & Kucera, 2022) show how the independent variable affects each indicator of the dependent variable, individually, as illustrated in Table 7, resulting in the following:

- The ELS model is significant with an F value of 5.628 and a p value of less than 0.001. The partial eta squared value is 0.430, demonstrating a strong impact of the independent variable. The R-squared value is equal to 0.430 with an adjusted R-squared of 0.353, demonstrating that 35 to 43 percent of the variance in ELS is explained by the independent variable.
- For AMO, the effect is strong with an F value of 7.835 and a p value of less than 0.001, and the partial eta squared is equal to 0.512. The adjusted R-squared of 0.447 shows that nearly 45% of the variance in AMO is due to the independent variable.
- For SCC, the F value is 5.705, and the p value is less than 0.001. The eta squared is equal to 0.433, reflecting a strong influence of the independent variable, with an adjusted R-squared of 0.357.

Thus, for all the indicators, the independent variable shows a statistically significant and practically meaningful effect, supporting the hypothesis that it substantially impacts the dependent measures.

Table 7. Tests of between-subjects effects: effect of the independent variable on indicators of the dependent variable.

Source	Indicator	Type III Sum of Squares	df	Mean Square	F	Sig. (p)	Partial Eta Squared
AIT	ELS	52.060 [a]	17	3.062	5.628	0.000	0.430
	AMO	55.526 [b]	17	3.266	7.835	0.000	0.512
	SCC	40.809 [c]	17	2.401	5.705	0.000	0.433

[a] R-squared = 0.430 (adjusted R-squared = 0.353). [b] R-squared = 0.512 (adjusted R-squared = 0.447). [c] R-squared = 0.433 (adjusted R-squared = 0.357).

The between-subjects tests demonstrate that AIT significantly affect ELS (see Table 7—ELS). This result demonstrates that approximately 35% of the variance in English language performance can be attributed to the use of AIT, showing that the study proves the secondary hypothesis H11. The independent variable, AIT, also demonstrates a significant effect on affective and motivational outcomes (see Table 7—AMO). Indeed, AIT accounts for nearly 45% of the variance in students' AMO, proving the secondary hypothesis H12 of this study. Although Levene's test for AMO showed some significant results (p is 0.001 for the mean value and 0.002 for the trimmed mean value), the median-based tests were non-significant with p values of 0.059 and 0.078, showing that assumptions are sufficiently met. AIT also significantly impacts social and collaborative competencies (see Table 7—SCC). The corresponding values prove that over one-third of the variance in social and collaborative outcomes is due to the use of AI technologies, showing that the study proves the secondary hypothesis H13.

Further, the scale of effects that were observed is also the evidence of their practical usefulness. The values of eta squared in Table 7 are reported as partial (values between 0.430 and 0.512), which can be considered moderate to large. These values provide a confirmation that the summarized percentages of the explained variance (around 43 percent in the case of English language skills and about 45 percent in the case of affective and motivational outcomes) are not only statistically significant correlations but also indicators of the significance of educational influence in the context of the study. Taking into account the context of the Lebanese high school, these findings imply that AI technologies can play a significant role in the learning process of students by helping them to practice languages, be motivated, and engage in cooperation. Nevertheless, it is important to consider a broader socioeconomic background. As mentioned in the introduction, the constant economic turmoil in Lebanon could affect students in their access to digital infrastructure, high-quality internet connection, and AI-powered educational resources. These differences can restrict the variety of students who can take advantage of AI-mediated learning conditions. Thus, it is important to consider equal access and institutional resources in terms of implementing AI-based technologies in learning environments.

4.10. Moderation Analysis

The moderation analysis tests the impact of the moderate variable DML on the effect between the independent variable AIT and dependent variable SLO (Memon et al., 2019). It requires many data preparation steps using the SPSS software.

First of all, AIT was mean-centered through the subtraction of its overall mean value from each observation using:

$$C_{AIT} = AIT_i - \overline{AIT} \tag{2}$$

where C_{AIT} denotes the mean-centered, AIT_i is the observation i of AIT, and $\overline{AIT}$ is the mean value of all C_{AIT}.

Similarly, DML is also mean-centered, using:

$$C_{DML} = DML_i - \overline{DML} \tag{3}$$

where C_{DML} represents the mean-centered value, DML_i is the observation i of DML, and $\overline{DML}$ is the mean value of all DML_i.

