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A Review of Artificial Intelligence Adoption in Second-Language Learning

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***Abstract*—Professionals are implementing artificial intelligence (AI) technology in different fields owing to its diverse uses and benefits. Similarly, AI professionals are also beginning to implement AI technology in foreign-language education and second-language learning. Therefore, through a systematic literature review, this paper analyzes the role of AI in helping learners of a second language to master pronunciation. A detailed and in-depth search of different well-known databases was conducted, and of 116 articles, only 39 were selected for this paper. AI algorithms can advance language learning and acquisition in almost every dialect and could be significant for different parties in different ways. For example, organizations could utilize AI technology to develop their workers' knowledge; individual learners could use AI technology to facilitate their studies anywhere and anytime; and traditional learning institutions could incorporate AI-powered methods of language learning to diversify learners' opportunities. There are many benefits to employing AI in language learning, particularly in second-language learning.**

***Index Terms*—AI, learning, second language, review, linguistics**

I. Introduction

The Fourth Industrial Revolution has strongly influenced the field of education, with the term "Education 4.0" having been introduced to cope with the rapid industrial developments of Industry 4.0 (Harkins, 2008; Puncreobutr, 2016; Hussin, 2018). Education 4.0 allows educational practitioners and educators to integrate modern technology into their teaching practices (Hussin, 2018), but adopting and utilizing the latest technologies, including social media, smartphone technology, and AI in advanced learning media, are proving challenging for educational practitioners (Haristiani, 2019). John McCarthy, who first used the term in a workshop proposal that he presented at Dartmouth College in the United States, initially coined the term "AI" in the 1950s (Russel & Norvig, 2010, p. 17). AI is a broad computer science discipline that primarily focuses on building smart machines that can perform tasks that usually require human intelligence. Moreover, AI can be defined as the process of simulating human intelligence by a machine, particularly a computer system (Brady, 2019). Baker and Smith (2019, p. 10) defined AI as "computers which perform cognitive tasks, usually associated with human minds, particularly learning and problem-solving." Furthermore, the researchers highlighted that AI is not based on one type of technology but a wide range of technologies, methods, and approaches that include data mining, machine learning, neural networking, and natural language processing. With the hype surrounding AI increasing every day, companies around the world are hastening to promote the ways in which their services and products utilize AI. In most cases, what these companies refer to as AI is basically a single constituent of the technology, such as machine learning (Velasquez, 2021). In essence, AI comprises specialized software and hardware that are used to write and train machine learning algorithms. Additionally, AI technology is not synonymous with any one particular programming language, but some such languages, including Java, R, and Python, are popular with AI (Luckin et al., 2016).

AI in education is currently the topic of much debate, and, for 30 years, educators have remained uncertain about whether to take advantage of AI in education and how AI could actually impact learning and teaching (Zawacki-Richter et al., 2019). The 2018 Horizon Report stated that adaptive learning technologies and AI represent significant advancements in educational technology (Educause, 2018). The artificially intelligent system works by consuming a large number of labeled training data, analyzing the data for patterns and correlations, and utilizing the patterns to make a prediction about a future state (Myagila & Kilavo, 2021). Thus, image recognition tools learn the process of identifying and describing objects in pictures by analyzing thousands of examples. Moreover, chatbots, which are fed text chat patterns, can learn to create real conversations with people. The chatbot is an example of the use of AI, and many language learners and instructors utilize the chatbot because it can be used anywhere and at any time. Learners also feel more confident in learning languages through chatbots than through human tutors (Haristiani, 2019). In language acquisition, AI programming focuses on three cognitive skills: learning processes, reasoning processes, and self-correction processes. Table 1 provides detailed explanations of these skills.

TABLE 1
LEARNING, REASONING, AND SELF-CORRECTION PROCESSES

AI-focused cognitive skills	
Skills	**Explanation**
Learning processes	This aspect of AI programming involves obtaining data and establishing rules regarding how the data are transformed into actionable information. The rules, which are basically referred to as algorithms, provide computing devices with specific instructions on how specific tasks should be completed (Myagila & Kilavo, 2021).
Reasoning processes	This aspect of AI programming involves choosing the right algorithms to obtain an anticipated result.
Self-correction processes	This aspect of AI programming involves continually fine-tuning the algorithms and ensuring that they produce the most accurate outcomes possible.

The prevalence of cloud-based technologies, such as the natural language processing (NLP) approach, open educational resources, and AI applications, has significantly influenced the current state of second-language education. In particular, AI tools that use NLP and automatic speech recognition are changing the methods of learning and teaching second languages (Kannan & Munday, 2018). Intelligent tutoring systems (ITS), which were developed in the 1980s and promised personalized education, predict and track the presence of AI in languages learning. The initial versions of intelligent tutoring systems (ITS) emphasized computer-based learning systems that attempted to adapt to the learner's requirements (Self, 1998). NLP is another AI modeling system that has played an important role in developing CALL. One example of CALL is the E-tutor, which uses natural language processing techniques to teach German as a second language (Heift, 2010). CALL's language teaching models have evolved from "simple rote-learning mechanisms" to "complex language teaching" and provided the connected and adaptive learning environments that have led to the development of ICALL. Ziegler et al. (2017) presented a case study about ICALL to examine the outcomes and developmental processes of second-language learning and highlighted "what learners do during visually enhanced instructional activities".

