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Research Article

Computational thinking scale: the predictive role of metacognition in the context of higher order thinking skills

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Abstract

This study aims to determine the predictive role of cognition in computational thinking. In this context, the research has two problem situations. The first one is the development of a computational thinking scale for prospective teachers. The second is to determine the predictive role of metacognition in computational thinking with this scale. In Study-1, the computational thinking scale was developed with (N= 365) participants. In Study-2 (N=306), the role of metacognition in computational thinking was explained with structural equation modeling. These findings show that, the computational thinking scale consisting of 28 items in Study-1 explained 48% of the total variance with a single factor structure and the internal consistency coefficient was found to be .985. In Study-2, the role of metacognition in computational thinking was tested with structural equation modeling. Accordingly, the planning, debugging and procedural knowledge sub-dimensions of metacognition explained 47% of the variance of computational thinking.

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Introduction

Thinking skills are among the essential 21st century competencies for success today (Saad & Zainudin, 2022). We can classify those thinking skills, characterized by cognitive functioning, as high order and low order thinking skills. While low order thinking skills refer to routine mental activities, high-order thinking skills emphasize the multidimensional and elaborate operation of the mind (Newmann, 1988; Bloom et al., 1956). Students are expected to acquire these skills in their social or academic life. The thinking skills of teachers, who have the leading role in conveying these skills, are of critical importance (Zohar, 1999; Zain et al., 2022). Metacognition and computational thinking (CT), which are high-order thinking skills, are similar concepts (Yadav et al., 2022), and their interactions arouse curiosity. The purpose of this research to develop a CT scale for practicing and preservice teachers and to explore the role of metacognition, which is effective in teaching high-order skills (Hamzah et al., 2022) in CT is one of the 21st century competencies that improve teachers' teaching skills (Kim et al., 2019; Uzumcu & Bay, 2021).

High-order thinking skills

Thinking is a complex mental process (Umay & Arıol, 2011), and high-order thinking involves elaborate and ambiguous mental functions (Nguyễn & Nguyễn, 2017). Several approaches in the literature define high order thinking skills. For example, Bloom et al. (1956) proposed a classification of knowledge from basic to complex, just like the classification of plants and animals. In their taxonomy, knowledge, comprehension, and application are low level steps, while analysis,

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synthesis, and evaluation are high level steps (Pegg, 2010). Newmann (1988) explains the distinction between high level and low level thinking: low level thinking covers routine tasks that do not require intellectual endeavor, and high order thinking is used for tasks that challenge the mind, such as analyzing, interpreting, and problem solving. According to another definition, high-order thinking is characterized by ambiguity and complex thinking and reflection, offering different solutions or criteria (Resnick, 1987).

The recent changes in information, technology, and interactions emphasize the significance of high order thinking skills (Rabadi & Selam, 2018; Meng et al., 2020). Using high order thinking skills in teaching offers effective learning environments for learners (Atkinson, 2000). In this regard, teacher training is a central issue. Practicing and prospective teachers' advanced higher-order thinking skills have direct and indirect effects on both their and students' professional development (Bravo et al., 2016; Husamah et al., 2018).

High order thinking skills are also featured in certain skills. Among such skills are creative, critical, reflective, problem-solving, and metacognitive (Ananadou & Claro, 2009; Brookhart, 2010; Canas et al., 2017; Husamah et al., 2018). Also being a skill on its own, creativity can also be combined with other competencies, for example creative thinking, creative problem solving (Casakin et al., 2010), and creative reading (Yurdakal, 2019). Creative thinking, defined as unique thinking for new and better outcomes (Lee, 2005), is one of the high order thinking skills can be observed through performance-based outputs and innovative processes (Mumford et al., 2013). Another high order thinking skill, critical thinking, is considered an integral part of education (Miri et al., 2007; Stanger-Hall, 2012). Reflective thinking, a systematic and disciplined thinking endeavor (Göğüş et al., 2020), allows learners to analyze and evaluate their learning (Ghanizadeh, 2017). It refers to making a judgment after a throughout analysis of a problem (Eby & Kujawa, 1994; Rodgers, 2002; Lee, 2005).

