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# Understanding and Measuring Computational Thinking: A Tripartite View of Competence

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*Short Paper*

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## Abstract

*Computation is critical to social development for information processing in today's digital world. Computational Thinking (CT), the underlying cognitive functioning of designing computation, has been under heated discussion. However, the conceptualization of CT and its measurements still require improvement when discussing CT as a competence for problem-solving. This study first conceptualizes CT in problem-solving context by identifying the framework of competence based on a tripartite view and applying it to clarify that CT competence consists of CT knowledge, skills, and attitudes. It then aims to develop a self-reported scale for complementing CT measurements based on the tripartite view. This work contributes to CT theories and measures through a more precise conceptual framework and an instrument developed based on it. It enriches IS studies by a new perspective that humans form their cognitive process for problem-solving under digital technologies, especially computational tools.*

**Keywords:** Computational Thinking, Competence, KSA View, Measurement

## Introduction

In today's digital age, social development focuses more on information. Computation has become an essential way to process information for daily work and potential innovations. As the underlying functioning of computation, Computational Thinking (CT) allows people to solve problems and deal with information more efficiently, even without computing tools (Barr and Stephenson 2011). In previous studies, CT could be defined as "a thought process involved in formulating a problem and expressing its solution(s) in such a way that an information-processing agent—human or machine—can effectively carry out" (Wing 2014). It is regarded as a type of high-level competence for tomorrow's world, making us change our way of thinking about problems and how to solve problems (Wing 2006, 2014). Not only is CT important to computer science but significantly influences various fields, such as biology, mathematics, chemistry (Yadav et al. 2017). Everyone and everywhere can benefit from CT (Wing 2006; Yadav et al. 2017), and researchers consider it as important as reading, writing, and arithmetic in the 21st century (Wing 2006). In addition, computation is a specific field driven by scientific questions, technological innovations, and societal demands (Wing 2008), which is a foundation of the modern IS framework in the digital world. As CT is the underlying functioning of computation, understanding it could enrich IS studies by recognizing how humans form cognitive processes for problem-solving and interact with computational artifacts.

Although CT plays an increasingly significant role in the digital world, its conceptualization still requires further improvements (Tikva and Tambouris 2021). First, some extant CT conceptualizations suffer from ambiguity due to only abstractly defining it as a thought process for problem-solving without any discussion on its components, such as the definition from Aho (2012). Second, although other conceptualizations try to list its components, such as definitions from Shute et al. (2017) and Selby et al. (2013), the comprehensiveness still requires improvement due to catching partial facets of CT, for example only skills. In problem-solving context, CT should be a problem-solving process involving different cognitive components (Wang et al. 2010; Polya 1954; Smith 1991), more than skills. In this study, competence, frequently mentioned in previous CT studies (Wing 2006; Barr and Stephenson 2011; Wing 2014; Denning 2017), is selected to improve the conceptualization of CT in problem-solving context. Competence covers main components essential to problem-solving, namely knowledge, skills, attitudes (Kaslow et al. 2004), called the tripartite view in this study, so that it can help clarify and integrate cognitive components of CT for problem-solving. Using competence to conceptualize CT, instead of assuming CT to be single type of cognition, such as a bundle of skills (e.g., Shute et al. 2017) or abilities (e.g., Selby et al. 2013), can also enhance comprehensiveness and accuracy. Skills are internal components of competence (Weinert 1999; Kirschner 2015), while abilities are operational outcomes underlain by competence as its cognitive functioning (Westera 2001). Furthermore, competence provides a flexible framework for future extension to CT conceptualization. To improve the conceptualization of CT, this study first raises the research question: what is the theoretical framework of CT as competence in problem-solving context?

