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# The development of a computational thinking model for KRG EFL learners

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## ABSTRACT

Computational thinking (CT) has become widely recognized as a critical skill for all learners, and there is growing interest in fostering CT as early as the comprehensive school level. Despite this recognition, there remains limited consensus on how CT skills should be measured in diverse educational contexts. This study adapts dimensions of CT identified in the existing literature and develops a scale to assess the computational thinking skills (CTS) of KRG EFL learners. The instrument, a five-point Likert scale with 29 items across five components, was administered to 450 undergraduate and associate degree students. Using exploratory factor analysis, confirmatory factor analysis, item distinctiveness studies, and reliability analyses, the scale was shown to be both valid and reliable for measuring CT among this population. Findings indicate that the instrument provides a trustworthy means to evaluate students' CT abilities and offers a basis for further pedagogical research and practice.

**KEYWORDS:** computer-mediated communication, computational thinking, pedagogical issues, teaching/learning strategies

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## 1. Introduction

Several publications and reports have discussed CT, but they do not fully agree on its definition or the factors that should be considered when developing or evaluating CT skills (Bubica & Boljat, 2018; Demir & Seferoglu, 2017; He et al., 2021; Saritepeci, 2019; Wing, 2014). Although numerous lists of CT skills exist, there is limited agreement on how these dimensions can be operationalized and measured across different contexts. Building on this gap, the present study aims to adapt CT dimensions identified in prior research and validate a scale for assessing the computational thinking skills of KRG EFL learners.

In this regard, the need is emphasized to prepare people for the future so they can use yet-to-be-invented future technology to solve problems that have not been encountered (Darling-Hammond, 2008). This is in line with Wing (2006), who contends that improvements in computer technology allow us to develop novel approaches to problem solving across all disciplines and test them in both the virtual and physical worlds. Wing (2006) adds that computational thinking is the problem-solving method used in the production of designs using technical equipment.

According to Wing (2006), 21st century skills are seen as crucial since they are capabilities that people should possess. This viewpoint is consistent with earlier findings, therefore studies concentrating on their acquisition, development, and evaluation may shed light on the problem. Computer Science (CS) is regarded as a crucial field in acquiring CT skills in this regard (Pellas & Peroutseas, 2016; Wang et al., 2022). Similarly, when research pertaining to the acquisition or development of CT abilities is investigated, it can be demonstrated that people's use of technology has an impact on CT skills (Durak-Yildiz & Saritepeci, 2018). Therefore, it can be said that CT is a vital tool for thinking, learning, and producing (Durak-Yildiz & Saritepeci 2018; Zhong et al. 2016). According to this viewpoint, it can be inferred that the concept of CT skill is closely related to technology use, including programming, design-based activities, and experiences obtained through information and communication technologies (Basogain et al. 2017; Lye & Koh 2014; Sartepeci 2017).

The earlier findings (Garc'a-Pen'alvo & Mendes, 2017) indicate the importance of programming training when evaluating studies on the development and acquisition of CT abilities. Although Wing (2008) argues that CT is not essential for solving everyday problems that do not include programming, programming training is crucial for the development and acquisition of this skill (Basogain et al., 2017; Saritepeci, 2019).

Several publications and reports have discussed CT, but they don't all agree on the same things, and there isn't a shared understanding of the factors that should be taken into consideration while developing or evaluating CT skills. There are numerous lists of CT skills that describe CT, but there isn't an integrated model with a common understanding of CT dimensions that can be applied to the development of CT skills. The objectives of this study will be to develop the model of CT for KRG EFL learners.

## 2. Review of literature

### 2.1 CT

Although it is not a new phenomenon, the CT term has become so widely popular that it has become the central topic of debates, and new regulations are being developed to encourage its adoption in educational settings. The phrase, first used by Papert in 1980, has gained popularity because of views advanced by Wing (2006, 2008), who said that CT is one of the fundamental skills—along with reading skills—that everyone should be able to master. Wing (2006) defined CT as a type of analytical thinking ability that comprises comprehending human behavior and seeing patterns connected to fundamental concepts for problem solving, building a system to address the issue, and computing knowledge utilizing CT based on CS concepts. After that, Wing (2014) amended this definition to read as follows: "a skill which incorporates thinking skills for conceiving and expressing solution(s) of a problem in a similar fashion that only a machine can perform." Like Lee et al. (2011), the term "CT" is frequently used to refer to a skill that involves determining whether an abstraction is valid by understanding a problem, defining it, and offering solutions, as well as by reasoning through some abstractions, understanding automation, and putting it into practice. From this vantage point, it is possible to argue that CT is an advanced way of thinking or unique problem-solving method where designs are created using digital technology to identify efficient answers to the challenges encountered (Aho, 2012; Heintz et al., 2018).

Wing (2008) added the following definitions to CT: 1. A conceptualization rather than a linguistic development process. As a result, the students are required to use several levels of abstract reasoning. CT is not limited to computer-based learning (Wing, 2008); 2. a rational process as opposed to merely mechanical repetition. People can therefore exercise their own knowledge through CT with greater flexibility; 3. a form of thinking unique to humans, not the calculation mode of a computer. Because people are smarter and more creative than computers, CT is the best way to solve human problems rather than simply mimicking computer thinking (Wing, 2008); 4. a combination of mathematical thinking and engineering thinking to extend the foundation of mathematics; 5. a finished product of thinking that aids in problem solving, managing daily behaviors, and developing communication and interpersonal skills; and; 6. The taxonomies of CT from the last ten years are described in the following part due to the fact that various academics have varied definitions and application techniques for the field.

It has been emphasized that people with CT skills must be able to develop strategies, using the power of digital methods to figure out, determine, and solve a problem. The standards are focused on technology usage in educational environments for teachers and students. To put it another way, CT makes it possible for people to solve issues in a manner comparable to that of a computer system (Egu'luz et al., 2018; Wang et al., 2022). Another definition of CT states that it is the knowledge, ability, and attitude that people must develop to effectively apply computer technology to real-world situations (Ozgen, 2015).

In this context, Chen et al. (2017) emphasize that CT includes breaking down problems into manageable pieces in order to solve them quickly, appropriately representing the problems, interpreting the data obtained, formulating algorithms toward solutions that can be implemented in a computer system, as well as taking into account the validity, effectiveness, and plausibility of these steps. The characteristics of a problem's solution can be described as (a) formulating the problems encountered with the aid of computers and other tools; (b) organizing and analyzing the data sensibly; (c) presenting the data through abstracting support such as models and simulations; (d) automating the solution via algorithmic thinking; (e) determining, resolving, and realizing possible solutions so as to provide a unified step for solutions; and (f) automating the solution.

