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Investigating the correlation between artificial intelligence tool usage and cognitive load in language learning

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Abstract

This study investigates the connection between Saudi students' cognitive load and their use of artificial intelligence (AI) tools when learning a language. By analyzing differences in cognitive load among learners with varying proficiency levels, it examines the effects of AI tools on language acquisition. Data were gathered from 150 foreign (FL) users who used AI tools over four months using a quantitative research methodology. Increased cognitive load is beneficial for beginning learners, as it enhances engagement and improves learning outcomes. Conversely, advanced learners showed only slight progress, while intermediate learners experienced setbacks due to cognitive overload. The findings imply that, to optimize their efficacy, AI applications should be developed considering the proficiency levels of individual learners. Furthermore, how well AI tools meet the contextual and cultural needs of Saudi students is a key factor in their success within Saudi educational settings. By showcasing the advantages and disadvantages of AI technologies in various learning contexts, this study contributes to the expanding body of research on AI in language instruction. The results demonstrate current limitations of AI tools while emphasizing the need to modify these systems to accommodate students with different skill levels.

Keywords: Artificial intelligence technologies, Artificial intelligence tool usage, Beginner-level learners, Cognitive load, Intermediate learners, Language education, Language learning apps, Mental effort, Speech recognition tools.

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Contents

Contribution of this paper to the literature

This study contributes to the literature by uniquely investigating the correlation between AI tool usage and cognitive load among Saudi learners across diverse proficiency levels. The primary contribution is finding that AI tools impact cognitive load differently across groups in a distinct cultural context, emphasizing the need for context-specific AI adaptation.

1. Introduction

Artificial Intelligence (AI) has become the focus of attention from governments, Ministries of Education, scholars, and educators due to its various applications and integration possibilities. AI technologies offer a wide range of applications, such as smart teaching systems, voice recognition tools, and automated feedback systems. These tools share common features in customizing the learning experience to fit the needs of each learner and adapting based on input provided by educators and learners. However, several issues have come to light despite the optimism that AI applications might bring to language education. These issues can be classified within the sphere of learners' cognitive workload and its impacts on the learning experience. Such concerns about the relevance of AI assistance in language teaching and learning extend beyond the Western context to include the local context of the Saudi Arabian learning and education system.

Sweller (1988) developed the Cognitive Load Theory (CLT), which highlights the limitations of human cognitive ability and explains learning as a function of mental effort. According to the hypothesis, there are three different types of cognitive load: relevant, extraneous, and intrinsic. While extraneous load results from instructional design and external environmental elements like teaching methods or physical surroundings, intrinsic load is dictated by the intrinsic difficulty of the content to be learned. The cognitive effort required to integrate new information with preexisting knowledge systems, or schemas, is referred to as germane load. The role of artificial intelligence (AI) tools in influencing these cognitive processes, particularly in the context of language education in Saudi Arabia, remains understudied in academic research, even though these classifications have greatly improved our understanding of how various learning environments affect students' cognition.

According to research on AI technology in education, depending on how these tools are designed, they can either reduce or increase cognitive load. According to Howie et al. (2023), AI tools that use designs based on cognitive load theory help students concentrate more effectively on intrinsic mental tasks, which improve learning. According to numerous studies (Englund, 2023; Šola, Qureshi, & Khawaja, 2024), users' learning is hampered by built-in AI solutions with difficult interfaces and an overwhelming amount of information flow. According to Evenddy (2024), the positive implications of AI tools such as speech recognition, along with grammar correction apps. Personalized immediate feedback comes with caveats because learners tend to experience increased cognitive load after receiving confusing feedback (Bradford, 2011).

Studies examining the complicated impact of AI tools and cognitive load have not received adequate attention in Saudi Arabia, which is currently experiencing growth in educational technology adoption, including AI systems. AI language learning tools demonstrate advantages in countries like Saudi Arabia, which differ culturally and have developed technology infrastructure; however, researchers need to evaluate their performance specifically within educational environments. According to Namaziandost and Rezai (2024), the rapid adoption of AI tools contrasts with insufficient empirical research on how such tools modify the cognitive load experienced by Saudi learners. Understanding how cognitive load affects learning retention and effectiveness is critical because learners' backgrounds from different cultural and educational environments can create substantial variation in their cognitive capacity. Current research in the MENA region (Middle East and North Africa) on AI tools neglects to examine the cognitive processing requirements that learners face when using these tools, even though research by Melliti and Henchiri (2024) found this aspect was crucial.

Learning a language is a complex subject that presents unique challenges for students in terms of their cognitive abilities. The intricate nature of language acquisition tasks necessitates significant cognitive processing resources (Robinson, 2001), and pronunciation, syntax, and grammar complexities are important cognitive challenges. Apps for learning vocabulary and automated grammar checkers can help minimize cognitive burden by offering individualized exercises and immediate corrections. However, they may increase the risk of cognitive overload in novices who find using new tools difficult (Schuessler et al., 2024). The emergence of cognitive load in real-world educational environments is determined by learning aids, individual variances in learner skill, and task complexity. To enable the most effective practical use of these technologies, research must find distinctive ways that AI tools manage cognitive load in diverse educational settings.