The trend in learning foreign languages or second languages continues to be popular, as doing so can transcend the benefits of simply gaining an academic qualification for employment. Moreover, foreign-language or second-language learning is a facilitator of globalization and can enhance world peace by providing learners with an understanding of the diverse world (Sirajudeen & Adebisi, 2012). English and Arabic are the two most common and dominant languages that non-natives prefer to learn (Sato & Loewen, 2019). Many people around the world wish to learn Arabic as a second language owing to its recognition in the international community and emerging importance in international communication (Moghazy, 2021). Therefore, many practitioners are focusing on adopting various tools and techniques when teaching Arabic to non-natives, the most significant of which is the use of AI. The various AI-based second-language learning or teaching systems and approaches are shown in Figure 1.

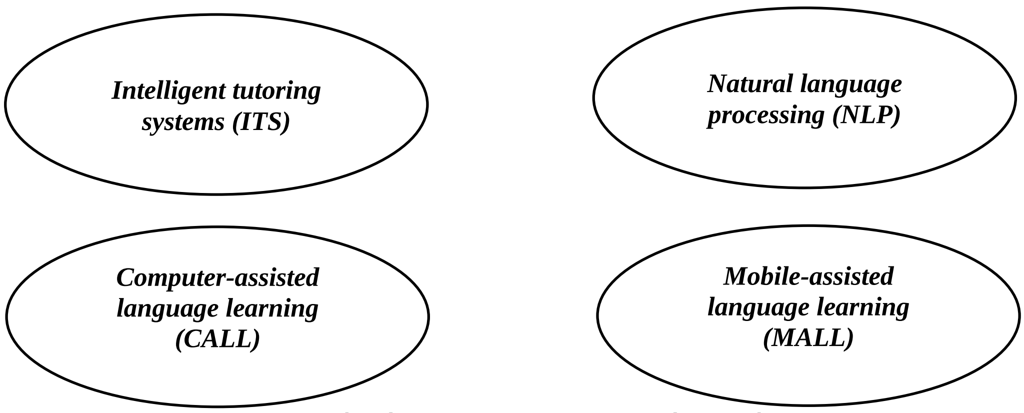

Figure 1 AI-based Language Learning Systems and Approaches

Over the last three decades, importance has been attached to the notion of AI in every industry, including manufacturing (Bullers et al., 1980; Zeba et al., 2021), healthcare (Rong et al., 2020), agriculture (Bannerjee et al., 2018), business (Loureiro et al., 2021), and education (Chen et al., 2020). Moreover, with the implementation of AI technology in various areas, from speech recognition and automated assessment to the adaptive and customized provision of learning resources, the significance of AI is well recognized. Although the potential of AI in supporting language teaching and learning is significant and some scholars have begun exploring the area, there remains an extensive gap in our understanding of the aptitude, benefits, and limitations of AI in helping learners of a second language to master pronunciation. Furthermore, there is a paucity of literature specifically exploring the way in which AI can be used to support the language skills involved in real-life language learning purposes, the types of instant feedback that AI programs can provide to help learners to achieve the goals of their language learning, and the way in which various feedback can be designed to enhance learners' independent studying on their mobile devices or computers. Therefore, this research addresses these points and makes contributions to several areas, which include but are not limited to

- *learners' motivations for using AI in language learning;*
- *the use of AI in automated assessment and error correction;*
- *the use of AI to provide feedback;*
- *the use of AI in listening, reading, writing, and speaking practice; and*
- *teachers' and learners' perceptions of using AI to learn and master new languages.*

II. Literature Review

According to Sarosiek (2018), AI can be traced back to Turing's theoretical contributions. Turing created a Turing machine, a perfect example of a computing device capable of following any formal set of instructions. Building on Turing's work, Rosenberg (2014) attempted to determine the mental processes of computational models. Rosenberg divided his research into two main areas: AI, which focuses on engineering machines to reason in the way that humans do, and computational psychology, which aims to make computational models for human mental activities. The below sections and subsections comprise a detailed literature review of AI and its background and relevant theories.

A. Theoretical Background of Artificial Intelligence

The notion of AI emerged in the 1950s when Turing established his renowned Turing test to examine whether machines could think. The initial or pioneering trends in AI made a significant distinction between strong AI and weak AI. Strong AI highlights systems that can actually and potentially think in the way that humans do (Kannan & Munday, 2018). The disciplines of computational psychology and AI are closely related. For instance, as Guerin (2022) pointed out, the "mind as computer" theory defines it as linear algorithmic machines processing symbolic languages, like a Turing machine or standard digital computers. This idea of mental computation, which is referred to as the computational theory of mind, was particularly prevalent between the 1960s and early 1980s. Subsequently, a new theory describing the mind as a system of interconnected nodes emerged. Both theories, respectively, relate to the two forms of AI: algorithmic AI and neural networks (Guerin, 2022).

The computational theory of mind

The computational theory of mind, which is also referred to as CTM, argues that the intentional state of the mind is determined by the thinker and the symbolic representation of the content of the state (Ludwig & Scheneider, 2018). For instance, believing that there is a dog on the rug implies a certain functional relationship between symbolic mental representations and the semantic value "there is a dog on the rug." Such representations include syntactic and semantic properties, and a reasoning process takes place using only the symbols' syntax. The semantics are unrelated to the processes. This process is referred to as a formal symbolic manipulation and considered a form of computation. While the symbols' semantic properties could be formalized (i.e., represented using a syntactic relationship), based on the theory, the semantic properties could also be represented mechanically. As Ludwig and Scheneider (2018) stated, it is possible to execute anything using a Turing machine provided that it can be formalized.

B. History of Learning Machines

AI is a broad domain, and it is not based on a single technology but rather on many technologies. For example, AI encompasses NLP, neural networking, data mining, and machine learning (Baker & Smith, 2019). Popenici and Kerr (2017) defined machine learning as "a subfield of AI that includes software able to recognize patterns, make predictions, and apply newly discovered patterns to situations that were not included or covered by their initial design" (p. 2).