According to the existing research (Basogain et al., 2012; Binkley et al., 2012; He et al., 2021; Sartepeci & Durak, 2017; Wang et al., 2022), computational thinking is the synthesis of algorithmic thinking, problem solving, creativity, critical thinking, and teamwork. Like this, the scale used to determine pupils' levels of CT competence includes sub-dimensions for algorithmic thinking, problem-solving, creativity, critical thinking, and cooperation. Such approaches may also support learners' strategic thinking and planning in digital contexts (Kannadhasan, 2025).

### 2.2 Empirical studies on CT

A survey of 17 of the 21 European countries revealed that several of them were attempting to include CT courses in their K–12 education curricula with relation to the development status of CT (Balanskat & Engelhardt, 2014). For instance, the UK has introduced a full suite of computer science, information technology, and digital literacy courses across all subject areas (Brown et al., 2014). However, not all nations incorporate computing into every topic.

An alternative to CT has been introduced in several nations. The primary causes are: 1. It is challenging for many teachers to modify the original curriculum and adapt to the new teaching content since they have been familiar with the teaching process and methods for a long time.

However, teachers must use new teaching strategies to increase students' enthusiasm in learning. 2. Teachers should use programming in many disciplines to increase the interest and level of success of the lower-achieving students to improve students' practical experience. 3. CT courses have grown in importance across several professions, and many instructors are starting to incorporate CT learning techniques into other courses (Angeli et al., 2016).

Australia's elementary and secondary school curricula now include a CT course, and CT training has been established as one of the country's official teaching courses (Falkner, Vivian, & Falkner, 2014). The DT course is described as a multidisciplinary course that encompasses such disciplines as English, mathematics, physics, and art in the original advocacy of integrating DT courses with CT courses. Children become accustomed to using technology to solve complicated issues and abstract concepts over several years, beginning with the foundational instruction of first grade and continuing through the program development classes of ninth grade (Armoni, 2012). Poland is yet another illustration, where in 1999 computer courses were split into three sections.

Students in elementary schools are first instructed in fundamental computer writing, drawing, and reading skills. Secondary school pupils are trained in computer computing, CT, and problem-solving skills at the second level. The computer course becomes one of the crucial subjects for the high school final exams by the third stage (Syso & Kwiatkowska, 2015). The fundamental objective of these three phases is to assist students in comprehending and analyzing issues, using computers or other technology to find solutions, and applying CT to society or their own lives.

A new curriculum for students has also been devised in South Korea. With more than 34 hours of computer classes in every grade from K–12, they began to promote computer education programs in 1971 (Heintz, Mannila, & Färnqvist, 2016). They first only concentrated on teaching computer theory and information science ideas, but eventually changed the curriculum to include instruction in digital literacy, computer science, and programming. As a country with a history of using textbooks as the basis for learning, South Korea similarly revised its student textbooks in 2018 (Heintz et al., 2016).

It is clear from the CT literature analysis that many countries currently consider it to be a crucial component of national education. Some nations have gone so far as to designate CT as a national program or to create new lesson plans and textbooks. Children are taught the skills of CT, independent thinking, and problem solving from an early age. CT may now be applied to other disciplines as well as to daily life and is no longer merely a standalone academic field or method of instruction.

The advantages of CT deployment have been extensively acknowledged by academics and educators, which bode well for the future study directions of CT. But it's more crucial to consider how to effectively promote CT learning activities (Denning, 2017). Denning (2017) also noted that as teachers were already accustomed to the traditional techniques of instruction, it was extremely challenging for them to change their course materials quickly. For instance, math professors are accustomed to employing formulas to solve mathematical issues. The child's learning task is to mimic the teacher's formula to produce the right response on the exam. This strategy, however, restricts the pupils' logical thinking and reasoning during the learning process.

Denning (2017) suggested two ways to aid educators and academics in looking at how the issue has been implemented. The educator's CT cognition is emphasized in the first step. Due to its accurate conception of CT, it can fully activate CT teaching activities. The following stage is to educate yourself on CT assessment techniques. Teachers can construct learning activities and alter their pedagogical approaches if they can accurately evaluate the efficacy of the students' CT. Teachers can assist students in completing learning assignments concurrently based on their academic achievement.

According to Heintz et al. (2016), CT is used in computer classes or other courses to teach students' CT in a variety of nations. Because different educational systems and cultures differ, it is challenging to replicate or imitate the CT development approaches. As a result, many nations have started to develop digital, coding, and CT abilities in primary education. The teachers who must instruct the children are, however, the key to implementing CT. In order for students to actively participate in the activities, develop their high-level thinking skills, and apply CT to other disciplines, the government must train the teachers on how to build CT activities and learning content (Orvalho, 2017).

According to the assessment of CT literature, many countries are still developing their CT implementation. However, a few performance-related issues, such as countries, learner ages, teaching methods, and learning efficacy, have not been fully addressed in previous studies. Therefore, in this study, we reviewed the relevant CT literature from 2006 to 2017 to understand the evolution and implementation of CT in education, including subjects, age groups, learning methodologies, and programming languages. Then, as a guide for upcoming study in this field, potential research trends and concerns are suggested.

## 3. Method

### 3.1. Participants

The participants in this study are divided into three distinct groups of learners, teachers, and experts on the topic, as explained below. This is because there are several sources of information for this study.

### 3.2. Student

A total of 462 KRG EFL students were initially recruited from several colleges in Iraq to participate in the study.

After screening for incomplete responses and excluding lower-level English learners who did not meet the study's inclusion criteria, the final sample consisted of 450 students (219 male, 231 female). Participants were enrolled in intermediate, upper-level, and advanced language courses and ranged in age from 18 to 32. This sampling was intentional, as CT requires students to be able to co-construct interaction in purposeful and meaningful ways that take into account sociocultural and pragmatic dimensions of language use (Nakatsuhara et al., 2018). Thus, beginner-level learners were excluded to ensure participants had sufficient language proficiency. The students all spoke Arabic as their native language.

**3.3. Teachers**

Ten teachers participated in the study as the main group of stakeholders and were asked to be questioned about how they saw the CT questionnaire, its many characteristics, and how they applied CT abilities in their classrooms. These teachers were chosen to participate in the interviews because their students took part in the study

**3.4. Experts**

An expert evaluation of the questionnaire was necessary to determine whether it was appropriate to accurately assess the CT skills; as a result, expert judgement was essential. Five experts in the field of CT who met the criteria (knowledge of CT and expertise in scale assessment and validation methods) took part in the study to offer their professional insight into the newly created questionnaire.

