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Generative Artificial Intelligence-Assisted Language Learning: Cognitive Mechanisms, Theoretical Tensions, and Ethical Governance

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Abstract. Generative artificial intelligence (AI) is changing the environment of language learning, but its theoretical basis and ethical boundaries have not been fully explored. This paper builds a multi-level analytical system for AI-assisted language learning based on cognitive load theory, the zone of proximal development, generative linguistics and the technology acceptance model. AI can help students learn better by reducing extraneous cognitive load and providing easy-to-access support and instant correction; however, due to technological limitations, it may also reduce students' sense of ability and self-management. Generative linguistics and generative AI are not in opposition; rather, the former advocates for data frugality and innate mechanisms, while the latter is characterized by data maximalism and statistical learning; they are in harmony at the level of third factors and the Minimalist Program. According to the above research, chatbots have shown a modest positive effect on language learning; this degree varies depending on the learner's level, interface Design, interaction characteristics, etc. Based on the above, this paper introduces a "Smart Chinese" collaborative learning plugin that integrates ChatGPT with special scaffolding tools for assessment, planning, practice, feedback and community support. Finally, it presents the ethical problems of algorithmic bias, data privacy, over-reliance, and educational gaps, and proposes a multi-level governance system at the institutional, technological and pedagogical levels.

Keywords: Generative Artificial Intelligence, Language Learning, Cognitive Load, Technology Acceptance Model, Ethical Governance.

1. Introduction

With the development of generative artificial intelligence (AI), the foundation of language education has been altered. ChatGPT is a large language model that can produce text in the style of people, and it is capable of various applications such as explaining concepts, translating languages, rewriting content, correcting errors and simulating dialogues. This is to say that for language learners, there will be high immediacy, interactivity and personalised support; they can receive real-time corrections of their grammar, practice speaking and writing several times in a low-pressure environment, and access a large number of language materials close to actual pragmatic use [1, 2].

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However, technological optimism cannot replace theoretical investigation. Language learning is not merely the absorption of information and pattern recognition; it also requires cognitive load allocation, sociocultural interaction, identity construction and the development of critical thinking. If artificial intelligence is only regarded as an "intelligent dictionary" or a "patient practice partner", its cognitive mechanism will not be explored and the ethical risks of its application will be ignored. Building on previous research, this paper will conduct the following five types of in-depth theoretical studies: First, based on cognitive load theory and the zone of proximal development, explore the cognitive mechanisms of AI-assisted language learning; Second, examine the synergy between data frugality and data maximalism by investigating the conflict among generative linguistics and generative AI; Third, combine the technology acceptance model with empirical research to explore the prerequisites for learner adoption and learning efficiency; Fourth, put forward a design concept for a "Smart Chinese" collaborative learning plugin; Fifth, critically analyze algorithmic bias, data privacy risks, overdependence issues and educational inequality, and construct a multi-stakeholder governance system.

2. Theoretical mechanisms of generative AI-assisted language learning

2.1. Cognitive load, zone of proximal development, and on-demand scaffolding

The Three Types of Cognitive Load in Learning are Extraneous Load, Intrinsic Load and Germane Load. Extraneous load is caused by poor instructional design; intrinsic load is due to the difficulty of the material itself; and germane load is used for schema construction and deep processing. A good learning environment should reduce extraneous load, regulate intrinsic load and promote germane load [3]. The main strength of generative AI is that it can quickly create materials that are tailored to the learning needs of students, incorporate vocabulary, sentence patterns and pragmatic rules in a cohesive way, reduce irrelevant information interference, and lower extraneous cognitive load.

However, the cognitive effects of AI are not all positive. Technical limitations of chatbots, such as bias in speech recognition, unnatural turn-taking, delayed or incorrect feedback, etc., may cause new extraneous burdens. According to the above research, such a load may not directly reduce self-regulated learning; rather, it can lower learners' motivation for self-regulation by diminishing their sense of self-efficacy [4]. Therefore, the design of AI-assisted language learning should not focus solely on "rich functions" but also address interaction fluency, error tolerance, and the learners' emotional experience.

According to Vygotsky's zone of proximal development (ZPD), an AI assistant can be viewed as an on-demand scaffolding device [5]. Human tutors' scaffolding is ad hoc, flexible and network-based; AI scaffolding is scalable, reproducible and data-driven. Ideally, AI should assess the current ability of learners, set tasks slightly beyond their independent capabilities, and gradually reduce support as the learners improve. That is to say, we need to know the child's stage of development in order to provide both cognitive and affective support at the same time. If AI only offers answers directly, it will fail to engage learners in the process of cognitive exploration through scaffolding.

2.2. Generative linguistics and generative AI:Data frugality and data maximalism

There is a problem of theoretical conflict between generative linguistics and generative AI. Chomsky's generative grammar believes that the acquisition of human language is driven by an innate universal grammar, and under conditions of "poverty of the stimulus", children can learn complex syntax quickly, in line with the principle of "data frugality" [6]. At the same time, large

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language models are based on massive amounts of data and statistical learning; therefore, their belief is often that "the more data, the better", and Chomsky once called ChatGPT "high-tech plagiarism" and did not believe in genuine language understanding [7].