Measurement of CT, on the other hand, also requires continuous development. Previous studies demonstrate that CT measurement tools can be categorized into seven types (Román-González et al. 2019). Some issues are identified from previous CT measurements, such as exogenous capability issue, specific stakeholder issue and lack of reliability and validity. The most critical problem is exogenous capability issue that most measurement are designed under programming environments, nearly half of ninety-six assessment tools, according to a systematic review (Tang et al. 2020). However, CT competence in problem-solving context is a high-level cognition, helping people solve problems even without computers (Shute et al. 2017). The necessity of programming for conducting assessments limits CT measurement on those who no longer do programming but still rely on CT to solve problems. Self-reported scales can supplement this by collecting the perceptions or self-reflections involved in the cognitive process of people when using CT to solve problems. Nevertheless, our analysis on existing main scales shows that extant self-reported tools can only measure partial facets of CT competence for problem-solving. Moreover, it also shows that some scales involve ambiguous conceptual components that should be discussed independently rather than nested in CT. Thus, it is essential to continuously develop self-reported tools for complementing CT measurement. This study then proposes the second research question: how to measure CT in digital age in the form of self-reported scale, especially based on competence framework in problem-solving context?

To answer these two questions, we discuss the tripartite view of competence, consisting of knowledge, skills, and attitudes, and adopt it to improve CT conceptualization in problem-solving context. And we try to develop a new CT scale based on the tripartite view of competence to supplement self-reported scales. The remainder of this study is organized as follows. First, we review related literature on competence and CT and propose a tripartite view of CT as competence to improve CT conceptualization. Second, we review extant CT measurements and point out research gaps. Third, we provide current study progress and future work plans with expected contributions.

## Theoretical Background and Literature Review

Although CT has been a flourishing concept since being proposed by Wing (2006), its conceptualization is still under study and improvement (Tikva and Tambouris 2021), leading to an inconsistent theoretical framework of CT and further influencing its measurement. Extant conceptualizations can be categorized into generic definition and definition model (Tikva and Tambouris 2021). For example, Aho (2012) considers CT as "the thought processes involved in formulating problems so their solutions can be represented as computational steps and algorithms." Brennan and Resnick (2012) develop a definition model of CT, consisting of CT concepts, practices, and perspectives. In this study, we make a thorough literature review on twenty extant CT conceptualizations and find the following issues. First, seven (35%) conceptualizations show ambiguity, e.g., the definitions from Aho (2012), to define CT as a problem-solving thought process without concrete cognitive components. Cognitive components should be clarified because how the mind is organized to produce intelligent thought involves many cognitive psychological aspects, such as representing knowledge, acquiring skills, performing skills and so on (Anderson 2011). Second, although other conceptualizations have listed what CT should contain, their comprehensiveness still requires improvement when considering CT in problem-solving context. For example, the definitions from Shute et al. (2017) and Selby et al. (2013) only focus on cognitive skills of CT for problem-solving, such as abstraction, decomposition and so on. However, a problem-solving process is a complex cognitive process depending on knowledge, skills, and attitudes (Wang et al. 2010; Polya 1954; Smith 1991). Therefore, a new conceptualization of CT is required to clarify its cognitive components, which can also integrate existing components proposed by previous studies and provides more comprehensiveness.

