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Exploratory and Confirmatory Factor Analysis for Disposition Levels of Computational Thinking Instrument Among Secondary School Students

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Abstract: Computational thinking (CT) is a method for solving complex problems, but also gives people an inventive inspiration to adapt to our smart and changing society. Globally it has been considered as vital abilities for solving genuine issues successfully and efficiently in the 21st century. Recent studies have revealed that the nurture of CT mainly centered on measuring the technical skill. There is a lack of conceptualization and instruments that cogitate on CT disposition and attitudes. This study attends to these limitations by developing an instrument to measure CT concerning dispositions and attitudes. The instruments' validity and reliability testing were performed with the participation from secondary school students in Malaysia. The internal consistency reliability, standardized residual variance, construct validity and composite reliability were examined. The result revealed that the instrument validity was confirmed after removing items. The reliability and validity of the instrument have been verified. The findings established that all constructs are useful for assessing the disposition of computer science students. The implications for psychometric assessment were evident in terms of giving empirical evidence to corroborate theory-based constructs and also validating items' quality to appropriately represent the measurement.

Keywords: *Attitudes, computational thinking, disposition, factor analysis.*

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Introduction

Computational Thinking (CT) is a universal attitude and skill that should be part of every child's repertoire, so it is an important competency that affects almost all disciplines. CT makes life more than you ever dreamed it could be, as Industry 4.0 accelerates Industry 3.0's computerization. Such recent developments impact virtually all communities and future jobs, including the opportunities for students, who need to prepare themselves for emerging digital technology challenges. Computational thinking encourages students' initiative and innovation to expand their thinking in problem solving, as well as a necessity in developing students' lifelong learning abilities (Sanford & Naidu, 2016). Despite the great level of interest in developing CT among school children and the substantial investment in CT projects, there are a number of concerns and challenges that must be addressed before CT can be fully integrated into the school curriculum. The education sector faces rising pressure on CT. Hence, an adaptation of the CT concepts in everyday life are not going to be easy and require thorough study. The most of the attention on embedding CT during the past decade has focused on integration of CT skill in students with only little concern about their perception, feeling or attitude towards the application of CT in problem solving across various discipline or specifically in daily life (Sondakh et al., 2020).

As we addressed previously, CT is a newer curriculum field that has very quickly to be adapted into classrooms. Studies have explored CT assessment at various level such as preschool, primary education, secondary education and so on. This is supported by several external studies that show that computational thinking can be applied to 4 to 6-year-old students as early as preschool (Bers, 2020; Bers et al., 2014; García-Valcárcel-Muñoz-Repiso & Caballero-González, 2019), students in primary school (Chalmers, 2018; Falloon, 2015; Yadav et al., 2011), secondary school students (Rode et al., 2015; Towhidnejad et al., 2014), university students (García-Peñalvo & Mendes, 2018), and even to teachers (Angeli et al., 2016; Mannila et al., 2014; Yadav et al., 2014). Researchers were unable to anticipate all of the challenges that might develop prior to execution as they were new to CT (Belanger et al., 2018).

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Although there has been a broad discussion demystifying pedagogical aspects of CT, the study on assessing CT skills and attitude continues to take place (Sondakh et al., 2020). The attitude established via the use of CT should be improved in order to assess systematic approaches and complex situations (Qin, 2009). Referring to studies on the last 5 years (2016 to 2020), it became evident that minimal studies were devoted to address the issue of CT disposition among students. CT is also defined by attitudes, not just skills (Wing, 2006). CT comprises mental process (Selby & Woollard, 2013), but it is not enough to solve problems using only the cognitive thinking. Then there are affective factors including problem-solving capability, attitudes, dispositions and beliefs (Jonassen, 2000). CT-relevant values, intentions, emotions, and personalities foster problem-solving skills (Barr et al., 2011). Attitudes encourage people to interact with complicated and crucial situations but also to collaborate to overcome challenges that are extraordinarily complex to solve alone (Missiroli et al., 2017).

Measuring the CT attitude is essential since there are no generally accepted standardized measures yet (Haseski et al., 2018; Weese, 2016). For instance, Gouws et al. (2013) designed a game-based approach instrument; Walden et al. (2013) developed a multiple-choice instrument with short answers. Nevertheless, the scale and tools have not been validated. The preceding research concentrated on gauging abilities and omitted attitudes. It is therefore not surprising that CT assessment continues to be a significant problem in this field. There is no commonly agreed method for assessing CT, making it difficult to assess the impact of intervention precisely and reliably (Grover & Pea, 2013; Kim et al., 2013; Settle et al., 2012; Shute et al., 2017; Sondakh et al., 2020). There is always an urge to distinguish ways to envision the measurement of CT across all disciplines. Consequently, the issue of assessment in current studies was found lacking compared to the studies investigating approaches to teach CT.