Cave (2019) explained that, with Charles Babbage's computing machine design, AI can be traced back to the 19th century. However, modern AI research, especially research that has been conducted to solve decision-making problems through use of mathematical solutions (Guerin, 2022), has its roots in the mid-20th century. According to Myagila and Kilavo (2021), AI began with Turing's (1980 in Kuddus, 2022) simple question "can machines think?" To determine whether machines could indeed possess human-like intelligence, Turing (1980) designed a test, which became known as the Turing test or the imitation game. The proposed system took the form of question-and-answer interrogations whereby a human communicated using a keyboard and on-screen texts while two participants conversed, with one being a machine and the other being the human. The interrogator was tasked with determining which was which. If a machine could produce responses that were satisfactory enough to convince the interrogator that it was really a human (i.e., if the machine could understand linguistic input and produce sufficient human-like output), then doing so was adequate evidence that machines really were intelligent. By this point, Turing had stopped using the static computational method. In 1937, Turing proposed learning machines capable of using "fuzzy logic" and predicting key aspects of neural networks (Rosenberg, 2014). The first truly recognizable form of AI was Marvin Minsky's 1952 machine the SNARC (Stochastic Neural Analog Reinforcement Computer). The device was built using neural networks' conceptual models in an effort to artificially recreate biological neural networks (Sarosiek, 2018).

Artificial intelligence research and linguistics

According to Ludwig and Scheneider (2018), by the 1950s, scientists had already considered the possibility of developing machines capable of learning and understanding human language. To handle the complexity of this undertaking, experts and researchers in the field of computer science began collaborating with linguists. Consequently, innovative information technologies capable of allowing millions of words from an assortment of sources to be organized and processed were developed, which allowed for a new, entirely empirical vision of language. Moreover, the gathered data could be used to form models for machines to simulate natural dialect.

Myagila and Kilavo (2021) highlighted that the ability of AI to process languages is based on linguistic understanding. As the field continues to innovate and new technologies are developed, it is expected that computers will continue to advance toward the creation of a model whose speech and abilities to understand and process information are fully akin to those of a human. Hence, Pace-Sigge (2018) concluded that, while other contradictory theories could be challenged, AI could present opportunities for linguistic models to be experimentally proven.

C. Artificial Intelligence Language Modeling

Generally, AI language modeling involves teaching an AI system to identify a particular language input and produce an output that resembles that of a human speaker in the given language as closely as possible. As Pace-Sigge (2018) stated, the entire discipline of AI language processing has its roots in Quillian's (1969 in Goertzel, 2019) theoretical works on the teachable language comprehender (TLC). The TLC involves simulations of the human mind understanding languages. Training the TLC requires providing inputs through which it learns. Quillian proposed 20 short texts for the TLC to learn, which, according to Sarosiek (2018), was a particularly ambitious number for the time of Quillian's work. Today, AI can process a practically unlimited number of data. The main challenges are to obtain the right texts, clean them, and ensure that they are machine-readable.

Quillian's semantic model

According to Quillian (1969 in Goertzel, 2019), the TLC acquired the ability to understand texts by learning from the inputs that it received during its training. In Quillian's work, the TLC's inputs included 20 short children's books on firefighters, which were used to train the machine to comprehend basic information about them. According to Münster and Knoeferle (2018), for Quillian, the result of this process was a digital simulation of the development of human language. Quillian assumed that there is a common central process underlying the reading of all texts (children's fiction, newspapers, etc.) and that it is this central process that the TLC attempts to model. As Quillian stated, natural language is conveyed by making the mind recollect thoughts and notions that it already understands and relating them to other thoughts and notions. The TLC was learning not by running on huge structures but, bit by bit, advancing the structure with time (Münster & Knoeferle, 2018). Essentially, Quillian's model is semantic, and his proposal was to resolve polysemies by utilizing texts' semantic clues, as with, for example, the two sentences:

a) *"She got to the bank." and*

b) *"She received a mortgage from the bank."*

While Sentence A is undoubtedly ambiguous, Sentence B contains sufficient clues that allow the reader to clearly comprehend the significance of the word "bank." In Quillian's TLC, in what is termed a "semantic web," words are semantically linked (Hitzler & Janowicz, 2020). The word "bank" can thus be linked to words such as, inter alia, "robbery," "loan," and "money." Quillian completely refuted Chomsky's generative linguistics. According to Quillian, the field of generative linguistics does not suitably solve the issue of resolving polysemantic ambiguities. Using only one grammatical feature and its location does not provide a complete representation of human intelligence.

D. Generative Linguistics and Artificial Intelligence

Chomsky (1957; as cited in Ali, 2020) highlighted that classification is the main problem of language analysis. Language analysis aims to separate a grammatically correct sentence of a particular language from a grammatically incorrect sentence. For instance, "the cheetah sprints" is a grammatically correct sentence, while "sprints cheetah the" is not (Goertzel, 2019). Establishing whether sentences are grammatical requires determining whether the sentences have been produced by a grammar, hence the label "generative linguistics".

One of the ways of encoding the differences between sentences is to allow transitions between the words and utilize models (finite-state machines [FSM]) that specify a group of states and allowable transitions between them. A finite-state grammar (FSG) allows for an infinite number of sentences to be created from limited resources. This process is feasible because finite-state models allow for looping.

As the example provided in Figure 2 indicates, an FSM can generate, inter alia, "old man comes", "the old man comes", and "the man comes". The loop allows for a limitlessly vast number of sentences.