**3.5. Instruments**

Several instruments were employed in this study, including the newly developed questionnaire, survey questions, and semi-structured interviews, to gather information for the development of a CT model. Below is a detailed explanation of each instrument.

**3.5.1. The Newly Developed CT Questionnaire**

This questionnaire is devised with the aim of measuring CT skills of Iraqi EFL learners. It is a 5-point Likert scale ranging from "always" to "never' to assessing the programming experience of the participants, and the CT learning experience of the participants.

**3.5.2. Interviews**

Participants are subjected to a series of semi-structured interviews to accomplish the study's goals. The interviews take the form of individual sessions depending on the participants' availability. Several general questions on CT-related material are prepared prior to the interview. Future questions are proposed throughout the interview depending on the viewpoints and concepts of the participants. The replies of the participants will remain anonymous and confidential. The interviews are semi-structured and include some open-ended questions that were scheduled in advance as well as follow-up enquiries to help the respondents understand the purpose of the study. To provide a seamless interview process and a relaxed, comfortable setting, the interviews are done in the participants' native language (Arabic). The interview data are verbatim transcribed with the participants' pseudonyms. Then, using the main themes and sub-themes identified by the content analysis, the transcribed data are qualitatively analyzed. After being extracted, the key topics are then grouped together to create categories. A second expert in the field of study is given the transcripts and the identified themes to double-check the thematic analysis.

**3.6. Data collection and analysis procedure**

**3.6.1. Search Procedure**

Using search engines, a systematic literature study is carried out to establish the definitions and dimensions of CT and create a model for acquiring CT skills. SCOPUS serves as the database for the present study. Then, the database is searched for paper topics, abstracts, and keywords using the keyword computational thinking. Setting up the search criteria to find pertinent scholarly publications is the first step in the search process. The following search criteria are entered into search engine: The abstract must contain the search term "computational thinking," be fully accessible, peer-reviewed, and written in English. The following stage involves eliminating duplicate results and those that are not written with computer science education in focus. Articles without a distinct illustration of CT skills will thus be disregarded. The final step is to add the remaining articles to the qualitative analysis. The systematic article review procedure for the chosen articles consists of the following three steps. An analytical framework is first developed, which contains a reference name, model number and type, definition, and dimensions of CT, to acquire an overview of the dimensions and CT skills given in the articles. Secondly, a graph based on the model type and number is created to show the systematic descendancy of the CT models utilized in the publications. This graph connects scientific articles with similar CT dimensions and highlights the primary original articles that are primarily cited. Lastly, a comparison analysis of the information from the publications is done consequently. The dimensions of CT abilities are organized in a systematic way, and descriptions of the dimensions from different authors are merged before being used in a new model for developing CT skills.

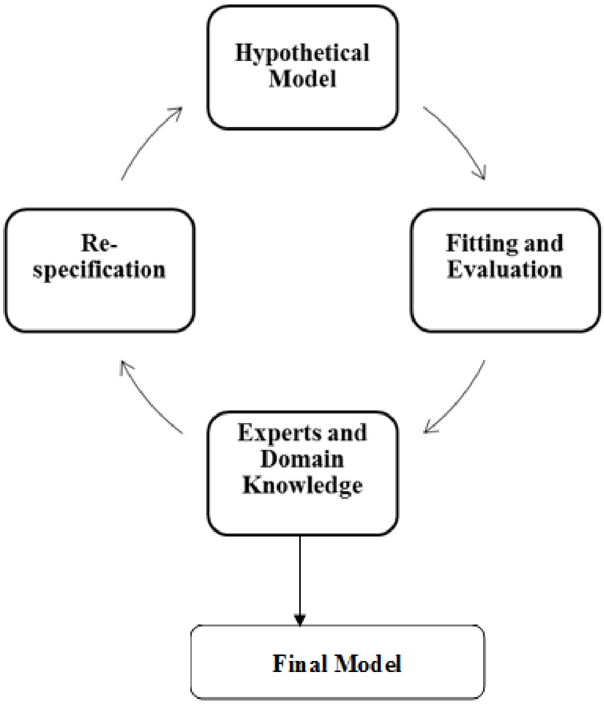


**Figure 1.** An iterative model validation

**3.6.2. Model development**

Although the dimensions of computational thinking (such as creativity, problem solving, critical thinking, algorithmic thinking, and cooperation) have been widely discussed in the literature, they have not been systematically validated within the context of KRG EFL learners. This study therefore adapts these existing dimensions into a measurement instrument and examines their validity and reliability in this new setting. Following the validation strategy outlined by Mulaik and Millsap (2000), the process included exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and model evaluation (Fig. 1). Exploratory Data Analysis (EDA) was used to identify latent variables that account for the variation in the data (Shultz & Whitney, 2005), while Confirmatory Data Analysis (CDA) tested the reliability and fit of the factor structure (Howitt & Cramer, 2000). Cronbach's alpha values were computed for the overall scale and each factor, ensuring strong internal consistency. This process allowed us to adapt well-established CT dimensions into a robust and context-sensitive scale for KRG EFL students).

Subject-matter experts (university professors) who are knowledgeable with CT and its theoretical foundations are interviewed to further support the conceptual relevance of the provisional model. The interviews are done according to a script designed to collect both general and detailed replies regarding the nature of CT and the aspects that can be grouped under its heading as constituent elements. Each interview is recorded, and the transcripts are then all reviewed for final content. The goal of this qualitative content analysis is to ascertain whether an alternative CT model can be created and whether the prospective categories that experts mentioned fit the categories that are created for the study.

The created items and tentative model are subjected to a second round of item assessment/reduction by 6 interview participants as the next stage of the instrument development process. This is done to give the instrument an analytical look. In fact, the goal at this stage is twofold: to obtain a second professional opinion on the model's component structure and to employ "experts' judgment" to determine item redundancy, clarity, and readability (Dornyei, 2003). This professional review of the tool improves it even more, and because certain duplicate items are eliminated at this stage, the resulting model is more condensed.

#### 3.6.3. Model Validation

For the second phase of the study, the validation procedure proceeded by distributing a total of 700 instruments to English students at centers of higher education in Iraq. Factor analysis (exploratory and confirmatory analysis) is conducted to validate the newly developed CT instrument.

## 4. Results

### 4.1. A proposed model of CT

As previously said, there has been limited progress in implementing the concept of CT, mostly due to a lack of agreement on its specific requirements. Consequently, the primary objective of the present study was to create a tool that aligns with a provisional framework of CT and its constituent elements.