High level cognitive abilities, which involve complex steps to arrive at a resolution, are often associated with problem solving. (Simamora & Saragih, 2019; Güner & Erbay, 2021). Although problem-solving is a practical skill when used separately, it can be applied to social, cognitive, or emotional problem situations. CT, frequently preferred in recent years, is a complex problem-solving skill as well (Wing, 2006), with a few different features from problem-solving (Pedaste et al., 2019). Those differences are related to the scope, dimension, and usage of CT.

Computational Thinking

Although CT is considered computer programming (Zhang & Nouri, 2019), it is chiefly characterized by problem-solving processes (Aho, 2012). Thus, it is described systematic problem solving skill that involves a number of strategies (Hooshyar et al., 2021). Considering extensive utilization of problem solving skills, this thinking skill can be effective in the solution of problems in branch courses such as science, mathematics, and social sciences (Bussaban & Waraporn, 2015; Knochel & Patton, 2015; Lu et al., 2022). Those technical and practical uses of CT have made it a popular competence integrated into the education system in various fields and methods (Tang et al., 2020). So, it is essential to address the scope and framework of CT correctly. CT is mainly applied in decomposition, abstraction, data, generalization, modeling, evaluation, algorithm, and debugging (Barr & Stephenson, 2011; Yadav et al., 2014; Kalelioglu et al., 2016; Rijo-García et al., 2022). As understood, CT is not a simple competence but requires high order thinking skills. It has been suggested that CT can be effective in students' acquisition and application of high order thinking skills (Tang et al., 2020). It also proves efficacious in nurturing creative and critical thinking abilities, both of which are considered advanced cognitive skills (Lee et al., 2022).

Metacognition

While cognition refers to understanding, remembering, and perceiving, metacognition is considered thoughts and awareness of these issues (Garner & Alexander, 1989). According to Flavell (1976), one of the leading figures in the field, metacognition includes cognitive processes and knowledge and regulation of these processes. Briefly described as cognitive awareness, metacognition is a high-order thinking skill (Ohtani & Hisasaka, 2018) as it requires individuals to plan, control, and evaluate the learning processes (Drmrod, 1990; Schraw & Dennison, 1994).

While cognitive functioning mostly has a single goal, metacognitive checks whether an appropriate cognitive pathway is chosen to achieve goals (Doğan et al., 2009). From this perspective, it can be inferred that individuals with metacognitive skills are competent in monitoring their cognitive processes with different methods (Meijer et al., 2006). According to Schraw & Dennison (1994), people with superior metacognitive skills are good at information planning and management, monitoring, debugging, and evaluating.

According to Flawell, metacognition significantly contributes to reading comprehension, concentration, memory, and problem solving (Flavell, 1979). According to Mayer (1998), metacognition significantly affects a person's learning also problem solving skill. At the same time making the thinking and learning processes effective, metacognition also interacts with other high order thinking skills, for instance critical thinking and problem solving (Hartman, 1998). In this sense, as high order thinking skills, metacognition and problem-solving are interrelated. Since that CT is considered a 21st century complex problem-solving skill, it is inevitably related to metacognition. Since CT is almost a new field, research on metacognition is minimal. In a study on the overlaps in CT metacognition, Yadav et al. (2022) revealed that CT could help develop students' metacognitive strategies. They discussed the content of metacognition under eight dimensions and two main headings: knowledge and regulation of cognition (Schraw & Dennison, 1994). The knowledge of cognition involves knowledge types. The processes of planning, monitoring, evaluation, debugging, and management are addressed in the regulation of cognition. Evaluation and debugging are both involved in CT. In this framework, the goal of this paper is to explore the predictive role of metacognition in CT. This research has two problems and was conducted as study1 and study2: *i. What are the validity and reliability studies of the computational thinking scale for prospective teachers? ii. According to the structural equation model, what is the predictive role of declarative knowledge, procedural knowledge, conditional knowledge, planning, monitoring, evaluation, debugging, and information management- components of metacognitive thinking in computational thinking?*

Method

Study 1

In Study 1, a scale for CT was developed using the survey method and its validity and reliability analyses were conducted.

Participants

The participants consisted of 365 pre-service teachers from 6 departments (Table 1) (classroom teaching, psychological counseling and guidance, special education teaching, preschool teaching, English teaching, Turkish teaching).

Table 1. Distribution of the participants

	Classroom Teaching	Psychological counseling and guidance	Special Education Teaching	Preschool Teaching	English Language Teaching	Turkish Teaching	Total
CT EFA	60	75	55	81	37		308
CT and Critical Thinking	34					23	57
Total							365

Why was a new scale needed?

