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Determining youths' computational thinking skills using confirmatory factor analysis

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ABSTRACT

As technological advancements shape the workforce, computational thinking skills (CTS) are becoming increasingly crucial. The objective of the study is to explore the potential mediating role of professional development and career planning in the association between robotic coding and software and computational thinking. The study selected 308 youths using simple random sampling and the collected data was subjected to structural equation modelling (SEM) and confirmatory factor analysis (CFA) using SmartPLS. Additionally, demographic data were analyzed using statistical package for social sciences (SPSS). The results concluded that the instrument adopted fulfilled the requirements and was valid for measuring CTS. This indicates that the instrument effectively assessed the participants' proficiency in CTS. The findings of this study have implications for addressing the skills gaps among youths. The outcomes of this research can aid in designing educational interventions and policies that focus on developing computational thinking skills among new graduates. By fostering these skills, youths can better adapt to the demands of the rapidly evolving technological landscape and contribute effectively to the industries and job market influenced by industry 4.0. Further research on longitudinal studies may be beneficial to assess the long-term impact of CTS development initiatives on reducing skills gaps and ensuring youths are equipped for future workforce requirements.

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1. INTRODUCTION

Computational thinking has emerged as a progressive field of study in recent years. Its significance is acknowledged by educational reforms worldwide, as it plays a crucial role in preparing individuals for the demands of the 21st-century economy. Computational thinking skills (CTS) are important in making advancements in science, technology, engineering, and mathematics (STEM) fields and are highly demand by industries undergoing the transformative changes of industry 4.0 [1]. Developing CTS can enhance employability by providing individuals with valuable skills for technology-driven industries. Lacking these skills may contribute to higher unemployment rates due to automation. According to previous study [2], it is projected that highly demanded positions in the country by 2025 will include data analysts, software engineers, and application developers.

These roles are expected to be in high demand due to the increasing reliance on technology and data-driven decision-making in various industries. Several studies [3]–[7] on CTS were not explicitly focused on the research subjects of robotics coding and software with professional career planning. As a result, a new scale has been developed to serve the purpose [8]. The scale is designed with an interdisciplinary approach in mind, allowing its application across various fields and subjects. This study determines youths' CTS using the instrument adapted from Ertugrul-Akyol [8] in Malaysia. The research aims to identify professional development and career planning that is likely expected to mediate the relationship between robotic coding and software and computational thinking. Exploring the influence of computational thinking on youth can provide valuable insights into its long-term effects on their educational and career pathways. It can help identify how CTS contribute to their academic success, career readiness and developing skills relevant to the digital age of industry 4.0.

The rapid evolution of technologies in industry 4.0 presents a significant challenge for organizations as they strive to acquire the high value skills to adapt to the changing job functions brought by technological disruptions [9]. A study [10] cited various reasons for the gap in graduate skills, including graduates' preparedness to enter the workforce, a lack of job creation and a skills gap. The rapid advancement of technologies in Malaysia has created a demand for professionals with expertise in areas like AI, IoT, robotics and cybersecurity. However, a shortage of qualified workers in these fields results in a skills gap. The limited availability of skilled professionals in these areas poses challenges to Malaysia's ability to exploit the opportunities presented by industry 4.0 and the ongoing digital transformation [11]. Therefore, in order to harness the potential of youths as a dynamic asset for development, it is essential to formulate a youth strategy aiming to capitalize on the capabilities and energy of young people to drive progress and growth [12]. While many previous researchers have contributed significant work to a growing knowledge base on teaching and learning computational thinking, studies do not often focus from the youth's perspective. Previous researchers prioritized the perspectives of educators, curriculum designers and policymakers rather than comprehensively examined the influence of computational thinking on youths. Thus, there is limited research that has comprehensively examined the influence of computational thinking and how to nurture it in today's youth [13]. Exploring this issue may help shed light on how to promote awareness on the importance of CTS among youth as preparation for their future job hunting and successful career.