In accordance with the established process for creating a measurement instrument that is both valid and reliable (Dornyei, 2003), we first conducted a thorough examination of relevant literature to identify any existing models of CT and/or its constituent parts. This literature review presented an initial version of the concepts and elements considered to be significant to critical thinking.

To be more precise, the review led to the collection of several CT categories and components, which would be used to create a temporary data-driven model of CT. To do this, a sequential process of item collecting, item arrangement, model construction, and model testing was implemented.

A comprehensive model was established, incorporating the training objective of CT and the studied literature. The model focuses on active learning as the primary goal and utilizes the cycle of discovery, design, and expression activities as the main teaching strategy. In this paradigm, the teacher's role consisted of suggesting tasks and helping and direction, while the students' role involved clarifying, altering, and improving upon those tasks (Figure 2).

Discovery practices play a crucial role at the start of learning activities and are essential for identifying harmless issues. To promote the use of discovery methods, teachers must create and distribute learning assignment sheets that align with the educational goals. Unlike conventional learning task sheets, these sheets not only contain the necessary information technology subject knowledge to answer the given problem, but also encompass other subject knowledge relevant to the problem. Subsequently, in accordance with the work sheets, pupils carry out previews prior to class. The professors assess the students' initial proficiency levels through these previews, engage in classroom discussions to establish progression and authentic problem scenario, and subsequently assist the students in resolving the actual challenge. The objective of this approach is to facilitate teachers in comprehending learning scenarios through self-examination prior to class, as well as fostering students' inclination towards independent learning and problem recognition.

The primary objective of design practices is to enhance the problem-solving skills of learners. Firstly, teachers must instruct students in the process of breaking down problems that demand resolution and employing interdisciplinary knowledge to create solutions. Furthermore, teachers must arrange teams to do research, implement innovative learning methods, and facilitate the sharing and exchange of ideas. Subsequently, they are responsible for guiding students to enhance their solutions. If the solutions are ineffective in resolving the issues, the students must revert back to the stage of breaking down the challenge, repeat the process of designing, and generate fresh answers through investigation and practical application.

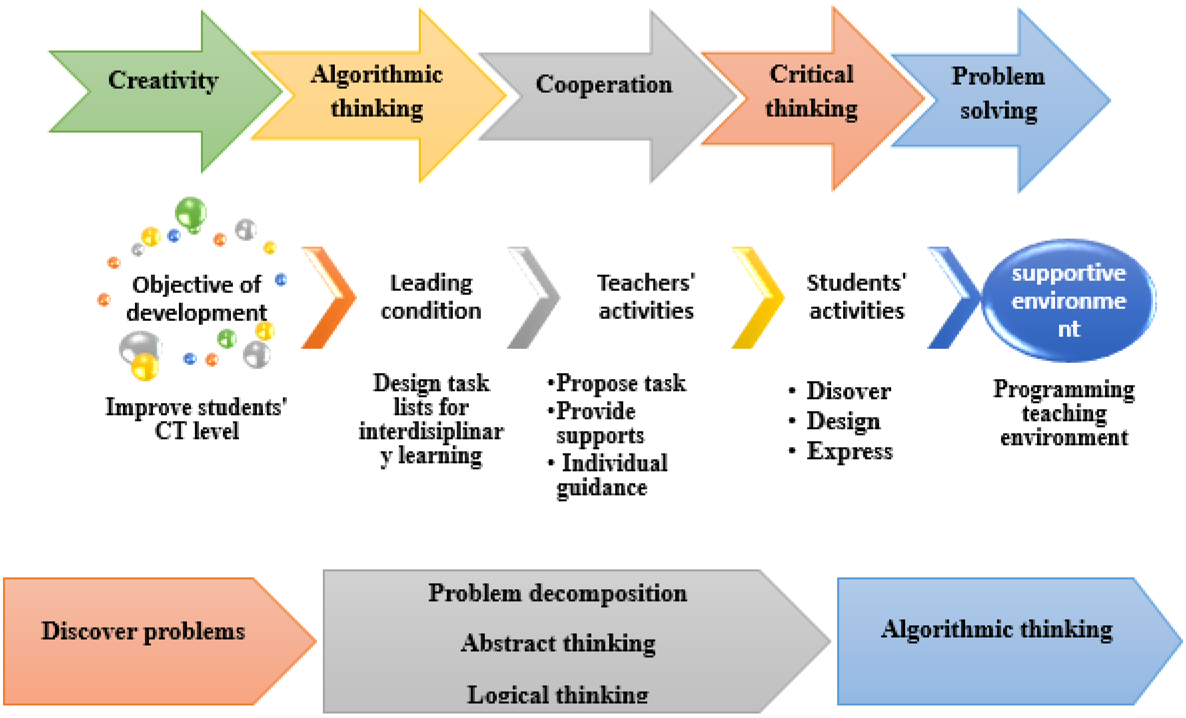


**Figure 2.** Validated Five-Factor Model of Computational Thinking for KRG EFL Learners.

### 4.1.1 Creativity

This component encompasses the items that pertain to a cognitive process in which humans must establish novel connections among preexisting concepts or ideas, as well as new ones, within a specific context (Jackson et al., 2012). According to Jackson et al. (2012), creativity is closely associated with critical thinking (CT). CT helps individuals enhance their creativity by allowing them to not only contribute to society in a productive way but also avoid being passive consumers of technology (Mishra and Yadav 2013). CT, or creative thinking, is a fundamental skill that involves both originality and the ability to generate new ideas by expanding upon existing ones.

### 4.1.2. Algorithmic thinking

This element is concerned with the capacity to properly identify and analyze an issue, devise an algorithm to solve the problem, critically evaluate the algorithm, and improve its quality (Futschek 2006). According to Choi et al. (2017), CT involves the process of abstracting, which means creating algorithms to analyze problems and automate processes. These algorithms are specifically meant to be executed by computers.

### 4.1.3. Cooperation

This component includes those items that deal with Skills can be defined as the ability to effectively communicate and collaborate with others to solve problems or accomplish shared objectives (Barr et al., 2011). According to Voogt et al. (2015), individuals who work together in a collaborative manner benefit more than those who adopt an individualistic approach. Cooperation is a crucial factor in teaching and strengthening CT abilities, as highlighted by Standl (2016).

### 4.1.4. Critical thinking

This component focuses on the requirement for individuals to apply critical thinking to solve real-life situations and acquire new information and skills (Wing 2006; Yılmaz et al. 2018). According to Korkmaz and colleagues (2017), critical thinking can be considered a key aspect of CT when it is actively used to solve a problem. A review of the literature has found that critical thinking and problem-solving skills are utilized to identify CT (DurakYildiz & Saritepeci 2018; Yadav et al. 2014).