There are several reasons for developing a new bid scale for pre-service teachers. The age groups of the CT scales developed in Turkey are at the middle school or high school level (Gülbahar et al., 2018; Yağcı, 2019; Kukul & Karataş, 2019; Karalar & Alpaslan, 2021). In the scales developed for teachers (Korkmaz et al., 2017; Dolmacı & Akhan, 2020), the current bid scale was needed because the subject content such as creativity, critical thinking, and collaborative work within the scope of the subject is not encountered in the international literature. In another scale developed for teachers (Ertugrul-Akyol, 2019), bid was directly included in the scale items as a concept, and robotics, coding and software were also included as subject content. In order for this scale to be used, teachers' readiness to use it requires them to know and internalize bid. Therefore, it would not be appropriate to apply it to teachers who are not conceptually familiar with the subject. For these reasons, a new bid scale was developed.

According to Devellis (2003), the development stages of the CT scale consist of eight stages. These are, respectively, identifying the construct to be measured, preparing the item pool, deciding on the scale form, ensuring language control, checking the items by an expert, ensuring item validity, applying the scale, evaluating the items and finalizing the scale. Accordingly, firstly, the structure of CT was examined with current studies and the most frequently used contents were determined (Wing, 2008; Brennan & Resnick, 2012; CSTA, 2017; Kukul and Karatas, 2019; Yağcı, 2019; Uzumcu & Bay, 2021; Tsai et al. 2022); these are decomposition, abstraction, model extraction or recognition, algorithm and evaluation, debugging.

While creating the item pool, current scale development studies and field research in this field were utilized. In this context, we generated a pool of 29 items using Likert type scale (with five point), including the topics of decomposition, abstraction, model extraction, evaluation, and debugging of CT (Table 2). These items were sent to two field experts, a measurement and evaluation expert, and a language expert for their opinions, and the relevant corrections were made.

Table 2 The item pool created for the CT Scale and the resources utilized

CT Topics	Order	Scale Items	Sources Utilized
Decomposition	2	I can break down a problem into its small parts.	Rıjke et al. (2018)
	3	I can understand the sub-headings of a problem.	Barr & Stephenson, (2011)
	4	I can see that a big problem consists of small problems.	Shute et al. (2017)
	17	I can break a problem into its parts in order to reach a solution.	Kukul & Karatas (2019)
	5	I can solve a problem more easily when I divide it into parts.	Selby & Woollard, (2013)
Abstraction	7	I can understand the important points of a problem.	Qian & Choi, (2022)
	8	I can understand the main topic of a problem without getting caught up in the details.	Cetin & Dubinsky, (2017)
	9	I do not get stuck in details when trying to understand a problem.	Wing, (2006)
	11	I can understand what the main problem is in a problem I encounter.	Gülbahar et al. (2018)
	13	I can understand the focus of a problem.	Tsai et al. (2022)
	14	I can distinguish the difference between a problem I have encountered and problems I have experienced before.	Wing, (2006) Wing, (2008)
Pattern extraction/	16	I can learn from a problem I have experienced.	Palts & Pedaste, (2020)
	18	When I encounter a problem, I can recognize whether it is similar to a problem I have experienced before.	Rich et al. (2021)
	28	I can use a solution that has worked for me before in different problems.	Calderon et al. (2015, July)
	19	I can find similar aspects of different problems I encounter.	Van Borkulo et al. (2021, October)
	20	I can benefit from my previous experiences when solving a problem.	Barrón-Estrada et al. (2022)
Algorithm	21	I try to find different ways to find a solution to a problem I encounter.	Choi et al. (2017)
	22	I know that the decisions I make will affect the decisions I will make.	Yağcı, (2019)
	6	I consider alternative solutions in the process of solving a problem.	Özmutlu et al. (2021)
	1	I consider both positive and negative consequences when making a decision in solving a problem.	Yağcı, (2019)
	23	I plan the tasks I will do in a problem step by step.	Gresse Von Wangenheım et al. (2019)
	24	I consider all kinds of possibilities in problems that I need to decide.	Tsai et al. (2022)
	10	When planning the solution of a problem, I calculate all the steps involved.	Shute et al. (2017)
Evaluation and debugging	25	When I look for a solution to a problem I encounter, I try to find the most effective solution.	Vourletsis et al. (2021)
	26	I can find the mistakes I made during the solution process of a problem I have experienced.	Fitzgerald et al. (2008)
	27	I check whether the solution I have developed for a problem I have encountered is correct or not.	Fitzgerald et al. (2008)
	15	I review the steps I take to reach the best solution in my problem solving processes.	Kim et al. (2018)
	12	When I search for a solution to a problem, if the solution I find does not work, I investigate why.	Yağcı, (2019)
	29	I check my planned steps in my problem solving process.	Tsai et al. (2022)