Indeed, centering is an important step in moderation analysis due to its capability to reduce multi-collinearity between variables and their interaction term. Thereafter, an interaction variable (Int) is calculated using:

$$Int = CAIT \times CDML \tag{4}$$

The use of Int allows to test the existence of any effect of the independent variable on the dependent variable, depending on the moderate variable.

Finally, a regression test is performed with SLO as the outcome and C_{AIT}, C_{DML}, and Int as predictors. This test permits the computation of an estimation of the main effects and the interaction effect, thereby testing for potential moderation. The results of the regression test are thereby elaborated and shown in Table 8.

https://doi.org/10.3390/educsci16040517

Table 8. The summary results of the regression model.

Model	R	R-Square	Adjusted R-Square	Std. Error of the Estimate
1	0.685 [a]	0.469	0.458	0.59548

[a] Predictors: (Constant), C_{AIT}, C_{DML}, and Int.

The regression model provides an R value of 0.685 that demonstrates a strong positive correlation between the set of predictors (AIT and DML) with SLO. The R-squared value is equal to 0.469, proving that the regression model including AIT and DML explains approximately 47% of the variance in SLO. However, the adjusted R-squared reaches a value of 0.458 that also represents an important amount of explained variance, confirming the robustness of the model.

The standard error of the estimate is equal to 0.595, which proposes a moderate level of prediction error. This value also indicates that, even if the model is effective, there remains some unexplained variance referable to other factors not included in the analysis. Thus, these results provide strong confirmation that the combination of the AIT, DML, and their interaction significantly predicts SLO. Therefore, the hypothesized moderating effect (H2) is supported.

The ANOVA result represented in Table 9 assesses the overall fit of the regression model predicting SLO based on the predictors C_{AIT}, C_{DML}, and Int.

Table 9. The ANOVA test of the regression model.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	44.158	3	14.719	41.510	0.000 [b]
	Residual	49.998	141	0.355		
	Total	94.157	144			

[b] Predictors: (Constant), C_{AIT}, C_{DML}, and Int.

The regression model is statistically significant with an F equal to 41.510 and a p of less than 0.001. These values prove that the combined predictors (AIT and DML) explain a significant portion of the variance in SLO.

Moreover, the regression coefficients illustrated in Table 10 offer a description of the contribution of each predictor to SLO.

Table 10. The coefficients of the regression model.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig. (p)
		B	Std. Error	β		
1	(Constant)	3.673	0.050		73.370	0.000
	C_{AIT}	0.695	0.065	0.667	10.685	0.000
	C_{DML}	0.044	0.038	0.073	1.170	0.010
	Int	0.048	0.042	0.071	1.144	0.001

The intercept with a B equal to 3.673 and a p value of less than 0.001 represents the value of SLO when all predictors are at their mean-centered values of zero. CAIT has a strong and statistically significant positive effect on SLO, illustrated by a B value of 0.695, a β value of 0.667, a t value of 10.685, and a p of less than 0.001. These values show that higher values of the AIT are associated with higher SLO scores.

However, the moderator C_{DML} does not have a significant direct effect with a B value equal to 0.044, a β value equal to 0.073, a t value of 1.170, and a p value of 0.244. Also, Int shows lower impact with a B value equal to 0.048, a β value of 0.071, a t value of 1.144, and a p equal to 0.255. These values suggest that DML with Int do not significantly predict SLO.

Consequently, the regression equation for SLO can be derived based on the above-mentioned observation, as follows:

$$SLO = 3.673 + 0.695C_{AIT} + 0.044C_{DML} + 0.048Int \quad (5)$$

For each one-unit increase in C_{AIT}, SLO is expected to increase by 0.695 units based on the above equation. However, each one-unit increase in C_{DML} or Int leads to a small improvement of SLO score by 0.044 or 0.048, respectively. These values demonstrate the moderate variable has an impact on dependent variables but not as important as the independent variable.

Moreover, the results illustrated in Tables 8–10 offer clear support for the hypothesis H2 that suggests that DML significantly strengthens the impact of AIT on student learning outcomes. Both the moderator C_{DML} with values for $B = 0.044$, and $p = 0.01$ and the interaction term Int with values $B = 0.048$ and $p = 0.001$ are statistically significant, proving that students with higher DML can benefit more from AI technologies than those who are not in high contact with digital media.