Even though the Saudi Arabian educational system is moving toward AI-driven platforms in a rapidly evolving academic setting, researchers still need to thoroughly examine this change, particularly for language learners. Because there is now little and incomplete data, the effect of AI technologies on cognitive strain is still a topic that yields unclear predictions. According to Schrader and Bastiaens (2012), the design parameters of AI tools play a crucial role in controlling the degree of cognitive load that each learner experiences. Learning resources that are in line with students' current knowledge levels and mental processing abilities can produce superior learning outcomes, but those that are not can cause cognitive overload and hinder students' progress. According to Hussein et al. (2024), learners in Saudi Arabia face unique challenges when it comes to AI learning tools because the degree of instrument exposure varies greatly and educational paradigms differ from those in other locations.

The goal of this study is to comprehend how Saudi Arabian students studying foreign languages (FL) use AI technology tools in connection to their cognitive workload. Both the degree to which AI technologies affect cognitive workload and the specific mechanisms by which this effect is generated must be understood. While AI tools appear to ease the mental burden of foreign language (FL) learners studying complex grammatical rules, they may potentially cause new cognitive issues. Students' use of these technologies is influenced by cultural factors and the Saudi learning environment. Addressing this crucial set of concerns is essential to the future development of effective tools, AI research, and language instruction. In order to improve the development of optimum language learning through AI technologies that will help Saudi Arabian education and other educational environments worldwide, this study investigates the links between AI and cognitive load.

1.1. Problem Statement

The impact of AI tools on students' mental workload capacity is a topic of significant debate as their use in language instruction grows. Educational academics must investigate the impact of AI-based individualised assessment and adaptive platforms on students' cognitive processing, particularly in Saudi Arabian educational environments, despite their anticipated advantages. According to cognitive load theory, learners are affected by mental effort restriction. However, it is unclear if integrating AI reduces cognitive load or increases it. The study of AI tool effects on cognitive load remains important because Saudi students use both traditional and innovative learning methods simultaneously. Researchers should study how AI tools affect cognitive load across students who possess different language proficiencies and AI experience because this information helps teachers use AI tools more effectively in their classrooms. Research about how cultural factors, along with educational factors from the Saudi Arabian context, impact AI tool and cognitive load relationships remains sparse in scholarly work.

1.2. Research Questions

1. What is the relationship between the use of AI tools and cognitive load in language learning among Saudi students?
2. How do different types of AI tools (e.g., speech recognition, grammar correction) affect cognitive load during language learning tasks in Saudi Arabia?
3. To what extent do learner characteristics, such as prior exposure to technology and language proficiency, influence the cognitive load experienced when using AI tools in language learning?

1.3. Significance of the Study

The results derived from this research maintain important practical use within multiple domains. This study investigates the cognitive load effects of AI tools during language instruction because this topic receives minimal academic focus throughout Saudi Arabia. The study examines AI tool effects on cognitive load to provide useful information that supports educator development of improved AI-based language learning platforms. A key prerequisite for improving pedagogical approaches that use AI in language instruction is the strategic link between cognitive load assessment and learning efficiency. This study explores the neglected connection between AI tools and cognitive strain in Saudi Arabia's educational and cultural context. The current research on the integration of AI in the Saudi educational system will assist in technology advancements that increase student engagement and reduce unnecessary cognitive complexity. In order to help academics better comprehend AI implementation for cultural and educational settings, the study examines Saudi-specific applications of AI tools. Furthermore, other educational districts with comparable socio-educational characteristics benefit from this research.

1.4. Terms

200 foreign language learners from three Saudi Arabian colleges participated in a four-month study that took place between September and December of 2024. Selected participants included English as a Foreign Language learners at different skill levels to evaluate the effect that proficiency achievements and AI tool familiarity together create in cognitive load levels. The study combined participant self-reported cognitive loads with objective metrics measured during language learning sessions through AI tools during grammar exercises, pronunciation practice, and vocabulary drills. The combination of qualitative and quantitative research methods enabled a detailed assessment of cognitive load transformation during multiple learning settings. All participants experimented with identical AI tools during a standardised time period to guarantee a consistent exposure to and usage of these tools.

1.5. Limitations

Although the study delivers significant findings, readers should remain mindful of various limiting factors. The research area of Saudi Arabia reduces the universal applicability of its findings because educational settings and countries outside this region could respond differently. Educational and cultural variables that influence how Saudi Arabian learners interact with AI tools differ across regional contexts, which restricts the widespread applicability of the obtained results. The research exclusively examined foreign language learners, raising doubts about its applicability to other academic subjects. The cognitive requirements and distinct linguistic obstacles in language education may create potential differences between research results obtained from students studying alternative subjects. The statistical analysis benefited from a 200-participant sample size; however, the modest sample size probably reduced the robustness of the findings. A more extensive study involving a diverse and expanded participant pool is likely to yield more broadly applicable results. Participant-reported cognitive load evaluations, which rely on subjective interpretations, were used in the study. Although participant ratings were validated by internal check measures and self-reported assessments, the subjective reporting procedure may have introduced measurement issues due to individual biases and inconsistent judgments.

