The JALT CALL Journal
ISSN 1832-4215, 22, 103986 (2026)
https://doi.org/10.29140/jaltcall.2026.103986

Navigating AI-assisted language learning through Computational Thinking Skills in Computer Assisted Language Learning (CTsCALLs): A qualitative investigation of learner perceptions

Amir Reza Rahimi
University of Valencia, Spain
rahimia891@gmail.com

Arefe Amini Faskhodi
Department of English, Faculty of Literature, Alzahra University, Tehran, Iran
arefe.amini@gmail.com

Computational thinking (CT) is the heart of 21st-century digital skills, serving as an essential problem-solving skill that enables users to address challenges using information and communication technologies (ICTs). Recently, CT has been recognized as a critical skill within STEM education; however, scholars in computer-assisted language learning (CALL) and applied linguistics have developed a specialized framework known as computational thinking skills in computer-assisted language learning (CTsCALL). Despite its novelty and potential, this innovative framework has garnered limited attention. For this reason, we integrated CTsCALL into our language teaching practices and aimed to cultivate these skills among 104 Iranian EFL learners in the context of Artificial Intelligence Language Learning (AILL). The results of the content analysis indicated that participants perceived skills such as algorithmic thinking, abstraction, collaboration, evaluation, and generalizability as facilitating their ability to achieve higher levels of reliability, trustworthiness, and individualized learning patterns while engaging with AI to accomplish learning tasks. Based on these findings, the study provides qualitative support for the relevance of the CTsCALL framework within language learning contexts and suggests that CTsCALL may offer a promising approach for addressing challenges associated with passive language learning and AI hallucinations in AILL.

Keywords: 21st-century digital skills, computational thinking skills in computer-assisted language learning (CTsCALL), Computational thinking skills in Applied Linguistics, Artificial Intelligence Language Learning

1. Introduction

Technological advancements and the pivotal role played by artificial intelligence (AI) have led to significant changes in various aspects of human life, including education and language learning. As a result of these developments, several organizations have been compelled to re-evaluate teaching practices, including the Assessment and Teaching of Twenty-First Century Skills (ATC21S), the Organization for Economic Cooperative and Development (OECD), the European Union (EU), the Computer Science Teachers Association (CSTA), the International Society for Technology in Education (ISTE) and the International Association for the Evaluation of Educational Achievement (IEA). The reforms focus on the integration of information and communication technology (ICT) and artificial intelligence (AI), emphasizing problem-solving skills and lifelong learning while embedding and cultivating 21st-century digital skills and competence with it (Rahimi, 2023; Rahimi & Teimouri, 2025). The recommendations mentioned above have resulted in the development of several curricula and frameworks, particularly in the STEM fields. These initiatives are founded on constructivist principles, problem-solving strategies, and the fostering of 21st-century digital skills and competencies (Rahimi, 2023). The fundamental skill among them is Computational Thinking (CT), which STEM educators and scholars have traditionally associated with their respective fields (Chevalier et al., 2020; Israel-Fishelson & Hershkovitz, 2022), where students apply a set of thinking skills involving computer science principles for individuals to solve problems with AI and programming (Zhang et al., 2025).

Several researchers have integrated Computational Thinking (CT) into various disciplines, including the arts (Leung et al., 2026) and STEM education (Chevalier et al., 2020). Building on this trend, Rahimi and Sevilla-Pavón (2025) have introduced the theory of Computational Thinking Skills in Computer-Assisted Language Learning (CTsCALL) along with an associated scale for CALL and applied linguistics. These contributions demonstrate that CT extends beyond STEM fields, showing its relevance across a broad spectrum of disciplines, particularly in CALL. However, due to its novelty, the CTsCALL theory necessitates further validation and exploration within the subfield of CALL. Rahimi and Sevilla-Pavón (2025) as well as Rahimi and Faskhodi, (2026) have recommended investigating the role of CTsCALL in exploring how it can influence language learners' performance in several language learning contexts. Additionally, CALL experts have suggested that as technology continues to advance, the scope of CALL should be broadened (Colpaert, 2020). In light of these recommendations and identified gaps in the literature, the present study qualitatively investigates learners' perspectives on CTsCALL as a problem-solving framework within their AILL.

2. Literature review

2.1. Theoretical framework: Computational Thinking Skills in Computer-Assisted Language Learning (CTsCALL)

As mentioned earlier, CT was defined by ISTE (2015) as a set of thinking skills encompassing cooperation and collaboration, problem solving, critical thinking, creativity, algorithmic thinking, and computational thinking (CT) and introduced into education with the premise that computers could enhance thinking processes and provide new patterns of access to knowledge (Papert, 1980). Later, Wing (2006) proposed the integration of CT into K–12 curricula and called for research into effective teaching methods to cultivate it. Since then, CT has been acknowledged as one of the key skills of the 21st century (Tang et al., 2020). However, the conceptualization and operationalization of CT may vary across disciplines. For this reason, Rahimi and Sevilla-Pavón (2025) developed the theory of CTsCALL for the field of applied linguistics and CALL and defined it as higher-order thinking skills that are transferable across language tasks and target-language contexts. These skills enable language learners to solve language tasks through CALL materials, which have several phases. In this regard, we operationally defined each of these phases based on the study context and objective as follows:

- **Algorithmic Thinking:** Language learners' skills to do language tasks step by step using AI-assisted (corpus-mediated) tools.
- **Abstraction:** Learners' ability to focus on the big picture rather than getting involved in details while doing language tasks using AI-assisted (corpus-mediated) tools.
- **Collaboration:** Language learners' ability to do language tasks in cooperation with one another using AI-assisted (corpus-mediated) tools.
- **Evaluation:** Language learners' skill to be critical of different solutions and possible responses, and to select the best response.
- **Generalization:** Language learners' skill in noticing language patterns while using AI-assisted (corpus-mediated) tools and applying them to similar language tasks or target language contexts in real life.

2.2. Literature review and its gap

An ever-increasing body of literature has shed light on how CT contributes to students' cognitive, academic, and problem-solving outcomes across educational contexts. For example, the result of a large-scale meta-analysis synthesizing empirical findings across grade levels and disciplinary contexts indicated a positive, moderate correlation between CT skills and academic achievement (Lei et al., 2020); i.e., students with greater CT abilities tend to perform better across manifold domains. The review also indicated that CT is not limited to programming and is associated with boosted problem-solving, reasoning, and task efficiency, contributing to performance outcomes. In another systematic review, Tang et al. (2020) analyzed 96 studies on CT assessment and its link to learning outcomes. The focus of this study was on assessment; however, the review indirectly examined the alignment of CT with gains in problem-solving and academic tasks requiring decomposition, abstraction, and logical reasoning, if CT is measured reliably. It is noteworthy that the review mainly critiques assessment methods, and the effects on performance were not directly measured but were inferred. Liu et al.'s (2024) systematic review also examined teacher professional development (TPD) and its impact on CT integration in

K-12 classrooms. While it is worth mentioning that many of the TPDs reviewed were one-shot, not only does the review highlight that high-quality training of teachers leads to students' better CT outcomes and improved performance on problem-solving and project-based tasks, but it also underscores instructional quality and teacher expertise as important mediators in the CT-performance association.

Durak et al. (2019) conducted a 10-week programming and robotics intervention on secondary school students, while focusing on CT, self-efficacy, and reflective problem-solving. The study's results showed a moderate improvement in CT skills, as well as increased confidence and effectiveness in solving complex tasks. The study further highlights the interplay between CT and broader performance-relevant constructs encompassing perseverance, strategy use, and meta-cognitive awareness. Similarly, in a more recent study by Cheng et al. (2023), with a quasi-experimental design, a structured CT curriculum was implemented in real classrooms and examined its effects on students' cognitive and creative outcomes. The results manifested significant improvements in CT skills and enhanced performance on problem-solving and creative-thinking tasks. The study also provides evidence that explicit teaching of CT through scaffolded activities results in measurable gains in both computational and general academic performance indicators.

