A Conceptual Framework for Learning Arabic Morphology Assisted By AI Chatbots: Integrating Three Theoretical Perspectives

***[1]Nur Shuhadak Ismail, [2]Dr Abdul Azim Mohamad Isa, [3]Dr Mohd Akashah Mohamad Yusof,**

[1] Academy of Language Studies, Universiti Teknologi MARA Cawangan Sarawak,

[2,3] Academy of Language Studies, Universiti Teknologi MARA Shah Alam

***Corresponding Author**

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ABSTRACT

Arabic morphology poses persistent challenges for second language learners due to its non-concatenative, root-and-pattern system, which imposes a high cognitive load. This complexity limits opportunities for active and interactive learning while demanding timely, individualised feedback that is difficult to provide in conventional classroom settings. While AI chatbots have emerged as promising tools for language learning, their application to Arabic morphology instruction remains underexplored and often lacks a coherent theoretical grounding. This conceptual paper proposes an integrated theoretical framework for Arabic morphology learning through AI chatbots by synthesising three complementary perspectives: Cognitive Load Theory, Social Constructivism, and Corrective Feedback Theory. Cognitive Load Theory informs how complex morphological content is structured into manageable units; Social Constructivism underpins the pedagogical approach in which learners actively construct knowledge through interaction with the chatbot; and Corrective Feedback Theory explains the mechanism through which the chatbot detects errors and delivers feedback that promotes self-correction. The paper discusses how these three perspectives complement one another and converge to support effective morphological acquisition. The proposed framework offers a theoretical foundation for designing AI chatbot-assisted modules and contributes to the limited literature on technology-enhanced Arabic language learning.

Keywords: Arabic morphology, AI chatbot, Cognitive Load Theory, Social Constructivism, Corrective Feedback Theory

INTRODUCTION

Arabic is a language of enormous religious and cultural importance and is commonly taught as a second or foreign language throughout the Muslim world, including in Malaysia. One of the many components of Arabic that holds a crucial place is morphology, or *sarf*. Morphology governs the construction and derivation of words and underlies learners' capacity to read, interpret, and write the language accurately. For this reason, a good grasp of Arabic morphology is a must for learners who wish to gain proficiency, but it is one of the most difficult aspects of the language to master. The complexity of Arabic morphology mostly arises from its non-concatenative, root-and-pattern framework. Words are constructed by intertwining a consonantal root with a vocalic structure (Cahya Setiyadi et al., 2025). Nawaz (2025) explains that an Arabic verb originates from a trilateral root, which is subsequently modified into several verb forms based on established patterns. This presents a specific barrier for students lacking a foundation in Semitic languages and minimal familiarity with the root-and-pattern system.

Therefore, students must engage in more than mere memorisation of vocabulary alterations. They must comprehend the relationship between root words and the patterns that produce different meanings, a need that demands a significant cognitive burden (Luqman Ibnul Hakim Mohd Saad et al., 2025). This strain is frequently exacerbated by conventional pedagogical approaches. These approaches are predominantly teachercentered and depend on rote memorisation, failing to foster a true comprehension of Arabic morphology, which hinders student's capacity to acquire this essential aspect of the language. These methodologies also render students as passive recipients of knowledge. Another hurdle is the difficulty of delivering instant feedback (Brosh, 2024; Jamil et al., 2024; Salim, 2024). Traditional training is mostly lecture-based with little opportunities for active, interactive practice and tends to delay feedback. So, learners often face three interconnected barriers: a heavy cognitive load from the complexity of morphological forms, passive learning contexts that provide few opportunities to actively construct knowledge, and the absence of timely, personalised feedback on the forms they produce.

In recent years, AI chatbots have emerged as potential aids for language learning. They offer interactive, personalized and instant feedback (Du & Daniel, 2024; Huang et al., 2022; Zhang et al., 2023). Such technologies have a great potential to overcome the challenges of Arabic morphology learning. They may present structured content, engage learners in interaction and provide corrective feedback at scale. However, there is little research on the use of AI chatbots in learning Arabic morphology. Most prior research has focused on other areas such as Arabic dialects, tourism engagement, Arabic as a foreign language, academic support services, and interactive learning of the Maghribi Arabic (Al-Ghadhban & Al-Twairesh, 2020; Alhumoud et al., 2022; Elsayed & Micahel, 2023; Alabbas & Alomar, 2024; El Alaoui & Cavalli-Sforza, 2025) . Moreover, the use of AI chatbots for language learning is often not grounded in an integrated theory, which limits the effectiveness of AI chatbots in the educational context.