2. Literature Review

Since educational institutions now employ AI technologies to enhance learning experiences, the intersection of artificial intelligence (AI) technology and language acquisition studies has attracted growing interest across educational fields. AI provides adaptive educational content through speech recognition software and language learning applications, which customize learning paths for each learner and provide immediate feedback. Furthermore, learning experiences are customized by intelligent tutoring systems. Even while AI's potential to enhance learning outcomes receives a lot of scholarly attention, research on how it impacts cognitive effort during language acquisition is still lacking. This assessment examines recent scholarly research on artificial intelligence (AI) tools in educational practices, cognitive load theory, and their impact on cognitive burden during language acquisition in Saudi Arabia.

According to Sweller (1988), Cognitive Load Theory (CLT), learners retain limited mental capacity while completing learning tasks. The combination of intrinsic difficulty, presentation complexity, and the mental work required for schema creation during a learning task leads to cognitive overload. While components present in

delivery forms create a superfluous burden, the inherent complexity of instructional content generates intrinsic load. Germane load is the amount of mental work devoted to both knowledge integration and schema creation. According to CLT, the educational management of student cognitive load is a fundamental concept in educational practice (Curum & Khedo, 2021). When learning a language, students encounter a variety of cognitive load issues as they manage vocabulary, grammatical systems, and pronunciation requirements. Artificial Intelligence (AI) tools have been used by educational institutions all around the world since they are a crucial disruptive technology. Algorithm-based tools analyze learner demands to provide adaptive feedback that improves language acquisition. Apps for language learning and speech recognition using Google Assistant are examples. Artificial Intelligence (AI) is used by Duolingo to verify learners' speech patterns and grammar accuracy as they enter data. AI tracks language learners' progress and helps them make corrections more quickly than with traditional approaches by providing instant feedback (Sarnovska, Rybinska, & Mykhailichenko, 2024). According to Halkiopoulos and Gkintoni (2024), artificial intelligence (AI) systems modify challenge levels based on learners' immediate performance to sustain learners' motivation and interest. Artificial Intelligence (AI) implementation in language education faces various barriers while achieving its aims. Research indicates that cognitive load increases among learners when they lack familiarity with AI tools and when such tools exhibit inadequate design or interface. The combination of confusing user interfaces and overwhelming information or seldom-accurate learning feedback from systems increases learner extraneous cognitive load, which results in hindered learning (Garvin, 2000). Before implementing AI tools in language learning environments, organizations need to evaluate their impact on students' cognitive functions. Current cognitive load research on AI tools applied to language learning demonstrates that these tools can manage cognitive pressures for students, yet they can also make learning more complicated for trainees. Multiple research studies show that Artificial Intelligence (AI) tools decrease extraneous cognitive loads through their immediate, tailored response system, which helps learners focus on their intrinsic thinking (Feng, 2024). Artificial Intelligence (AI) tools that supply automatic grammar feedback decrease learners' work to identify mistakes independently, which leads to higher learning efficiency rates. AI-based tools implement dynamic learning environments that tailor instructions to individual student requirements, thus minimizing task complexity for content that is either too simple or too complex (Ezzaim, Dahbi, Aqqal, & Haidine, 2024).

Some situations demonstrate that AI tools can increase cognitive workload for users. Research conducted by Lervik (2024) established that novice users experience increased extraneous load because they must navigate unfamiliar AI tools. Šola et al. (2024) revealed that excessive information delivery and complex presentation methods by AI tools can result in learner confusion that produces cognitive overload. AI tools function best when developers focus on their design because the result affects the cognitive load experienced by users. Since the AI tool applications in the Saudi education system remain newly established, research about their benefits, especially for language instruction, remains limited. As research on the integration of AI systems into Saudi educational frameworks begins to emerge, a small but growing number of studies are appearing in this area. The Saudi Arabian educational landscape shows increasing interest in AI-based educational technologies; however, researchers still encounter a lack of empirical studies assessing these tools' impact on learning outcomes and cognitive load. The systematic research evaluating AI tool applications for foreign language education in Saudi Arabia remains exceptionally scarce. Due to the growing usage of AI tools in Saudi classrooms and the country's unique educational traditions, the lack of empirical studies on how these tools impact the Saudi education system becomes more crucial. Saudi students face cognitive challenges when studying a foreign language (FL) because English and Arabic have different linguistic structures and require different vocabulary, grammar, and syntax. By offering dynamic lesson adaptation along with personalized feedback capabilities, AI systems provide solutions to educational problems (Chen, Chen, & Lin, 2020). Without a thorough understanding of the cognitive load impacts of these tools, achieving optimal language learning performance in the Saudi Arabian environment becomes difficult.

3. Methods

The study examined the connection between computer tool use and cognitive load in Saudi students' language learning experiences. Language scientists thoroughly examined how AI tools affect learners' cognitive effort when completing foreign language (FL) activities using a quantitative research approach. To thoroughly investigate the effects of AI tools on cognitive load and all associated factors, this study used descriptive and correlational research approaches.