2. LITERATURE REVIEW

2.1. Computational thinking

The field of computational thinking has been a subject of active exploration and research in recent years. Scholars have dedicated their efforts to understanding and advancing this field, leading to significant advancements and progress. This area of study has become a focal point for educational reforms worldwide, as many countries recognize the importance of computer technology in preparing their citizens for the demands of the 21st-century economy [14], [15]. Computational thinking has long been recognized as a valuable skill set that contributes to breakthroughs in STEM fields. By applying principles and concepts from computer science, experts have been able to make significant advancements in their respective domains.

As a result, students who possess knowledge of computational thinking and understand its underlying concepts are more likely to pursue further education in STEM-related disciplines and consider careers in STEM fields upon graduation. This is particularly relevant in the context of the labor needs in the era of industry 4.0, where skills related to computational thinking are in high demand. The term "computational thinking" was initially defined by Wing [16] as the ability to solve problems, build systems, and understand human behavior using principles derived from computer science. Regardless, a recent study has expanded upon this definition. They describe computational thinking as a set of thinking skills that can be effectively taught, implemented and utilized in real-world scenarios and large-scale problem-solving processes [17].

2.2. Robotic coding and software

The expansion of educational robotics into the curriculum beyond traditional STEM fields aligns with the broader recognition of the importance of computational thinking in the 21st century. This expansion recognizes the value of robotics as a tool to foster CTS among students [18]. This has led to a growing exploration of robotics as a prospective educational environment for acquiring CTS. A research on a robotics curriculum found that the activities and curriculum had a positive impact on students' CTS, particularly in the context of robotics coding [19]. The hands-on nature of robotics activities and the application of coding principles enable students to develop problem-solving abilities and algorithmic reasoning. This suggests that the integration of robotics activities and coding exercises can effectively enhance students' CTS. Coding robotics can significantly increase participants' CTS [20], [21]. Robotic coding and software development skills are increasingly valued in the job market, particularly as automation and technology-driven industries grow. Proficiency in these areas can enhance one's employability by providing the skills needed to work in robotics, artificial intelligence, software development and data analysis. Therefore, by developing CTS since they were in school, youths may enhance their job prospects and reduce the risk of unemployment. Industries that require technological expertise often seek individuals with strong CTS, making these individuals more competitive in the job market [22]. Thus, the first hypothesis of the study: Robotic coding and software have a significant positive relationship with computational thinking skills (H1).

2.3. Professional development and career planning

Professional development is defined as the continuous process of acquiring new knowledge, skills, and competencies relevant to one's chosen profession. It provides individuals with opportunities to expand their understanding and expertise in specific areas, including computational thinking. Career planning refers to the proactive process individuals engage in to prepare for their desired occupations and positions, especially when they are not currently in the workforce or have not yet attained their desired positions [23]. Career planning enables youth to identify how CTS can enhance career opportunities and contribute to professional growth. Moreover, professional development and career planning provide individuals with the necessary resources, guidance, and support to develop and strengthen their CTS. They offer access to relevant training programs, mentorship, networking opportunities and industry insights, all of which contribute to acquiring and applying the skills. By integrating professional development and career planning into their journey, young individuals can enhance their CTS effectively and consequently leverage them in their professional pursuits. Thus, the hypothesis of the study: Professional development and career planning are significantly related to computational thinking skills (H2) and robotic coding and software positively correlate with computational thinking skills through professional development and career planning (H3). Figure 1 illustrates the theoretical framework of the study.