The findings give the theoretical framework substantial empirical support. Lebanese high school students' English language proficiency, affective and motivational outcomes, and social and collaborative competences were all greatly improved by AI technologies. Furthermore, these impacts were reinforced by DML, supporting its hypothesized moderating role.

The findings fill the gaps of the existing study mentioned in Section 2.7 regarding the AI-assisted EFL teaching. In contrast to the past research studies that concentrated on the independent language skills, the present study reveals that AI technologies have a comprehensive pedagogical effect in various aspects, such as English language proficiency, affective and motivational outcomes, and social and collaborative competencies. Moreover, by making DML a defining construct, the study suggests the power of the learners' abilities to process AI technologies critically, which can be the primary beneficial factor in AI-assisted learning. This comprehensive approach, mixed with the cultural lens applied to the Lebanese high school context, provides new insights into how AI technologies can support EFL learning in secondary education, extending the empirical scope beyond higher education and offering a theoretically grounded explanation for the observed learning outcomes.

Thus, this approach guarantees that only students with AI learning experience were included. The aggregated measure of AIT reflects the overall pedagogical effect of AI-assisted learning on English language skills, affective and motivational outcomes, and social and collaborative competencies. This methodology balances statistical rigor by integrating ecological validity that reflects students' real-world use of multiple AI technologies in high school EFL learning environments. Future studies may assess the differential influence of specific types of AI technologies, given that some technologies are corrective and deterministic, such as Grammarly (extension version 8.935.0), while others are generative and conversational, such as ChatGPT GPT-4o and Gemini 2.0 Flash.

As for Hofstede's cultural dimensions:

- Power distance: In a high-power-distance educational setting where teacher authority predominates, the significant positive benefits of AI on English language proficiency may seem counterintuitive. However, pupils were able to practice language abilities on their own without directly challenging instructor authority, thanks to AI technologies that offered private, nonjudgmental feedback. Learners in high power-distance cultures prefer organized yet non-confrontational learning support (Dorji & Smet, 2022; Hofstede, 2001). The widespread acceptance and influence of AI can be explained by the fact that it served as a culturally acceptable supplementary authority, rather than a teacher substitute.

- Collectivism and social collaboration: The notable advancement in social and cooperative skills aligns with Lebanon's collectivist mindset. Culturally embedded peer-learning norms were well aligned with AI-supported group tasks, shared editing platforms, and collaborative preparation technologies (Al-Hoorie, 2021; Oyserman et al., 2002). This result confirms that AI can enhance, rather than replace, collective learning practices in collectivist classrooms and supports sociocultural theory, which sees learning as socially mediated. Even though the Lebanese education system suggests high power-distance standards that prioritize the authority of a teacher, AI learning technologies are actively used by students in the country, implying that AI technologies do not substitute for teachers. They are considered supplementary teaching technologies that offer systematic aids with the main teacher role remaining intact.
- Uncertainty Avoidance and Structured Feedback: Strong affective and motivational outcomes are explained by the high uncertainty avoidance of Lebanese students. AI technologies offered: prompt rectification, predictable rules of grammar, and regular feedback on language. These characteristics improved motivation and confidence by lowering uncertainty and learning anxiety (Shane, 2020; Vlachopoulos, 2022). This result clarifies why, out of all the indicators, affective outcomes had the highest variance explained.
- As for TAM: students thought AI technologies were practical and simple to use, which increased their engagement and learning outcomes. Cultural factors increased the effects of TAM; adoption was significantly influenced by social influence and trust, which is in line with findings from Arab educational contexts (Tarhini et al., 2014).
- As for CLT: it is supported by DML's moderating function. Students who were more digitally literate had less unnecessary cognitive load, which allowed them to concentrate on language processing instead of using technologies (Lankshear & Knobel, 2021). In terms of culture, digital literacy also enabled students to use AI on their own in teacher-centered settings, strengthening autonomy without upending hierarchical conventions.

After the deep discussion illustrated above, the findings indicate a strong compatibility between the integration of AI technologies in learning English as a foreign language and the previous literature, particularly regarding their effectiveness in enhancing grammar, vocabulary, and writing skills. In this study, it is demonstrated that 35% of the variance in English language skills can be attributed to the use of AI technologies, aligning with previous studies that have shown that AI technologies enhance students' intellectual performance, particularly in language learning circumstances (e.g., AlTwijri & Alghizzi, 2024).