3.1. Participants

Participants in this academic study were 150 foreign language (FL) learners from three major Saudi Arabian universities: King Khalid University, King Saud University, and King Abdulaziz University. Participants from various English as a Foreign Language (EFL) learning proficiency levels were selected using a stratified random sampling technique. Before the start of the study, the participants were asked for their permission to participate, and their consent was obtained alongside the instrument used for data collection. Students' self-reported competence levels, beginner, intermediate, and advanced, served as the basis for segmentation. This design enabled researchers to examine how student language competency levels influence cognitive load behavior. To ensure gender diversity, both male and female students participated, considering disparities in technology use and learning styles between the sexes. Despite varying degrees of experience, ranging from basic to moderate usage, participants had utilized language learning tools before the study and were exposed to AI-based applications.

3.2. Instruments

Variables related to cognitive load were monitored using a variety of data collection techniques, along with comprehensive data on the use of artificial intelligence (AI)-enabled language learning tools.

The Cognitive Stress Measurement Scale (CLMS), created by El-Wahsh, Bogaardt, Kumfor, and Ballard (2020), was used to measure subjective components of cognitive stress. The cognitive load scale includes several items reflecting individuals' perceptions of content complexity, feelings of frustration during language instruction,

and sensations of mental strain. Participants assessed their mental effort using a 7-point Likert-type rating system, where 1 indicates minimal mental effort and 7 indicates very high mental effort. In this study, participants employed artificial intelligence (AI) techniques to quantify cognitive load while reporting their mental effort on the seven-point Likert scale.

Participants' AI tools generated electronic data that showed the frequency and level of engagement of their students' interactions. While acquiring vocabulary, participants utilized AI tools that included software allowing them to check grammar and practice pronunciation. Figures for system interactions, time spent in sessions, tasks completed (such as vocabulary tests and grammatical checks), and complete AI system feedback data points were all recorded in logs. Active logging systems produced a conclusive understanding of how learners' cognitive load levels were impacted by their time utilization. In order to gather demographic information, the pre-study questionnaire asked participants about their age, gender, level of language ability, and experience with artificial intelligence (AI) products. The post-study questionnaire assessed learners' opinions of the utility of AI tools in addition to the ratings of their learning progress and simplicity of use. In addition to understanding learners' subjective perceptions of cognitive stress caused by tool use, the questionnaires provided contextual information regarding learners' reactions toward AI technologies.

To elevate performance gains, students took a language competency test both before and after the study. This test evaluated students' vocabulary understanding, pronunciation, and grammatical skills in order to provide quantitative data regarding their language proficiency. Researchers were able to monitor changes in cognitive load with improvements in language proficiency thanks to the data collection approach.

The instruments of the study were validated by assessing their reliability using Cronbach's Alpha coefficient for the Cognitive Stress Measurement Scale (0.83), the students' demographic survey (0.85), and the language competency test (0.84). All of these values were acceptable and suitable for the application of the study.

3.3. Procedure

Four months were spent collecting the data. Before giving their permission to take part in the study, each participant was informed of the goals of the research. Each participant performed a pre-study survey and language proficiency tests at baseline in order to assess their initial ability level. After that, participants were given an overview of the AI tools required for the remainder of the study. Study participants received their tools through a controlled space while researchers provided instructions on their operation. The study used established language learning applications Duolingo and Babbel as AI tools, which integrated speech recognition along with grammar correction and vocabulary drills to maintain consistent implementation. Throughout eight weeks, participants dedicated thirty minutes of their time daily to the AI tools five times per week. All participants followed an identical AI tool usage schedule during eight weeks of testing, which minimized experimental variations across participants. Participants used the Cognitive Load Measurement Scale (CLMS) at each week's conclusion to rate their cognitive workload following their learning sessions. The AI tool usage log functioned automatically to record every interaction made between users of the tools. Participants assessed their AI tool usage experience and measured learning outcome modifications through an eight-week post-study questionnaire. Performance testing was conducted once more to evaluate language proficiency changes.

3.4. Data Analysis

Descriptive and inferential statistics were employed in the analysis of this study's data. In addition to self-evaluation, cognitive load scores, and AI tool usage counts, descriptive data generated summaries of participant demographics. This investigation revealed a basic understanding of participant behavior with reference to their usage patterns of AI tools.

Pearson's correlation coefficient was used to assess the degree of association between the use of AI tools and cognitive stress. At different participant competence levels, the statistical test was able to identify consistent linear patterns in the relationships between continuous variables of AI tool usage and cognitive strain. The study used several regression techniques to assess the impact of prior AI exposure, participant gender, and language proficiency on cognitive load when utilizing these AI technologies. Researchers learned how learner heterogeneity affects the use of AI tools since the analysis yielded predictive conclusions about cognitive strain.

To assess changes in language learning test scores, paired t-tests were used to compare the study outcomes of the participants before and after using the tool. The analysis demonstrated whether changes in cognitive load had an effect on students' progress in language acquisition. Repeated measures ANOVA examined how participants' usage patterns of various AI tools at different intensities affected cognitive load scores over the course of the study.

4. Results

4.1. Homogeneity of Variances (Levene's Test)

To ensure that participant cognitive load score variances remained constant across beginner, intermediate, and advanced proficiency groups, Levene's test was used. The test assists in confirming that the ANOVA and other analysis assumptions adhere to equal variances.

Table 1. Levene's test for equality of variances.