Validity and Reliability Studies of the Scale

The construct validity of the CT scale was firstly evaluated by two different field experts. Afterwards, EFA was conducted for the statistical validity study.

To determine the criterion based validity of the CTS, the "Marmara Critical Thinking Scale" (MTCS) developed by Özgenel and Çetin (2018) was applied to 57 students simultaneously with the CTS. Developed with 410 teachers, this scale has a 28-item, 5-point Likert-type, 6-factor structure. The Cronbach Alpha internal consistency coefficient value was calculated as .91 during the development/adaptation process of the MTCS. In this research, the Cronbach's Alpha value of MTCS was calculated as .96. Pearson product-moment correlation coefficient was calculated by performing correlation analysis to determine the relationship between the scores obtained with CTS and MTCS.

We computed item-total correlation coefficients using item analysis methods as part of the reliability assessment process. Item total correlation coefficients are expected to be higher than .30. In addition, lower-upper group item analysis was also conducted within the context of the investigation into reliability. In this analysis, the result of the comparison of the differences between the item mean scores of the lower 27% and upper 27% groups to the total scores of the test with the unrelated t-test is accepted as an indicator of the internal consistency of the scale. In addition, Cronbach Alpha coefficient, which is the consistency coefficient of the scale, was calculated.

Study 2

In Study 2, to determine the role of metacognition in CT, structural equation modeling was used in the correlational research type.

Participants

The participants consisted of 306 pre-service teachers studying in five different departments at a foundation university (Table 3).

Table 3 Distribution of participants of Study 2 according to departments

	Classroom Teaching	Psychological counseling and guidance	Special Education Teaching	Preschool Teaching	English Language Teaching	Total
CT CFA and MC	73	55	52	68	58	306

Data Collection Tools

For the purpose of Study 2, bid and metacognition scales will be used. For the Bid scale, a 28-item Likert-type, single-factor scale with a reliability coefficient of .985, developed with 365 pre-service teachers in Study 1, was used. For metacognition, the iteration of the metacognitive awareness inventory formulated by (Schraw & Dennison, 1994) and adapted into Turkish (Akın et al., 2007) was used in this study. The correlation between the original and the adapted version of the measurement tool, which was adapted with 607 students, was found to be .93. Accordingly, the inventory consists of 8 factors; declarative knowledge, procedural knowledge, conditional knowledge, planning, monitoring, evaluation, debugging, debugging, information management.

Data Analysis

The data obtained from 306 participants were tested with structural equation modeling to determine the role of metacognition in CT.