As for affective and motivational outcomes, 45% of the variance in affective and motivational outcomes has a significant influence on learners' activities and independence while using AI technologies, showing alignment with prior studies (e.g., Javaid et al., 2024), which have emphasized that AI self-learning environments increase student motivation by offering self-determination.

Additionally, AIT has a significant impact on social and collaborative competencies, extending the literature; some recent studies (e.g., Sun, 2025) have shown that collaborative platforms powered by AI can foster interaction and teamwork, in consonance with the results of this study, which indicate that AI technologies comprise over one-third of the variance in social and collaborative competencies, positioning AI as a cognitive support system and a facilitator of social engagement (Al-Hattami, 2025).

https://doi.org/10.3390/educsci16040517

According to the resonance between this study and previous ones, it is plainly shown that the necessity of integrating AI technologies in education, especially in EFL, is no longer considered as additional aid; instead, it represents an efficient instruction tool for shaping learning processes.

5. Conclusions and Recommendations

This paper has employed a descriptive analysis methodology based on three main types of variables: an independent variable represented by AI technologies, a dependent variable (student learning outcomes) with three indicators (English language skills, affective and motivational outcomes, and social and collaborative competencies), and a moderated variable represented by digital and media literacy. Thus, a survey of 20 questions, discussing the three variables, was built and distributed to high school students in Mount Lebanon; 180 answers were collected and analyzed using SPSS. Data analysis included descriptive statistics, reliability checks (Cronbach's alpha), sampling adequacy tests (KMO), and a multivariate analysis of variance (MANOVA) to explore relationships among the independent variable (AI technologies), the dependent variable's indicators (English language skills, affective and motivational outcomes, and social and collaborative competencies), and the moderating variable (digital and media literacy). The results of the statistical analysis demonstrate that AI technologies have a significant positive impact on students' learning outcomes with their three indicators. The results of the MANOVA test indicated that approximately 43% of English language skills can be attributed to the use of AI technologies. Additionally, artificial intelligence technologies account for 45% of the variance in affective and motivational outcomes. Furthermore, around 35% of social and collaborative competencies are influenced by the implementation of AI technology. These findings reinforce the conceptual place of AI technologies as both cognitive scaffolds and social mediators, particularly in EFL contexts where interaction and learner engagement are critical. Moreover, the considerable explanatory power of AI on all learning outcome dimensions supports its role as a primary and essential instructional component, rather than a supplementary tool, mainly when equipped with adequate levels of digital and media literacy. In the context of Middle Eastern education, AI technologies are considered assistive teaching technologies to help teachers. Thus, they should correspond to classroom norms while enhancing practice and feedback opportunities.

The regression equation shows that the independent variable (AI technologies) contributes the strongest effect ($\beta = 0.695$), while the moderating variable, digital and media literacy ($\beta = 0.044$), and the interaction term ($\beta = 0.048$) also add to the prediction. In addition, the significant interaction effect in the regression analysis proves that the moderating variable (digital and media literacy) enhances this impact. Thus, students with higher digital and media literacy can use AI-assisted learning more effectively and benefit from collaborative digital activities. However, the study suffers from several limitations. The sample was geographically limited to Mount Lebanon, potentially reducing generalization. Moreover, the analysis focused on short-term learning outcomes, without taking into consideration long-term retention and performance, which remain unexplored. Differences in school resources and access to AI technologies may also have an impact on student experiences.

In conclusion, the findings permit several generalizations associated with the role of artificial intelligence in secondary education. The study indicates that the integration of AI technologies can significantly improve students' language learning, motivation, and collaborative engagement when reinforced by appropriate levels of digital and media literacy. These results point out the practical and important role of AI as an educational innovation that supports personalized learning, interactive practice, and learner autonomy in EFL environments. From a theoretical perspective, the findings demonstrate the value of technology-enhanced learning and traditionalist perspectives, where digital technologies play a role as cognitive platforms that produce active knowledge technologies and social interaction. Therefore, the responsible adoption of AI technologies in schools can be used to enhance educational quality, improve students' digital competencies, and prepare learners for technology-driven academic and professional environments.