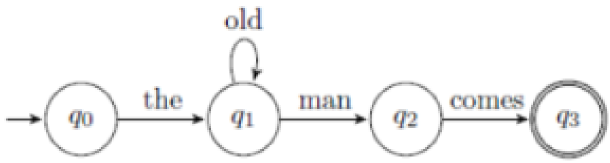

Figure 2 An FSG Generating an Infinite Set of Grammatically Correct English Sentences

Chomsky (1957; as cited in Chrisley, 2020) mentioned that an FSG cannot represent the complete complexity of English sentence structure. Generally, a finite grammar set cannot account for center-fixed clauses, such as “the teenager who hit the ball which went over the hedge is shouting.” Satisfactory English grammar models must perform beyond any sequential restriction and be able to represent sentences’ hierarchical structures. Chomsky’s efforts go beyond languages’ surface structures to propose a transformational grammar in which deep structures derivationally generate surface structures (i.e., the actual spoken sentence). The two types of structures are hypothesized in a generative analysis of language aspects rather than syntax, like phonology.

Error analyses and corrections

Although the literature on second-language acquisition differs as regards theoretical approaches to error correction, one of the points upon which cognitive theorists agree is that corrections are beneficial and contribute to learning (Burling, 2019). While some researchers have emphasized the significance of the communicative contexts in which correction occurs (e.g., Robinson & Long, 1998; Williams & Doughty, 1998 in Burling, 2019), others have stressed the importance of raising awareness. Burling’s (2019) main theory was that error correction is undoubtedly advantageous and that AI can be a valuable tool in this regard.

Accordingly, to the Intelligent Tutor’s systematic error correction would substantially impact learning outcomes. Consequently, the study was narrowed to include a single group and a single treatment protocol, which was preceded by a pretest and followed by a posttest, both of which related to seven typical structural errors (Table 2) and some morphological errors.

TABLE 2
THE SEVEN COMMON TYPES OF ERROR IDENTIFIED BY THE INTELLIGENT TUTOR (DODIGOVIC, 2007)

Type of error	Example
Nonfinite/finite verb constructions	It will cause death of both baby and mother
Missing copulas	Secondly, communities* affected
Malformed expressions of states/reactions/feelings	The disease had* dominant over human
Existential constructions	There is a new problem occur
Tough movements	More difficult to be realized
Ergative constructions	The immune system can be failed
Pseudo passives	Malaria can find all over the world

The pretest included 12 multiple choice questions, and the learners were asked to assess the utterances’ grammaticality. The learners’ skill in the task was considered a sign of their proficiency in the assessed structures. The posttest included a brief answer test where the learners were asked to write their own individual sentences. The posttest’s design differed from that of the pretest to ensure that learnings from the pretest did not influence the results.

The Intelligent Tutor’s ability to identify and correct some of the learner errors was influenced by the communicational, gravity, and frequency significance of the detected errors in a learner corpus, along with the exposure of the target learners to the structure in questions and its specific requirement. One of the advantages of the Intelligent Tutor is that it can accommodate each learner to some degree. Learners differ in many ways. ICALL is yet to attempt to support each learner difference, despite the fact that affective language aptitude and intelligence factors appear vital to success in language learning. The Intelligent Tutor made modest efforts to accommodate various styles of learning using Willing’s (1989, 1988 in Dodigovic, 2017) learner-type approach.

Dodigovic (2017) explained that concrete learners could take corrections as recasts, whereas authority-oriented learners could interpret them as the authorities’ solutions. The hints could be part of communicative techniques for communicative learners. Analytical learners could enter the correct versions and obtain a parse tree providing analyses that were precisely what this category of learners required. Additionally, the parse tree was more likely to reinforce correct language while increasing structural understanding. Put differently, analytical learners’ necessity to comprehend both what is correct and why it is correct could be efficiently satisfied. Hence, the Intelligent Tutor was developed to enhance awareness by providing learners with a solution to what they did not understand on the one hand while raising awareness by providing clues regarding what the learners were supposed to understand on the other. Additionally, upon successful completion of the assignment, the parse tree was shown to learners, allowing them the opportunity to explicitly learn something that they could have already implicitly known. When compared with those of the pretest, the posttest results demonstrated an 83% average decrease in error rate across the three learner samples (United Arab Emirates, Australia, and Taiwan). Learners from Taiwan had the top results (with an error reduction rate of 94%), followed by learners from Australia (with an error reduction rate of 85%). Learners from the United Arab Emirates followed (with an error reduction rate of 79%), while Australian international English language students (with an error reduction rate of 73%) were last. In addition, the results revealed that AI could potentially help individuals to learn English as a second language and rectify L2 errors, which was a key step toward a profounder knowledge of the processes of second-language teaching and acquisition.

III. RESEARCH METHODOLOGY

Researchers can conduct their research by focusing on one of three research approaches: the qualitative approach, the quantitative approach, or the mixed-method approach (Williams, 2007). The quantitative approach attempts to quantify any social phenomena and gather and examine numerical data. Whereas the qualitative approach is based on an understanding of the meaning of social phenomena (Tuli, 2010), quantitative research is based on the positivism paradigm. The basis of qualitative research is subjectivity (Cleland, 2015). There is always a distinct and specific concept on which all qualitative research is based (Duffy & Chenail, 2009). The present research is qualitative in nature, and, through a systematic literature review, its aim is to highlight the role of AI in helping learners of a second language to master pronunciation.