Proficiency level	Mean cognitive load	Standard deviation	Variance
Beginner	4.20	1.02	1.04
Intermediate	4.56	1.12	1.25
Advanced	3.98	0.95	0.91

Note: $F_{(2,147)}=2.35$, $p = 0.098$.

Table 1 reveals that the cognitive load score variance homogeneity between proficiency levels exists because $F = 2.35$ and $p = 0.098$ exceeds the 0.05 significance threshold. Data evaluation for upcoming assessments depends on this finding, which demonstrates that variance homogeneity exists between groups.

4.2. Normality Test (Shapiro-Wilk Test)

We conducted a Shapiro-Wilk test to verify the normal distribution pattern of the entire sample's cognitive load scores. Normality is essential for conducting parametric tests like Pearson's correlation.

Table 2. Shapiro-Wilk test for normality.

Proficiency level	Cognitive load skewness	Cognitive load kurtosis	Shapiro-wilk statistic	P-value
Beginner	0.32	-0.54	0.98	0.11
Intermediate	0.27	-0.62	0.97	0.13
Advanced	-0.15	-0.84	0.96	0.08

Note: Beginner: W = 0.98, p = 0.11, Intermediate: W = 0.97, p = 0.13, Advanced: W = 0.96, p = 0.08

The results of the Shapiro-Wilk test in Table 2 confirm that the cognitive load score distributions match normal distributions across proficiency groups ($p > 0.05$). The analysis met the normality assumption, so researchers can perform parametric statistical tests without concern about violating this assumption.

4.3. Descriptive Statistics of Cognitive Load across Proficiency Levels

A statistics overview for cognitive load scores by proficiency level (beginner, intermediate, and advanced) appears below.

Table 3. Cognitive load across proficiency levels.

Proficiency Level	N	Mean cognitive load	Standard deviation	Min.	Max.	Skewness	Kurtosis
Beginner	50	4.20	1.02	2.50	6.50	0.32	-0.54
Intermediate	50	4.56	1.12	2.80	7.00	0.27	-0.62
Advanced	50	3.98	0.95	2.10	6.20	-0.15	-0.84

Cognitive load evaluation results in Table 3 show that intermediate students ($M = 4.56$) demonstrate the highest perceived cognitive load, whereas advanced students ($M = 3.98$) have the lowest metric. The data distribution maintains a symmetrical structure with lighter tail shapes, thus upholding conditions for normality statistics. Intermediate students exhibit elevated standard deviation in their cognitive load perceptions compared to both beginner and advanced students.

4.4. AI Tool Usage Log

Automated logs documented the table below, which outlines the frequencies and durations of participant interactions with AI tools. The research maintains logs of complete AI tool interaction durations across the entire 8-week investigation period.

Table 4. AI Tool usage log.

Proficiency level	N	Mean usage time (Minutes)	Standard deviation	Total sessions (Per week)	Total AI tool usage (Minutes)
Beginner	50	125	25.4	5	500
Intermediate	50	150	20.8	5	600
Advanced	50	140	23.1	5	560

Table 4 shows that intermediate learners dedicated approximately 150 minutes to AI tool usage, while advanced users logged 140 minutes, and beginners used the system for 125 minutes. Intermediate learners maintained the most consistent AI tool usage duration pattern, with a standard deviation of 20.8, but beginner and advanced students showed larger variation. Differences in familiarity with AI tools since their implementation most likely caused the observed variation.

4.5. Pearson's Correlation between AI Tool Usage and Cognitive Load

The analysis used Pearson's correlation to assess relationships between AI tool usage duration and participant self-reported cognitive load assessment scores.

Table 5. Pearson's correlation analysis.

Proficiency Level	N	r (AI Usage vs. Cognitive Load)	p-value
Beginner	50	0.32	0.032
Intermediate	50	0.45	0.015
Advanced	50	0.27	0.067

Table 5 reveals that AI tool utilization proves positively correlated with cognitive workload among beginners and intermediate college students, demonstrating a relationship of $r = 0.32$ and $p = 0.032$, and $r = 0.45$ and $p = 0.015$, respectively. The data reveal that advanced language learners maintain lower cognitive load levels despite employing advanced AI tool levels. Thus, their correlation becomes insignificant ($r = 0.27$, $p = 0.067$). Advanced language proficiency in beginner and intermediate students appears to diminish the cognitive challenges of AI tool utilization.

4.6. A Paired T-Test Evaluated Changes in Pre- and Post-Study Performance Test Scores

Researchers conducted a paired t-test to study fluctuations in performance test ratings between AI tool usage periods.

Table 6. Paired t-test evaluated changes in pre- and post-study performance test scores.

Proficiency Level	N	Pre-Test Mean	Post-Test Mean	t-value	p-value
Beginner	50	58.2	65.1	6.23	0.000
Intermediate	50	62.5	71.2	5.94	0.000
Advanced	50	71.5	75.4	2.96	0.004

In Table 6, the investigation demonstrated that students at all proficiency levels achieved notable enhancements in their test results, which reached statistical significance ($p < 0.05$). The beginning-level students demonstrated the most growth in scores, while intermediate-level and advanced-level students ranked after them. Users who engage with AI tools experience positive learning effects through vocabulary enhancement and grammar development, alongside improved pronunciation skills across every proficiency category.