Interestingly, Shimizutani et al. (2025) conducted a randomized controlled trial aiming to evaluate CT-focused computer science lessons delivered via robotics/math activities in primary schools in Iraq. The results of the study indicated significant positive effects on students' computational thinking scores, specifically for lower-performing girls. Moreover, the gains persisted for more than three months for some groups. In another relevant randomized controlled trial in Colombia, Robledo-Castro et al. (2025) examined the influence of a 12-week CT training program on executive functions, especially working memory, cognitive flexibility, and inhibition, while combining unplugged activities with plugged experiences in game programming and educational robotics. While children in the CT group demonstrated large gains in auditory working memory, moderate improvements in visuospatial working memory, and a small but significant increase in inhibitory control compared with the control group, there was no measurable impact on cognitive flexibility. The results may suggest that CT training can transfer to and boost certain executive functions, especially working memory; however, the effects on all domains may not be equal.

In the context of language learning, Rottenhofer et al. (2022) examined the employment of CT strategies in language learning contexts and found that although students initially manifested limited CT strategy use, after the explicit intervention, their use improved noticeably. The intervention also assisted students in better structuring linguistic tasks, analyzing errors, and applying stepwise problem-solving techniques, which contributed to boosted performance outcomes in language learning. In a recent review, Yu et al. (2024) synthesized emerging experimental work on the integration of CT into foreign language pedagogy and argued that CT supports language learning by promoting systematic strategy use, problem decomposition in complex tasks, and metacognitive awareness. According to preliminary empirical studies, CT-based activities can improve learners' performance in language tasks by enhancing task structuring, error analysis, and overall learning efficacy.

Despite considerable research increasingly demonstrating the positive effects of computational thinking on academic achievement and cognitive skills, most empirical evidence comes from STEM subjects or general education contexts. Furthermore, studies examining CT in foreign language learning remain limited. For clarification, Rahimi and Sevilla-Pavon (2025), in their study that applied a bi-symmetric research design to explore how CTsCALL skills can shape learners' intentions to participate in virtual exchange programs, used a bi-symmetric approach that balances pedagogical design (supply) with learner perceptions (demand). The findings indicate that CTsCALL can effectively shape language learners' intentions to use VE, particularly for those students who applied abstraction skills—focusing on key information rather than details while solving language tasks—as well as recognizing patterns of task solving (algorithmic thinking) and applying them to other tasks (generalization). These learners found VE and CTsCALL to be aligned with their current capabilities, learning environment, and problem-solving skills, which mediated their intention to learn and exchange information in this context in the future. To extend and validate CTsCALL to the Iranian EFL context and intelligent CALL, Rahimi and Faskhodi (2026) cultivated CTsCALL for university language learners through AI and explored how it can shape learners' motivation as well as their deep and organizing approaches to AI. According to their bi-symmetric research design, abstraction and evaluation skills were among the necessary conditions to shape language learners' deep approach to ICALL, and higher levels of these skills can further enhance their deep approach to it. However, while generalization was not among the necessary conditions, its presence can assist language learners in adopting a deep language-learning approach to cross-referencing ideas with AI. Despite these findings, CTsCALL as a new theoretical framework needs much further investigation, especially through qualitative findings to validate its generalizability in applied linguistics and CALL, which has been recommended by several CALL scholars (Rahimi & Daneshvar Ghorbani, 2025; Rahimi & Sevilla-Pavón, 2025; Rahimi & Faskhodi, 2026; Rahimi et al., 2026). Addressing this gap, our study aims to investigate the following research question qualitatively:

- How do language learners perceive and experience the role of CTsCALL in their AI-assisted language learning?

3. Methodology

3.1. Research design

Presently, 21st-century skills, particularly computational thinking, are at the forefront of educational research, especially in light of advancements in artificial intelligence (Rahimi & Teimouri, 2025). To explore this emerging area, the researcher adopted a qualitative design, as recommended by Creswell (2014), who argued that such an approach is suitable for examining topics that are underrepresented in the literature, where "variables are unknown" and the understanding of participants' "subjective meaning-making" is of primary importance. Furthermore, qualitative methods are particularly effective in uncovering learners' perceptions of new methods, approaches, and skills (Creswell, 2014). Therefore, the researcher chose narrative inquiry in the form of a descriptive design, which allows for an examination of the current status of the phenomenon and provides insights into existing conditions and experiences among participants (Edmonds & Kennedy, 2016).This helped us gain a better understanding of how events are sequenced and connected (Adu, 2019) in order to create a meaningful experience for language learners participating in AILL and applying CTsCALL, particularly some of CTsCALL's skills such as algorithmic thinking, which is not simply possessed by a student but is enacted through a series of steps in which they encounter obstacles, make revisions, and evaluate their progress.

3.2. Study procedure and its context

This study collected data during a general English course in which 104 Iranian EFL students at a state university, in Iran participated. These undergraduate students were from various academic disciplines and aged 19 to 25. All the students received the same instruction. Participants were selected through purposive sampling to allow for the inclusion of information-rich cases, from which in-depth understanding of the phenomenon could be obtained (Patton, 2015). Although classroom observation was available, we selected interviews as the sole data source because they enable researchers to obtain detailed accounts of participants' experiences, perceptions, and interpretations of a phenomenon (Creswell & Poth, 2018).

They attended a General English course emphasizing reading comprehension across two class sections, and one of the researchers facilitated the procedure in the classroom and collected the data. It is noteworthy that CTsCALL was implemented using a number of AI tools. The instructional setting was equipped with video projectors, and, aiming to integrate multiple AI and AI-assisted applications, the instructor used her internet-connected laptop. During the initial session, participants completed the Oxford Placement Test (OPT) to provide the instructor with more information on their English proficiency levels, facilitating the selection of level-appropriate texts. Students were also introduced to the course objectives, assignments, and textbook, *Focus on Vocabulary 1: Bridging Vocabulary,* published by Pearson Longman, from which the selected texts were extracted.

To cultivate algorithmic thinking, learners engaged with a structured, stepwise protocol for all textual analyses. The process of gist inference began with the examination of AI-generated lexical frequency clouds derived from a corpus of the target text. The visual salience of high-frequency terms enabled students to formulate initial predictive hypotheses, after which they could access contextualized examples or concordance lines by selecting individual words. Learners subsequently refined their predictions by integrating information from the text's title and accompanying visual elements. In parallel, they were guided to use structural discourse markers—such as transitional phrases and the thematic sentences commonly appearing at the openings and conclusions of paragraphs—to identify central arguments and overall coherence. This integrative approach promoted abstraction by allowing students to apprehend the macro-structure of the text without resorting to exhaustive line-by-line reading. All analyses were conducted collaboratively and culminated in the presentation of jointly constructed interpretations. The inherently sequential nature of the task design reinforced the pedagogical principle that progression through each unit depended on the successful completion of preceding steps.

Several tasks were systematically designed to cultivate students' evaluation abilities. To reinforce mastery of complex lexical items, learners first completed AI-generated gap-fill exercises that required the selection of contextually appropriate synonyms. They then engaged with AI-supported corpus analysis tools to collaboratively examine vocabulary across genres, analyze collocational patterns, and identify frequent synonymic alternatives using AI-generated lexical clouds. Within their groups, students critically assessed competing lexical options, selected the most contextually suitable forms, and articulated clear justifications for their decisions. Another activity required paraphrasing phrases or sentences containing target expressions. Here, learners jointly interpreted meanings using AI platforms such as ChatGPT and DeepSeek, consulting more proficient peers when necessary and cross-checking interpretations through online dictionaries and machine translation tools to ensure accuracy. Through these scaffolded, multi-source evaluative tasks, students developed a more robust capacity to critically appraise linguistic information, synthesize evidence from multiple digital resources, and construct well-reasoned optimal solutions.