However, the two are not in opposition according to recent studies. Studies on the compatibility of generative AI and generative linguistics have shown that large language models generally do not rely on language-specific knowledge before training; instead, they are based on general cognitive learning mechanisms and efficient communication principles, referred to as the "third factors" [8]. These are exactly the problems that the Minimalist Programme aims to solve. Another way to look at it is that a large language model can be viewed as a computational laboratory for testing linguistic hypotheses; if such a model can learn complex syntactic structures from data, it may indirectly reveal which parts of linguistic knowledge are due to third factors. At the same time, generative grammar provides theoretical tools to describe the behaviour of these models and helps researchers move beyond "statistical correlation" to explore linguistic concepts such as structural hierarchy, recursion, and movement.

Theoretically, there are now some deficiencies in language teaching. Artificial intelligence can choose between explicit rule instruction and implicit exposure to the input in learning. A good Design will have two types: when learners make organised errors, the AI will provide explicit explanations and contrastive analysis; when learners need to learn language intuition, a large amount of comprehensible input and contextualised practice can be offered. The generation of endless practice cases by AI can be viewed as "infinite use of finite rule systems", mirroring the generative capacity of human language.

2.3. Technology acceptance model and learner agency

The effect of any educational technology depends on whether learners are willing to use it, continue using it and use it in depth. The first two causes of the Technology Acceptance Model (TAM) for new-technology adoption are perceived ease of use and perceived usefulness [9]. Trust, hedonic motivation and perceived adaptability have also been added to the explanatory system for AI teaching assistants. Research shows that when learners believe AI tools are simple to use, effective and trustworthy, their attitude and behaviour intention are more positive [9, 10].

Learners' previous knowledge and level of education may also be negatively related to behavioural intention. Learners with a good foundation in knowledge are more likely to find deficiencies in AI in pragmatics, culture or facts. Therefore, the purpose of AI-assisted language learning should not be solely to reduce the threshold; rather, learners need to develop critical AI literacy by learning when to trust AI, when to doubt it, and how to validate the results provided by AI. Learner agency is not innate but gradually developed through interaction with AI. Without metacognitive guidance, learners may be in a state of "dependence-frustration-abandonment"; with appropriate direction, AI can serve as a reflective partner to promote independent learning.

3. Empirical evidence and application design

3.1. Main findings of empirical research

Recently, there have been many studies abroad on artificial intelligence-aided language learning. A meta-analysis of the 28 studies and 70 effect sizes found that chatbot-assisted language learning has a moderate positive effect compared with non-chatbot conditions, and this effect is moderated by educational level, language proficiency, interface design and interactional capability [1]. Therefore,

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AI cannot achieve good results on its own; it is only effective when matched with suitable teaching plans and students.

Natural language processing tools can be used to conduct interactive and personalised exercises for learning specialised vocabulary. A case study showed that the learners' understanding of sustainability-related vocabulary increased significantly, and they could use the new words in context [11]. In pronunciation training, a speech-based ChatGPT intervention showed that learners continuously improved in multiple recordings and maintained the gains in a delayed posttest; thus, AI interaction can promote both immediate performance and long-term learning [12]. AI-simulated interlocutors in interactional competence can generate preferred responses, repair strategies and culturally appropriate closing remarks, but different models vary in the clarity and pragmatism of scaffolding [13]. Additionally, the impact of AI-generated stories and gamified learning on vocabulary retention and engagement has also been studied [14]. Together, these studies indicate that the effectiveness of AI is related to task authenticity, high-quality feedback and deep learner involvement.

3.2. Design of the "Smart Chinese" collaborative learning plugin

Based on the above theories, this paper designs a "Smart Chinese" collaborative learning plugin. The plugin uses ChatGPT as the dialogue and generation engine, and specialised plugins for scaffolding and recording to form a closed-loop system of "assessment-planning-practice-feedback-updating-community".

First, Language Proficiency Tests. The four aspects of the plugin's initial diagnosis are listening, speaking, reading and writing, and ChatGPT is used to generate personalised test questions. Second, Learning plan personalisation. According to the analysis results, the plugin will present a list of courses, exercises and interactive conversations. Thirdly, course learning and interactive practice. Learners can have real-life conversations with ChatGPT in a simulated environment, and a plugin provides interactive exercises, such as fill-in-the-blank and role-playing. Fourth, real-time feedback and progress recording. Collect learners' data; give specific feedback on accuracy, flow and politeness; show a history graph of study achievements. Fifthly, auxiliary resource access. The plugin offers authentic Chinese materials, video lectures and real corpora. Sixthly, regular assessment and adjustment. Periodically retest and adjust the plan based on performance via the plugin. Seventh, community interaction support. A plugin can connect to the online learning community and organise virtual salons and Q&A sessions

(The design is shown in Figure 1).