In this study, we utilize competence to conceptualize CT in problem-solving context and apply it to improve previous literature with three reasons. First, competence is frequently mentioned by previous CT studies when discussing CT (Wing 2006; Barr and Stephenson 2011; Wing 2014; Denning 2017) explicitly (Wing 2014; Denning 2017) or implicitly (Grover and Pea 2013), some of which are listed in Table 1. Second, competence provides a conceptual framework to clarify cognitive components of CT for problem-solving and to describe CT more comprehensively, integrating existing ones such as skills. Cognitive psychology considers that the problem-solving process is mainly determined by scope of knowledge, various skills (abstraction, synthesis, problem representation, etc.) and attitude (Wang et al. 2010; Polya 1954; Smith 1991). Knowledge and skills distinguish expertise and novice problem-solvers, while attitudes can influence problem-solving efficiency and effectiveness (Wang et al. 2010; Polya 1954; Smith 1991). When conceptualizing CT in problem-solving context, competence can integrate these main components, based on the frameworks proposed by previous competence literature (Kaslow et al. 2004; Kirschner 2015; McLagan 1997; Westera 2001, Weinert 1999). Moreover, using competence to conceptualize CT can enhance comprehensiveness and accuracy, problematizing previous studies that assumed CT to be skills or abilities, namely single type of cognition (Román-González et al. 2017; Selby et al. 2013). Only using skills to conceptualize CT ignores the position of knowledge and attitude in problem-solving process. Using abilities to replace competence makes the conceptual boundary vague between the operational outcome (ability) and the underlying cognitive functioning (competence) (Westera 2001). Third, the conceptualization of CT based on competence provides future researchers a flexible and concise framework to discuss CT. If there were any new cognitive components discovered to impact CT, they could be added into the competence framework for a flexible extension. Theoretical parsimony can also be promised by sorting components into corresponding dimensions, avoiding a lengthy list describing what CT contains.

| Opinion | Literature |
|---|---|
| CT is one of the basic competencies that everyone should acquire. | Wing (2006) |
| CT is a united competence that consists of three key components. | Denner et al. (2012) |
| CT as a competence allows people to scale and deal with complexity, which has been influencing more disciplines. | Wing (2014) |
| CT is a competence for establishing appropriate computational models for new problems in various fields. | Denning (2017) |

**Table 1. Literature of CT as competence**

## *The Tripartite View of Competence*

Researchers suggested that competence consists of different cognitive components, including knowledge, skills, attitudes, metacognition, strategic thinking, and so on (Kaslow et al. 2004; Kirschner 2015; McLagan 1997; Westera 2001). We select knowledge, skills, and attitudes (KSA) to establish the conceptual framework of competence in problem-solving context according to the following reasons. First, literatures in cognitive psychology consider that problem-solving process mainly depends on knowledge, various types of skills and attitudes (Wang et al. 2010; Polya 1954). Although there are additional components proposed in competence framework, we select KSA in problem-solving context to describe competence based on contextualization strategies in IS study, refining previous models to fit the context (Hong et al. 2014). Second, KSA provides a concise framework that is generally used to define competence (Baartman and De

Bruijn 2011). Not only can KSA clearly describe competence from a pragmatic perspective but provides parsimony to meet aesthetic criterion of theory building (Bacharach 1989).

We call the conceptual framework of competence in problem-solving context based on KSA the tripartite view of competence. First, knowledge reflects the representation of facts, information, principles, and theories in a particular domain (Westera 2001). Knowledge could be categorized as declarative and procedural knowledge (Anderson 2011). Declarative knowledge (knowing that) refers to the facts of a topic that a person knows and can report on, while procedural knowledge (knowing how) means how to do cognitive tasks using declarative knowledge (DeKeyser 2020). Second, skills can be categorized into motor skills and cognitive skills (Newell 1991), and sometimes they are unified under the term "skills" (Baartman and De Bruijn 2011). Motor skills indicate functions emphasizing physical movements (Newell 1991), while cognitive skills indicate exclusively mental operations when people process thought (Westera 2001). Skills are interwoven with knowledge; more specifically, cognitive skills could reflect processes of different knowledge, similar to "knowing how" (Westera 2001). Finally, attitude reflects the affective characteristic of people and could be distinguished from mere knowledge and skills (McLagan 1997), representing an individual's disposition to respond favorably or unfavorably to something (Ajzen 2011).