Vuori and Vaisanen (2009) highlighted the importance of the systematic literature review and explained that “it is the valuable strategy, when the aim is to identify, evaluate, and synthesize all of the important research on a certain topic to acquire a complete picture of the studies and their findings”. According to Gough et al. (2017), the systematic literature review emphasizes the answering of specific research questions based on systematic, explicit, and replicable search strategies using proper inclusion and exclusion criteria to consider the most relevant research. Figure 3 highlights all the steps that comprise the SQAT-based systematic literature review, but these steps also apply to the general systematic literature review.

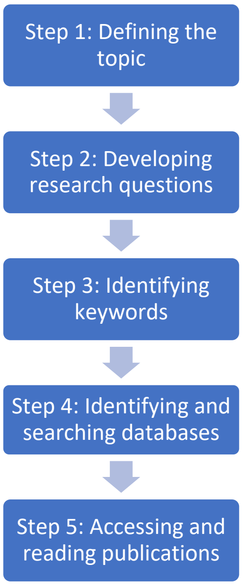

Figure 3 The Five SQAT-based Steps Followed in This Research

The methodology of this research is based on a step-by-step process that specifically aims to verify the relevance of the materials identified and selected for use in the study. This process is also important because it aims to ensure that the study’s selected journals, publications, articles, and other materials include the smallest number of or no research errors or biases. Additionally, through a meticulous and comprehensive approach, when selecting and synthesizing various literature themes relating to the research topic, the process seeks to facilitate the obtaining of relevant research. This is because the method is based on a repetitive cycle, which helps to identify the germane search keywords, assess the relevant research sources, and perform an in-depth analysis of each publication to facilitate accurate findings for the study. Thus, intrinsically, the data collection process was based on an analysis protocol defining the entire exercise, from the execution of the methodology and collection of the relevant data to the acquisition of sources of literature that could be reviewed and discussed to achieve the aims and objectives of the study. All relevant peer-reviewed journal articles from well-known databases were searched to gather the data (i.e., research articles). The used databases are listed in Table 3.

TABLE 3
DATA COLLECTION DATABASES

SR #	Database
1	Google Scholar
2	ScienceDirect
3	JSTOR
4	ProQuest Dialog
5	EBSCO
6	Web of Science (Clarivate)
7	Scopus (SJR)

Table 3 shows that data were gathered from different online databases, including Google Scholar, ScienceDirect, JSTOR, ProQuest Dialog, EBSCO, Web of Science, and Scopus, to obtain the most relevant sources of literature for the study. In these databases, the searches were conducted using different keywords to reach and shortlist the most relevant articles. The keywords are provided in Table 4.

TABLE 4
DATA COLLECTION KEYWORDS

Sr #	**Keyword**	**Sr #**	**Keyword**
1	AI	3	AI and learning skills acquisition
2	The significance of AI	4	The role of AI in language learning

During the process of searching the data from the databases using the different keywords, specific criteria (i.e., inclusion and exclusion criteria) were designed. Details of the criteria are provided in Table 5.

TABLE 5
INCLUSION AND EXCLUSION CRITERIA

Inclusion Criteria	**1**	Studies published within the last 11 years
	2	Qualitative, quantitative, and mixed-method studies
	3	Studies published in English
Exclusion Criteria	**1**	Studies published before 2011
	2	General reports
	3	Studies published in languages other than English

The initial searches of the databases using the keywords “AI,” “the significance of AI,” “AI and learning skills acquisition,” and “the role of AI in language learning” generated 116 articles from professional journals, edited academic books, peer-reviewed journal articles, statistical data from verified sources, and website materials from reputable organizations, such as, inter alia, IBM, Google, and Amazon. All 116 articles were considered relevant to the research topic. For the purpose of validating and enhancing the relevance and accuracy of the study’s results, any material that was missing any metadata, such as, inter alia, an abstract, a date of publication, and references, or included replica information was eliminated from the list of articles. Consequently, only 84 sources of literature remained, all of which were considered relevant to the research.

As the aim of this study is to obtain the most accurate data to reach substantiated conclusions regarding the role that AI plays in helping individuals to learn and master new languages, each of the 84 publications was meticulously evaluated and scanned using the four-eyes principle. Moreover, the publications were sifted according to article title, abstract, provided keywords, and information relevant to the role of AI in helping individuals to learn and master new languages. Subsequently, based on this analysis, 41 publications were found to be inappropriate for the study and were thus removed from the list of articles. The removed publications included publications whose content, title, and/or used keywords were either irrelevant or vague regarding the focus of the study. In addition, although some of the removed publications briefly examined the topic of AI and its significance in automation and, perhaps, teaching to some degree, the removed publications’ discussions of the topic were mostly generalized and not comprehensive when it came to explaining the role of AI in helping individuals to learn and master new languages and were thus considered unsuitable for the study. Lastly, the texts of the remaining 43 publications were thoroughly scanned to determine whether they were worthy of inclusion in the study. This analysis determined that 29 of the 43 publications were most relevant to the topic and aims of the research, had the smallest number of or no research biases or errors, and were all cited and referenced using credible sources. These 29 publications were thus considered appropriate for the study and were consequently retrieved for subsequent analysis in the study. The entire process and all steps followed to obtain the relevant materials for the study are presented in Figure 4.