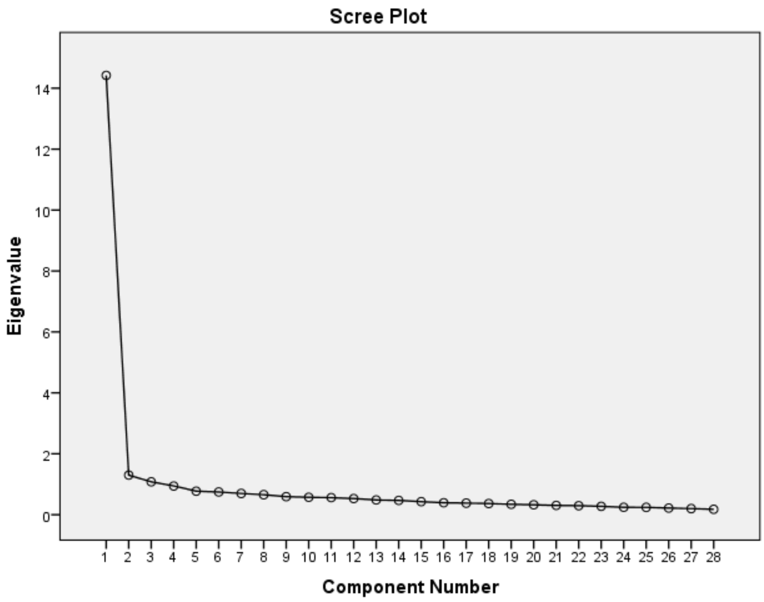
Results

Study-1

Development of Computational Thinking Scale: *Exploratory factor analysis*

An EFA (Exploratory Factor Analysis) was conducted to review the properties of the CTS draft. Since the sample size in a factor analysis should be ten times the number of items (Ho, 2006, Can, 2014; Büyüköztürk, 2011), the draft scale including 29 items was applied to 308 university students. The EFA results (KMO=.958, χ^2=5325.84 (df=406; p<0.001) showed that the sample size was adequate and there was a sufficient correlation between the variables to perform EFA (Tabachnick & Fidell, 2001; Can, 2014). Additionally, we determined that the scale had a 3-factor structure with an eigenvalue greater than 1, which explained approximately 56% of the variance. The first three factors are respectively explained approximately 46.7%, 5.9%, and 3.7% of the variance, respectively. Figure 1 shows the eigenvalues in more detail.

Figure 1 The Factors in CTS



As seen in Figure 1, the graph became more stable after the 1st factor, and the tool had a single-factor structure (the eigenvalue of the 1st factor was 13.5 while it was 1.7 for the 2nd factor) that explained approximately 46.71% of the variance. The factor load of the 9th item on the scale was .334, which was acceptable. It is knowns that if factor load values are above .45, item discrimination is considered high (Ho, 2006; Buyukozturk, 2011; Bayram, 2016). Since the discrimination power of other scale items was high, item 9 was removed from the scale, and EFA was performed again. In the second EFA [KMO=.960, χ^2=5211.46 (df=378; p<0.001)], it explained 48% of the variance. The factor loads obtained for each item are shown in Table 4 below.

Table 4 Factor loads for CTS items

Item No	Factor Load value	Item No	Factor Load value
m1	,551	m16	,558
m2	,684	m17	,781
m3	,626	m18	,678
m4	,562	m19	,717
m5	,629	m20	,720
m6	,715	m21	,732
m7	,718	m22	,674
m8	,554	m23	,732
m10	,675	m24	,754
m11	,751	m25	,733
m12	,581	m26	,730
m13	,739	m27	,772
m14	,701	m28	,737
m15	,742	m29	,758

As seen in Table 4, the highest factor loading value was .772, and the lowest value was .551 in EFA. It can be concluded that the items on the scale had a high level of discrimination. The Cronbach Alpha internal consistency coefficient was calculated as .98 in this study.

We computed item-total correlation coefficients as a measure of item reliability. If the item-total correlation coefficients are higher than .30, the discrimination power of the items is considered high (Ho, 2006; Büyüköztürk, 2011). Additionally, the scale scores were ordered from smallest to largest and extreme scores in each item were compared. Accordingly, the CTS scores obtained from two groups of 83 participants (27%) with lower and higher scores were measure the differences between the independent group t-test. The item analysis results are shown in Table 5 below.

Table 5 CTS item analysis results

Item No	Item-Total Correlation	The t-test for the Scores of the Extreme Groups
m1	,52	-8,06*
m2	,66	-13,47*
m3	,60	-12,36*
m4	,53	-10,69*
m5	,60	-9,06*
m6	,69	-12,45*
m7	,69	-14,08*
m8	,52	-10,33*
m10	,64	-17,30*
m11	,73	-17,54*
m12	,55	-10,34*
m13	,71	-16,19*
m14	,67	-14,67*
m15	,72	-14,81*
m16	,52	-10,66*
m17	,76	-14,69*
m18	,65	-12,50*
m19	,69	-13,45*
m20	,69	-13,23*
m21	,70	-15,10*
m22	,64	-12,02*
m23	,70	-13,56*
m24	,73	-16,56*
m25	,70	-13,88*
m26	,70	-14,97*
m27	,75	-15,85*
m28	,71	-12,24*
m29	,73	-13,70*

*p<.01

The highest correlation coefficient was .75, the lowest was .52, which proved that all items were similar and served the purpose of the scale (Table 5). The item analysis on extreme values revealed the CTS scores from the lower and upper groups as statistically significant (p< .01). Therefore, it was concluded that each item could distinguish the lower as well upper groups.