#### 4.1.5. Problem solving

This component comprises elements that pertain to the application of concepts learned from past experiences to solve a problem (Patterson et al., 2017). Individuals must cultivate their abilities and competencies to apply them effectively in real-world scenarios, rather than merely possessing information and skills in the modern era (Choi et al., 2017).

**Table 1.:** *The list of the suggested components with their sample item(s) for each component*

| Component | Sample item |
|---|---|
| Creativity | I am confident in my ability to address any potential challenges that may arise in a novel environment. |
| Algorithmic thinking | I am capable of formulating a formula that will get the desired solution. |
| Cooperation | I get pleasure from engaging in collaborative problem-solving activities with my peers in the context of a group project. |
| Critical thinking | I possess an organized strategy when evaluating and making decisions between several choices. |
| Problem solving | I can generate numerous different options while carefully considering potential solutions for a given situation. |

To enhance the conceptual significance of our preliminary model, interviews were conducted with 12 domain experts who are well-versed in CT and its theoretical foundations. These experts include university professors and PhD students in the field of applied linguistics. The interviews, which varied in duration from 20 to 40 minutes, were carried out using a semi-structured interview aimed at obtaining both broad and specific responses regarding the concept of CT and its various components. The interviews were recorded using tape and subsequently transcribed for the purpose of final content analysis. The aim of this qualitative content analysis was to determine if an alternative CT model could be created and if the prospective categories mentioned by experts aligned with the ones we had established for the study. The interview results confirmed the validity of our model and did not introduce any novel themes or patterns to incorporate.

Throughout the subsequent phase of instrument development, the preliminary model and the created items (referred to as CT components) were subjected to a second round of evaluation and refinement. This process involved participants who agreed to thoroughly analyze the instrument throughout the interview phase. Our purpose in this stage was twofold: to obtain a second professional opinion on the composition of the model's components and to utilize specialists' judgment about item redundancy, clarity, and readability (Dornyei, 2003). This expert analysis refined the questionnaire and resulted in a more concise model by eliminating superfluous items that were still present at this stage. Furthermore, slight modifications were made to the phrasing of several questions, considering the experts' assessment of the items' clarity and readability. This was done to ensure that the instrument is ready for the future validation phase. The participants also prioritized the items by assessing their perceived level of significance to the corresponding factor.

A total of forty items were chosen to be included in the instrument, with seven items allocated to each component. The selection of these items was based on the frequency with which each item was deemed important by the experts. Subsequently, adhering to the conventional guidelines for constructing questionnaires (Brown, 2001; Dornyei, 2003), a 5-point Likert scale was selected, spanning from 'always' to 'never', to evaluate the critical thinking skills of Iraqi students. After completing the initial version of the questionnaire, it was provided to two applied linguistics professors who specialize in CT for the purpose of proofreading and evaluating its face validity. As a result, a few items underwent slight modifications in their phrasing. The measure was subsequently tested on 32 students, and the reliability of the questionnaire was assessed using Cronbach's alpha.81.

### 4.2. Quantitative analysis

#### 4.2.1. Scale validation

The validation procedure involved the distribution of 700 instruments to Iraqi EFL students. Both in-person and email techniques were utilized to distribute the instruments. A total of 462 instruments were filled out by the participants and subsequently returned to the researchers, resulting in a response rate of 65%. Upon initial examination, 12 of the finished instruments were rejected due to either being incomplete or carelessly filled out (such as questionnaires where one response was consistently chosen).

There is no universally accepted paradigm for constructing and evaluating models. Nevertheless, certain studies have suggested a more uniform method for implementing such a procedure. The current study utilized the validation scheme suggested by Mulaik and Millsap (2000), which involved the implementation of Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and model evaluation. For the sake of simplicity, we have divided our validation process into two main phases: Exploratory Data Analysis (EDA) and Confirmatory Data Analysis (CDA). Each phase consists of several well-established micro processes. Simultaneously, professionals utilized their opinions and domain knowledge to validate the reasonableness of the conclusions obtained at every stage of data analysis. The following is a concise and descriptive overview of our data analysis framework for the study.

**Table 2.:** Items of the instrument

| Component | Item |
|---|---|
| Creativity | 1. I respect individuals who possess a high level of certainty in the majority of their choices. |
| | 2. I appreciate individuals that possess a pragmatic and unbiased mindset. |
| | 3. I am confident in my ability to resolve the majority of challenges I encounter by dedicating enough time and exerting consistent effort. |
| | 4. I am confident in my ability to overcome any challenges that may arise when I face unfamiliar circumstances. |
| | 5. I am confident in my ability to implement the strategy effectively in order to resolve my problem. |
| | 6. My most significant projects materialize as a result of dreaming. |
| | 7. I rely on my senses and perceptions of accuracy and error when I tackle the resolution of a challenge. |
| | 8. When faced with a dilemma, I pause before moving on to another topic and carefully analyze the issue. |
| Algorithmic thinking | 9. I can quickly determine the fairness or fairness that will provide an answer to a situation. |
| | 10. I possess a distinct inclination towards the study and understanding of mathematical processes. |
| | 11. I prefer learning instructions that are presented using mathematical symbols and concepts, as I find it enhances my understanding. |
| | 12. I am confident in my ability to readily perceive the connection between the figures. |
| | 13. I can mathematically represent the various solutions to the difficulties I encounter in my everyday life. |
| | 14. I am capable of changing a mathematical issue that is described verbally into a digital format. |
| Cooperativity | 15. I enjoy engaging in collaborative learning with fellow students. |
| | 16. I believe that I will get more successful outcomes in cooperative learning due to the collaborative nature of group work. |
| | 17. I enjoy engaging in collaborative learning with other students to collectively tackle group projects and solve associated challenges. |
| | 18. Cooperative learning fosters the emergence of additional ideas. |
| Critical thinking | 19. I am excellent in formulating systematic strategies for resolving complex issues. |
| | 20. Attempting to tackle complex issues can be an enjoyable experience. |
| | 21. I am eager to acquire knowledge and skills in complex and demanding subjects. |
| | 22. I take pleasure in my ability to think with exceptional accuracy. |
| | 23. I employ a methodical approach while evaluating the available options and making a decision. |

| | |
|---|---|
| Problem solving | 24. I am experiencing difficulties in presenting the solution to a topic that I have been thinking. |
| | 25. I am facing difficulties in determining the appropriate usage and placement of variables, such as X and Y, when solving a problem. |
| | 26. I am unable to implement the solution that I have planned in a sequential and progressive manner. |
| | 27. I struggle to generate a multitude of alternatives when considering the potential approaches to solving a problem. |
| | 28. I am unable to generate original thoughts within the context of collaborative learning. |
| | 29. Engaging in cooperative learning with my group friends is mentally exhausting for me. |