This conceptual article aims to solve this gap by presenting an integrated theoretical framework for Arabic morphology learning through AI chatbots. The framework is based on three complementing theoretical views, Cognitive Load Theory, Social Constructivism and Corrective Feedback Theory. Each of these three theories addresses one of the three problems listed above. The research offers a theoretical foundation for the design of morphological modules facilitated by AI chatbots by explaining how these viewpoints complement each other and adds to the small collection of studies on technology-enhanced Arabic language learning.

LITERATURE REVIEW

Over the past five years, more researchers have started using educational theories to explain how learners understand, use, and correct language when learning with AI chatbots. Related to this, three areas still need closer discussion: how much mental effort learners put into using chatbots, how learner-chatbot interaction helps build knowledge, and how error correction improves accuracy. These areas need to be examined in more detail to better support language learning through AI chatbots. Studies based on Cognitive Load Theory (CLT) show that AI tools can reduce the mental effort learners need during language tasks. Research comparing AI-assisted learning with traditional methods found that learners using AI tools experienced lower cognitive load and better learning outcomes (Bahari et al., 2023; Feng, 2025). In addition, studies based on Vygotsky's social constructivism describe AI chatbots as a "more knowledgeable other" that guides learners within their Zone of Proximal Development. Findings from mixed-methods research show that learning with AI improves language achievement, motivation, and self-regulated learning compared to traditional teaching (Wei, 2023). Meanwhile, research on Corrective Feedback (CF) shows that chatbots can spot learners' errors and give quick correction, helping learners notice mistakes and avoid repeating them long-term. Recent studies report that chatbot feedback improves grammar accuracy (Afriana et al., 2025), and some researchers have even tried adapting large language models specifically to correct Arabic grammar errors (Kwon et al., 2023). All these three theories and approaches need to be integrated in order to produce a unified solution for the use of AI chatbots in language learning, particularly for Arabic, such as in the area of morphology.

Cognitive Load Theory

Cognitive Load Theory (CLT), developed by John Sweller et al. (1980), is a theory that guides the development of learning materials by taking human cognitive limitations into account, particularly the fact that working memory is limited in both capacity and duration when processing new information. Sweller et al. (2022) noted that CLT adds value to the design of learning materials by helping instructors understand and manage the types of cognitive load involved in the learning process. According to CLT, three types of cognitive load occur simultaneously during learning, and the theory seeks to manage these loads to make learning more efficient. The three types of cognitive load are described below (Mungai et al., 2024; Sweller et al., 1998; Uysal, 2026):

1. Intrinsic Load: Intrinsic Load is directly related to the inherent complexity of the learning material. Various factors influence intrinsic load, including students' prior knowledge, the complexity of the information presented, and the number of elements that must be processed simultaneously in working memory.

2. Extraneous Load: Extraneous load refers to external interference imposed by ineffective instructional design. Poorly structured learning materials, text-heavy slides, overly complex instructions, or the need to process information from multiple disjointed sources will increase this type of load. High levels of extraneous load divert students' attention from the main content topics.

3. Germane Load: Germane Load refers to the mental effort expended in the process of organizing and integrating new knowledge into existing knowledge. In an optimized learning environment, germane load can be maximized, thereby enhancing student engagement with and understanding of the learning content.

Theoretical advancement must align with the rapid evolution of Artificial Intelligence (AI) and digital Learning Management Systems (LMS). These developments underscore the need to enhance Cognitive Load Theory by integrating AI, establishing a framework that draws on AI's adaptive capabilities to personalise learning, optimise content delivery, and cater to the varied needs of learners.