Assuming that CT is a compilation of problem-solving abilities and attitudes (Wing, 2006), this study suggests "Instrument for Computational Thinking Disposition". The term 'disposition' to describe the incorporation of mental modes, mental habits and attitudes within the CT context. Overall, research aims to establish a tool for evaluating CT for secondary computer science students on the disposition aspect. In this regard, Malaysia has taken the initiative with integrating computational thinking into the Malaysian education syllabus in 2017 through the new curriculum, namely the Primary School Curriculum Standard (KSSR) and the Secondary School Curriculum Standards (KSSM) (Abas, 2016) as well as being a support to the subject Science, Technology, Engineering, Mathematics, (STEM). Past a few years, initiatives to promote CT are being made in Malaysia; even the idea of integrating CT skills in education curricula has been supported. Malaysia also joins Bebras International, a global program aimed at promoting CT among all age groups of pupils. Furthermore, the Malaysian Ministry of Education places a strong emphasis on technical components such as specific task knowledge and logical reasoning, as well as soft skills such as ethics, problem solving, interpersonal skills, communication, cooperation, leadership, and social skills (Curriculum Development Division [CDD], 2015).

Teamwork, communication, problem solving, adaptability, ambiguity and personal qualities were consolidated based on Association for Computing Machinery (ACM) and Institute of Electrical and Electronics Engineers (IEEE) computer curriculum (ACM & IEEE Computer Society 2013). Meanwhile, Computer Science Teachers Association (CSTA) and International Society for Technology in Education (ISTE) defined CT - Attitude as confidence in complexity, perseverance when working on complex problems, tolerance of ambiguity, the capability to interact with indefinite problems, and the potential to collaborate with others to achieve a common goal.

Methodology

Research Design

A quantitative approach was used in this research, whereby a quantitative cross-sectional survey was conducted. The quantitative method was used by the researcher due to its ability to collect and analyze numbers to explain the phenomena under study (Mills & Gay, 2018). The data was collected through an independent web-based survey because it is less expensive, there are no copying costs, and no coding is required. That allows for quick statistical analysis (Hair et al., 2017). Despite this, participants were required to reply to all questions and this prevented data loss.

Sample and Data Collection

A total of 535 secondary school students with computer science background, including 247 males (46%) and 288 females (54%) was involved in the first study using EFA analysis. They were selected using simple probability sampling from four zones representing North (80, 15%), East (80, 15%), West (252, 47%) and South (123, 23%). The samples were selected through probability sampling. Probability sampling uses a form of random selection that allows the sampling error to be calculated, thereby reducing selection bias. Accordingly, permission from the Ministry of Education was required to carry out the data collection. Therefore, the approval of the head teacher is mandatory before the researcher can meet the respondents. Accordingly, to accomplish the EFA criteria, a sample size of over 300 pupils was eventually attained. A second batch of 500 students was selected for item testing using CFA in the second phase. The samples for each phase are distinct. CFA corroborates the EFA finding by utilizing distinct research samples (Cabrera-Nguyen, 2010). Moreover, a parameter of 150 is acceptable for measuring less than seven constructs and minor communalities using the structural equation modelling (SEM) technique (Hair et al., 2010). Participants in this study were invited to participate until an adequate sample size was reached. The following criteria were used to select respondents: (1) they must have a background in computer science; (2) they must be ready to participate in the survey; and (3) their ability to fill out online surveys.

Analyzing of Data

Each student self-assessed the instrument in Malay. The instrument is composed of 55 items. The instrument has three CT disposition dimensions, namely, cognitive, affective and conative (Hilgard, 1980; Schiffman et al., 2012). Likert 1-to-4-point scale scores range from "strongly disagree" to "strongly agree". The survey must be completed within a week. A mean score is used to compute raw scores on scales. During the process of constructing the scale, a survey of literature and interviews with experts (both professional and lay) were conducted first, after which a list of the dispositions that an 'individual' must possess was compiled. It was decided to translate the list into expressions of behaviors that students may use to evaluate their own performance.

Expert opinion was sought for validity purposes to determine whether the items were appropriate in gauging the desired study questions and whether the statements were intelligible. In that regard, 25 professional and field experts used the Fuzzy Delphi technique to assess the instrument's content validity. The item review was carried out based on the experts' recommendations. A lecturer assessed the instrument's face validity. A language specialist and two educational experts assessed the drafted scale in terms of flaws in expression, wording, orthography and punctuation to ensure that the instrument could be understood by form four pupils. Following that, ten students were chosen for face validation. They were given the task of identifying and documenting any unfamiliar word or terminology. They were also required to provide feedback on the font size and design, so that the research sample could understand the items better.