Criterion Validity

The relationship between CT and critical thinking was examined to determine the criterion based validity of the developed CTS. Studies have reported that CT and critical thinking are interrelated (Buckley, 2012; Doleck et al., 2017; He et al., 2021). The Pearson product-moment correlation coefficient was measured to define the correlation between the scores from the CTS and MCTDS. The analysis results suggested a positive, statistically significant correlation between CT and critical thinking. (r= .87; p<.01), which also proves the reliability of the CTS.

Study 2 Findings

What is the predictive role of metacognition, one of the high-order thinking skills, in computational thinking?

The mean scores, standard deviation, skewness, and kurtosis coefficients regarding participants' metacognitive awareness and CT were calculated and shown in Table 6 below.

Table 6 Descriptive statistics of variables

	N	Avg	Sd	Skewness	Kurtosis
Declarative knowledge,	306	3,90	0,63	-0,40	0,18
Procedural knowledge	306	3,81	0,66	-0,32	-0,02
Conditional knowledge	306	3,91	0,66	-0,53	0,39
Planning	306	3,78	0,65	-0,38	0,37
Monitoring	306	3,77	0,63	-0,35	0,12
Evaluation	306	3,83	0,65	-0,44	0,31
Debugging	306	3,88	0,64	-0,49	0,16
information management	306	3,79	0,61	-0,30	0,25
Metacognitive Awareness	306	3,83	0,56	-0,34	0,32
Computational Thinking	306	3,99	0,71	-0,96	0,98

As seen in Table 6, participants' metacognitive awareness level was 3.83 out of 5 (sd=0.56), and the CT level was 3.99 (sd=0.71). The kurtosis and skewness coefficients ranged between -1 and +1, which suggests that the variables did not deviate significantly from normality. Pearson correlation coefficients were calculated to determine the level of relationship between the scores and the variables. The results are shown in Table 7 below.

Table 7 Correlation analysis results

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Declarative knowledge (1)	-									
Procedural knowledge (2)	,773**	-								
Conditional knowledge (3)	,820**	,703**	-							
Planning (4)	,810**	,731**	,756**	-						
Monitoring (5)	,807**	,772**	,797**	,826**	-					
Evaluation (6)	,761**	,755**	,746**	,784**	,816**	-				
Debugging (7)	,628**	,619**	,671**	,651**	,669**	,665**	-			
Information management (8)	,734**	,702**	,763**	,755**	,812**	,783**	,691**	-		
Metacognitive Awareness (9)	,903**	,846**	,884**	,902**	,929**	,895**	,780**	,897**	-	
Computational Thinking(10)	,600**	,600**	,566**	,592**	,627**	,585**	,541**	,604**	,669**	-

N=306; p<.01

Table 7 shows a positive, moderate, and statistically significant correlation between metacognitive awareness and CT (r=.604, p<.01). In parallel, there was a positive, moderate, and statistically significant correlation relationship between CT and the sub-dimensions of metacognitive awareness.

The structural equation modeling was used to examine the effects of metacognitive thinking sub-dimensions on CT. The structural equation model shown in Figure 2 was tested on the AMOS.