Students developed generalization skills by transferring acquired summarization strategies to new textual contexts. The process began with individual activation of prior knowledge, during which learners articulated their existing conceptions of effective summarization. The instructor subsequently provided comprehensive instructional materials, including demonstration videos that illustrated the stages of summarization through concrete examples. Drawing on these resources, students collaborated to produce summaries of assigned texts, deliberately incorporating skills developed in earlier sessions. This iterative cycle was repeated for each text, enabling learners to integrate insights from previous attempts and to refine their techniques based on peer and instructor feedback. Working in groups, students critically evaluated draft summaries before presenting finalized versions to the class, thereby engaging in reflective dialogue to deepen their metacognitive awareness. The course also included explicit training in the pedagogically informed use of AI tools. Learners used the free version of Grammarly to evaluate writing suggestions generated for their summaries and received instruction on crafting precise prompts for platforms such as ChatGPT, Grok, and DeepSeek. Importantly, they were trained to critically appraise AI-generated feedback, adopting or rejecting suggestions based on principled understandings of summarization conventions rather than relying on the tools uncritically. In subsequent sessions, students independently applied these competencies by using AI tools to refine their summaries prior to submission through the designated platform. This structured scaffolding progressively strengthened their ability to generalize summarization strategies while critically negotiating both human and AI-mediated feedback. Throughout the semester, students further enhanced their textual comprehension and task performance through sustained engagement with diverse digital resources, including AI-generated imagery and media, instructional videos, multimedia websites, online search engines, and AI-assisted corpus tools. This collaborative discovery process reinforced three core competencies: (1) Engagement, demonstrated through the formulation of informed predictions about textual themes (e.g., societal transformations affecting adolescents); (2) Practice, evidenced by the integration of AI-generated media to reconstruct narrative structures using chapter-specific vocabulary and expressions; and (3) Personalization, reflected in the analytical connections students made between textual content and their lived experiences, as well as in their ability to identify cultural parallels and divergences between the text and their own sociocultural contexts.

The collaborative language learning sequence unfolded across three structured phases: engagement, study, and activation (Harmer, 2012). In the engagement phase, students both mobilized prior knowledge and referred to the AI-generated relevant content in their pairs and groups to formulate initial thematic hypotheses and establish a shared conceptual orientation. During the study phase, groups collectively integrated AI-supported multimedia resources and textual inputs to construct coherent and contextually grounded narratives. In the activation phase, learners personalized the content by articulating connections between academic themes and real-world applications and by engaging in comparative cultural analysis. All thematic materials were intentionally aligned with learners' linguistic proficiency levels and cultural backgrounds to ensure both accessibility and cognitive challenge. This multimodal instructional design—combining AI-enhanced resources with collaborative learning—promoted deeper textual comprehension while simultaneously fostering adaptable digital literacy skills transferable to broader academic and communicative contexts.

Notably, learners first engaged in abstraction to predict text genres and identify central ideas before activating three core competencies central to the instructional design. Algorithmic thinking was operationalized through adherence to structured, sequential task-completion procedures; collaboration supported the joint implementation of concepts and the co-construction of required outputs, and evaluation was enacted through the use of AI tools and corpus-assisted resources to refine, verify, and optimize responses. This integrated framework enabled students to interact systematically with a range of reading comprehension tasks. Throughout the course, learners practiced essential strategies—including skimming, scanning, paraphrasing, and summarizing—while simultaneously developing more targeted analytic skills, such as tracing pronoun references, predicting subsequent paragraph content, and applying generalization techniques to parallel tasks across chapters. In completing these activities, students relied on collaborative problem-solving processes and AI-assisted platforms to verify interpretations, refine solution quality, and enhance the final outputs they produced. Collectively, these practices illustrate the coordinated deployment of cognitive, social, and technological resources across their learning trajectory. Table 1 presents representative classroom activities, the AI tools employed, and the corresponding critical thinking skills activated during task performance. Table 1 summarizes the procedure followed in the class.

Table 1. CTsCALL activities in AILT

Activities/AI (assisted) (corpus) tools	CT skills
Identifying the **main idea**/the **genre** of the text (VERSATILE)	**Abstraction:** Identifying the overarching topic of a text by interpreting AI-generated word-frequency clouds and selectively consulting only the sentences associated with high-frequency terms, rather than engaging in a full, detailed reading of the entire passage. **Algorithmic Thinking:** Applying a structured, sequential procedure for genre identification tasks, this began with exposure to multimodal instructional materials—introducing various genres alongside AI-generated images exemplifying each—followed by an examination of complete sentences containing the most frequent words highlighted in AI-generated lexical clouds, enabling students to infer the appropriate genre.
Eliciting the new related vocabulary (Steve.ai, PIXLR, Canva, Fotor, and other similar tools/ ChatGPT/DeepSeek/Grok/ Google search engine)	**Generalization:** Drawing on previously acquired vocabulary and relevant background knowledge to articulate informed perspectives on the topic and extend understanding to new but related contexts. **Collaboration:** Engaging jointly with peers and AI-based tools to co-construct topic-related lexical sets or generate vocabulary needed for interpreting and producing AI-generated multimodal content.
Finding responses for a variety of reading comprehension check questions (Murf and similar tools to change the target texts to audio/Twee and similar tools/ ChatGPT/DeepSeek)	**Algorithmic Thinking:** Implementing a structured sequence of comprehension strategies to systematically locate and verify answers within the text, with each procedural step logically preparing the ground for the next. **Generalization:** Transferring and applying previously learned concepts to new items by identifying salient lexical cues in question stems, isolating target terms within the passage, and attending to negation, modifiers, and concluding signals in order to formulate accurate, evidence-based responses collaboratively. **Collaboration:** Engaging in coordinated group problem-solving by consulting diverse AI-based resources and jointly constructing responses, followed by using AI-generated audio models to refine pronunciation and ensure accurate oral reporting of the final answer.

Continue

Table 1. Continued

Activities/AI (assisted) (corpus) tools	CT skills
Reinforcing mastery of the complex vocabulary/phrases (Twee and similar AI tools, CorpusMate.com, Skell, Netspeak/ChatGPT/DeepSeek)	**Algorithmic Thinking:** Engaging in a systematic, step-wise procedure to interpret vocabulary, beginning with dictionary definitions and illustrative examples, followed by the examination of collocations, synonyms, and word-cloud–generated semantic associations via AI tools, and culminating in the contextual verification of meanings within AI-generated stems from platforms such as Twee and related resources. **Generalization:** Identifying recurring lexical and semantic patterns across examples and collocational structures and drawing on the identified patterns in similar tasks. **Collaboration:** Working cooperatively with group members while strategically integrating insights from multiple AI tools to reach a well-reasoned, shared response. **Evaluation:** Critically assessing input from various AI resources, cross-checking interpretations with more proficient peers when needed, and verifying the appropriateness of proposed answers through additional AI-based validation.
Paraphrasing the complex phrases and sentences (ChatGPT/DeepSeek/Grok/Google Translate/Online dictionaries)	**Collaboration:** Engaging collaboratively within groups, integrating diverse digital tools, and exchanging ideas to co-construct the most accurate and contextually appropriate paraphrase. **Evaluation:** Critically appraising responses generated by AI tools, more proficient peers, Google Translate, and online dictionaries to determine the most accurate and effective solution.
Activating the new vocabulary by presenting a final story for the AI-generated media (Steve.ai, PIXLR, Canva, Fotor, and other similar tools/ChatGPT/DeepSeek/Grok/Google Translate	**Abstraction:** Synthesizing key insights and ideas from the texts and distilling them into simplified representations, while drawing connections to accompanying visual materials. **Generalization:** Applying previously acquired vocabulary, concepts, and structural knowledge to new contexts or tasks.
Producing written summaries of the texts (Grammarly, ChatGPT/DeepSeek)	**Algorithmic Thinking:** Following a structured, stepwise procedure as outlined in class instructional videos to systematically complete tasks. **Abstraction:** Synthesizing key insights and identifying the main points within the text to form a coherent understanding. **Evaluation:** Refining the final product by critically incorporating feedback from instructors, peers, and AI tools such as Grammarly, ChatGPT, or DeepSeek.