After making the necessary modifications, a preliminary scale consisting of 55 items was constructed. The scale's validity and reliability were assessed using SPSS 26.00 data. The scale's data were subjected to (1) construct validity and (2) item discrimination power studies. For the construct validity, we employed exploratory analysis. Item-total correlation was used to analyze item discrimination. The internal consistency and stability measurement tests were used to gauge the scale's reliability. In addition, given the benefits of CFA, the goal of this study is to offer more evidence for the construct validity of the instrument among secondary school computer science students by using CFA to assess its measurement model validity.

Findings / Results

Descriptive Statistics

On the basis of the data in Table 1, the following findings were made. The highest mean value of the respondents on the affective dimension describes the interest, enjoyment, enthusiasm, awareness and empowerment to learn and use CT in daily life. Finally, the cognitive dimension shows that the respondents are able to acquire connections in CT, creative thinking, rationale thinking and perception. The lowest mean value of conative dimension determines perseverance, tolerance, collaboration and confidence in using CT in daily life. This result illustrates how willing someone is to engage in in-depth CT. Thus, the findings emphasize construct validity, or the degree to which an instrument's items correspond to a significant theoretical construct (DeVon et al., 2007). This includes findings on the dimensionality of the subconstructs and confirmation of the conceptual framework.

Table 1. Descriptive Statistic

No	Construct	Mean	Standard deviation	Number of respondents
1.	Cognitive	3.2407	0.4885	535
2.	Affective	3.2604	0.5213	535
3.	Conative	3.1409	0.5473	535

EFA Analysis

EFA is a procedure that involves finding, minimizing, and organizing a large number of questionnaire items into a precise framework for the study's independent variable. SPPS version 26 was used to run EFA on 55 items with varimax rotation. Three conceptions of CT disposition, namely (i) cognitive, (ii) emotional, and (iii) conative, were employed to develop the framework for fifty-five items of CT disposition and to build a scree plot, based on theory and literature research. Three variables were considered in factor analysis: (i) sample, (ii) the Kaiser-Meyer-Olkin (KMO) sampling sufficiency or Bartlett's Test of Sphericity, and (iii) communality value of each item.

CFA Analysis

In the social sciences, confirmatory factor analysis (CFA) is a sophisticated tool for examining construct validity. CFA is renowned to verify the factor structure of a set of observed variables (Hair et al., 2012). Furthermore, CFA is a structural equation model technique for evaluating the quality of fit between hypothesized models and sample data. If the goal is to ensure that the recently acquired data fits inside the current research model, CFA will be proposed. CFA is useful for verifying item-factor interactions because it incorporates them into the measurement model and assesses their fit to the gathered data (Brown, 2006; Stevens, 2009).

Six criteria are used in the generic quality of a fit model: Model Chi-Square over degrees of independence (χ2/df), Goodness of Fit (GFI), Adjusted Goodness of Fit (AGFI), Comparative Fit Index (CFI), Tucker Lewis Index (TLI), and the Root Mean Square Error of Approximation (RMSEA) (Ahmad, 2017). Following that, Zainuddin (2013) divides the structural equation model into three categories for testing model goodness and fit: absolute fit (RMSEA, Chisq, and GFI), incremental fit (CFI, AGFI, NFI, and TLI), and parsimonious fit (Chisq/df). As a result, the fit indices given by Hair et al. (2018) and Holmes-Smith et al. (2006) are used to assess the suitability of a measurement model's fitness. For a measurement model, at least three categories of fit indices are analyzed, with one indicator from each category used to form the model. In this study, the root mean square of error approximation (RMSEA) was used for absolute fit, while comparative fit index (CFI) and Tucker–Lewis's index (TLI) were used for incremental fit, and Chi-square/degrees of freedom ratio (Chisq/df) was utilised for parsimonious fit. TLI ≥ 0.90, CFI ≥ 0.90, RMSEA ≤ 0.08, and Chisq/df ≤ 5.0, as indicated in Table 2, indicate that a model is fit.