Studies by Lademann et al. (2025) and Olugbade et al. (2024) highlight the potential of integrating artificial intelligence (AI) chatbots to manage students' cognitive load within the Cognitive Load Theory (CLT) framework. Olugbade et al. (2024) found that the "iLearnTech" chatbot, used in secondary-level Basic Technology, significantly reduced students' cognitive load by providing personalised learning support and real-time feedback. This reduction improved learning performance, attitudes, and knowledge retention. In line with these findings, Lademann et al. (2025) showed that chatbot-generated explanations, used as supplementary material in mathematics and physics, significantly reduced both intrinsic and extraneous load compared with traditional textbook materials alone. Although the effect on test performance was limited, the study confirmed clear gains in students' positive emotions and self-efficacy.

This alignment of AI with established educational theory points to more dynamic and responsive learning environments. The integration is not merely a matter of adding technology to existing frameworks. It requires a conceptual restructuring of how cognitive load is managed in AI-assisted learning. The key theoretical implication is AI's capacity to manage cognitive load in real time, according to each learner's performance and needs, a capability beyond the reach of conventional pedagogy. Applied to complex linguistic structures such as Arabic morphology, Cognitive Load Theory therefore demands careful attention to instructional design that optimises learning while avoiding cognitive overload.

Social Constructivism

Constructivist theory, pioneered by Jean Piaget (1977), holds that learning is not passive but occurs through the active construction of meaning. Piaget explained that when learners encounter experiences that challenge their existing cognitive schemas, a state of disequilibrium arises, and to restore equilibrium they must modify their thinking. This occurs through assimilation, the linking of new information with existing knowledge. When assimilation is insufficient, accommodation becomes necessary, involving the restructuring of existing knowledge to a higher cognitive level (Jafari Amineh & Davatgari Asl, 2015). Vygotsky later expanded this perspective through a social constructivist approach, arguing that knowledge construction does not occur solely within the individual mind. For Vygotsky (1986), social interaction and cultural context are the key catalysts of meaningful learning.

Within the social constructivist framework, knowledge construction is explained through three interconnected concepts, the Zone of Proximal Development (ZPD), the More Knowledgeable Other (MKO), and scaffolding.

The ZPD is the gap between what a learner can do independently and what they can achieve with guidance from an adult or a more capable peer. The MKO refers to any person or entity with a deeper understanding or greater capability than the learner, such as a teacher, a peer, or a competent adult. Scaffolding is the guidance the MKO provides, gradually withdrawn as the learner's competence grows (Chen et al., 2025; Hui Ye, 2025; Naik, 2026).

Integrating social constructivist theory into the design of language-learning chatbots foregrounds social interaction, scaffolding, and the ZPD as foundational elements. Studies indicate that chatbots built on these principles can support learner development in ways aligned with Vygotsky's framework (Liu, 2025; Mungai et al., 2024; Yin & Hanif, 2024). This extends existing theory by realising social constructivist concepts through artificial intelligence in a digital environment.

In this study, the role of the MKO is no longer limited to human figures such as teachers or peers. A chatbot system acts as a digital MKO, providing the scaffolding students need to master complex Arabic morphological structures. The chatbot can correct errors and offer detailed explanations, functioning much like a virtual tutor and fostering student engagement in the learning process. Social constructivism therefore frames the chatbot not as a delivery tool but as an interactive partner through which learners actively construct morphological knowledge.

Corrective Feedback Theory

Corrective Feedback Theory grew out of research on interaction in second language acquisition, which holds that learners advance not only by receiving input but by producing language and being alerted when their output is inaccurate. Within this tradition, corrective feedback refers to the responses a teacher or interlocutor gives to a learner's linguistic errors, signalling that a form is not target-like and creating an opening for repair (Lyster & Ranta, 1997). Its central concern is not merely correcting the error but drawing the learner's attention to the gap between their output and the correct form, so that the learner notices it and can act on it.

Lyster and Ranta (1997), based on observations in French immersion classrooms, established a taxonomy of six corrective feedback types and introduced the concept of uptake, the student's response immediately following the feedback. The first is recasts, where the teacher reformulates the student's utterance correctly without explicitly flagging the error. The second is explicit correction, where the teacher states directly that the utterance is incorrect and supplies the correct form. The third is clarification request, where the teacher signals that the utterance was not understood and asks the student to restate it. The fourth is metalinguistic feedback, where the teacher gives clues or grammatical information about the error without supplying the correct form. The fifth is elicitation, where the teacher prompts the student to produce the correct form themselves. The sixth is repetition, where the teacher repeats the erroneous part of the utterance, usually with emphatic intonation, to draw attention to the error. These six types fall into two categories, feedback that supplies the correct form directly, namely recasts and explicit correction, and prompts, which withhold the correct form and instead push students to self-correct, namely clarification requests, metalinguistic feedback, elicitation, and repetition.