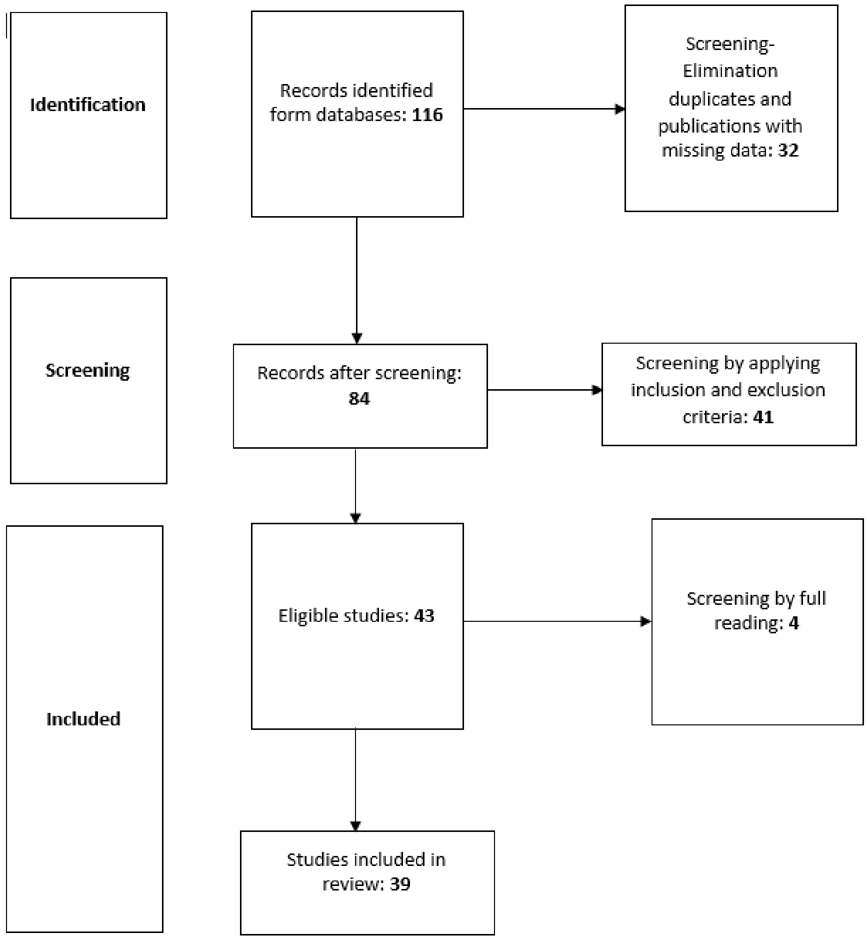

Figure 4: Schematic Illustration of the Process of Acquiring the Sources of Knowledge Used in the Systematic Literature Review

IV. Discussion

CALL (computer-assisted language learning) is not a new concept, as using information and communication technology (ICT) in language learning can be traced back to as early as the 1960s (Shadiev & Yu, 2022). Generally, CALL covers everything from using multimedia in learning to using, inter alia, virtual worlds, distance learning, and interactive whiteboards. Utilizing these techniques, which are mostly suitable for remote learning, has become central to the teaching of most languages. ICALL (intelligent computer-assisted language learning), which unites CALL and AI, has its roots in the late 1970s (Shadiev & Yu, 2022). However, the field is yet to reach its full potential, as it is particularly reliant on modern evolving technologies, its tasks are highly complex, and typical algorithmic AI is not suitably proficient in such tasks. Nonetheless, ICALL is largely benefiting from the evolving disciplines of deep learning and neural networks.

Computer-assisted language learning technologies have been accessible to new language learners for years. For example, Rosetta Stone, a CALL software, was made available approximately 29 years ago (Inman, 2021), and ever since, applications such as, inter alia, Duolingo and Babbel have begun to appear. These types of learning applications, which are used to assist learners and even include some degree of interaction with a chatbot, raise the question of whether language coaches will be necessary in the decades to come (Inman, 2021). Despite the sanguinity of certain neural network scholars, AI technology is yet to be sufficiently advanced to replace language tutors, although such technology can be used to improve learners' skills to allow them to achieve much more within the limits of their resources and time.

Digital assistants, such as Amazon's Alexa and Apple's Siri, utilize speech synthesis and recognition to help users with day-to-day errands. In addition to simple commands, AI can be applied to more intricate situations, such as those of learning environments (Clancey & Soloway, 2020). The issue with most modern computer-aided platforms, such as the aforementioned Duolingo, is that they are mostly based on obsolete models, such as translation methods. Other applications utilize artificial instructors (i.e., chatbots) who provide learners with support when they communicate in a given target language. Although technology is not common in foreign-language teaching, it has been incorporated into university teaching to some degree. For example, Leibniz University Hannover utilizes eLearning content, which features El Lingo (an artificial instructor) for German orthography, grammar, and linguistics.

With the expected increase in the number of English learners globally in the years to come, there is a necessity to relieve teachers of some of the tutoring work and provide learners with a better learning experience, especially in places where language tutors and learning resources are limited. Professionals in real-world settings are already implementing AI, with China currently being one of the main players in the AI market. According to Dizon et al. (2022), $568 million was spent on AI-assisted learning in China over the past three years, and the figure is expected to rise to $26 billion in the next three to five years. This expected increase in money spent on AI-assisted learning is undoubtedly due to the lack of English tutors in most Chinese learning institutes.

Recent developments in neural networks, as well as the current availability of large datasets, mean that it is now possible to gain clearer insights into, inter alia, the ways in which learners advance in a particular language, the specific language aspects that learners find difficult to learn, and the language aspects that learners can easily forget. This, at least theoretically, allows for a more tailored and, thus, effective teaching and learning process to take place, as well as the formation of truer placement tests (Rohalevych, 2022).