Recommendations

These findings suggest that governments should enforce policies to incorporate AI technologies into education, promoting their proper use in schools. AI technologies can be integrated into STEM courses, skills or competency development programs, language learning, and academic writing courses to improve student learning. The main goal is to improve students' engagement with the learning material and to receive immediate and relevant feedback. In the context of Lebanese culture, the findings of this paper suggest considering the use of AI technologies as an aid to the teacher, not as a substitute for them. Thus, the teacher's role should not be undermined by the use of AI technologies, and students should not perceive them as an authority instead of the teacher.

In addition, schools should be encouraged to integrate AI technologies into curricula and provide structured digital literacy programs to ensure fair access to AI resources. Furthermore, educational institutions should provide appropriate training for the instructors to support the effective and ethical integration of AI in classrooms.

Moreover, research should be extended beyond Mount Lebanon to enhance generalization and examine the enduring effects of AI on knowledge retention, critical thinking, and academic performance. In addition, investigating the long-term effect of the use of AI-based learning technologies on students' knowledge and on their ability to demonstrate higher-order thinking skills and to achieve better academic grades is highly recommended. Furthermore, other moderate variables should be considered, such as socioeconomic background, school resources, and instructors' readiness.

This study relied heavily on quantitative methodology, and therefore, future studies are recommended to employ mixed-methods research to investigate students' attitudes toward using AI-based learning technologies and to investigate students' behavior toward the new technology within the context of the teacher-centric pedagogical practices that still prevail in Lebanese schools.

Author Contributions: Conceptualization, A.E.A., O.A.-K., R.O. and G.N.; methodology, A.E.A., R.O. and G.N.; software, G.N. and O.A.-K.; validation, A.E.A., A.E.C. and O.A.-K; formal analysis, A.E.A.; investigation, R.O. and O.A.-K.; resources, G.N.; data curation, G.N.; writing—original draft preparation, A.E.A., O.A.-K. and G.N.; writing—review and editing, A.E.C., O.A.-K.; visualization, A.E.A.; supervision, O.A.-K. and G.N.; project administration, A.E.A. and O.A.-K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Research Ethics Committee of Rafik Hariri University (approval date 7 January 2025).

Informed Consent Statement: All participants were informed about the purpose of the study and provided voluntary consent to participate. Anonymity and confidentiality were maintained. This study does not include any individual person's data in any form (including individual details, images, or videos); hence consent for publication is not required. All authors have read and agreed to the published version of the manuscript. All procedures performed in this study have been approved by the Research Committee at Rafik Hariri University. All procedures were performed in accordance with relevant guidelines and regulations. This study adhered to the Declaration of Helsinki and its later amendments or comparable ethical standards.

Data Availability Statement: The data presented in this study are available upon request from the corresponding author due to the survey participants' privacy.

Conflicts of Interest: The authors declare no conflicts of interest.

References

Abdul-Latif, E. (2023). Hofstede's dimensions in Arab schooling systems: An empirical study. *Education & Society*, *41*(3), 455–474.

Abdulmajeed, I., Nassreddine, G., El Arid, A., & Younis, J. (2023). Machine learning approach in human resources department. In *Handbook of research on AI methods and applications in computer engineering* (pp. 271–294). IGI Global.

Abuhussein, H. F., & Badah, A. (2025). The Role of AI-based writing tools on L2 writing competency: Evidence from palestinian EFL learners. *Dirasat: Human and Social Sciences*, *52*(5), 6566. [CrossRef]

Ahmad, D., Latif, I., Arafah, B., & Suryadi, R. (2024). Defining the role of artificial intelligence in improving English writing skills among Indonesian students. *Journal of Language Teaching and Research*, *15*(2), 568–578. [CrossRef]

Aijun, Y. (2024). On the influence of artificial intelligence on foreign language learning and suggested learning strategies. *International Journal of Education and Humanities*, *4*(2), 107–120. [CrossRef]

Alhalangy, A., & AbdAlgane, M. (2023). Exploring the impact of AI on the EFL context: A case study of Saudi Universities. *Journal of Intercultural Communication*, *23*(2), 41–49. [CrossRef]

Al-Hattami, H. M. (2025). Empowering business research with ChatGPT: Academic and student insights through the UTAUT lens. *Discover Computing*, *28*(1), 179. [CrossRef]

Al-Hoorie, A. H. (2021). Collectivism and its influence on collaborative language learning in Middle Eastern classrooms. *Language Teaching Research*, *25*(5), 731–754.