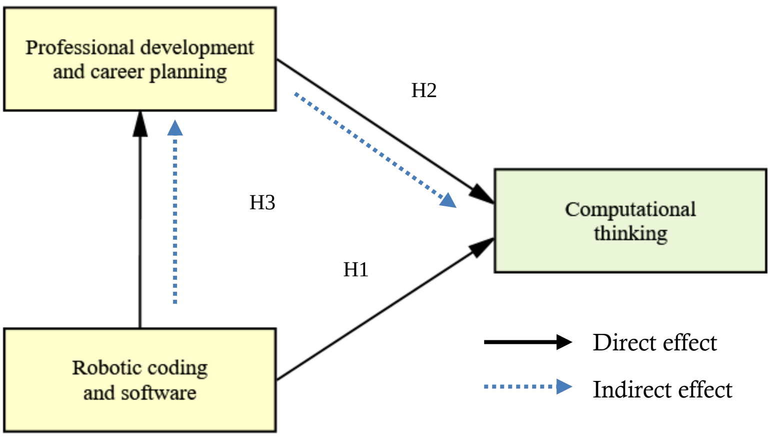

Figure 1. Theoretical framework of the study

3. RESEARCH METHOD

This study employed a quantitative research study via survey online questionnaire using non-probability and convenience sampling techniques. Regardless of gender and educational level, 308 young individuals (aged 15 to 30) from different states in Malaysia took part in this study. A total of 30 items were measured through a five-point Likert scale ranging from 1 signifying 'strongly disagree' to 5 signifying 'strongly agree'. The 30 items represent constructs of computational thinking (CT) (15 items), robotic coding (RC) (10 items), and personal development (PD) (5 items). The items were adapted from a scale development study by Ertugrul-Akyol [8], in which the author established a questionnaire set to measure computational thinking scale. The proposed hypotheses were analyzed using SmartPLS (v.3.3.9) software to perform PLS-SEM. SPSS (v27) was used for demographic analysis. The total sample size of 308 met the requirement to apply SEM since a minimum sample size of 200 is considered suitable [24]. First, we used the two-stage approach to analyze the constructs' reliability and validity. In the second stage, we tested the hypotheses by running bootstrapping in SmartPLS.

4. RESULTS AND DISCUSSION
4.1. Demographic analysis

For the demographic analysis, out of the 308 participants, 67% were female, while males accounted for 32.80%. Although the gender distribution was not balanced, previous research studies have indicated that both males and females can have positive and satisfying experiences when engaging in robotics-related activities [25]. The age range of the surveyed youth in Malaysia was between 15 and 30 years old. The largest age group was 27-30 years old, comprising 35.40% of the respondents. The second-largest age group was 19-22 years old, representing 29.50% of the participants. The age group of 23-26 years old accounted for 28.90%, while the smallest group was 15-18 years old, constituting 6.20% of the respondents. In terms of educational background, the majority of respondents had a bachelor's degree, making up 54.20% of the participants. Youths who graduated with a diploma comprised 15.90%, while with a master's degree accounted for 15.60%. Respondents with SPM/O-Level qualifications represented 14.30% of the sample. Regarding employment status, the study found that 54.20% of the respondents were students, 29.50% were employed, 8.40% were self-employed, and 7.80% were unemployed. In terms of awareness of the term "Industry 4.0," 62% of the respondents reported being familiar with it, while 38% had not heard of it before.

4.2. Assessment of measurement and structural models

We used structural equation modelling (SEM) and confirmatory factor analysis (CFA) tools for data analysis and testing relationships between variables. Structural equation modeling (SEM) is a family of multivariate statistical analysis methods used to model complex structural relationships between measured variables and latent constructs [26]. CFA is commonly used to verify or confirm the factor structure of a set of observed variables [27]. It examines the strength and significance of the relationships between the observed variables and their corresponding latent factors, represented by factor loadings. The validity of the measurement model for latent constructs was evaluated using three types: convergent validity, construct validity, and discriminant validity [27], [28]. The average variance extracted (AVE) was calculated to assess convergent validity. Construct validity was evaluated by examining the fitness indices of the measurement model. Discriminant validity was established through the development of the Discriminant Validity Index Summary. Composite reliability (CR) was used instead of the traditional Cronbach alpha method of analysis to determine the reliability of CRIS. These approaches were suggested by various studies [24], [27], provided more robust measures for assessing validity and reliability. The measurement model depicted in Figure 2, consists of the indicators and the path coefficients between constructs.