Lyster and Ranta (1997) found that although recasts are the feedback type teachers use most often, prompts are more effective at leading students to self-correct. Lyster (2004) further showed that prompts outperform recasts specifically on morphosyntactic features, that is, morphology and grammar. Prompts require students to recall and restructure their knowledge of the target form, rather than repeat a form already supplied. Several recent studies support this theory in chatbot-assisted learning. Kim (2024) showed that learning improves when students respond to automated corrections from chatbots, and that the effect depends on how far students notice the feedback. Shin, Lee, and Noh (2024) found that chatbots built for specific learning tasks can deliver corrective feedback on grammatical errors, leading to uptake and successful correction. These findings reinforce the potential of AI chatbots to provide corrective feedback, though their effectiveness still depends on the design of appropriate feedback types.

This theory is directly relevant to the present study. As noted, prompts suit morphosyntactic features, which include Arabic morphology. Although the taxonomy was developed for teacher feedback in the classroom, the same principles apply to non-human feedback providers. In this study, a chatbot assumes the teacher's role,

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delivering the same corrective feedback types automatically and immediately. The chatbot serves as a medium through which students produce morphological forms in text, detects inaccuracies in those forms, and provides prompt-type feedback that pushes students to recognise and correct their own errors. Lyster's theory can therefore operate within a learning environment that supplies timely feedback, a requirement conventional teaching often struggles to meet.

DISCUSSION

The three theories are not rivals but complements. Each answers a different design question for the chatbot module. One governs content, one governs pedagogy, one governs feedback. Cognitive Load Theory answers what to present and how much at once, managing the difficulty of Arabic morphology by segmenting and sequencing forms so that working memory is not overloaded. Social Constructivism answers how learning should happen, positioning the chatbot as a digital More Knowledgeable Other that scaffolds the learner within the Zone of Proximal Development. Corrective Feedback Theory answers how errors are handled, equipping the chatbot to deliver prompt-type feedback that pushes the learner to notice and self-correct morphosyntactic errors. Because each theory addresses a distinct question, content, pedagogy, and feedback, they layer without redundancy, forming one coherent basis for the module rather than three parallel accounts.

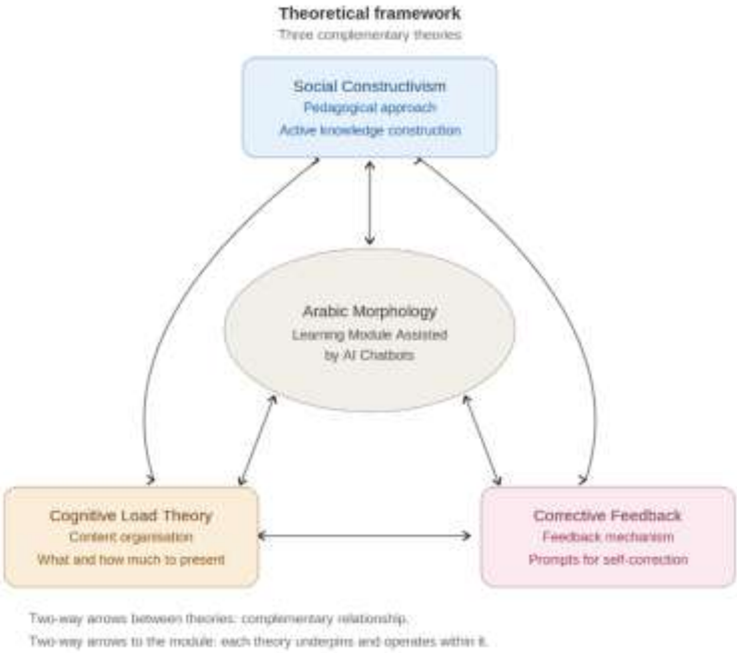

Figure 1 Integrated theoretical framework for AI chatbot-assisted Arabic morphology learning