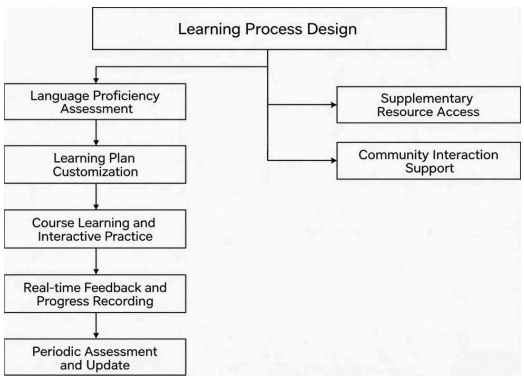


Figure 1. Intelligent Chinese collaborative learning plugin

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In theory, the design has the advantages of reduced extraneous load via AI, structured scaffolding provided by plugins, focus on immediate feedback and periodic reflection, support for personalised paths, and integration of social interaction. It is not to substitute for teachers with artificial intelligence; rather, AI can be employed to manage routine, high-volume practice and feedback tasks, and thereby free up teachers' time for more profound cultural explanations, emotional support, and leading advanced-thinking guidance.

4. Ethical dimensions and governance

4.1. Algorithmic bias and cultural representation

The output of generative AI is based on training data, and this data often contains historical biases, cultural stereotypes and linguistic inequalities. Denigration of some dialects, simplification of some cultures, and universalisation of particular pragmatic norms are all examples of this in language learning [2, 15]. Differences in dialects of Chinese learning, formal and colloquial registers, as well as regional cultural conventions may all be lost in Standard Mandarin corpora. If the AI introduces Anglo-American conversational norms in the Chinese class, the students may learn grammatically correct expressions that are pragmatically inappropriate [13]. Therefore, AI language-learning tools need to build bias-auditing mechanisms, add various corpora, and annotate pragmatic conditions and cultural contexts in their feedback.

4.2. Data privacy and security

Language-learning tools typically collect a large amount of user data, such as speech and text, learning paths, emotions, etc. If such data are used or disclosed improperly, it will violate privacy and damage trust [15]. The governance plan should have data minimisation and anonymisation, encrypted storage, access control, etc. At the same time, strengthen the education of digital literacy for learners to help them understand the value and risks of personal data. Research shows that users are less aware of the privacy risks in language-learning applications; therefore, platforms should not only obtain "user consent" but also proactively apply privacy-by-design [2, 15].

4.3. Overdependence and critical thinking

The immediacy and convenience of AI may lead some learners to avoid necessary cognitive effort out of habit [2, 15]. Over-reliance is not conducive to the all-around development of language ability and may also hinder the growth of metacognition; that is, learners fail to regulate their own learning processes and cannot proactively correct errors. To avoid the problem mentioned above, AI systems can add a mechanism of "delayed feedback", provide "hints instead of answers", and offer "reflection logs" to motivate learners to study independently first and seek help later. Teachers can then be transformed from knowledgemennts to learning designers and critical mediators to help students construct rational trust in AI.

4.4. Multi-stakeholder governance framework

Ethical Governance of AI-assisted Language Learning Requires Coordination at Institutional, Technological and Pedagogical Levels. Schools and language education institutions need to develop policies on the use of artificial intelligence that clarify academic integrity, data protection and teacher training requirements. At the level of technology, developers need to implement bias audits,

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transparency reports, privacy-by-design and explainable feedback. At the level of pedagogy, teachers need to be critically literate in AI, select suitable tools, design integrated teaching activities, and guide students to think about the deficiencies in AI's results. Only in this case will AI be an agent of change for educational equity and high-quality education, not a new source of division [2].

5. Conclusion

In this paper, the five directions of research for generative AI-assisted language learning are: cognitive mechanisms, theoretical contradictions, empirical evidence, application design and ethical governance. According to the study, the main goal of artificial intelligence in education is not to substitute teachers but to enlarge the scope of language learning by reducing students' extraneous cognitive load, providing on-demand scaffolding, generating contextualized materials and offering timely feedback. The conflict between generative linguistics and generative AI is not absolute; rather, at the level of third factors and the Minimalist Program, the two are in harmony. Based on the above empirical research, chatbots have provided some help for language learning, but this advantage varies according to the level of study and the design of interaction. Based on the above analysis, this paper puts forward a "Smart Chinese" collaborative learning plugin that integrates ChatGPT with special scaffolding tools to build a closed-loop system of assessment, planning, practice, feedback, updating and community support. Finally, this paper presents some ethical problems of AI language education, such as algorithmic bias, data privacy, over-reliance and educational disparity, and proposes a multi-stakeholder governance system to address these issues. Future research can explore the long-term effects of AI on minority and marginalized languages, pragmatics, cultural adaptation, and thus move from "instrumental assistance" to "ecological integration".

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