3.3. Data collection procedure

The researchers opted for unstructured interviews to collect rich and thick information for the study objective (Fusch & Ness, 2015), which have been reported to be the best approach when the researchers select a few cases for intensive inquiries (Merriam & Tisdell, 2015). Moreover, it can provide insight into participants' personal understandings, experiences, values, perspectives, opinions, and knowledge (Creswell & Poth, 2018). The researchers sent the participants written informed consent before collecting the data. A written informed consent explains the purpose of the study, why the participants were selected, and assures them that their information and personal information will remain confidential. This led us to change the names of the participants to pseudonyms. Table 2 presents the demographic information of participants aged 19 to 25, focusing on their language learning experience both in general and in relation to AI. The data indicate that participants possess 2 to 7 years of overall language learning experience, with a majority accumulating between 3 and 5 years, and their experience with AI-assisted language learning spans from 1 to 3 years.

Table 2. Participants' demographic information

Participants	Gender	Age	Language learning experience (years)	Language learning experience with AI (years)
P1	Female	20	3	2
P2	Female	21	5	3
P3	Female	22	7	3
P4	Female	22	3	1
P5	Female	21	4	3
P6	Female	19	5	2
P7	Female	25	7	2
P8	Female	19	5	2
P9	Female	21	4	2
P10	Female	22	3	1
P11	Female	19	2	2
P12	Female	19	3	3
P13	Female	21	3	2
P14	Female	22	6	3
P15	Female	22	4	2
P16	Female	21	4	2
P17	Female	21	4	3
P18	Female	22	5	2
P19	Female	21	3	2
P20	Female	22	5	2
P21	Female	19	5	1

As a next step, we developed eleven interview questions based on the CTs-CALL framework, and they were reviewed by three CALL experts to check their content validity. Before conducting interviews with the study participants, we assessed the face validity of the interview items with three individuals who were similar to the target population. This evaluation aimed to determine whether the items were comprehensible. The participants reported no challenges in understanding the questions and indicated that they did not encounter any problems with the content. The interviews were conducted in person and lasted for about 40 to 60 minutes. The interviews were held at the participants' convenience on different days. The questions were asked in their native language while trying to employ the original terms, i.e., algorithmic thinking, abstraction, collaboration, evaluation, and generalization in English. The interviews were recorded, transcribed, and translated into English by the second author. To ensure translation accuracy, the translated excerpts were reviewed by an expert with a good command of the linguistic and disciplinary context of the study. Revisions were made based on the expert's feedback to enhance the accuracy of the translations (Beaton et al., 2000).

To achieve data saturation, the researchers employed the following strategies:

- **Saturation Grid Method**: We compiled a list of topics and objects pertinent to the study, marking each object during the interviews to ensure comprehensive coverage of the subject matter (Brod et al., 2009).
- **Probing Questions**: We utilized probing questions to create a state of epoché, which aids in the quest for data saturation. This allows us for deeper exploration of participants' responses and facilitates a more thorough understanding of their perceptions (Bucic et al., 2010; cited in Fusch & Ness, 2015, p. 2).
- **Data Repetition**: We maintained the interviews until participants reiterated the same findings, thereby confirming that data saturation had been reached (Saunders et al., 2017).
- **Reanalyzing**: After data collection, we transcribed and analyzed the data employing both deductive and inductive methods. This dual approach enabled us to determine whether additional information, codes, or themes could be derived from each participant's responses. Once a new theme or code was identified, we continued data collection and reiterated the analysis process to ensure that no further findings could be elicited from the participant (Fusch & Ness, 2015).

3.4. Data analysis

The researchers employed thematic content analysis to examine the data, as this method facilitates meaningful analysis and identification of patterns aligned with the research objectives (Tesch, 1990). A deductive approach to thematic content analysis was chosen, enabling the generation of codes based on the phases of CTsCALL. To implement this approach, the researcher adapted the stages outlined by Braun and Clarke (2006). The first step involved transcribing the collected data to create a written record for analysis. Following transcription, the researchers read the data multiple times to become thoroughly familiar with its content. Due to the nature of the study and also the **objective,** which is not to explore unknown phenomena but to systematically examine how the predefined CT components were applied and manifested by language learners during AI-assisted language learning tasks, the researchers then adopted a deductive content analysis approach. They coded the themes according to the CTsCALL framework, which enabled them to "code data according to a pre-existing coding scheme that reflects the theoretical framework guiding the study, thereby ensuring that the analysis remains systematically anchored in the research question and the theoretical constructs under investigation (Fereday & Muir-Cochrane, 2006). Accordingly, relevant codes were generated based on the identified themes, which were subsequently categorized into their respective sections, with appropriate names assigned to each theme. After generating the codes, the researchers reviewed them to ensure their relevance and coherence. A thorough review and re-checking of the entire process was conducted to confirm the reliability of the findings. Finally, the researcher reported the findings in a structured manner, detailing the insights gained from the analysis.

3.4.1. Trustworthiness. To assess the trustworthiness of the study's results, the researchers adhered to four criteria: credibility, transferability, confirmability, and dependability, as outlined by Lincoln et al. (1985). The second author conducted interview sessions with participants until data saturation was reached, yielding consistent results across interviews (Saunders et al., 2017). As noted by Fraenkel and Wallen (2006), ensuring credibility requires that researchers extend data collection over an extended period to allow participants to provide clear and considered responses or to gather data from varied contexts. For transferability, cross-case sampling was employed, allowing for the inclusion of participants with diverse language learning experiences both with and without AI (Ary et al., 2013).

In terms of confirmability, findings and study data were rigorously checked by two additional researchers. The second author also implemented member checking (Creswell & Poth, 2018) by inviting participants to review the study's results and patterns to determine whether these aligned with their perceptions; if discrepancies were identified, participants were encouraged to provide further information. Additionally, participants expressed their views through open-ended responses, which were subsequently re-evaluated and analyzed by the researcher to ensure the dependability of the findings.

4. Findings

Our content analysis highlighted the role of CTsCALL and its subcomponents in facilitating language learning among language learners in the context of AILL. The initial components appeared to relate differently to various aspects of language acquisition, as perceived by the participants.

4.1. Abstraction

Based on the content analysis, several participants indicated that the abstraction phase of CTsCALL appeared to support them in achieving **quicker responses** while addressing challenges with AI. P1 articulated this benefit by stating, *"Focusing on the big picture rather than details is the most helpful technique for me, as it gives me a general overview, enabling me to navigate problems more efficiently."*

Moreover, this abstraction phase appeared to enhance learners' **motivation and L2 grit** in learning a second language. P2 expressed, *"I think, for what we are doing in the class, the big picture was perhaps more involved. It gives me motivation to continue and be more engaged with the material."* Additionally, one participant emphasized that abstraction facilitated more **straightforward decision-making**. P3 noted, *"I think when I receive general information, I can make decisions much more easily. I recognize my mistakes and, based on that, I can adjust my work, whether it concerns grammar, vocabulary, or summarization. To me, this approach is more effective."*

4.2. Generalization

Generalization has also been noted to enhance language **learners' confidence** in AILL, as illustrated by P6, who remarked, *"Sometimes when I solve a task with AI and days later the professor explains it in class, I feel confident that I already understood the concept, allowing me to use it more quickly and easily compared to those students who have not encountered it."*