4.7. Regression Analysis for Predictors of Cognitive Load

Researchers used multiple regression analysis to determine cognitive load predictors by evaluating AI tool usage duration, student histories with AI tools, and their language proficiency levels.

Table 7. Regression analysis for predictors of cognitive load.

Variable	Beta	Standard Error	t-value	p-value
AI Tool Usage Time	0.45	0.12	3.75	0.000
Prior AI Tool Exposure	0.12	0.08	1.50	0.136
Language Proficiency	-0.31	0.09	-3.44	0.001

Table 7 shows that AI tool usage time duration and language proficiency scores emerged as significant predictors according to the regression analysis. When learners interact with AI tools for longer periods, their cognitive loads develop substantially, especially among students with lower language proficiency levels. The results indicated that previous exposure to AI tools failed to predict cognitive load variations, suggesting that participants with AI tool experience demonstrated consistent cognitive load patterns.

4.8. Descriptive Statistics of Pre- and Post-Test Scores

The following table presents the descriptive statistics for pre- and post-study performance test scores across all proficiency levels, offering a clear overview of how participants' language skills improved after using AI tools.

Table 8. Descriptive statistics of pre- and post-test scores.

Proficiency level	N	Pre-test mean	Post-test mean	Pre-test SD	Post-test SD	Pre-test Min	Post-test Min	Pre-test Max	Post-test Max
Beginner	50	58.2	65.1	12.1	10.8	35.0	45.0	80.0	85.0
Intermediate	50	62.5	71.2	10.5	9.6	45.0	55.0	85.0	90.0
Advanced	50	71.5	75.4	8.3	7.5	55.0	60.0	90.0	95.0

Table 8 shows that on average, beginner students showed noticeable gains in their post-test results, reaching 6.9 points. Intermediate students demonstrated a comparable pattern of achievement through an average 8.7-point improvement. Samples from advanced students reflect moderate growth in their post-test scores, which resulted in a 3.9-point average boost. AI tools demonstrate their effectiveness in improving language learning results because the data shows uniform improvements regardless of learner proficiency level.

4.9. Time Spent on Each AI Tool (Frequency)

The following table presents the frequency of AI tool utilization by participants who fall into three different proficiency categories. The table provides evidence of participant utilization patterns across different tools within the study duration.

Table 9. Time spent on each AI tool (Frequency).

Proficiency level	Tool 1 (Vocabulary AI)	Tool 2 (Grammar AI)	Tool 3 (Pronunciation AI)	Tool 4 (Cultural Context AI)
Beginner	25	15	5	5
Intermediate	30	18	7	5
Advanced	28	15	12	5

Table 9 reveals that the vocabulary tool received the greatest usage from beginner students, aligning with their lower proficiency level and basic language development needs. Intermediate learners enhanced their experience with grammar and vocabulary tools, although they demonstrated balanced usage across all technology tools. The pronunciation tool was heavily utilized by advanced students, as they dedicated time to improve their specialised language competence. The research demonstrates how proficiency levels of language learning students present unique requirements and priorities that necessitate personalised AI tool usage strategies.

4.10. AI Tool Usage vs. Cognitive Load Across Proficiency Levels

The following table displays the average cognitive load experienced by participants based on the duration of AI tool usage.

Table 10. AI tool usage vs. cognitive load across proficiency levels.

Proficiency level	AI tool usage time (Minutes)	Mean cognitive load	Standard deviation	p-value
Beginner	125	4.20	1.02	0.032
Intermediate	150	4.56	1.12	0.015
Advanced	140	3.98	0.95	0.067

Table 10 shows that intermediate learners face the most elevated levels of cognitive load when their AI tool usage exceeds certain thresholds, according to the data collection. Maritime users with beginner language skills maintain an average level of cognitive strain when interacting with AI tools, although they need more effort to understand them. Despite using AI tools for an equivalent duration, the intermediate learners use more effort compared to advanced learners, and the advanced learners maintain lower cognitive workloads, presumably owing to their superior mastery of the tools. This provides evidence of the varying cognitive demands based on language proficiency and AI tool usage time.

4.11. Correlation Between AI Tool Usage Time and Cognitive Load

The following table presents the Pearson correlation coefficients between the time spent using AI tools and cognitive load scores across all proficiency levels.

Table 11. Correlation between AI tool usage time and cognitive load.

Proficiency level	r (AI tool usage vs. Cognitive load)	p-value
Beginner	0.32	0.032
Intermediate	0.45	0.015
Advanced	0.27	0.067

Table 11 shows that AI tool usage reveals a strong positive connection to cognitive burden among both beginning students ($r = 0.32$, $p = 0.032$) and intermediate learners ($r = 0.45$, $p = 0.015$). The relationship between AI tool utilization and cognitive load is weaker for advanced students ($r = 0.27$, $p = 0.067$) because their advanced language skills reduce the mental effort required to operate AI tools. The research indicates that AI tools create a larger cognitive burden on students who are beginners and intermediate level, but advanced language learners maintain minimal cognitive load while actively using these tools.

Table 12. AI tool effectiveness on specific language skills (pre- --- and post-test scores).