Alhusaiyan, E. (2025). A systematic review of current trends in artificial intelligence in foreign language learning. *Saudi Journal of Language Studies*, *5*(1), 1–16. [CrossRef]

Al-Raimi, M., Mudhsh, B. A., Muqaibal, M. H., & Al-Yafaei, Y. (2024). To what extent has artificial intelligence impacted EFL teaching and learning? A systematic review. *Jurnal Arbitrer*, *11*(3), 399–412. [CrossRef]

AlTwijri, L., & Alghizzi, T. M. (2024). Investigating the integration of artificial intelligence in English as foreign language classes for enhancing learners' affective factors: A systematic review. *Heliyon*, *10*(10), e31053. [CrossRef]

Atkinson, D. (2023). Arab learners and cultural influences on EFL behavior. *Applied Linguistics Review*, *14*(1), 1–22.

Cahyono, A. E., & Rosita, R. (2023). The impact of Using AI-based language learning platforms on English speaking skills of college students. *Transformational Language Literature and Technology Overview in Learning*, *2*(2), 1–8. [CrossRef]

Chea, P., & Xiao, Y. (2024). Artificial intelligence in higher education: The power and damage of AI-assisted tools on academic English reading skills. *Journal of General Education and Humanities*, *3*(3), 287–306. [CrossRef]

Chou, C.-M., & Ting, C.-C. (2023). Factors influencing teachers' behavioral intention to adopt artificial intelligence teaching applications: A cross-cultural perspective. *Education and Information Technologies*, *28*, 15327–15352.

Cress, U., & Kimmerle, J. (2023). Co-constructing knowledge with generative AI tools: Reflections from a CSCL perspective. *International Journal of Computer-Supported Collaborative Learning*, *18*(4), 607–614. [CrossRef]

Daweli, T. W., & Moqbel Mahyoub, R. A. (2024). Exploring EFL learners' perspectives on using AI tools and their impacts in reading instruction: An exploratory study. *Arab World English Journal*. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4918005 (accessed on 18 March 2026). [CrossRef]

Dja'far, V. H., & Hamidah, F. N. (2024). The effectiveness of AI technology in improving academic English writing skills in higher education. *Journal of Language and Literature Studies*, *4*(3), 579–593. [CrossRef]

Dorji, R., & Smet, M. (2022). Power distance and teacher authority in Asian classrooms: A Hofstede-based perspective. *International Journal of Educational Research*, *115*, 102119.

El Shazly, R. (2021). Effects of artificial intelligence on English speaking anxiety and speaking performance: A case study. *Expert Systems*, *38*(3), e12667. [CrossRef]

Emerson, R. W. (2022). ANOVA assumptions. *Journal of Visual Impairment & Blindness*, *116*(4), 585–586. [CrossRef]

Falloon, G. (2020). From digital literacy to digital competence: The teacher digital competency (TDC) framework. *Educational Technology Research and Development*, *68*(5), 2449–2472. [CrossRef]

Fountoulakis, M. S. (2024). Evaluating the impact of AI tools on language proficiency and intercultural communication in second language education. *International Journal of Second and Foreign Language Education*, *3*(1), 12–26. [CrossRef]

Fuchs, K. (2024). Challenges with gamification in higher education: A narrative review with implications for educators and policymakers. *International Journal of Changes in Education*, *1*(1), 51–56. [CrossRef]

Hawkins, D. M., & Esquivel, R. N. (2024). A Quantile–Quantile toolbox for reference intervals. *The Journal of Applied Laboratory Medicine*, *9*(2), 357–370. [CrossRef]

Heil, C., Wu, J., Lee, J. J., & Schmidt, T. (2020). A review of mobile language learning applications: Trends, challenges, and opportunities. *Educational Technology Research and Development*, *68*(5), 2321–2349. [CrossRef]

Hofstede, G. (2001). *Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations* (2nd ed.). International Educational and Professional.

Hofstede, G., & Hofstede, G. J. (2005). *Cultures and organizations: Software of the mind* (2nd ed.). McGraw-Hill.