P4 further emphasized the **motivational** aspect of this process, stating, "*It is very helpful to have some patterns to utilize later. You feel as though you are actively doing something, which is motivating. Moreover, having learned it previously reinforces your sense of progress."* In addition, participants reported **improvements in output quality** and **vocabulary knowledge** in their academic projects. For instance, P8 detailed their approach: "*Yes, I first defined all of these for AI. I instructed it to translate them into a dictionary for me. I requested the origin of the words, particularly for conjugated terms, because English lacks conjugated words. I mean, I want the root; if the word is a verb, I want the infinitive. If it's a conjugated adjective, I expect the base form (Padezh), presented as an entry. I also requested examples suitable for all language levels. For the examples provided, I asked it to adapt the new vocabulary for A1 level and higher, converting them into entries so that by clicking these words, I can access the new vocabulary in the context of previous examples."* Furthermore, the participants indicated that it can help their understanding of **grammatical** tasks in AILL. For example, P11 noted, "*In grammar, particularly. When I see a vocabulary item that has a preposition associated with it, the next time I encounter that vocabulary, I remember the preposition I am expected to use with it.*"

Through the process of generalization, learners reported enhanced **speed** in tackling various tasks. P19 expressed this sentiment by stating, "*It prevents a waste of time. I achieve what I want quickly. When I look at DeepThink, I recognize more of my mistakes and understand what led to my inability to arrive at the correct answer, as well as the process I followed in solving it with AI for that specific question."*

Having provided the **personal patterns** for language learners, generalization also provides the **authenticity gap** between traditional language classes and AI as well. For example, P9 reported that "*I usually have learnt better compared with when I've been in our classes. I mean, I remembered it more. I keep the history of my chat where I solve my problems with AI, and for another exercise, I open a new chat. If the exercise I want to ask AI is similar to the previous* *exercise I have solved with AI, I open that from the history and ask AI my question there, because it has a pattern and knows what I want."*

4.3. Evaluation

The evaluation skill within CTsCALL pertains to language learners' abilities to compare various responses provided by AI and select the most effective answer. According to our content analysis, this skill supports learners in cultivating their **innovation**. During the interview, P10 articulated, "*I always review every answer provided by AI because it helps you stand out from others; you learn things that others may not have noticed. These insights gradually enhance your language proficiency. For instance, focusing on details significantly improves language skills in tasks like summarizing. Rather than relying on vague statements, using precise language and incorporating key themes and supporting evidence demonstrates a deeper understanding and facilitates clearer communication."*

Furthermore, several participants addressed how it elevated the **reliability** of what they learned and solved with AI. For instance, the P2 reported that "*sometimes I grill it to see what it means. Sometimes I compare its response with others' opinions to see whether AI's response is new information or not it is old, because AI is based on a search engine.*" Moreover, it assists participants in having **multiple references.** For clarification, the P3 asserted that "*you compare your responses with one another to see the differences and ask AI about the reason, then it can provide you with several references.*"

4.4. Collaboration

As noted in the current study, collaboration is defined as language learners' ability to work cooperatively with AI to address their tasks. Thematic content analysis revealed that this collaboration provided learners with a ***broader perspective*** and enhanced **reliability** in their problem-solving efforts. For instance, P18 stated, "*Because I am working with AI, which connects to numerous websites and resources, I also discuss my ideas with friends who share similar views and my professor, who has been studying this field for twenty years. This collaborative approach broadens my perspective significantly*." Similarly, P17 mentioned, "*Many times, I have copied the exercise and asked AI to solve it. I then shared my responses with my friend to see whether she agreed with me*." Furthermore, P21 remarked, "*Due to the different viewpoints available, one person may provide an alternative response. AI is analogous; it offers a specific perspective, and the answer it provides may not align with my needs. Therefore, I must analyze its response and decide on my next steps based on the viewpoint from which it generated that answer."*

4.5. Algorithmic thinking

Algorithmic thinking is the skill employed by language learners to solve their problems with AI in a stepwise manner. Like generalization, the deductive content analysis showed that this skill can assist language learners in learning and solving their language problems with AI. In light of this, the findings showed that it assists learners to be **innovative problem solvers.** For example, **P10** claimed that *"I separated the ideas of the text and wrote my summary. My next step was to ask AI about my grammatical errors. Alternatively, I asked it to provide me with some vocabulary to replace the overused vocabulary in my text, so that my writing is not so dull. Although it may be time-consuming, it has enabled me to become more innovative in my writing."* It can also assist language learners to ***get more resources*** as they solve their problems with AI. In this regard, P11 reported that *"When I ask AI about the references, and it introduces me to some websites in response, this adds to my information; I get familiar with a good website to which I can refer in the next task, and this website is useful to me."*

Likewise, it assisted language learners to **feel the progress** while solving their language tasks via AI, particularly through algorithm thinking, since P3 said that *"I try to give AI my prompt in detail. Then I ask it to talk in a certain domain and in a specific way, and provide some examples, in an understandable manner. As I said, as Copilot improves itself, [it has gotten familiar with your personality.] Yes, it sets examples related to my own work. It uses examples concerning the areas it thinks I have a better feeling about."* Furthermore, P9 reported that *"I used AI as my language partner and asked it to solve my problems, such as writing the sentence step by step. It has a voice that it uses, though it is not that accurate, and most of the time, I use translators (apps) for the voice. It motivates me step by step very much," which* shows that it escalated language learners' **motivation**.

Having employed algorithmic thinking to solve problems using AI, learners gained a deeper understanding and enhanced clarity regarding complex concepts, as P16 reported that *"the adjective 'interested' is used with the verb 'be', 'to be interested in something/ doing something' is a pattern. It's more complicated for some verbs, like 'look forward to doing something'. One may use it wrongly with an infinitive. If I ask it about this pattern, it explains it very completely. It's not only about English. It is the same with even Russian, and I take note of these things one by one. Even if AI doesn't tell me about these, when AI has written a text or has offered me a suggestion, or has set an example/ sentence, I analyze these myself and take note of them, and then ask AI about them again. For example, I ask AI if the use of a certain preposition is right with a specific verb or not, and what the difference is when another preposition accompanies this verb."*

Language learners also indicated that utilizing AI for language tasks through algorithmic thinking can facilitate **meaningful language acquisition**. For instance, P5 remarked, *"For me, it has been more about my mental creativity to work on it more myself, because I have received new ideas that hadn't occurred to me at times. These ideas often revealed connections that I had not previously recognized."* It also assisted participants in **organizing** their language tasks for improved clarity. For example, P7 stated, *"I asked AI what vocabulary I could use as a replacement for certain words, or why a particular grammatical case is used. After asking the initial question, additional questions emerged, and I believe the steps are structured in this manner."*

Algorithmic thinking also enabled language learners to assess the **trustworthiness** of their solutions, whether they utilized AI or not. For clarification, P19 claimed, *"First, I read the material and look up vocabulary in dictionaries to familiarize myself with the terms. Then, if I feel I may have overlooked something or that my approach is not conventional, I ask AI about the general principles to determine whether my understanding aligns with what AI presents."*

In Figure 1, the thematic map derived from the content analysis is illustrated, which illustrates the main themes identified.