V. Conclusion

Researchers and practitioners have focused on AI for many years, and AI continues to have considerable potential owing to its diverse uses in and implications for different fields and areas of life. AI promises to bring about change throughout the world, from how people interact with technology and the way in which they do their jobs to the way in which they learn. As regards language learning and acquisition, the texts presented here show that AI holds great promise regarding its use as a tool to experimentally prove linguistic theories and a starting point to understand some of the aspects of human cognition (e.g., Quillian's TLC, which paved the way for research into the concepts of priming in psycholinguistics and cognitive science). Theoretically, the insights obtained from connectionist accounts of language acquisition can be incorporated into generative linguistics investigating universal grammar. The likely practical uses of AI in second-language acquisition are numerous and include, inter alia, analyses of individuals' abilities to learn language, performance predictions, dynamic difficulty adjustments, and error corrections. In conjunction with neural networks in particular, AI has proven that it merits its place in the learning process.

VI. Implications

A. Theoretical Implications

AI is a broad domain and is being used in various industries, including education. Both learners and educators are taking advantage of the uses of AI. This systematic literature review has focused on identifying the role of AI in helping learners of a second language to master pronunciation and has several implications. First, this review has provided extensive literature on AI, AI's implications for education, and AI's importance in helping learners of a second language to master pronunciation. Second, this review differs significantly from previous systematic literature reviews, which either focused on using AI in student assessment (González-Calatayud et al., 2021) or considered AI's uses in higher education (Zawacki-Richter et al., 2019).

B. Practical Implications

Not only does this review have theoretical implications, but it also has many practical implications. First, the findings of this review can serve as a guideline for teachers and teaching trainers, as it is important to train teachers in the use of AI (Cabero-Almenara et al., 2020). Second, this review could help learners and teachers of Arabic, who, because the Western world is now focusing on learning Arabic, are learning or teaching it as a second language. Hence, there is now a necessity to develop new and effective pedagogical approaches to teaching Arabic to non-native speakers (Najjar, 2020), and one important approach that could actually facilitate learning Arabic is the use of AI. Moreover, it is important to highlight how learning and teaching a second language using AI-driven chatbots could be effective in environments with low budgets and, most importantly, when sufficiently knowledgable human tutors are lacking and there are language datasets with few resources (Kerly et al., 2007; Hamed et al., 2022). Furthermore, using NLP, AI, and chatbots could help to develop an intelligent self-learning environment for learners learning Arabic as a second language. Additionally, an AI-based Arabic language and speech tutor could help non-native Arabic speakers to identify their pronunciation errors and monitor their performances (Shao et al., 2022).

VII. Limitations and Recommendations

This review has some limitations that authors of future studies should consider. First, this research adopted the general approach for its systematic literature review. Authors of future studies could focus on conducting systematic literature reviews using the PRISMA or SQAT approaches. Second, this review only considered peer-reviewed articles and ignored reports; thus, when conducting their reviews, authors of future studies could consider reports.