Hussein, R. N., Nassreddine, G., & Younis, J. (2023). The impact of information technology integration on the decision-making process. *Journal of Techniques*, *5*(1), 144–155. [CrossRef]

Iqbal, J., Asgarova, V., Hashmi, Z. F., Ngajie, B. N., Asghar, M. Z., & Järvenoja, H. (2025). Exploring faculty experiences with generative artificial intelligence tools integration in second language curricula in Chinese higher education. *Discover Computing*, *28*(1), 128. [CrossRef]

Ismoilovna, A. D. (2025). Harnessing AI tools to enhance foreign language acquisition: Innovations and impacts. *American Journal of Social Sciences and Humanity Research*, *5*(1), 22–25. [CrossRef]

Javaid, Z. K., Ramzan, M., & Ijaz, S. (2024). A systematic review on cognitive and motivational impact on English language learning through artificial intelligence. *International Journal of Literature, Linguistics and Translation Studies*, *4*(1), 44–71.

Karakas, A. (2023). Breaking down barriers with artificial intelligence (AI): Cross-cultural communication in foreign language education. In *Transforming the language teaching experience in the age of AI* (pp. 215–233). IGI Global.

Khoudri, I., Zeriouh, M., Fauzan, U. M. A. R., & Khoudri, A. (2024). The use of ai in learning English: A comparative study between Moroccan and Indonesian undergraduate students from the English department. *Edelweiss Applied Science and Technology*, *8*(4), 1271–1282. [CrossRef]

Kirschner, P. A., & De Bruyckere, P. (2017). The myths of the digital native and the multitasker. *Teaching and Teacher Education*, *67*, 135–142. [CrossRef]

Kovalenko, I., & Baranivska, N. (2024). Integrating artificial intelligence in English language teaching: Exploring the potential and challenges of AI tools in enhancing language learning outcomes and personalized education. *Europian Socio-Legal & Humanitarian Studies*, *1*(1), 86–95.

Kristiawan, D., Bashar, K., & Pradana, D. A. (2024). Artificial intelligence in English language learning: A systematic review of AI tools, applications, and pedagogical outcomes. *The Art of Teaching English as a Foreign Language*, *5*(2), 207–218. [CrossRef]

Lankshear, C., & Knobel, M. (2021). Digital literacy and digital literacies: Policy, pedagogy and research considerations for education. *Nordic Journal of Digital Literacy*, *16*(1), 1–17. [CrossRef]

Le, T. T. H., Dang, H. K., & Nguyen, T. T. (2025). Applying AI tools to develop a curriculum Based on expected learning outcomes and personalize learning program for students at the university of languages and international studies. *European Journal of Educational Research*, 14(2), 415. [CrossRef]

Liu, Y., Wang, H., & Tai, T. Y. (2022). Artificial intelligence in second and foreign language education: A systematic review. *Journal of Educational Computing Research*, *60*(6), 1527–1555.

Madhavi, E., Sivapurapu, L., Koppula, V., Rani, P. E., & Sreehari, V. (2023). Developing learners' English-speaking skills using ICT and AI tools. *Journal of Advanced Research in Applied Sciences and Engineering Technology*, *32*(2), 142–153. [CrossRef]

McCoy, S., Everard, A., & Jones, B. M. (2007). An examination of the technology acceptance model in a cross-cultural context. *Communications of the ACM*, *50*(3), 74–78.

Memon, M. A., Cheah, J. H., Ramayah, T., Ting, H., Chuah, F., & Cham, T. H. (2019). Moderation analysis: Issues and guidelines. *Journal of Applied Structural Equation Modeling*, *3*(1), 1–11. [CrossRef]

Nassereddine, M., & Nassreddine, G. (2024). The impact of continuous professional development activities on student learning outcomes and employability. *International Journal of Evaluation and Research in Education*, *13*(5), 2971–2978. [CrossRef]

Nguyen, H. A. (2024). Harnessing AI-based tools for enhancing English speaking proficiency: Impacts, challenges, and long-term engagement. *International Journal of AI in Language Education*, *1*(2), 18–29. [CrossRef]

Noor, N. I. A., Nassreddine, G., & Younis, J. (2023). Impact of artificial intelligence on employee development at Basrah University. *Journal of Techniques*, *5*(2), 272–284. [CrossRef]

Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. *Computers and Education: Artificial Intelligence*, *2*, 100020. [CrossRef]

Oyserman, D., Coon, H. M., & Kemmelmeier, M. (2002). Rethinking individualism and collectivism: Evaluation of theoretical assumptions and meta-analyses. *Psychological Bulletin*, *128*(1), 3–72. [CrossRef]

Puniatmaja, G. A., Parwati, N. N., Tegeh, I. M., & Sudatha, I. G. W. (2024). The effect of E-learning and students' digital literacy towards their learning outcomes. *Pegem Journal of Education and Instruction*, *14*(1), 348–356.