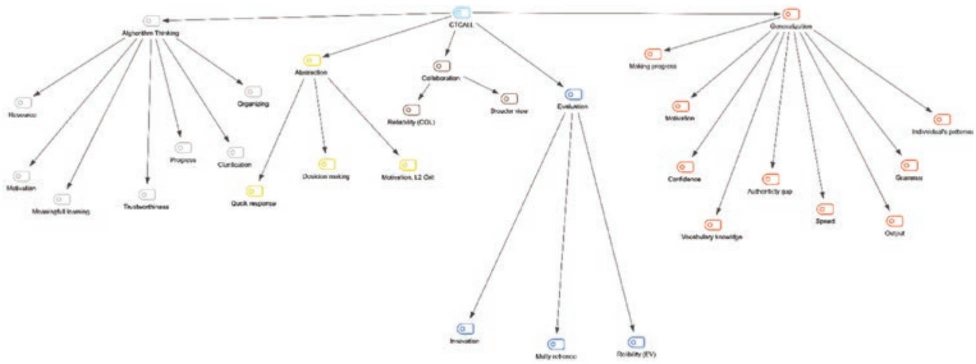

Figure 1. Thematic map codes

5. Discussion

The results of the deductive content analysis indicated how differently language learners perceived the role of CTsCALL and its subcomponents in their learning in AILL. The findings suggest that the abstract skills employed by language learners—specifically their ability to concentrate on key information rather than extraneous details—facilitated more efficient problem-solving in their language learning endeavours. This focus on essential information enabled learners to achieve quicker responses and make better decisions when addressing their language-related challenges through AI tools. To understand this phenomenon, learners can engage in abstraction, a process in which irrelevant details are filtered out, allowing them to identify core patterns within a given problem. By constructing a model that emphasizes "what" and "why," rather than being overwhelmed by the intricate details of "how," learners can effectively transition from specifics to generalities (Agbo et al., 2023; Jha & Tsai, 2026). As a result of this cognitive strategy, they can manage complex problems more effectively.

Moreover, it influenced language learners' motivation and their L2 grit, characterized by a high degree of interest and sustained effort. This finding builds on previous research regarding the role of abstraction skills in shaping psycholinguistic factors in language learners. Notably, Rahimi and Sevilla-Pavón (2025) reported that abstraction skills can provide support for learners' attitudes toward virtual exchange. Similarly, Rahimi and Faskhodi (2026) observed that abstraction and generalization skills in CTCALL can boost learners'

L2 motivation and their approaches to AILL. Our research extends and qualitatively validated these findings to encompass not only learners' motivation but also their L2 grit in CALL and AILL.

The findings also showed that generalization, where language learners can recognize patterns in problem-solving with AI and apply these patterns to various language tasks or contexts, showed that such recognition enhances their confidence and accelerates their solution processes, leading to improved outputs. This phenomenon may be attributed to an increase in problem-solving agility; as learners encounter new tasks, they no longer perceive them solely as challenges to be overcome. Instead, they begin to assess each new task in relation to previously solved problems, prompting reflections such as, "How does this compare to something I've already addressed?" This mindset facilitates the application and adaptation of existing solutions with greater efficiency (Chen et al., 2017).

More importantly, the findings suggested that, through generalization, learners developed transferable problem-solving patterns that they could apply to similar problems in novel contexts beyond those encountered during instruction. These findings indicate the potential of AI-assisted CTsCALL to help narrow the authenticity gap and foster learners' self-authenticity in technology-mediated language learning environment (Henry, 2013), as participants perceived that their previous language-learning experiences and instructional procedures had not equipped them with such capabilities. This finding may address concerns raised by researchers who suggest that AI promotes passive learning among students (Bauer et al., 2025; Crompton & Burke, 2024). However, it is not the technology itself that shapes the learning process; rather, it is how the technology is utilized that determines its effectiveness. The CTsCALL theory and its procedural framework, particularly generalization, provide a counterargument to these criticisms, where learners have their active algorithms to solve several similar problems with AI.

Similarly, the generalization was reported to support language learners to enhance their vocabulary and grammatical accuracy in AILL. These findings extend the previous studies that reported decomposition and abstraction can appear to assist language learners in acquiring grammar and writing (Yu et al., 2024). Now we extend those findings to vocabulary acquisition by leveraging generalization as another CT factor in language acquisition in AILL.

Another CTsCALL factor that assisted learners in their language learning in AILL was evaluation. According to content analysis, the more language learners evaluate AI responses and compare their feedback, the more they can solve their problems innovatively. This phenomenon may be attributed to the evaluation skills that language learners employ, which prevent them from blindly accepting information provided by AI. Instead, they engage in an active analysis of assumptions and limitations, demonstrating a *mindset oriented toward iterative refinement rather than a "one-and-done" approach*. Such critical engagement facilitates the incorporation of multiple references, thereby enhancing the reliability of their problem-solving processes with AI. This approach could be effective in addressing inaccuracies, hallucinations, and potential biases associated with AI, as highlighted by several researchers (Crompton & Burke, 2024; Zhai et al., 2024).

Similarly, the participants addressed that the collaboration skill in CTsCALL, where they collaboratively solve their language learning problems with AI and their classmates, supported them in addressing their language learning challenges. By collaboratively solving problems with AI and their peers, they achieved a broader perspective and enhanced reliability in AILL. This improved effectiveness may stem from the diverse perspectives brought into the processes of decomposition, abstraction, and design (Chen et al., 2026; Kong et al., 2018), which ensure that solutions are holistic, human-centric, and context-specific. Since individuals within the same context possess a deeper awareness of their specific needs than the AI, which lacks contextual presence. Consequently, AI feedback may inadvertently overlook the psychological needs of learners as well as their contexts, highlighting the importance of collaboration as part of CTsCALL in AILL. Thus, AI's brittleness can be patched by a mesh of human verification.

The last CTsCALL sub factor is algorithmic thinking, where language learners solve their language problems in a stepwise manner. According to the content analysis, this approach helps learners perceive their progress in problem-solving with AI, enhances their ability to organize challenges, and fosters greater innovation and trustworthiness in executing tasks. This might link to the deliberate and structured nature of algorithmic thinking. Rather than posing isolated questions to AI, learners are encouraged to develop a multi-step learning algorithm to attain their desired outcomes (Rahimi & Sevilla-Pavón, 2025). This strategy allows them to redefine their problems and reanalyse solutions not only with the assistance of one AI but also another one or in collaboration with peers and other human resources within the target context (Yu et al., 2024). Such interaction provides additional insights and critiques that may not be addressed by AI alone.

Additionally, language learners indicated that this skill could facilitate meaningful language acquisition and enhance their motivation. This finding aligns with the work of Parsazadeh et al. (2020), which found that computational thinking can improve language learners' performance and motivation in digital storytelling. However, our study expands on this by detailing how algorithmic thinking, as one of the components of CTsCALL, can positively influence language learners' ability to engage in meaningful learning within the context of AILL.

6. Study implications

Based on our findings, this study may have several theoretical and practical implications for applied linguistics, CALL, and AILL. Firstly, we adhered to the recommendations put forth by various pedagogical organizations, including ATC21S, OECD, EU, CSTA, ISTE, and IEA, advocating for the integration and development of 21st-century digital skills within classrooms at the forefront of AI and ICT. Additionally, we align with the recommendations of CALL scholars to extend teaching beyond mere language skills and sub-skills, striving to cultivate 21st-century digital competencies within the realms of CALL and applied linguistics (Rahimi & Daneshvar Ghorbani, 2025; Rahimi & Sevilla-Pavón, 2025; Rahimi & Faskhodi, 2026; Rahimi et al., 2026). We also acknowledge the suggestions made by key figures in CALL, who advocate for advancements in the field in light of the evolution of ICT, necessitating a new direction for CALL methodologies (Colpaert, 2020; Gimeno-Sanz, 2015). Furthermore, we consider the limitations noted by Rahimi and Sevilla-Pavón (2025) as they emphasize applying qualitative methodologies to validate the CTsCALL theory within applied linguistics and CALL to show that the heart of the 21st-century digital skills is not confined solely to STEM fields.

Our practical implications can be observed from micro, meso, and macro perspectives. From the micro perspective, we recommend that students refrain from blindly accepting the outputs provided by AI. Instead, they should engage in solving academic problems through abstraction, algorithmic thinking, collaboration, and evaluative skills to achieve reliable results and address issues of AI inaccuracies and hallucinations. This approach enables students to generalize their learning and apply these strategies in similar contexts, ultimately fostering their problem-solving abilities with increased confidence, motivation, and persistence in learning a second language (L2 grit).