#### 4.2.1.1. Phase 1 exploratory data analysis

Exploratory Data Analysis (EDA) is a method of examining data to develop hypotheses that are worth testing. It utilizes many strategies to gain the most insights from a dataset, reveal hidden patterns, and identify significant underlying components. As depicted in Figure 1, our analysis commenced with the process of data cleaning, wherein some questionnaires were manually excluded due to their incomplete and careless filling. This was followed by the computation of descriptive statistics. In addition to the descriptive statistics phase, cluster analysis, which involves dividing a data set into subsets or clusters that have similar characteristics, was performed. This step of the study has two objectives: firstly, to identify subgroups within the data, and secondly, to locate outlier cases that have remained after the data cleaning phase. The analysis is organized into two clusters: Fitting Data and Validation Data. These clusters serve as the foundation for the final step of the EDA, which is Exploratory Factor Analysis. During the exploratory phase, attempts were undertaken to identify the underlying variables that could account for a significant portion of the variability in the data (Shultz and Whitney, 2005).

#### 4.2.1.2. Phase 1 confirmatory data analysis

After the exploratory data analysis (EDA) phase, the model that was generated underwent additional expansion and validation in the succeeding confirmatory data analysis (CDA) step. Initially, a series of analyses were conducted to assess the reliability of the sum scale and each of the components obtained from the exploratory phase. This was done by calculating Cronbach's Alpha. Next, the Fitting Data, obtained from the previous step of clustering and EFA, was subjected to Confirmatory Factor Analysis (CFA), a technique for reducing data that determines the expected number of components in advance for the purpose of validating the model (Shultz and Whitney, 2005). The purpose of conducting a confirmatory factor analysis (CFA) is to ensure that the factor structure produced in the exploratory factor analysis is reliable and not influenced by random fluctuations in the data. (Howitt and Cramer, 2000: 329).

Ultimately, to impartially assess how well the model aligns with the data under examination, we utilized "Goodness of Fit Indices" (GFI) as heuristic measures for both Fitting and Validation. This was the final phase in our model evaluation/validation process. This encompassed the often-utilized indices for empirical evaluation of model fit, specifically tests of absolute fit and tests of incremental fit. This study utilized four commonly used absolute fit indices to assess the goodness of fit: the normed Chi Squared statistic (chi-square divided by the degrees of freedom), Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), and the relatively new Root Mean Square Error of Approximation (RMSEA). These indices provide a comprehensive evaluation of the fit, considering factors such as sample size and the accuracy of the approximation. The reason for using these three fit indices simultaneously is that there is no universally agreed criterion for evaluating model fit (Heubeck and Neill, 2000). The minimum threshold for model validation is 3 for the Chi-Squared statistics. The corresponding values for GFI, AGFI, and RMSEA are 0.9, 0.85, and 0.08, respectively (Sharma, 1996). Simultaneously, Incremental Fit Indices, such as Incremental Fit Index (IFI), Tucker-Lewis Index (TLI), and Comparative Fit Index (CFI), were produced to assess model fit. These indices have a cut-off value of >.9. It is recommended to use Incremental Fit Indices to measure model fit since they utilize more sophisticated computational matrices, resulting in more precise estimations for researchers (Smith and McMillan, 2001). Simply put, a model that surpasses these minimum acceptance thresholds can be considered a valid tool. In order to achieve such a model, it was necessary to use an iterative procedure (Fig. 1). If the resultant model is deemed satisfactory, it is considered the final model. However, if the model is not satisfactory, it should be respecified until the most satisfactory model is achieved.

### 4.2.3. Descriptive analysis and clustering

After confirming the absence of kurtosis, highly skewed distribution, bi-modality, or significant departures from a normal distribution, we employed Ward's Method to determine the optimal number of clusters in the dataset. The studies conducted using STATISTICA resulted in the identification of four unique clusters. These clusters exhibited a high level of association among its members within the same group, but a low level of association among individuals from different groups. Subsequently, the K-Means Method was employed to categorize the respondents into four distinct categories. Analysis of Variance (ANOVA) verified a statistically significant difference in means among the four clusters of analysis ($p < 0.01$), which consisted of 114, 93, 93, and 8 respondents, respectively.

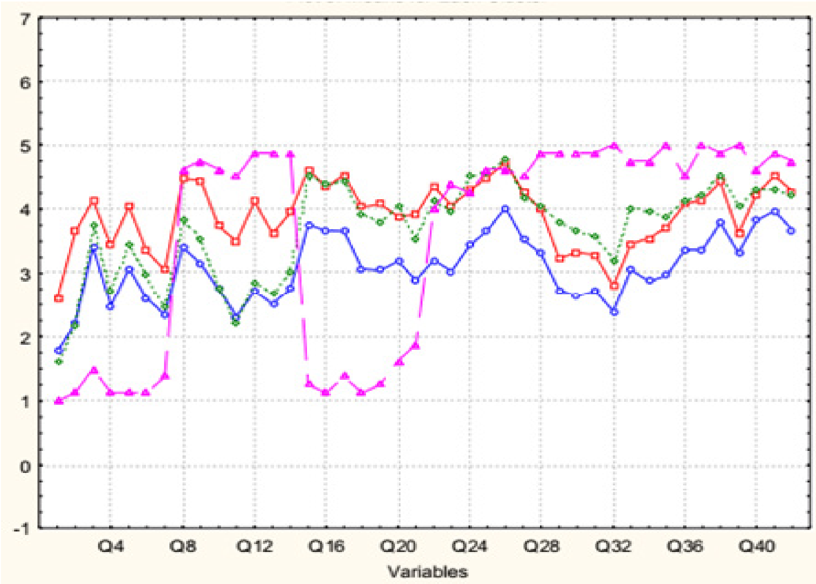


**Figure 3** Plot of means for each cluster over variables

However, according to Fig 4, cluster 4, consisting of 8 items, was significantly distant from the other clusters in terms of its relative mean across the indicators. The disparity is caused by the presence of outlier cases inside the cluster that have survived the cleaning stage. As a result, to improve the accuracy of the data, this group was eliminated. In the second stage, the validation and fitting datasets were created from the remaining three clusters for additional studies. Each cluster was randomly divided into two pieces with a ratio of 3:1. The initial portion of the 3 clusters were combined to form the Fitting Dataset, and model-fit analysis. The remaining subsets formed the Validation data, which included cases reserved as an independent sample for the final model-fit analysis.