The three theories operate together on a single learning task, not in sequence. Consider one cycle in the module. The chatbot first presents a morphological pattern in a controlled unit, one morph (*wazan)* at a time, so the learner is not asked to process more than working memory can hold. This is Cognitive Load Theory setting the boundaries of the content. The learner then produces a form in response, actively constructing the rule rather than receiving it, with the chatbot acting as the digital More Knowledgeable Other that holds the task within reach. This is Social Constructivism setting the mode of engagement. When the learner produces an incorrect form, the chatbot delivers a prompt rather than the answer, pushing the learner to notice the error and repair it. This is Corrective Feedback setting the response to error. Each theory governs a different moment in the same cycle, and each hand off to the next: load management makes room for construction, construction generates output, output invites feedback.

The framework relies entirely on automated feedback, since the module is designed for independent self-study. This makes the limits of chatbot feedback consequential. Su and Huang (2025) found that AI feedback draws high engagement in error detection, yet learners still prefer teacher feedback for future-oriented guidance. Khojasteh, Soori, and Javed (2025) reported that a hybrid model, combining teacher and AI feedback, outperforms either source alone. A further limit is affective. The chatbot cannot read the learner's emotional state, whether frustration, waning motivation, or growing confidence, and so cannot adjust its manner to the individual. The framework does not eliminate these limits. It works within them. Cognitive Load Theory reduces the frustration that overload produces, Social Constructivism sustains engagement through active production, and Corrective Feedback keeps the learner oriented toward the correct form. The three theories together compensate, in part, for the absence of a human tutor, without claiming to replace one.

Furthermore, a notable challenge with AI chatbots for Arabic is the difficulty of processing the language computationally, given its morphological richness, orthographic ambiguity, and non-concatenative structure (Farghaly & Shaalan, 2009). Undiacritised Arabic is highly ambiguous, since a single word can carry multiple interpretations, which complicates automated morphological analysis (Farghaly & Shaalan, 2009). Such risks, including inaccurate analysis and hallucinated output, are most pronounced in generative systems that produce responses in real time (Mubarak, Al-Khalifa, & Alkhalefah, 2024). The present framework mitigates this risk through a rule-based design, in which all content and feedback are verified by teachers before deployment and the chatbot delivers only approved responses. This design trades the flexibility of generative systems for accuracy and control, a compromise well suited to a self-study module where no instructor is present to correct errors during use. The cost is reduced adaptability, since a rule-based chatbot handles only anticipated forms and responses. Future work may explore how generative capabilities could be added without sacrificing this verified accuracy.

Therefore, this paper set out to address a gap. AI chatbots are applied to language learning, but rarely to Arabic morphology, with a clear theoretical basis. The framework proposed here answers that gap at the level of design. It gives a theory-grounded basis for building an Arabic morphology learning module assisted by AI chatbots, drawing each design decision from an established theory rather than from intuition. Arabic morphology is a fitting case. Its forms impose a high cognitive load, which Cognitive Load Theory addresses through segmentation and sequencing. It demands active engagement, which Social Constructivism supplies through construction and scaffolding. It calls for feedback on morphosyntactic errors, which Corrective Feedback delivers through prompts.

CONCLUSION

Based on this discussion, the proposed conceptual framework integrates content, pedagogy, and feedback into a single model. It positions AI chatbots as self-study tools grounded in established theory, not as ad hoc applications of technology. Cognitive Load Theory structures the content, Social Constructivism shapes the pedagogy, and Corrective Feedback governs the response to error. The framework gives educators and curriculum designers a theory-based basis for building AI chatbot modules in Arabic morphology learning. Its contribution is conceptual, not empirical. Future research should test the framework empirically. A quasi-experimental design could compare the chatbot-assisted module with conventional instruction among Arabic learners at different proficiency levels, measuring morphological understanding, engagement, retention, and cognitive load. A mixed-methods approach would add depth, drawing on learners' experiences of the module and on the judgements of teachers and curriculum designers who evaluate its content and usability. Such studies would establish whether the theoretical integration proposed here translates into measurable gains and would refine the framework for wider use.

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