Rad, H. S., Alipour, R., & Jafarpour, A. (2024). Using artificial intelligence to foster students' writing feedback literacy, engagement, and outcome: A case of Wordtune application. *Interactive Learning Environments*, *32*(9), 5020–5040. [CrossRef]

Salloum, S. A., Al-Emran, M., Shaalan, K., & Tarhini, A. (2019). Factors affecting the E-learning acceptance: A case study from UAE. *Education and Information Technologies*, *24*(1), 509–530. [CrossRef]

Schroeder, N. L., & Kucera, A. C. (2022). Refutation text facilitates learning: A meta-analysis of between-subjects experiments. *Educational Psychology Review*, *34*(2), 957–987. [CrossRef]

Shahid, A., Khan, A., & Rao, R. R. (2024). An exploration of effectiveness of artificial intelligence (AI) tools in English language learning at the undergraduate level in Pakistan. *Human Nature Journal of Social Sciences*, *5*(2), 347–357. [CrossRef]

Shane, S. (2020). Cultural influences on uncertainty avoidance in education. *Journal of Cross-Cultural Psychology*, *51*(7), 530–547.

Soegiyarto, M. S., Putri, R. A., & Saputra, S. D. (2022). *The importance of getting automated grammar feedback via Grammarly for increasing students' English language proficiency*. OSF.

Son, J. B., Ružić, N. K., & Philpott, A. (2025). Artificial intelligence technologies and applications for language learning and teaching. *Journal of China Computer—Assisted Language Learning*, *5*(1), 94–112. [CrossRef]

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. [CrossRef]

Suharto, R. P., Putri, A. N., & Sekarsari, P. (2025). The use of AI-based writing tools (QuillBot and ChatGPT) in developing the writing competence of language learners. *Esteem Journal of English Education Study Programme*, *8*(2), 259–269. [CrossRef]

Sun, L. (2025). Enhancing intercultural competence of Chinese English majors through AI-enabled Collaborative Online International Learning in the digital era. *Education and Information Technologies*, *30*(6), 7995–8027. [CrossRef]

Tang, R. (2023). Hierarchical teacher–student relationships in EFL contexts: A cross-cultural study. *TESOL Quarterly*, *57*(3), 740–764.

Tarhini, A., Hone, K., & Liu, X. (2014). Measuring the moderating effect of national culture on e-learning acceptance in developing countries: A structural equation modeling approach. *Computers in Human Behavior*, *41*, 153–163. [CrossRef]

Vlachopoulos, P. (2022). Uncertainty avoidance and technology adoption in education: A cross-cultural review. *Computers & Education*, *185*, 104160.

Wei, X. (2025). Cultural sensitivity in AI language learning: Using NLP to enhance language understanding across cultural contexts. *Theoretical and Natural Science*, *79*(1), 167–172. [CrossRef]

Wen, F., Li, Y., Zhou, Y., An, X., & Zou, Q. (2024). A study on the relation- ship between AI anxiety and AI behavioral intention of secondary school students learning English as a foreign language. *Journal of Educational Technology Development and Exchange*, *17*(1), 130–154. [CrossRef]

Wu, H., & Liu, W. (2025). Exploring mechanisms of effective informal GenAI-supported second language speaking practice: A cognitive-motivational model of achievement emotions. *Discover Computing*, *28*(1), 119. [CrossRef]

Xia, Y., Shin, S. Y., & Kim, J. C. (2024). Cross-cultural intelligent language learning system (CILS): Leveraging AI to facilitate language learning strategies in cross-cultural communication. *Applied Sciences*, *14*(13), 5651. [CrossRef]

Zhang, S., Shan, C., Lee, J. S. Y., Che, S., & Kim, J. H. (2023). Effect of chatbot-assisted language learning: A meta-analysis. *Education and Information Technologies*, *28*(11), 15223–15243. [CrossRef]