#### 4.2.3.1. Exploratory factor analysis (EFA)

EFA is a statistical technique used to identify underlying factors or dimensions in a set of observed variables.
In the subsequent phase, to ascertain the presence of distinct variables related to reflective practice, the Fitting Data obtained from the previous clustering stage underwent Principal Components Factoring (PCF) using varimax rotation to determine any empirical support. Before doing this research, a determinant was produced to assess multicollinearity. The determinant value was found to be greater than 0.00001. This analysis also involved the use of KMO (Kaisor-Mayor-Olkin) as a metric. Furthermore, the Sampling Adequacy value of .84 and Bartlett's Test of Sphericity result of .0 were both statistically significant, suggesting that the data may be factored.

Principal Component Analysis (PCA) with varimax rotation was performed on the 29 items of the Fitting Dataset. The analysis resulted in the identification of 5 components with eigenvalues greater than one, which collectively accounted for 52% of the total variance. The scree test, developed by Cattell (1966), was employed to determine the optimal number of factors supported by the dataset. The test indicated that 5 components may be recovered. After analyzing the initial component, which has an eigenvalue of 10.3, we established a minimum item loading threshold of .45 as a cautious heuristic measure (Raubenheimer, 2004).

Subsequently, the acquired factor structure was thoroughly examined by engaging in systematic interaction with domain knowledge and expert opinions. The analysis of this stage revealed that all the factors identified were clearly distinguishable according to our preliminary model (Table 3). These factors include creativity (Factor 1 with 8 items explaining 24% of the variance), algorithmic thinking (Factor 2 with 6 items explaining 8% of the variance), cooperativity (Factor 3 with 4 items explaining 7% of the variance), critical thinking (Factor 4 with 5 items explaining 6% of the variance), and problem solving (Factor 5 with 6 items explaining 5% of the variance).

**Table 3** Exploratory factor analysis

| Item content | Exploratory factor analysis | | | | | |
|---|---|---|---|---|---|---|
| | | Critical thinking | Algorithmic thinking | Creativity | Cooperativity | Problem solving |
| Q1. | Creativity | | | .53 | | |
| Q2. | Creativity | | | .58 | | |
| Q3. | Creativity | | | .53 | | |
| Q4. | Creativity | | | .74 | | |
| Q5. | Creativity | | | .48 | | |
| Q6. | Creativity | | | .53 | | |
| Q7. | Creativity | | | .64 | | |
| Q8. | Creativity | | | .61 | | |
| Q9. | Algorithmic thinking | | .53 | | | |
| Q10. | Algorithmic thinking | | .72 | | | |
| Q11. | Algorithmic thinking | | .59 | | | |
| Q12. | Algorithmic thinking | | .77 | | | |
| Q13. | Algorithmic thinking | | .76 | | | |
| Q14. | Algorithmic thinking | | .70 | | | |
| Q15. | Cooperativity | | | | .65 | |
| Q16. | Cooperativity | | | | .63 | |
| Q17. | Cooperativity | | | | .56 | |
| Q18. | Cooperativity | | | | .54 | |
| Q19. | Critical thinking | .78 | | | | |
| Q20. | Critical thinking | .76 | | | | |
| Q21. | Critical thinking | .63 | | | | |
| Q22. | Critical thinking | .70 | | | | |
| Q23. | Critical thinking | .65 | | | | |
| Q24. | Problem solving | | | | | .78 |
| Q25. | Problem solving | | | | | .76 |
| Q26. | Problem solving | | | | | .63 |
| Q27. | Problem solving | | | | | .70 |
| Q28. | Problem solving | | | | | .65 |
| Q29. | Problem solving | | | | | .55 |

Factor loadings (Varimax Raw).
Extraction: Principal components.
(Marked loadings are >450,000).

**4.2.3.2. Confirmatory factor analysis**

The EFA results, supported by domain knowledge and experts' judgment, revealed a five-factor model of reflective practice retrieved from the Fitting Dataset. Therefore, it was necessary to validate this hypothetical model to establish its suitability as a reliable assessment tool for reflective teaching. At this point, because assumptions were established in advance about the quantity and characteristics of the hidden variables, Confirmatory Factor Analysis (CFA) was performed on the Fitting Data using STATISTICA. Before doing this analysis, the Cronbach's alpha coefficients were determined for the indicators of Creativity, Algorithmic thinking, Cooperativity, Critical thinking, and Problem solving. The resulting coefficients were .74, .73, .85, .83, .66, and .81, respectively. Figure 4 demonstrates that the Confirmatory Factor Analysis (CFA) supported a five-factor model consisting of Creativity, Algorithmic thinking, Cooperativity, Critical thinking and Problem-solving factors. In this model, all the connections between the indicators and the latent factors, as well as the relationships among the factors, were statistically significant at a significance level of 0.001 (p-value ≤ 0.001). As a result, we obtained a tool consisting of five components and 29 items to assess CT.