Table 2. Model Fit Indices for Measurement Model

Fit Index	Name of Index	Fit Index Value	Source
Absolute Fix	Chi-square/Degrees of freedom ratio (χ 2/df)	χχ2/df ≤ 5	Hair et al. (2018), Bentler (1990)
Incremental fit	Comparative Fit Index (CFI) Tucker-Lewis Index (TLI)	CFI ≥ 0.9 TLI ≥ 0.9	Hair et al. (2018), Bagozzi and Yi (1988) Bentler (1990)
Parsimonious fit	Root Mean Square Error of Approximation (RMSEA)	RMSEA ≤ 0.08	Hair et al. (2018) Browne and Cudeck (1993), Byrne (2010)

Sample Size

The number of respondents should be limited to 100 or greater (DeVon et al., 2007). According to Tabachnick and Fidell (2007), the factor analysis would require at least 300 examples. In the meantime, Chua (2014) suggests a sample size that is five times the number of variables. Thus, 535 respondents took part in this study which is adequate. Meanwhile, 10 items per construct or less is still widely used as a thumb rule for determining a preliminary sample size by many studies (Costello & Osborne, 2005).

Normality Analysis

The data must be provided on a regular basis, which is one of the conditions for doing EFA and CFA. Empirical normality tests such as Kolmogorov-Smirnov (KS) and Shapiro Wilk (SW) cannot be utilized since they are insufficient for samples larger than 300 (Kim, 2012). Kim (2013) emphasized the importance of skewness and kurtosis testing for a valid normality test, regardless of the sample size. For sample sizes bigger than 300, however, rely on histograms and absolute values of skewness and kurtosis instead of z-values. Additionally, when employing SEM, appropriate skewness values are between 3 and + 3, whereas acceptable kurtosis values are between 10 and + 10 (Brown, 2006). Hair et al. (2010) defined normal data as having skewness between -2 and +2 and kurtosis between -7 and +7. Tabachnick and Fidell (2013) state that sample sizes over 200 often do not affect Skewness and Kurtosis deviations from normality. Kline (2011) states that Skewness values over 3 and Kurtosis values over ten indicate a problem, whereas values over 20 indicate a more significant issue. Skewness and Kurtosis should not exceed 3 and 10. All objects in this study have Skewness and Kurtosis values between 3 and 10. Table 3 demonstrates that the skewness (-0.281) and kurtosis (0.161) values were regularly distributed due to their range. As a result of the normality assumptions being met, the research data may be continued utilizing CFA.

Table 3. The Skewness and Kurtosis Analysis for Data Normality

	Cognitive	Affective	Conative	Overall
Valid	535	535	535	535
Missing	0	0	0	0
Skewness	-0.173	-0.367	-0.386	-0.281
S.E. of skewness	.106	.106	.106	.106
Kurtosis	-0.028	0.119	0.373	0.161
S.E. of kurtosis	.211	.211	.211	.211

Psychometric Properties of EFA analysis

The sample suitability index of Kaiser-Meyer-Olkin is a statistical measure that indicates whether or not a sample is sufficiently large to undertake factor analysis. The Bartlett sphericity test is a secondary criterion to assess the sample size which eventually assesses the correlations between all items on the scale. This test should yield a statistical significance chi-square score, which will validate the use of EFA. The Kaiser-Meyer Olkin (KMO) method is used to determine the adequacy of a sampling which must be more than 0.50 (Hair et al., 2018). The condition that KMO be greater than 0.50 reaffirms this (Field, 2009). Additionally, the sample was verified using Bartlett's sphericity test (Field, 2013). Table 4 shows the results of Bartlett's test of sphericity (Bartlett, 1954) are significantly different from zero, $\chi2 = 6794.417$, $p < .001$, and the KMO statistic (Kaiser, 1974) was 0.96, considerably exceed the minimal threshold for performing factor analysis. Finally, communalities for each item were calculated, with a value more than 0.3 necessary for all item (MacCallum et al., 1999; Tabachnick & Fidell, 2007).

Table 4. KMO and Bartlett's Test

KMO and Bartlett's Test			
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.			0.963
Bartlett's Test of Sphericity	Approx. Chi-Square		6794.417
		df	300
		sig	0.000

The estimation of factor loadings is inaccurate when communalities are low (Izquierdo et al., 2014). According to Table 5, the values are between 0.307 to 0.666 and considered acceptable.

Table 5. Communalities

	Communalities	
	Initial	**Extraction**
K6	1.000	.556
K21	1.000	.579
K5	1.000	.560
K10	1.000	.467
K50	1.000	.563
K43	1.000	.307
K49	1.000	.438
K46	1.000	.417
A41	1.000	.554
A18	1.000	.554
A9	1.000	.549
A26	1.000	.627
A27	1.000	.652
A40	1.000	.505
C19	1.000	.505
C45	1.000	.597
C42	1.000	.596
C38	1.000	.617
C31	1.000	.607
C10	1.000	.540
C39	1.000	.633
C28	1.000	.548
C29	1.000	.578
C44	1.000	.666
C40	1.000	.587
Extraction Method: Principal Component Analysis.		