The macro-level recommendation is to encourage language teachers to take proactive measures to avoid having passive learners who blindly follow or simply copy and paste information provided by AI. By implementing the CTsCALL framework, educators can promote an active language learning process. Encouraging students to employ abstraction skills, and algorithm thinking by focusing on key information, identifying patterns, and collaborating enables them to harness the capabilities of AI more effectively. This approach transforms learners from passive consumers of information into active strategic directors of their own learning processes. Allowing AI to manage the myriad details and examples on demand permits learners to concentrate on higher-order tasks such as pattern recognition, comparative solution audits, strategic planning, and problem-solving. Consequently, this not only cultivates active language learners but also develops them into adept problem solvers capable of collaborating effectively. Students become more proficient in identifying multi-referencing sources, assessing trustworthiness, and generalizing knowledge across various language tasks. This leads to accelerated progress and enhanced language use, as evidenced by improved decision-making and a more meaningful approach to language education.

At a meso level, we recommend that stakeholders and pedagogical experts reconsider the perception of AI as merely an instrument that fosters passive language learning among students. Instead, we advocate for an approach that challenges and transforms this view. To achieve this, stakeholders should encourage and support language teachers in adopting a problem-solving framework within their AILT, specifically through the incorporation of CTsCALL. This approach would actively engage learners in addressing their own challenges with AI, rather than encouraging them to rely passively on the solutions provided. Furthermore, in addition to establishing guidelines for language learners and educators on the integration of AI use in language classrooms, it is essential to leverage the latest approaches and skills, such as CTsCALL, to enhance the learning experience with AI and ICTs.

7. Conclusion

The objective of this qualitative study was to explore how language learners perceived and experienced the CTsCALL skill within AILL, which encompasses abstraction, generalization, evaluation, collaboration, and algorithmic thinking. As a result of these skills, participants were able to engage with AI more actively and strategically. To clarify, abstraction helped them make quicker decisions and sustained their motivation; generalization contributed to their confidence and efficiency while enabling the development of personalized learning patterns; evaluation supported innovative and critical engagement with AI-generated content; collaboration offered diverse perspectives that enhanced the reliability of their solutions; and algorithmic thinking provided a structured approach to problem-solving alongside a sustained sense of progress. Together, participants described these skills as helping them move from passive consumption of AI outputs toward more active, strategic engagement in their own learning processes. As a result of this study, a number of contributions have been made to the fields of CALL and applied linguistics. As a theoretical contribution, it provides empirical insights into how learners engage with the emerging CTsCALL framework, showing that it is perceived to be relevant beyond STEM fields. Practically, it offers qualitative accounts that may inform educators seeking to cultivate 21st-century digital skills and address challenges such as passive learning and AI hallucinations. In the era of artificial intelligence, frameworks like CTsCALL may play an important role in supporting language learners in developing the critical, analytical, and collaborative competencies necessary to engage with AI effectively and responsibly.

8. Study limitation

Despite providing valuable insights, it is important to note that this study is situated within a particular Iranian EFL context, which may limit its applicability to other educational settings. The majority of participants in the study were female, with all 21 interviewees being female, reflecting the demographic composition of the courses from which the sample was drawn. Consequently, the findings are primarily based on the experiences of female EFL learners. Future studies should explore the application of CTsCALL in a variety of EFL and ESL contexts to gain a better understanding of how it can assist learners in addressing their challenges related to the use of technology and artificial intelligence. Future research should investigate possible gender differences in CTsCALL's application and impact. The use of longitudinal approaches as well as case studies could provide additional insight into how CTsCALL supports language learners in navigating ongoing challenges associated with AI. By examining CTsCALL across a wide range of educational environments, a deeper understanding of its effectiveness will be gained. Finally, since the findings in this study were drawn exclusively from participants' insights during interviews, they may be constrained, and future studies might incorporate observations and diaries to complement self-reported data.

9. References

Adu, P. (2019). *A step-by-step guide to qualitative data coding*. Routledge.

Agbo, F. J., Olaleye, S. A., Bower, M., & Oyelere, S. S. (2023). Examining the relationships between students' perceptions of technology, pedagogy, and cognition: The case of immersive virtual reality mini games to foster computational thinking in higher education. *Smart Learning Environments*, *10*(1). https://doi.org/10.1186/s40561-023-00233-1

Ary, D., Jacobs, L. C., Irvine, C. K. S., & Walker, D. (2013). *Introduction to research in education*. Cengage Learning.

Bauer, E., Greiff, S., Graesser, A. C., Scheiter, K., & Sailer, M. (2025). Looking beyond the hype: Understanding the effects of AI on learning. *Educational Psychology Review*, *37*(2). https://doi.org/10.1007/s10648-025-10020-8

Beaton, D. E., Bombardier, C., Guillemin, F., & Ferraz, M. B. (2000). Guidelines for the process of cross-cultural adaptation of self-report measures. *Spine*, *25*(24), 3186–3191.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Brod, M., Tesler, L. E., & Christensen, T. L. (2009). Qualitative research and content validity: Developing best practices based on science and experience. *Quality of Life Research*, *18*(9), 1263–1278. https://doi.org/10.1007/s11136-009-9540-9

Chen, G., Shen, J., Barth-Cohen, L., Jiang, S., Huang, X., & Eltoukhy, M. (2017). Assessing elementary students' computational thinking in everyday reasoning and robotics programming. *Computers & Education*, *109*, 162–175. https://doi.org/10.1016/j.compedu.2017.03.001

Chen, Y., Zhang, X., Hu, L., Hwang, G.-J., Xie, H., & Tu, Y.-F. (2026). Incremental project-based robot programming: Effects on young children's computational thinking, executive function, and learning behavioral patterns. *Computers & Education*, *241*, 105471. https://doi.org/10.1016/j.compedu.2025.105471

Cheng, Y.-P., Tsai, C.-C., & Huang, C.-Y. (2023). Enhancing students' computational thinking skills with an SGQ strategy in problem-solving tasks. *Computers & Education*, Article 104794. https://doi.org/10.1016/j.compedu.2023.104794

Chevalier, M., Giang, C., Piatti, A., & Mondada, F. (2020). Fostering computational thinking through educational robotics: A model for creative computational problem solving. *International Journal of STEM Education*, *7*(1). https://doi.org/10.1186/s40594-020-00238-z