## *Tripartite View on Computational Thinking as Competence*

According to the tripartite view of competence, we propose CT competence consisting of CT knowledge, skills, and attitudes. First, about CT knowledge, we only consider declarative knowledge because procedural knowledge is similar to cognitive skills. To clarify knowledge and skills, we discuss procedural knowledge in the form of cognitive skills in this study. Declarative knowledge of CT indicates facts and concepts utilized in problem-solving. More specifically, previous studies suggest that the core of CT is to establish a computational model to solve the problem (Aho 2012). Therefore, we consider declarative CT knowledge to be the concepts helping establish the logical structure of computational models during problem-solving. Second, about CT skills, this study explicitly indicates cognitive skills that engage in problem-solving processes based on CT literatures. Five basic cognitive processes for problem-solving are considered based on previous studies, including abstraction, decomposition, evaluation, generalization, and algorithmic thinking (Shute et al. 2017; Tsai et al. 2021; Wing 2008). Finally, this study tries to discuss CT attitudes in the problem-solving context. CT attitudes could be categorized into two aspects, deduced from CT literatures: attitude towards algorithmic solutions and computing tools assistance. First, in previous studies, researchers in CT emphasize formulating and solving problems in a logical and algorithmic way (Shute et al. 2017). Once CT is formed, people should realize the importance of solving problems logically and algorithmically. Such an attitude can also influence the implementation of CT when solving interdisciplinary problems (Yadav et al. 2017). The second part of CT attitudes is the attitude towards the assistance of computing tools. CT can be seen as the effective use of the basic principles of computer technologies (Shute et al. 2017), which associate CT with computing tools. The new digital world also requires people to begin to work with computational tools (Barr and Stephenson 2011). With the development of CT in mind, people could realize the importance of computing tools in problem-solving so as to change their attitudes towards using them. In Table 2, we proposed detailed definitions of components of CT competence and their sub-dimensions, adapted from previous studies (Brennan and Resnick 2011; Kılıç et al. 2021; Tsai 2021; Ajzen 2011).

| | |
|---|---|
| **CT Knowledge**: Declarative knowledge for constructing the logical structure of computational models to solve problems. (Brennan and Resnick 2012; Kılıç et al. 2021) | |
| Sequence | A particular activity or task expressed as a series of individual steps or instructions that can be executed by computers. |
| Loop | A mechanism that the same sequence is run multiple times. |
| Parallelism | Sequences of instructions run at the same time. |
| Conditional | Make decisions based on certain conditions. |
| **CT Skills**: Cognitive skills for formulating problems, designing algorithmic solutions. (Tsai et al. 2021) | |
| Abstraction | The mental process focusing on the key information rather than the details to solve a problem and figure out the main framework of a problem. |
| Decomposition | The mental process breaking problems down into smaller and manageable parts. |

| | |
|---|---|
| Evaluation | The mental process comparing different solutions to a problem and figure out the best one given constraints of the problem. |
| Generalization | The mental process recognizing the patterns of how to solve specific problems and applying these patterns to other similar problems. |
| Algorithmic Thinking | The mental process organizing solutions in step-by-step procedures with clear logic. |
| **CT Attitudes**: Affective factors on solving problems in algorithmic way and assistance of computing tools. (Ajzen 2011, Venkatesh et al. 2003) | |
| Towards algorithmic solutions | The disposition to respond favorably or unfavorably to solutions in algorithmic form. |
| Towards computing tools assistance | The disposition to respond favorably or unfavorably to using computing tools to help solve problems. |