Summary of the Standardized Residual Variance

Considering these general indicators, 55 items were then extracted. The cumulative total variance extracted using varimax rotation in the study may also be used to reduce the number of items before further analysis. In this method, the components of value more than 1.0 are extracted into different components (Zainuddin, 2012). Scale items account for 55.21 percent of the overall variance using principal component analysis, as displayed in Table 6. In the humanities, the variance explained is usually 50-60% (Pett et al., 2003). It is enough that the variance in behavioral sciences is 40% explained (Yeşil, 2017).

Table 6. Total Variance Explained (N= 535)

Component	Extraction Sum of Squared loadings			Rotation Sum of Squared loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10.983	43.932	43.932	6.166	24.663	24.663
2	1.591	6.366	50.298	4.195	16.782	41.445
3	1.228	4.912	55.210	3.441	13.765	55.210

Reliability Measures

Internal consistency assesses the consistency of results between factors within a test. Internal consistency is typically measured by Cronbach's alpha and generally taken as the mean of all possible split-half coefficients (Cortina, 1993). It is a summary of an earlier procedure for estimating internal consistency. An internal consistency reliability test establishes the relationship between all of the test's variables. It is applied to groups of factors designed to measure different characteristics of the same concept. Cronbach's alpha coefficient calculated for each subconstruct and dimension to determine the internal consistency of the instrument (DeVon et al., 2007). It can be measured by the values of Cronbach's alpha coefficient, inter-item correlation, item-total correlations, and Cronbach's alpha for deleted items. Table 6 shows that the alpha values for the three constructs (21 items) are above 0.7 and vary between 0.770 and 0.928. Thus, the results indicate that the internal consistency of the instrument is satisfactory for newly constructed research instruments (Hair et al., 2018; Nunnally & Bernstein, 1994; Radhakrishna, 2007). The overall Cronbach's alpha of the instrument also shows a reliability value of 0.941, which is considered very good, i.e., above 0.9 (DeVellis, 2017). The range of Cronbach's alpha is between 0.770 and 0.928, indicating a high level of internal consistency for a scale with these specific samples.

In addition, the corrected correlation coefficients of the item totals were calculated to analyze the extent to which the individual items of the scale are able to measure the traits they are intended to measure. Table 7 shows that the corrected item-total correlation coefficients for 21 items ranged from 0.564 to 0.751, indicating that the items are appropriate for the construct. This means that the internal consistency values in terms of item-to-item correlation between the variables were above 0.3. Thus, each item on the scale serves the aim of assessing the feature it is designed to measure at a significant level in relation to the total scale and is discriminative at the appropriate level (Pallant & Tennant, 2007). The result indicated a corrected item-total correlation that exceeded a value of 0.30 (Cristobal et al., 2007; Field, 2013; Maltby et al., 2007; Streiner et al., 2015). Items that have an item-total correlation value greater than 0.2 can be retained in the scale because the item has good differentiating characteristics (Pallant & Tennant, 2007; Rantz et al., 2006; Rust & Golombok, 1989). Moreover, Robinson et al. (1991) recommended that construct validity is achieved when the item-to-total correlations value is more than 0.50 and the inter-item correlations are more than 0.30. Thus, the instrument indicates a good relationship between the items and the construct.

Table 7. Reliability for Each Construct (N=535)

Construct	Cronbach's Alpha	Cronbach's Alpha based on standardized items	Corrected Item Total Correlation	Inter-Item Correlation	Number of items
Cognitive	0.770	0.771	0.564 – 0.586	0.415-0.499	4
Affective	0.855	0.856	0.594 – 0.708	0.421-0.592	6
Conative	0.928	0.928	0.651 – 0.751	0.424-0.638	11

Extraction Method

Table 8 depicts a rotating matrix of all items' factor loadings. Researchers use available data to decide which items to keep on each final factor. Accordingly, researchers decide to load items using the protocols stated before, where Q54, Q51, Q49, Q42, Q47, Q50, Q55, Q53, Q48, Q44 and Q52 on Factor 1, Items Q33, Q32, Q36, Q29, Q25 and Q35 on Factor 2, Items Q5, Q2, Q18 and Q3 on Factor 3. The items aggregate into these three components based on the item's highest loading. A total of 21 items were generated for the CT disposition construct, including conative (11 items), affective (6 items) and cognitive (4 items). Components with less than three items loaded were discarded. Meanwhile, Mvududu and Sink (2013) suggested that a more acceptable number of items per factor would be four to ten.