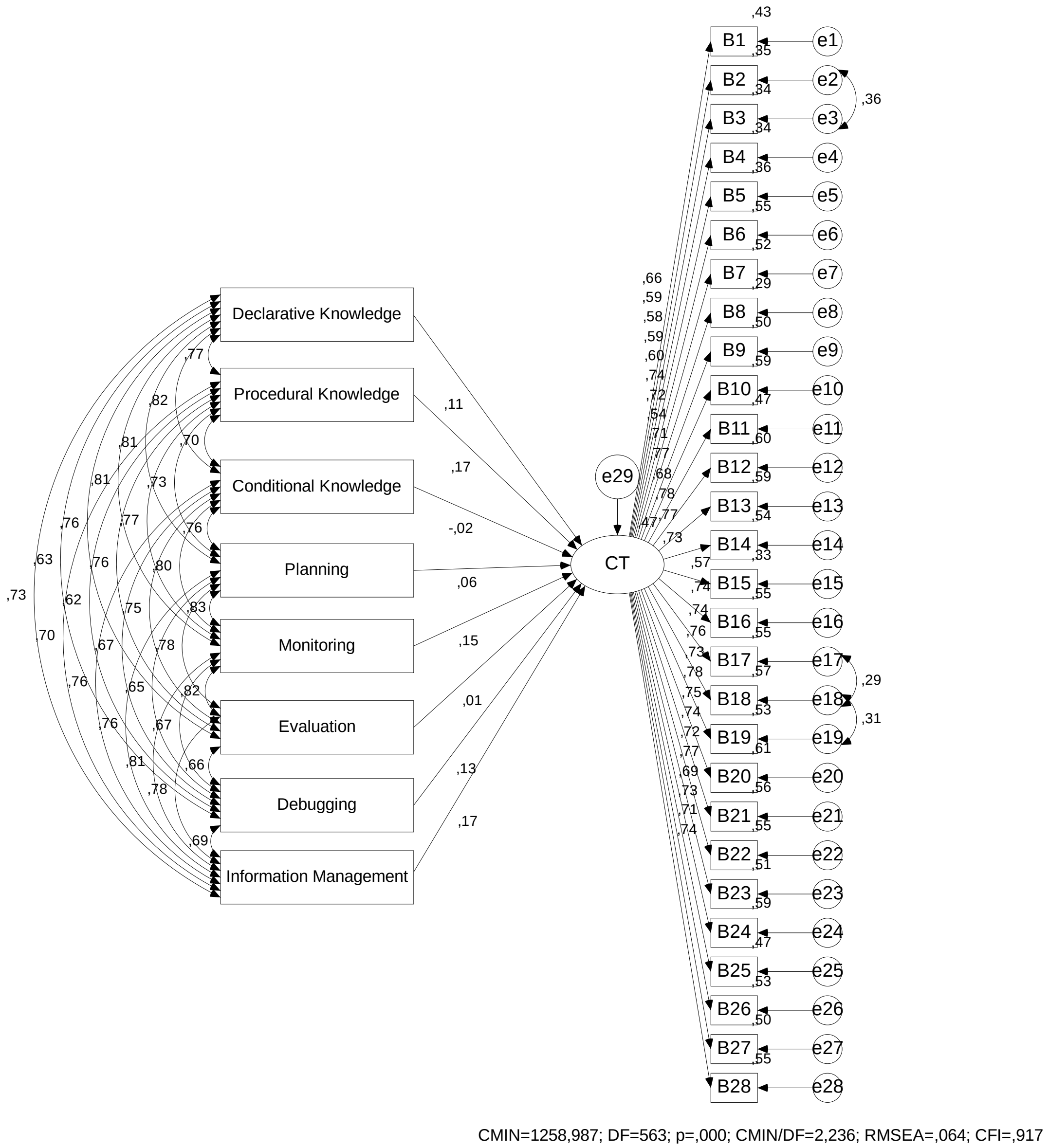


Figure 2. The structural equation model on the effect of metacognitive awareness on computational thinking

As seen in Figure 2, according to the CFA results, the fit value of the model ($\chi 2$/df) was 2.236, which indicates a perfect fit as it is less than 3. The fit indices were also acceptable (RMSEA =.064, CFI =.917; and SRMR=.0426) (Jackson et al., 2009; Browne & Cudeck, 1993). The structural equation model explained 47% of CT. The findings are shown in Table 8 below.

Table 8 Analysis results regarding the structural equation model

Measurement Model			β_0	β_1	S.E.	C.R.	P
CT Scale	<---	Declarative knowledge	0,11	0,12	0,11	1,16	.246
CT Scale	<---	Procedural knowledge	0,18	0,19	0,08	2,25	.025
CT Scale	<---	Conditional knowledge	-0,02	-0,02	0,09	-0,26	.799
CT Scale	<---	Planning	0,06	0,07	0,10	0,69	.488
CT Scale	<---	Monitoring	0,15	0,16	0,11	1,45	.146
CT Scale	<---	Evaluation	0,01	0,01	0,09	0,12	.902
CT Scale	<---	Debugging	0,13	0,14	0,07	1,99	.047
CT Scale	<---	Information management	0,17	0,20	0,10	1,99	.046

β_0: Standardized path coefficients; β_1: non-standardized path coefficients; S.E.: Standard error C.R.: Critical ratio

At the Table 8, procedural knowledge was a positive and significant predictor of CT (β_0=.11, p<.05). Similarly, debugging (β_0=.13, p<.05) and information management (β_0=.17, p<.05) sub-dimensions were also positive and significant predictors of CT. It was found that declarative knowledge, conditional knowledge, monitoring, planning, and evaluation sub-dimensions did not significantly predict CT.