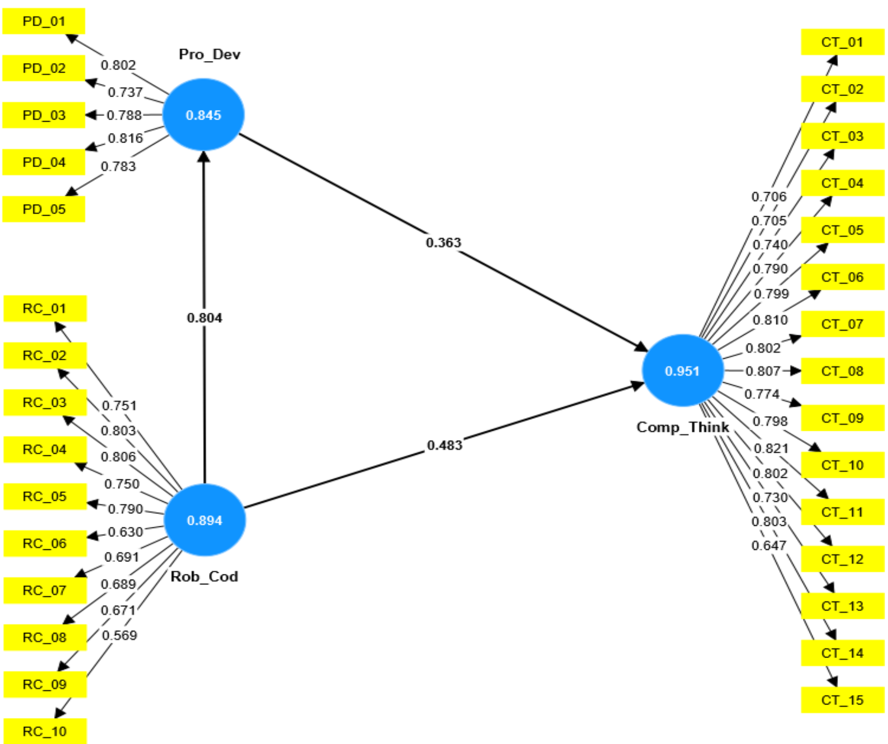

Figure 2. PLS-SEM model

According to Table 1, no multicollinearity was found between the constructs. The outer and inner models of Variance Inflation Factor (VIF) values must be less than 10 [24], [27]. The values were ranging from 1.930 to 3.360, supporting the assessment of low multicollinearity. Since the collinearity value VIF < 3 except one (RC_03=3.360), the collinearity issues in this study are uncritical. All indicators are significantly and accurately assessing their respective latent variables. According to the rule of thumb, the outside loading values must exceed 0.7 [29]. Hence, it can be concluded that the outer loading, which ranges from 0.704 to 0.859 with a p-value <0.001, indicates that the convergent validity has been reached or indicator reliability exists, and all the latent variables of this study are valid and reliable. Consequently, all reflective indicators have been retained in the study.

The internal consistency reliability is evaluated using composite reliability and Cronbach's alpha values. The acceptable range for composite reliability is typically between 0.70 and 0.90 [30]. Values exceeding 0.90 to 0.95 may indicate redundant effects on the content validity of the measures [31]. In this study, the composite reliability value for computational thinking approaches 0.95, but it does not have an adverse impact on the model. Convergent validity is established when a significant amount of variance is shared among the indicators, indicating convergence on a specific construct. This can be assessed through the AVE. The AVE value should exceed 0.5 to establish convergent validity [24]. We observed sufficient outer loadings, and all AVE values exceed 0.5, indicating that convergent validity has been achieved.