Table 8. Rotated Component Matrix (Each Construct)

	Components		
	1	**2**	**3**
Q54	.762		
Q51	.721		
Q49	.716		
Q42	.691		
Q47	.688		
Q50	.681		
Q55	.656		
Q53	.654		
Q48	.652		
Q44	.623		
Q52	.621		
Q33		.740	
Q32		.729	
Q36		.669	
Q29		.660	
Q25		.653	
Q35		.631	
Q5			.725
Q2			.662
Q18			.661
Q3			.660

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]
a. Rotation converged in 6 iterations.

Psychometric Properties Based on CFA Analysis

Model Fit

The measurement model illustrated in Figure 1 demonstrates that the 14 items maintained have factor loadings greater than 0.6, as predicted by Hair et al. (2018). As per Figure. 1 and Table 8, the fit indices CFI = 0.968 and TLI = 0.962 were greater than the stated fit index cut off value of 0.9 (Bagozzi & Yi, 1988; Hair et al., 2018). Similarly, the RMSEA value of 0.05 was permitted as long as it did not surpass the stated fit index threshold value of 0.08 (Browne & Cudeck, 1993; Hair et al., 2018), as was the value of 2/df with 2.357, which failed to exceed the specified threshold value of five (Hair et al., 2018). Meanwhile, Figure. 1 and Table 9 illustrate the correlation values for each of an instrument's 3 factors. Correlations less than 0.9 imply that each attribute has an appropriate value for differentiation. The multicollinearity issue was not existing as the correlation matrix with correlations was not more than 0.90 (Zainuddin, 2014). These findings indicate that the measuring model is valid in terms of construct validity and item fit for 14 items reported in Figure. 1 and Table 8. Each item has a standardized factor loading of between 0.69 and 0.78. The loading factor values also met the advice of Raubenheimer (2004), who stated that the factor loading should be 0.50 or greater for a newly created item. As a result, the newly developed instrument's findings met the acceptable range. Additionally, each attribute has at least three items and is deemed enough for measuring the instrument's characteristics or latent variables (DeVellis, 2017; Hair et al., 2018; Little et al., 1999). As a result, all fit values were accepted. Each factor in this study had a minimum of three elements, if there are too many, different repercussions occur. For instance, when the number of items obtained for each component increases, the likelihood of the factor being repeated increases (Kline, 2005; Velicer & Fava, 1998). Thus, it was determined that the measurement model met all criteria for validity, reliability, and unidimensionality.