Discussion

Study-1

A CT scale was developed in the first part of this study. CT is interrelated to critical thinking, one of the high-order thinking skills, so the correlation between both skills was examined for the criterion validity of the scale. Accordingly, there was a high correlation between them. The internal consistency coefficient of the 28-item scale was .98, explaining 48% of the variance. The results confirmed the accuracy and consistency of the CTS

The fact that the scale was found to be unidimensional may have caused it to be expected to be five-dimensional since it includes the five most common topics of the bid, which I mentioned in the method section. However, actually the item correlation coefficients ranged between .52 and .75 in the statistical analyses I conducted reflects the strength of the items in the scale, and indeed the scale explained 48% of the variance also reveals the strong structure of the scale. The strong evidence for the content validity of the scale items can be explained as the references from which each item was inspired.

In addition, the correlation of the scale with the Marmara Critical Thinking Scale developed by Özgenel and Çetin (2018) for criterion-based validity was found to be positive and high ($r= .87$; $p<.01$). Studies have also shown that there is a correlation between CT and critical thinking (Buckley, 2012; Doleck et al., 2017; He et al., 2021). Therefore, it can be said that the scale meets the standards of validity and reliability.

Study-2

According to the structural equation model based on the metacognition sub-dimensions and the CTS, procedural knowledge, debugging, and information management sub-dimensions significantly predicted 47% of CT, which suggests a close interrelation between metacognition and CT. Procedural knowledge is primarily used in solving routine problems and is similar to algorithms (Anderson, 2005; Braithwaite & Sprague, 2021). Procedural knowledge, described as task-oriented (Anderson, 1995) and showing how to do a task (Schraw & Dennison, 1994), resembles algorithms because algorithms provide the knowledge of how to do a task step by step. Procedural knowledge also shows how to use suitable methods or strategies for problem-solving (Kumar, 1998) and allows for managing this information (Cross & Paris, 1988). As for the role of procedural knowledge in metacognition, Schneider and Lockl (2002) suggest that most developmental researches on metacognition deal with the procedural dimension.

The information management sub-dimension of metacognition was also a significant predictor of CT. According to Schraw & Dennison (1994), information management is characterized by a set of "skills and strategies for efficient information use," such as an elaborative introduction, analysis, organization, or summary of a particular subject. However, abstraction in CT refers to a distinctive focus. As abstraction entails focusing on a given issue in challenging problems (Shute et al., 2017), information management may also be related to abstraction.

Debugging similarly operates in both metacognition and CT. It is defined as removing comprehension and performance errors (Schraw & Dennison, 1994) and also refers to eliminating errors in the specific problem-solving steps in CT (e.g., decomposition, abstraction, pattern recognition) (Bers et al., 2014). Although the content of debugging changes, its function remains the same, which overlaps with the obtained findings. Although the evaluation dimension is present in both metacognition and CT, it is not a significant predictor. At this point, conducting more research on this issue would be beneficial.

Conclusion

The purpose of this paper to develop a CT scale for practicing and prospective teachers and to determine the role of metacognition, one of the high-order thinking skills, in CT. A CTS was developed with 365 participants. The one-factor scale has 28 items and includes: decomposition, abstraction, pattern recognition, algorithm, evaluation and debugging. The Cronbach Alpha, internal consistency coefficient, was .98, which explained 48% of the total variance.

A SEM was developed (N=306) to determine the role of metacognition on CT (see Figure 2). Accordingly, procedural knowledge, debugging, and information management, which were the sub-dimensions of metacognition, substantially explained CT (47%). The procedural information sub-dimension may be related to algorithms in terms of content; the information management sub-dimension is partially similar to abstraction; the debugging also exists in CT, with the same purpose of use but in different usage areas.

Those findings significantly point to the interactions between metacognition (Rhodes, 2019), which contributes to comprehension and decision-making in any aspect of life, and CT skill, a new and popular problem-solving competency characterized by programming. In this sense, it will be useful to conduct studies that address metacognition and CT together to investigate their effects on learning and teaching.

Recommendations

Applied research on CT and metacognition will be supportive in explaining the relationship between these two thinking skills.

Limitations of Study

The research is limited to pre-service teachers.

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