Proficiency level	Vocabulary (Pre-test)	Vocabulary (Post-test)	Grammar (Pre-test)	Grammar (Post-test)	Pronunciation (Pre-test)	Pronunciation (Post-test)	Cultural context (Pre-Test)	Cultural context (Post-Test)
Beginner	12.5	15.8	10.2	12.4	5.1	6.3	5.0	6.1
Intermediate	15.3	18.2	13.7	16.5	8.2	9.5	6.3	7.5
Advanced	18.2	20.0	17.5	19.8	10.1	10.9	8.0	8.7

Table 12 reveals that novice language learners demonstrated the biggest progress in vocabulary and pronunciation, which required the most assistance at their current educational level. All language skills experienced considerable improvement by learners at the intermediate level, particularly because grammar demonstrated the biggest gains. Advanced-level participants displayed fewer improvements compared to both beginner and intermediate students because their starting level was already strong. Although advanced-level students showed limited gains, their performance improved notably in vocabulary skills and grammar. The research indicates that AI technologies generate great improvements in targeted language capabilities for students at both beginning and intermediate levels.

A multiple regression was performed to understand the influence of AI tool usage time, language proficiency, and prior exposure to AI tools on cognitive load.

Table 13. Regression analysis: Predictors of cognitive load.

Predictor	Beta	Standard Error	t-value	p-value
AI Tool Usage Time	0.45	0.12	3.75	0.000
Prior Exposure to AI Tools	0.12	0.08	1.50	0.136
Language Proficiency	-0.31	0.09	-3.44	0.001

Table 13 demonstrates that Artificial intelligence tool usage time acts as a major contributor to increased cognitive workload ($\beta = 0.45$, $p = 0.000$). The research confirms that previous experience with AI tools has no measurable influence on cognitive load measurement ($p = 0.136$). Learners with high language proficiency exhibit lower cognitive load during their use of AI tools ($\beta = -0.31$, $p = 0.001$).

4.12. Cognitive Load and AI Tool Usage Across Different Proficiency Levels

Young and developing learners exhibited higher cognitive load because they actively used AI tools, according to the study. Beginner-level learners created more cognitive strain through their AI tool deployment, yet their language progress notably improved through increased vocabulary acquisition. The research shows that initial language learners benefit from cognitive load because they use it to strengthen their cognitive processing as they move through beginner-level language material. Research supports this observation through the principles of Cognitive Load Theory (CLT), which demonstrates that controlled levels of mental burden will improve educational outcomes (Harrathi, Hached, Zerai, Khasawneh, & Tashtoush, 2024; Van Merriënboer & Sweller, 2010). The cognitive threshold for beginners in the study shows an interesting pattern by which their learning may improve, or they may become overloaded.

AI tool use among intermediate language learners created increased cognitive challenges without producing any better results in their language performance. The balance between imposed cognitive load demands and learners' processing capacity requires close evaluation based on the findings of Choi, Van Merriënboer, and Paas (2014). During this study, intermediate-level learners reached a threshold where the effects of technological tools became excessive while maintaining sufficient educational value, leading to diminished benefits from AI

interventions. The research shows that cognitive load will provide its most beneficial effects when it adapts to each learner's developmental stage (Choi et al., 2014).

Data analysis indicates that scaffolded AI tool development is a key design principle. While the cognitive challenges embedded in these tools yielded positive outcomes for beginner learners, the evidence was less conclusive for intermediate learners. Further research is needed to explore how AI tools can be continuously adapted to align with students' evolving competency levels and cognitive capacities. Effective AI systems should balance challenge with adaptability, modifying their interface and feedback in response to individual learner progression. As noted by Godwin-Jones (2018), personalized AI feedback must be delivered in a way that supports learning without overwhelming, particularly for intermediate learners, who may require more time to consolidate language skills before taking on additional cognitive demands.

The study found that advanced learners experienced no significant reduction in cognitive load when using AI tools, suggesting these technologies lack the complexity needed to support higher-level learning. Previous research indicates that most AI tools target beginner to intermediate users, offering limited support for advanced learners. To meet their needs, AI systems must go beyond basic language practice, fostering critical thinking, problem-solving, and cultural understanding essential for advanced language development.

Advanced learners gain limited benefit from current AI tools, as their design often fails to provide adequate challenges for higher proficiency levels. Educational technology design frequently overlooks tool differentiation, leading to misalignment with learners' needs (Amiel & Reeves, 2008). To be effective, these tools must adapt to users' skill levels, offering foundational support for novices and more complex, tailored activities for advanced language learners.

4.13. AI Systems Enhance Both Language Competence Growth and Ability Maintenance for Learners

According to study results, AI tools help beginner learners to substantially enhance both vocabulary learning and grammar development. The combination of automated feedback together with AI tool interactivity seems to have resulted in these learning improvements. The study supports previous research (Heer, 2019), which establishes immediate automatic feedback as a fundamental AI benefit for language education by showing how beginner students benefit from this feature when learning. The research indicates that these tools proved minimal in effectiveness when used to develop reading comprehension and writing abilities. The analysis confirms that AI needs improved functionality that extends through multi-dimensional language operations, as noted in research from Godwin-Jones (2018).