Colpaert, J. (2020). Editorial position paper: How virtual is your research? *Computer Assisted Language Learning*, *33*(7), 653–664. https://doi.org/10.1080/09588221.2020.1824059
Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches* (4th ed.). SAGE Publications.
Creswell, J. W., & Poth, C. N. (2018). *Qualitative inquiry and research design: Choosing among five approaches* (4th ed.). SAGE Publications.
Crompton, H., & Burke, D. (2024). The educational affordances and challenges of ChatGPT: State of the field. *TechTrends*, *68*(2), 380–392. https://doi.org/10.1007/s11528-024-00939-0
Durak, H. Y., Yilmaz, F. G. K., & Yilmaz, R. (2019). Computational thinking, programming self-efficacy, problem solving and experiences in the programming process conducted with robotic activities. *Contemporary Educational Technology*, *10*(2), 173–197. https://doi.org/10.30935/cet.554493
Edmonds, W. A., & Kennedy, T. D. (2016). *An applied guide to research designs: Quantitative, qualitative, and mixed methods.* SAGE publications.
Fraenkel, J. R., & Wallen, N. E. (2006). *How to design and evaluate research in education*. McGraw-Hill Companies.
Fereday, J., & Muir-Cochrane, E. (2006). Demonstrating rigor using thematic analysis: A hybrid approach of inductive and deductive coding and theme development. *International Journal of Qualitative Methods*, *5*(1), 80–92. https://doi.org/10.1177/160940690600500107
Fusch, P., & Ness, L. (2015). Are we there yet? Data saturation in qualitative research. *The Qualitative Report*. https://doi.org/10.46743/2160-3715/2015.2281
Gimeno-Sanz, A. (2015). Moving a step further from "integrative CALL". What's to come? *Computer Assisted Language Learning*, *29*(6), 1102–1115. https://doi.org/10.1080/09588221.2015.1103271
Harmer, J. (2012). *Essential teacher knowledge: Core concepts in English language teaching*. Longman.
Henry, A. (2013). Digital games and ELT: Bridging the authenticity gap. In E. Ushioda (Ed.), *International perspectives on motivation: Language learning and professional challenges* (pp. 133–155). Palgrave Macmillan. https://doi.org/10.1057/9781137000873_8
Israel-Fishelson, R., & Hershkovitz, A. (2022). Studying interrelations of computational thinking and creativity: A scoping review (2011–2020). *Computers & Education*, *176*, 104353. https://doi.org/10.1016/j.compedu.2021.104353
Jha, N. K., & Tsai, M.-J. (2026). Using machine learning approaches to predict Taiwanese eighth graders' computational thinking performance in ICILS 2023 study. *Computers in Human Behavior Reports*, *21*, 100896. https://doi.org/10.1016/j.chbr.2025.100896
Kong, S.-C., Chiu, M. M., & Lai, M. (2018). A study of primary school students' interest, collaboration attitude, and programming empowerment in computational thinking education. *Computers & Education*, *127*, 178–189. https://doi.org/10.1016/j.compedu.2018.08.026

Lei, H., Chiu, M. M., Li, F., Wang, X., & Geng, Y. (2020). Computational thinking and academic achievement: A meta-analysis among students. *Children and Youth Services Review*, *118*, Article 105439. https://doi.org/10.1016/j.childyouth.2020.105439

Leung, S. K. Y., Li, J. W., Ng, O.-L., & Wu, J. (2026). Applying computational thinking to facilitate children's mathematics learning through animation making. *Early Childhood Education Journal*. https://doi.org/10.1007/s10643-026-02176-x

Lincoln, Y. S., Guba, E. G., & Pilotta, J. J. (1985). Naturalistic inquiry. *International Journal of Intercultural Relations*, *9*(4), 438–439. https://doi.org/10.1016/0147-1767(85)90062-8

Liu, Z., Gearty, Z., Richard, E., Orrill, C. H., Kayumova, S., & Balasubramanian, R. (2024). Bringing computational thinking into classrooms: A systematic review on supporting teachers in integrating computational thinking into K-12 classrooms. *International Journal of STEM Education*, *11*, Article 51. https://doi.org/10.1186/s40594-024-00510-6

Merriam, S. B., & Tisdell, E. J. (2015). *Qualitative research: A guide to design and implementation*. John Wiley & Sons.

Parsazadeh, N., Cheng, P.-Y., Wu, T.-T., & Huang, Y.-M. (2020). Integrating computational thinking concept into digital storytelling to improve learners' motivation and performance. *Journal of Educational Computing Research*, *59*(3), 470–495. https://doi.org/10.1177/0735633120967315

Papert, S. (1980). *Mindstorms—Children, Computers and Powerful Ideas*. Basic Books, Inc.

Patton, M. Q. (2015). *Qualitative research and evaluation methods* (4th ed.). SAGE publication.

Rahimi, A. R. (2023). Beyond digital competence and language teaching skills: The bi-level factors associated with EFL teachers' 21st-century digital competence to cultivate 21st-century digital skills. *Education and Information Technologies*, *29*(8), 9061–9089. https://doi.org/10.1007/s10639-023-12171-z

Rahimi, A. R., & Daneshvar Ghorbani, B. (2025). Developing and validating the scale of language teachers' computational thinking competency in Computer Assisted Language Learning (LTCCTCALL): Empowering language teaching by cultivating the heart of the 21st-century digital skill. *Asian-Pacific Journal of Second and Foreign Language Education*, *10*(1). https://doi.org/10.1186/s40862-025-00353-w

Rahimi, A. R., & Faskhodi, A. A. (2026). Shaping AI-driven language learners' learning approaches, and motivation through computational thinking skills in computer-assisted language learning (CTCALL): A bisymmetric research design. *Smart Learning Environments*, *13*(1). https://doi.org/10.1186/s40561-026-00451-3

Rahimi, A. R., Gimeno-Sanz, A., & Sevilla-Pavón, A. (2026). Beyond language teaching skills: How to cultivate computational thinking skills through computer-assisted language learning. *The JALT CALL Journal*, *22*, 103651. https://doi.org/10.29140/jaltcall.2026.103651

Rahimi, A. R., & Sevilla-Pavón, A. (2025). Scaling up computational thinking skills in computer-assisted language learning (CTsCALL) and its fitness with language learners' intentions to use virtual exchange: A bi-symmetric approach. *Computers in Human Behavior Reports*, *17*, 100607. https://doi.org/10.1016/j.chbr.2025.100607

Rahimi, A. R., & Teimouri, R. (2025). Advancing language education with ChatGPT: A path to cultivate 21st-century digital skills. *Research Methods in Applied Linguistics*, *4*(2), 100218. https://doi.org/10.1016/j.rmal.2025.100218

Robledo-Castro, C., Castillo-Ossa, L. F., & Hederich-Martínez, C. (2025). Computational thinking training and its effects on working memory, flexibility, and inhibition: Randomized controlled trial in fifth-grade children. *Journal of Applied Developmental Psychology*, *100,* Article 101850. https://doi.org/10.1016/j.appdev.2025.101850

Rottenhofer, M., Kuka, L., Leitner, S., & Sabitzer, B. (2022). Using computational thinking to facilitate language learning: A survey of students' strategy use
in Austrian secondary schools. *IAFOR Journal of Education*, *10*(2). https://doi.org/10.22492/ije.10.2.03

Saunders, B., Sim, J., Kingstone, T., Baker, S., Waterfield, J., Bartlam, B., Burroughs, H., & Jinks, C. (2017). Saturation in qualitative research: Exploring its conceptualization and operationalization. *Quality Quantity*, *52*(4), 1893–1907. https://doi.org/10.1007/s11135-017-0574-8

Shimizutani, S., Taguchi, S., & Yamada, H. (2025). The impact of computer science education in primary schools: Evidence from a randomized controlled trial in Iraq. *PLOS One*, *20*(5), e0323166. https://doi.org/10.1371/journal.pone.0323166

Tang, X., Yin, Y., Lin, Q., Hadad, R., & Zhai, X. (2020). Assessing computational thinking: A systematic review of empirical studies. *Computers & Education*, *148*, Article 103798. https://doi.org/10.1016/j.compedu.2019.103798

Tesch, R. (1990) *Qualitative research: Analysis types and software tools.* Falmer.

Wing, J. M. (2006). Computational thinking. *Communications of the ACM, 49*(3), 33–35. https://doi.org/10.1145/1118178.1118215

Yu, X., Soto-Varela, R., & Gutiérrez-García, M. Á. (2024). How to learn and teach a foreign language through computational thinking: Suggestions based on a systematic review. *Thinking Skills and Creativity*, *52*, 101517. https://doi.org/10.1016/j.tsc.2024.101517

Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: A systematic review. *Smart Learning Environments, 11*(1). https://doi.org/10.1186/s40561-024-00316-7

Zhang, X., Chen, Y., Hu, L., Hwang, G.-J., & Tu, Y.-F. (2025). Developing preschool children's computational thinking and executive functions: Unplugged vs. robot programming activities. *International Journal of STEM Education*, *12*(1). https://doi.org/10.1186/s40594-024-00525-z