**Table 2. Components of Tripartite View of CT and Corresponding Definitions**

## Measurement of Computational Thinking

CT measurements can be categorized into seven types, including CT diagnostic tools, CT summative tools, CT formative-iterative tools, CT data mining tools, CK skills transfer tools, CT perceptions-attitudes tools and CT vocabulary assessment (Román-González et al. 2019). There are three problems in existing CT measurement tools, requiring reconsiderations. First, many CT measurements heavily rely on exogenous capabilities, especially programming, limiting measurement populations. According to Tang et al. (2009), among ninety-six CT assessment tools, 48.9% of them involve programming. As CT is a cognitive concept that helps solve problems even without computing tools, its measurement should also consider people who no longer do programming. Moreover, assessing CT through programming means using behaviors to reflect competence. However, competence is not always reflected in observational behaviors (Anderson 2011). The association between CT, which is competence for problem-solving, and observational behaviors can be explored from its three main components. Successfully performing behaviors reflects that a person knows something and how to do them. However, knowing how to do something does not mean that corresponding behaviors are necessarily performed (Westera 2001). Observational behaviors can reflect the existence of cognitive skills but holding them does not necessarily lead to observational behaviors (Westera 2001). Attitudes have also been demonstrated not to be directly associated with behaviors, which only immediately influence the intention to behave (Ajzen 2011). As a result, it is not a bi-directional mapping from competence to behaviors. This means that measurements relying on programming fail to measure people who have CT competence but do not program. Second, many previous CT measurements involve "specific stakeholder issues," as they are explicitly designed for pedagogical goals to particular populations, such as primary or secondary school students. Measurement tools for assessing CT on other people beyond pedagogical situations for adults or non-students are still required. Among ninety-six measurement tools, only fifteen (15.6%) involve measurements for non-student population, while only thirty-two studies (33.3%) involve measurements for non-primary or non-secondary school students (Tang et al. 2020). Third, many studies on CT measurements have been demonstrated to not appropriately report reliability and validity evidence, reducing users' confidence in them (Tang et al. 2020, Tsai et al. 2021). Tang et al. (2020) also indicates that among 96 studies fewer than half (45%) reported reliability evidence and 18 % provided validity evidence.

In this study, we would like to develop a new measurement for assessing CT, precisely a self-reported scale that could be used on non-students and beyond pedagogical situations. First, the self-reported scale could exclude the engagement of exogenous capability when measuring CT, which can assess those no longer coding but still rely on CT to logically solve problems. Second, a self-reported scale can collect data providing perceptions or self-reflections involved in cognitive processes which are not easily observed (Tsai et al. 2021). From the practical perspective, survey questionnaires produced based on self-reported scales are widely used in academic studies and organizational operations, which have relatively lower costs than other data collection methods (Tsai et al. 2021). To our best knowledge, there are 5 main scales published in CT area listed in Table 3. These CT scales face two significant issues that impact the effectiveness of measurements. This study aims to address these problems by developing a new scale. One issue is that previous scales lack comprehensive understanding of the CT framework. As mentioned, we propose the tripartite view of CT competence for problem-solving and further consider CT knowledge and CT attitudes. According to Table 3, most components in some extant scales can actually be integrated into CT skills so they can only partially measure CT competence. We consider CT knowledge and attitudes in our scale to augment comprehensiveness. Another issue is that some dimensions in previous scales could lead to conceptual ambiguity. In scales developed by Korkmaz et al. (2017) and Yağcı (2019), critical thinking, creativity and cooperativity are considered as sub-dimensions of CT, but this may lead to ambiguity. Critical thinking covers a wide area, indicating a cognitive process to understand the nature of analyzing (Ennis 1993). Almost all thought processes stem from critical thinking, and CT could be regarded as a special type of critical thinking, covered by it. Moreover, including creativity and cooperativity as sub-dimensions of CT also causes ambiguity. Israel-Fishelson et al. (2022) indicates that studies focusing on CT and creativity tend to explore their bidirectional linkage. Creativity and CT are two constructs which could influence each other (Israel-Fishelson et al. 2022), instead of a part-whole relationship. Creativity could be a catalyst of CT, while CT could in turn motivate creativity (Israel-Fishelson et al. 2022). We also do not consider cooperativity as a sub-dimension of CT because it is a disposition which supports and enhances CT (Barr and Stephenson 2011) instead of an inner part of CT.

| Scales | Dimensions |
|---|---|
| Korkmaz et al. (2017) | Creativity, Algorithmic Thinking, Cooperativity, Critical thinking, Problem solving |
| Kukul et al. (2019) | Reasoning, Abstraction, Decomposition, Generalization |
| Yağcı (2019) | Problem solving, Cooperative Learning & Critical Thinking, Creativity, Algorithmic thinking |
| Kılıç et al. (2021) | Evaluation, Conceptual Knowledge, Algorithmic thinking |
| Tsai (2021) | Abstraction, Decomposition, Algorithmic Thinking, Evaluation, Generalization |