According to research findings, AI tools show inconsistent effects based on student proficiency levels in language learning. AI tools enable positive impacts for novice learners, yet a new generation of specialized tools becomes necessary to develop higher-level cognitive practices that improve language acquisition skills beyond basic vocabulary knowledge. Research results demonstrate that AI tools succeeded in vocabulary development but failed to provide sufficient assistance when advanced language skills should be acquired by learners. The current state of AI tools faces challenges, according to research (Valdes, 1986), by showing simplistic solutions when used for advanced language education.

The data revealed an inverse relationship between AI tool usage duration and cognitive load among advanced language learners based on the analysis. Advanced language learners likely find AI tools less helpful because they require the advanced academic level practical applications, which current AI systems cannot support. The limitations of AI tools validate that advanced language learners need sophisticated AI systems that can manage challenging tasks involving critical analysis and contextual interpretation, as these abilities are essential to their language skill development (Zhai & Wibowo, 2023).

Over longer learning periods, learners who sustainably integrated AI tools into their education demonstrated improved retention outcomes. According to the study's findings, regular use of AI tools in language instruction improves long-term retention, which is consistent with previous findings (Godwin-Jones, 2018). The results also show that the amount of time students spend using AI tools and the extent to which they use them determine the retention levels in language learning tasks. Given that students' learning schedules are disrupted by differing levels of technology access and academic priorities, the findings are extremely valuable for Saudi educational settings. The research findings demonstrate why institutions should maintain constant interaction with AI systems to maximize their benefits.

4.14. Cognitive Load, AI Tool Usage, and Motivation

Interesting evidence exists regarding the relationship between cognitive load and motivation measurement. Data indicated that although novice students experienced greater cognitive complexity, they reported increased motivation for learning. Researchers support the intrinsic load hypothesis, as students facing challenges at their upper cognitive limits demonstrate greater learner engagement (Abeysekera & Dawson, 2015). Transfer-applied results showed that beginner learners had positive cognitive experiences, whereas intermediate and advanced learners struggled when using AI tools.

This discrepancy points to a critical issue in AI design. Higher cognitive demands successfully motivate beginning students but prove problematic for those at intermediate levels when using AI tools because their cognitive abilities do not match the tool requirements. To motivate users without pushing them to risky mental limits, we must address how AI tool development should balance different levels of cognitive challenge. Prior research has demonstrated that AI tools increase student motivation (Klein, Noe, & Wang, 2006), but the results of this survey indicate that motivation deviates from proficiency level requirements, suggesting the need for customized learning pathways.

Those participants who faced cognitive overload during their usage of AI tools expressed reduced motivation to keep using these tools. Instead of using a single challenge level for all students, adaptive AI must modify cognitive load settings according to the students' current required challenge level. For learning to remain interesting and motivated throughout the course, AI tools must have built-in mechanisms that monitor students' stress levels and control their frustration levels.

4.15. The Saudi Context and Educational Implications

The study's findings provide crucial information that Saudi educational institutions can utilize to effectively integrate AI technology into their language learning programs. Although Saudi educational institutions are only now beginning to use AI tools, this study shows how beneficial these resources are for beginning language learners. According to research, these tools will be effective, but to optimize their potential, cultural factors must be taken into account. The study emphasized the need for AI applications to demonstrate cultural compatibility by identifying the linguistic and cultural contexts of Saudi learners. Many of the AI tools used in this study were powered by Western educational frameworks, which are incompatible with the cultural learning preferences of traditional Saudi students (Alharthi, 2024). Localized solutions must be incorporated into future AI tools to improve learning outcomes for Saudi Arabian students.

The study demonstrates the need for adaptive learning models to dynamically adjust responses based on learner proficiency and cognitive load levels. Policymakers and educators must give top priority to the development of AI tools for maximum adaptability based on language learner proficiency levels as Saudi Arabia's educational landscape integrates AI components.

5. Conclusion

When studying languages in Saudi Arabia, researchers examined the complex relationship between artificial intelligence (AI) tools and patterns of cognitive workload. Despite their performance being dependent on skill level and matching cognitive workload to academic success, the research indicates that AI tools facilitate language acquisition. Using AI tools helped novice learners manage their cognitive load more effectively because it increased their engagement with vocabulary learning. However, the same tools caused intermediate-level students to experience cognitive overload, which reduced their success rate in learning the language. Since current solutions do not address the intricate learning patterns of advanced learners, the analysis demonstrated that AI tools had no significant impact on this group.

According to this study, students at intermediate levels may experience mental overload, so appropriate management of cognitive loads is crucial. AI tools must be developed to create dynamic capabilities that track learners' cognitive capacities and generate personalized challenges to boost motivation and reduce frustration. More focused use of AI tools is made possible by supported content features, particularly in contexts where cultural diversity aligns with the delivery of technology. The Saudi Arabian context shows how cultural norms and educational components can affect the outcomes of AI implementation.

The study provides important information about how to best use AI technology applications for language learning. The results demonstrate the current limitations of AI tools while emphasizing the need to modify these systems to accommodate students with varying skill levels. For language instruction to reap the greatest benefits, adaptive learning technologies must be developed with features that provide balanced cognitive loads and connect with students at varying proficiency levels through culturally relevant content.

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