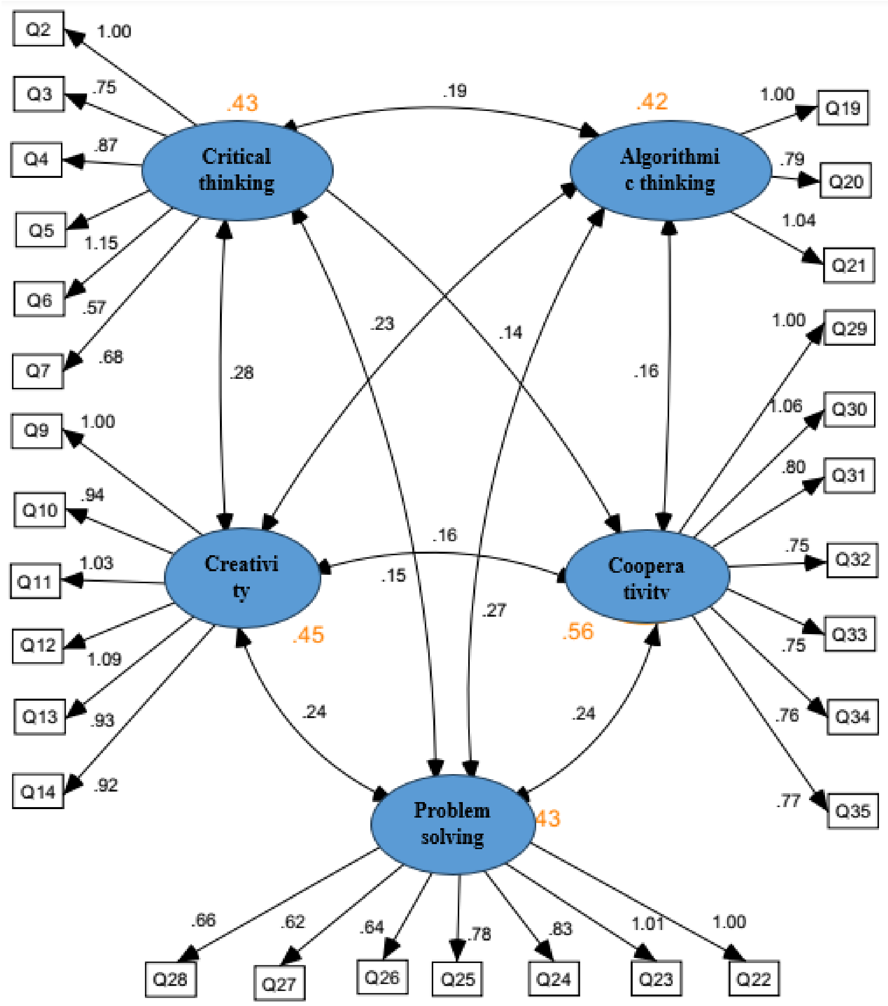


**Figure 4** The Confirmatory Factor Analysis (CFA)

To assess the adequacy of this hypothetical model in fitting the data, both the Fitting and Validation Datasets were subjected to model-fit analysis. The validation data is essential for this study because it was set aside during the clustering stage and has not been exposed to the supplied model before. However, to validate the findings, the Fitting Data, which has already undergone Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), was also included in this step of the fitting analysis.

**Table 4** Absolute and incremental fit indices for CFA model

| Dataset | Index | | | | | | |
|---|---|---|---|---|---|---|---|
| | Absolut fit indices | | | | Incremental fit indices | | |
| | Chi-Sq/DF | GFI | AGFI | RMSEA | IFI | TLI | CFI |
| Fitting dataset | 1.455 | .995 | .862 | .024 | .943 | .964 | .953 |
| Testing dataset | 1.432 | .886 | .870 | .042 | .867 | .854 | .863 |

Table 4 demonstrates that the assessment indices for both the Validation and Fitting Data exceeded the minimum cutoff criteria. Specifically, the normed Chi-Squared value was less than 3, the GFI, AGFI, and RMSEA values were greater than 0.9, 0.85, and 0.08 correspondingly, and the TLI and CFI values were greater than 0.9.

Although there was a small decline in the assessment indices of the Validation dataset, the model-fit estimates validate the agreement between the data and the CFA model. This, in turn, confirms the construct validity of the final version of the instrument for its intended purpose.

## 5. Discussion

This study aimed to develop and validate a model and instrument for assessing computational thinking (CT) abilities in English as a Foreign Language (EFL) learners. The proposed five-factor model—comprising algorithmic thinking, creativity, cooperation, critical thinking, and problem-solving—was evaluated through Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). The EFA confirmed the presence of all initial components, while the CFA provided statistical support for the five-factor structure, despite the exclusion of the moral component.

Contrary to expectations based on ISTE (2015), the analysis did not identify a separate communication factor. Instead, items related to communication were integrated into critical thinking, problem-solving, and cooperative learning. This finding aligns with recent research suggesting that communication skills are inherently embedded within these higher-order cognitive and collaborative skills (Liu et al., 2024).

Each of the five factors in our model can be summarized as follows:

**Creativity:** Defined as the ability to generate novel ideas and solutions, creativity supports scientific discovery and innovation (Craft, 2003; Aksoy, 2004). Recent studies also emphasize its central role in enhancing CT skills (Zhong et al., 2025).

**Algorithmic Thinking:** The capacity to comprehend, apply, evaluate, and create algorithms to solve problems effectively (Brown, 2015). Coding and robotics activities have been shown to strengthen algorithmic thinking (Yang et al., 2025).

**Critical Thinking:** The use of cognitive strategies to analyze, evaluate, and make reasoned decisions (Halpern, 1996). Teachers' understanding of CT assessment and its challenges plays a key role in fostering this skill (Sáez-López & Cózar-Gutiérrez, 2024).

**Problem Solving:** The process of overcoming obstacles to achieve desired goals, demonstrating adaptability and reasoning skills (Aksoy, 2004). Integrating CT into virtual laboratories has been found to improve students' problem-solving abilities (Alqahtani et al., 2024).

**Cooperation:** A learning approach that maximizes both individual and group outcomes through collaborative efforts (Veenman et al., 2002). Cooperative language exchanges have also been shown to enhance creativity, motivation, and intercultural competence (Wu & Lin, 2025).

These factors collectively represent the core skills of CT, which enhance human problem-solving abilities and support digital-age learning (ISTE, 2015; Wing, 2006; Barr, Harrison, & Conery, 2011). The findings align with prior work emphasizing the importance of introducing CT skills at school age (Barr et al., 2011; Brown, 2015). Based on the results of this study and the supporting literature, it is recommended that educational programs actively integrate activities aimed at developing creativity, algorithmic thinking, critical thinking, problem-solving, and cooperation. Regular engagement in these activities within a structured curriculum can foster the growth of CT skills and better prepare students for learning and problem-solving in the digital age.

## 6. Conclusion

Statistically, the CT scale developed in this study is a valid and reliable instrument for assessing learners' computational thinking abilities. This tool addresses a significant gap in the literature, as prior research has lacked a trustworthy and standardized measure for evaluating CT across diverse learners.

The relationship between CT scores and lexical diversity was also explored. The correlational analysis indicated no significant relationship between lexical diversity and CT, particularly in argumentative writing. These findings suggest that lexical diversity alone is not a suitable predictor of CT. Future research should investigate other components of writing—such as text length, genre variations, and topic differences—to determine their potential associations with CT and lexical diversity.

The study was conducted with a large sample of participants, which enhances the generalizability of the findings within the EFL learner population. Nevertheless, caution should be exercised when extending these results to populations with different characteristics or educational contexts.

The CT scale offers several practical advantages. It can be used in pretest settings to gauge the initial level of CT development in students who have not previously engaged in programming. It is suitable for large-scale screenings and for early identification of students with high abilities or special needs in programming tasks. Additionally, it allows for quantitative evaluation of the effectiveness of curricula or programs aimed at fostering CT, complementing the predominantly qualitative approaches in previous studies (Lye & Koh, 2014). Finally, this instrument has potential applications in academic and professional guidance, particularly for students pursuing STEM-related fields.

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