**Table 3. Comparison of Dimensions of CT Scale**

# Methodology and Work Progress

CT competence in this study is hypothesized as a formative construct, aggregated by CT knowledge, CT skills and CT attitude. These three constructs are also hypothesized as formative constructs, aggerated by their first-order reflective constructs demonstrated in Table 2, adapted from previous studies (Kılıç et al. 2021; Tsai 2021; Venkatesh 2003). We propose this construct nature by following guidelines from Petter et al. (2007). First, competence consists of knowledge, skills, and attitudes so that the level of competence depends on these three sub-dimensions. Furthermore, the CT competence is conceptualized in problem-solving context, and problem-solving mainly depends on knowledge, skills and attitudes (Wang et al. 2010; Smith 1991). We theorize that a change of any one of them can cause change on total magnitude of CT competence. Second, these three dimensions are not interchangeable. If anyone of the tripartite view were dropped, the conceptual domain of competence for problem solving would change. Third, CT knowledge, CT skills and CT attitudes are three different dimensions so that they do not necessary covary. People can still fail to solve problems by wrong problem representation that depends on various skills, even they are taught appropriate knowledge (Anderson 2011), and attitude is the affective characteristic of people and could be distinguished from mere knowledge and skills (McLagan 1997). Finally, these three dimensions are not expected to have the same antecedents and consequences. The reasons why CT knowledge, CT skills and CT attitudes are hypothesized as formative constructs are the same.

The instrument development procedure rigorously follows a systematic scale development approach in IS research (Moore and Benbasat 1991). As illustrated in Figure 1, based on the robust paradigm in IS literature, we propose the development process of the self-reported scale by following three stages. The first stage focuses on "Item Creation" with the objective of ensuring content validity. We create pools of items for each first-order construct by adapting items from existing instruments and by creating additional items that fit into the constructs. In step 1.1, dimensions of CT competence demonstrated in Table 2 are identified through the deductive approach (Schwab 1980), whose nature is discussed above. We also conduct a thorough, iterative literature review to survey existing self-reported instruments of CT and to generate initial item pool for dimensions. In step 1.2, multiple items are generated to ensure internal consistency (Allen and Yen 2001). Once the item pools are created, items for each dimension of CT competence will be reevaluated by 5 professionals in the CT field to remove ambiguous items (Moore and Benbasat 1991). The second stage will focus on scale development with the objective to assess the construct validity of the instrument that is being developed and to remove the items that are ambiguous and redundant (Moore and Benbasat 1991). Panels of judges will be recruited to sort candidate items into the dimensions of CT competence and to evaluate candidate items (Moore and Benbasat 1991). All panel members hold a Ph.D. degree or are pursuing a Ph.D. study, and they possess significant research or professional experience in the field of CT. In step 2.1, two rounds of card sorting will be conducted on two different groups of judges after trial sort. In each round, judges will be asked to sort each item into the most corresponding dimensions they think. In step 2.2, "Inter-Rater Reliabilities" will be measured to assess the reliability of the card sorting according to Cohen's Kappa and item placement ratios. The card sorting data in this step will also be used to measure content validity by calculating the proportion of substantive agreement and the substantive validity coefficient proposed by Anderson and Gerbing (1991). Furthermore, the second-round card sorting will be conducted based on the result of the first round in which some items may be removed or reworded. The third stage focuses on instrument testing for evaluating the reliability and validity of the scales. In step 3.1, we will conduct a pilot test to assess the questionnaire's mechanics. 20 respondents will complete the questionnaire and provide feedback on its length, wording, and instructions to determine its reliability. The target population covers those employees who graduated from universities, because CT competence can be trained during education (Yadav et al. 2017). Given the consideration of stability over time, college-graduated people are focused since their educational programs are finished, having a relatively stable competence level. In step 3.2, a field test will be conducted on a new larger sample from the same population through an online survey platform. In step 3.3, factor analyses will be conducted to refine the scale. Exploratory factor analysis (EFA) based on principle component analysis will be conducted to assess whether all expected factors emerge cleanly. Once EFA is finished, confirmatory factor analysis (CFA) will be conducted on a new sample for validating the instrument. We will first focus on the measurement model discussed before and explore whether there will be other competitive models. Finally, the nomological validity will be tested to confirm the theoretical usage of CT competence. Nomological validity can be supported by demonstrating that the constructs are related to other constructs that are not included in the model in a manner that supports the theoretical framework (Hair et al. 2009). Based on the previous study exploring CT nomological network, we expect a positive relationship between the factors underlying CT competence and problem-solving ability, reasoning ability, spatial ability, verbal ability, ICT self-efficacy and Big Five personality (Román-González et al. 2017). This study will follow assessments of the measurement model to test the reliability and validity of reflective and formative constructs (Moore and Benbasat 1991; Petter et al. 2007). The construct validity of formative constructs will be assessed by examining both the item weights and the loadings. Reliability of the formative constructs will be assessed by examining the possible multicollinearity among indicators. In contrast, all first-order constructs are reflective constructs so that the reliability of them will be assessed by Cronbach's alpha and average variance extraction (AVE). Convergent validity and discriminant validity will be assessed by checking items loading.