REFERENCES

[1] Bannerjee, G., Sarkar, U., Das, S., & Ghosh, I. (2018). Artificial intelligence in agriculture: A literature survey. *International Journal of Scientific Research in Computer Science Applications and Management Studies*, *7*(3), 1-6.
[2] Bullers, W. I., Nof, S. Y., & Whinston, A. B. (1980). Artificial intelligence in manufacturing planning and control. *AIIE transactions*, *12*(4), 351-363.
[3] Cabero-Almenara, J., Romero-Tena, R., & Palacios-Rodríguez, A. (2020). Evaluation of teacher digital competence frameworks through expert judgement: The use of the expert competence coefficient. *Journal of New Approaches in Educational Research (NAER Journal)*, *9*(2), 275-293.https://doi.org/10.7821/naer.2020.7.578
[4] Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access*, *8*, 75264-75278.
[5] Clancey, W., & Soloway, E. (2020). Artificial intelligence and learning environments: Preface. *Artificial Intelligence*, *42*(1), 1-6. https://doi.org/10.1016/0004-3702(90)90092-e
[6] Cleland, J. (2015). Exploring versus measuring: considering the fundamental differences between qualitative and quantitative research. *Researching medical education*, 3-14.https://doi.org/10.1002/9781118838983.ch1
[7] Duffy, M., & Chenail, R. J. (2009). Values in qualitative and quantitative research. *Counseling and values*, *53*(1), 22-38.https://doi.org/10.1002/j.2161-007x.2009.tb00111.x
[8] Dizon, G., Tang, D., & Yamamoto, Y. (2022). A case study of using Alexa for out-of-class, self-directed Japanese language learning. *Computers and Education: Artificial Intelligence*, *3*, 100088. https://doi.org/10.1016/j.caeai.2022.100088
[9] Educause. (2018). *Horizon report: 2018 higher education edition.* Retrieved October 11, 2022 from https://library.educause.edu/~/media/files/library/2018/8/2018horizonreport.pdf
[10] González-Calatayud, V., Prendes-Espinosa, P., & Roig-Vila, R. (2021). Artificial intelligence for student assessment: A systematic review. *Applied Sciences*, *11*(12), 1-15.https://doi.org/10.3390/app11125467
[11] Gough, D.; Oliver, S. (2017). *Thomas, J. An Introduction to Systematic Reviews;* SAGE: Los Angeles, LA, USA.
[12] Hamed, I., Denisov, P., Li, C. Y., Elmahdy, M., Abdennadher, S., & Vu, N. T. (2022). Investigations on speech recognition systems for low-resource dialectal Arabic–English code-switching speech. *Computer Speech & Language*, *72*, 101278.https://doi.org/10.1016/j.csl.2021.101278
[13] Haristiani, N. (2019). Artificial Intelligence (AI) chatbot as language learning medium: An inquiry. In *Journal of Physics: Conference Series*, *1387*, 1-6. https://doi.org/10.1088/1742-6596/1387/1/012020
[14] Harkins, A. M. (2008). Leapfrog principles and practices: Core components of education 3.0 and 4.0. *Futures Research Quarterly*, *24*(1), 19-31.
[15] Heift, T. (2010). Developing an intelligent language tutor. *CALICO journal*, *27*(3), 443-459.https://doi.org/10.11139/cj.27.3.443-459
[16] Hussin, A. A. (2018). Education 4.0 made simple: Ideas for teaching. *International Journal of Education and Literacy Studies*, *6*(3), 92-98.https://doi.org/10.7575/aiac.ijels.v.6n.3p.92
[17] Kannan J. y Munday P. (2018). New Trends in Second Language Learning and Teaching through the lens of ICT, Networked Learning, and Artificial Intelligence. *Círculo de Lingüística Aplicada a la Comunicación*, *76*, 13-30. https://doi.org/10.5209/CLAC.62495
[18] Kerly, A., Hall, P., & Bull, S. (2007). Bringing Chatbots into Education: Towards Natural Language Negotiation of Open Learner Models. *Knowledge-Based Systems*, *20*(2), 177-185. https://doi.org/10.1007/978-1-84628-666-7_14
[19] Loureiro, S. M. C., Guerreiro, J., & Tussyadiah, I. (2021). Artificial intelligence in business: state of the art and future research agenda. *Journal of business research*, *129*(C) 911-926.https://doi.org/10.1016/j.jbusres.2020.11.001
[20] Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed - an argument for AI in education.* Retrieved November 5, 2022, from https://discovery.ucl.ac.uk/id/eprint/1475756/
[21] Moghazy, M. (2021). Teaching and Learning Arabic as a Second Language: A Case Study of Dubai. *Teaching and Learning*, *10*(05), 52-61.https://doi.org/10.7753/ijsea1005.1002
[22] Najjar, M. (2020). Teaching Arabic Syntax for Non-Speakers: A Pragmatic Approach. *International Journal of Learning and Teaching*, *6*(4), 252-256.https://doi.org/10.18178/ijlt.6.4.252-256
[23] Puncreobutr, V. (2016). Education 4.0: New challenge of learning. *St. Theresa Journal of Humanities and Social Sciences*, *2*(2), 92-97.
[24] Rohalevych, V. (2022). *Essentials of Artificial Intelligence for Language Learning*. intellias. Retrieved 28 September 2022, from https://intellias.com/how-ai-helps-crack-a-new-language/.
[25] Rong, G., Mendez, A., Assi, E. B., Zhao, B., & Sawan, M. (2020). Artificial intelligence in healthcare: review and prediction case studies. *Engineering*, *6*(3), 291-301.https://doi.org/10.1016/j.eng.2019.08.015
[26] Russel, S., & Norvig, P. (2010). *Artificial intelligence - a modern approach*. New Jersey: Pearson Education.
[27] Sato, M., & Loewen, S. (2019). Towards evidence-based second language pedagogy: Research proposals and pedagogical recommendations. In M. Sato & S. Loewen (Eds.), *Evidence-based second language pedagogy: A collection of Instructed Second Language Acquisition studies*. New York, NY: Routledge.
[28] Self, J. (1998). The defining characteristics of intelligent tutoring systems research: ITSs care, precisely. *International Journal of Artificial Intelligence in Education (IJAIED)*, *10*, 350-364.
[29] Shao, S., Alharir, S., Hariri, S., Satam, P., Shiri, S., & Mbarki, A. (2022). AI-based Arabic Language and Speech Tutor. *2022 IEEE/ACS 19th International Conference on Computer Systems and Applications (AICCSA)*, 1-8.
[30] Sirajudeen, A., & Adebisi, A. (2012). Teaching Arabic as a second language in Nigeria. *Procedia-Social and Behavioral Sciences*, *66*, 126-135.https://doi.org/10.1016/j.sbspro.2012.11.254
[31] Tuli, F. (2010). The basis of distinction between qualitative and quantitative research in social science: Reflection on ontological, epistemological and methodological perspectives. *Ethiopian Journal of Education and Sciences*, *6*(1), 97-108.https://doi.org/10.4314/ejesc.v6i1.65384

[32] Vuori, V., & Väisänen, J. (2009). The use of social media in gathering and sharing competitive intelligence. In *Proceedings of ICEB 2009, The Ninth International Conference on Electronic Business, November 30 - December 4, 2009, Wynn Macau* (pp. 8 p). International Consortumi for Electronic Business.
[33] Williams, C. (2007). Research methods. *Journal of Business & Economics Research (JBER)*, *5*(3), 65-72.
[34] Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education–where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1), 1-27.https://doi.org/10.1186/s41239-019-0171-0
[35] Zeba, G., Dabić, M., Čičak, M., Daim, T., & Yalcin, H. (2021). Technology mining: Artificial intelligence in manufacturing. *Technological Forecasting and Social Change, 171*, 120971.https://doi.org/10.1016/j.techfore.2021.120971
[36] Ziegler, N., Meurers, D., Rebuschat, P., Ruiz, S., Moreno-Vega, J. L., Chinkina, M.,. & Grey, S. (2017): Interdisciplinary research at the intersection of CALL, NLP, and SLA: Methodological implications from an input enhancement project. *Language Learning, 67*(1), 209-231.https://doi.org/10.1111/lang.12227

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- Almelhes, S. (2021). Teachers' perceptions about integrating technology in teaching ASL: A descriptive study. *Journal of the Islamic University of Educational and Social Sciences*, *6*(2), 299-329.
- Almelhes, S. (2020) Second language acquisition through the flipped learning paradigm a systematic literature review. *Journal of the Islamic University of Educational and Social Sciences*, *7*(2), 525-558.