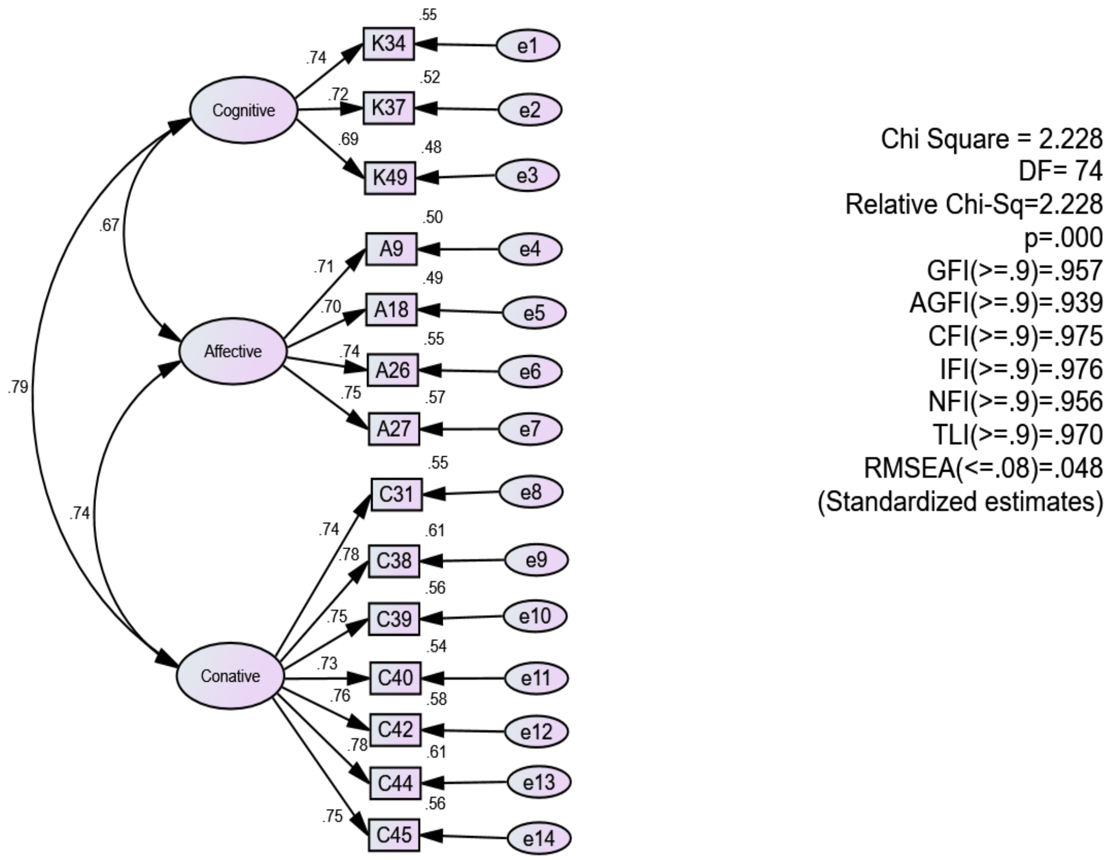

Figure 1. Measurement Model

Table 8. Model Fit of the Instrument

Fit Indices	Fit Indices Threshold	Fit Indices Value	Result
Absolute Fix	χχ2/df ≤ 5	2.228 ≤ 5	Accepted
Incremental fit	CFI ≥ 0.9	0.975 ≥ 0.9	Accepted
	TLI ≥ 0.9	0.970 ≥ 0.9	
Parsimonious fit	RMSEA ≤ 0.08	0.048 ≤ 0.08	Accepted

Table 9. Correlation

	Cognitive (K)	Affective (A)	Conative (C)
Cognitive (K)			
Affective (A)	0.67		
Conative (C)	0.79	0.74	

Composite Reliability

Additionally, the composite reliability, as well as the convergent and discriminant validity, were all analyzed using the IBM® SPSS 26, resulting in the following: (i) All factor loadings were significant and greater than 0.5; (ii) All CR and Cronbach's alpha coefficients were greater than 0.7 in all dimensions; and (iii) Each construct had an AVE greater than 0.5. (See Table 7).

Table 10. The CFA Results for the Measurement Model

Construct	Item	Loading Factor	AVE (Above 0.5)	Composite Reliability (Above 0.6)	Cronbach's Alpha Coefficient (Above 0.7)
Cognitive	K34	0.74	0.514	0.761	0.759
	K37	0.72			
	K49	0.69			
Affective	A9	0.71	0.526	0.817	0.815
	A18	0.70			
	A26	0.74			
	A27	0.75			
Conative	C31	0.74	0.571	0.903	0.904
	C38	0.78			
	C39	0.75			
	C40	0.73			
	C42	0.76			
	C44	0.78			
	C45	0.75			

We outlined the construction of a scale to assess secondary school students' CT dispositions in terms of attitudes. To begin, the instrument had satisfactory psychometric qualities. The investigation established that the three sub-constructs have a high degree of reliability. The CT disposition constructs were empirically validated in Malaysia using CFA. 14 of 55 items had loading values greater than 0.6. The researcher fulfills the criteria for using model fit indices as a measure of construct validity. We also assessed the convergent and discriminant validity of the model, which included all of the study's 14 items. Three approaches were used to determine the items' convergent validity: the loading factor value, the average variance extracted (AVE), and composite reliability (CR). In conclusion, all items have a factor loading value greater than the given threshold value of 0.7(Tabachnick & Fidell, 2013).

Accordingly, the AVE value was between 0.51 to 0.57, thus indicated that the 14 items were consistent with the constructs. Additionally, the composite reliability value range between 0.76 to 0.9. Likewise, all three constructs have enough discriminant validity when the correlation between them does not exceed 0.85 (Kenny, 2016; Zainuddin, 2015). Correlation coefficients below than 0.85 suggest that there is no confusion among students while they are responding the items, assuming that the operational meanings of the constructs are given explicitly.

The construct validity and reliability index analyses were conducted using the composite reliability (CR) index and Cronbach's alpha, respectively. All reliability indices in this investigation exceeded the 0.70 cut off value (Nunnally & Bernstein, 1994). As a result, the instrument has been shown to be very consistent across the majority of study populations.

Discussion

Previous studies on thinking dispositions (Beyer, 1995; Ennis, 1996; Facione, 2000; Facione et al., 1994; Perkins & Tishman, 2001), i.e., a person's thinking, such as attitudes, beliefs, habits, and values, secondly, mind or mental functioning (Hilgard, 1980), and the three-component attitudinal model (Schiffman et al., 2012), but also CT measurements (Brennan & Resnick, 2012; Korkmaz et al., 2017) have laid an important foundation for the development of the measurement model. Our proposed framework was based on the three common conceptual features of thinking dispositions in the literature review: cognitive, affective, and conative. Overall, the study contributes to the current interest in CT (CSTA, 2017) by developing a valid and reliable instrument from a dispositional perspective. We reported the development of a scale to measure secondary students' CT disposition. First, the instrument had adequate psychometric properties. The analysis showed that the constructs were quite reliable and the items played a significant role in the instrument.