The study is currently in phase 1.2, and 37 candidate items have been generated. We have generated 4 candidate items of CT knowledge, 25 items of CT skills and 8 items of CT attitudes. The conceptualization for instrument development is the tripartite view of CT competence for problem-solving, which is hypothesized as a third order formative construct with three reflective-formative second-order constructs.

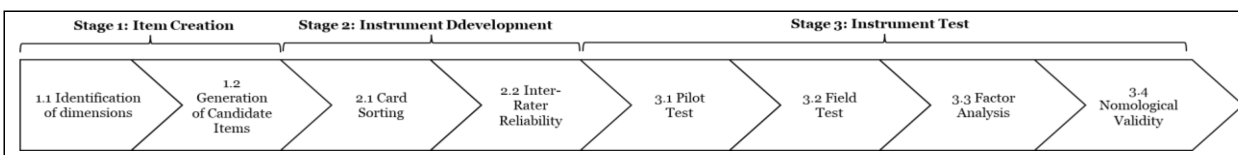


**Figure 1. The Instrument Development Process of CT**

## Expected Contribution

The concept of CT has sparked intense debates and has the potential to enhance IS studies by offering a fresh perspective on how humans shape their cognitive processes for problem-solving in the digital era, particularly with the influence of computing tools. CT is widely recognized as a crucial competence for problem-solving in the 21st century. However, current research on CT lacks comprehensive conceptual frameworks and effective measurement approaches. Previous CT conceptualizations lack specificity regarding its components, resulting in ambiguity in both theoretical and practical aspects. Furthermore, existing CT measurements, especially self-reported scales, have limited applicability. To address these gaps, this study aims to conceptualize the dimensions of CT based on the tripartite view of competence and apply it to provide a clear understanding that CT encompasses three key dimensions in problem-solving context: CT knowledge, CT skills, and CT attitudes. This tripartite view offers a more precise conceptual framework for CT theories, improving conceptualizations in problem-solving context. From a practical standpoint, a more comprehensive conceptualization for CT competence contributes to a more accurate and valid measurement process. Additionally, based on this tripartite view, we propose the development of a new self-reported scale to supplement CT measurements, which is currently underway. This scale will enable the assessment of individuals who are not necessarily engaged in programming, which could also be used for adult assessment, thereby expanding the study population for CT research. It can also fit industrial practice, allowing organizations to assess employees' CT competence without a programming environment.

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