The testing of the CT dispositional constructs in Malaysia was empirically demonstrated using the EFA and CFA. All the results of the psychometric measurements confirmed the validity and reliability of the instrument as all the scores exceeded the proposed cut-off. Furthermore, at the item level, all factor loadings were greater than 0.3, indicating that all items were significant (Pituch & Stevens, 2016). All communalities were also closer to one, meaning that the extracted component explained a greater proportion of the variance in a single item. With three competing measures, this study has very strong internal consistency, including a Cronbach's alpha of .941, reasonable construct validity based on the accepted value of item-total correlations >0 .50, and inter-item correlations >0 .30, and the items are measurable for secondary students' dispositions with three major constructs. The construct and its items have been proven to be beneficial to students and future researchers, even though the development of a new instrument to assess the disposition of students in Malaysia (CT) is underway. Nevertheless, it has the potential to contribute to CT related exploration and applications.

Therefore, for researchers to explore the disposition of CT in detail, empirical evidence, such as EFA and CFA should be used to choose items that can sufficiently delineate the distinct framework. The constructive application of factor analysis methods can lead researchers to believe in the implementation of dispositional constructs, especially in a new research setting. The recommended items can now be modified to match students' preferences to increase their overall effectiveness, and further statistical analyses may be useful, such as the Rasch model.

The items can be used to assess three basic constructs of secondary school pupils' CT disposition. Despite the fact that a new CT disposition instrument for Malaysian students is being developed, the items and constructions have shown to be valuable to students and future researchers. It has the potential to contribute to the CT body of knowledge and applications. The study's main flaw is that it was only conducted on secondary school pupils in one country, Malaysia. However, we focused our research on frequently cited literature that deals with CT in numerous domains. As a result, the instrument should be applicable to a variety of fields. Furthermore, replications in other nations would strengthen the relevance of the study in a diverse group of countries. Because the researchers' viewpoints on thinking dispositions and CT dispositions are complex and varied, this study piloted a questionnaire to measure CT dispositions among secondary school students who had some CT knowledge and skills.

The successful use of factor analysis techniques might increase researchers' confidence in using disposition constructs, especially in varied study settings. This work presents a verified CT competency assessment tool for researchers and academics. This research adds to the body of knowledge in CT teaching and learning by providing a more comprehensive overview of CT dispositions and attitudes, as well as their impact on their readiness to work in digital environments.

Conclusion

In conclusion, this research reveals that the created scale is valid and psychometrically sound using classical procedures. This study provides researchers and academicians with a validated instrument for measuring CT competence. The finding of this research adds to the corpus of information regarding CT teaching and learning by providing a more comprehensive account of CT dispositions and attitudes that affect their readiness to participate in digital workplaces. Although it was developed in the context of secondary school students, with some modifications, there is scope to adapt the instrument to higher levels of education, such as primary education. This is necessary to meet the different requirements of computational thinking.

Recommendations

The scale has to be validated in a diverse sample, such as students in higher educational institutions, students in primary and secondary schools, and also in private schools. Comparing research across tests may also offer a statistical overview of the outcomes from several viewpoints. More significantly, this study will not only affect subsequent analyses, but may also enhance the items' construct validity. Most notably, the researcher needs to relate the acceptable dispositions with the students in the Malaysian context. Nevertheless, this questionnaire still does not include all the characteristics described in the literature and it is possible that some related aspects have been omitted. Future research could extend the current work by exploring other aspects of CT dispositions. To maximize overall efficiency, the items offered should be tailored to student preferences, and further influential statistical analyses incorporating classical test theory and item response theory could be beneficial. This would necessitate additional and in-depth study to discover more relevant topics prior to conducting CFA.

Limitations

The main shortcoming of this study is that it was conducted on secondary school students in only one country, Malaysia. However, we have drawn on a wide body of literature that deals with CT in various fields. The instrument should therefore be relevant to different domains. Replication in different countries would also increase the relevance of the instrument in different countries. Nonetheless, this questionnaire does not yet encompass all of the features described in literature, and it is possible that some related aspects were left out. Future research could expand on the current work by looking into other aspects of CT dispositions.

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Authorship Contribution Statement

Saralah: Methodology, validation, data analysis, and writing. Kamisah: Funding acquisition, project supervision, conceptualization, methodology, validation, data analysis, writing and final approval. Matore: Conceptualization, validation, data analysis, and writing.

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