Table 2 summarizes the findings, indicating that factors such as robotic coding software, professional development, and career planning collectively account for 65.70% of the variation in the computational thinking construct. Professional development and career planning contribute to 53.90% of the robotic coding and software construct variation. The R^2 values, which exceed 0.50, indicate that the independent variable moderately explains the dependent variable [28]. In a similar vein, the R^2 values imply that the model may be overly tailored to the data, indicating an appropriate fit for the proposed theoretical framework [24]. The impact of the exogenous constructs on the endogenous constructs is moderate, as evidenced by f^2 values ranging from 0.15 to 0.34, in accordance with Cohen [32]. The Q^2 value, which reflects the predictive relevance of the model, is 0.407 for computational thinking and 0.327 for robotic coding and software. These values surpass the threshold of 0.350, thus indicating a substantial level of predictive relevance in the study.

Table 1. Assessment of consistency, validity, and reliability

Items	VIF	CT	PD	RC	Cronbach's alpha	Composite reliability	Average variance extracted
CT_03	1.930	0.732			0.947	0.953	0.631
CT_04	2.442	0.790					
CT_05	2.528	0.796					
CT_06	2.654	0.818					
CT_07	2.516	0.806					
CT_08	2.765	0.821					
CT_09	2.442	0.780					
CT_10	2.647	0.808					
CT_11	2.812	0.822					
CT_12	2.744	0.815					
CT_13	2.024	0.731					
CT_14	2.515	0.806					
PD_01	1.774		0.809		0.845	0.889	0.616
PD_02	1.642		0.748				
PD_03	2.112		0.774				
PD_04	2.007		0.822				
PD_05	2.099		0.769				
RC_01	2.729			0.814	0.899	0.920	0.624
RC_02	2.319			0.807			
RC_03	3.360			0.859			
RC_04	2.179			0.793			
RC_05	1.955			0.772			
RC_07	2.169			0.771			
RC_08	1.719			0.704			

Note: VIF = Collinearity Assessment, CT = Computational thinking, PD = Professional development and career planning, RC =Robotic coding and software and all the loadings (estimates) are significant at a p-value of 0.001

Table 2. Assessment of the structural model

	Inner Collinearity statistics	R Square	F^2	Q^2
Computational thinking	2.171	0.657	0.242	0.0407
Robotic coding and software	2.171	0.539	0.267	0.327

Table 3 presents the path coefficients, standard deviations, absolute T values, and significance values. The significance of the coefficients was determined through bootstrapping, considering a significance level of 5% and critical values of 1.96 for two-tailed tests. All T values exceed 1.96, and the p-values are <0.05, indicating the significance of the relationships between the latent variables. The path coefficients are examined to evaluate the strength of these significant relationships. Notably, the path coefficients from professional development and career planning to computational thinking and from robotic coding and software to computational thinking are moderately strong, surpassing 0.4. The path coefficient from professional development and career planning to robotic coding and software demonstrates a strong relationship with a coefficient of 0.734. Consequently, we draw a conclusion that the three proposed paths are relevant and significant. According to Awang [27], when path coefficients are close to +1, it indicates a robust positive relationship. Apart from assessing the sizes of the path coefficients, it is crucial to establish their statistical significance. Based on the path coefficient values presented in Table 4 for the theoretical model, all estimated values exceed 0.4 and are statistically significant (p<0.05).

Table 3. Structural model (Inner model) and path coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T Statistics (|O/STDEV|)	P values
Structural model					
Professional development and career planning → Computational thinking scale	0.424	0.427	0.057	7.498	0.000
Professional development and career planning → Robotic coding and software	0.734	0.734	0.029	25.066	0.000
Robotic coding and software → Computational thinking scale	0.446	0.445	0.062	7.203	0.000
Path coefficients					
Direct effects					
Professional development and career planning → Computational thinking scale	0.424	0.43	0.055	7.663	0.000
Professional development and career planning → Robotic coding and software	0.734	0.736	0.028	25.978	0.000
Robotic coding and software → Computational thinking scale	0.446	0.44	0.06	7.487	0.000
Indirect effect					
Professional development and career planning → Computational thinking scale	0.328	0.324	0.044	7.498	0.000

With reference to the Table 4, the researchers found that the indirect effect size is 0.324, and it is statistically significant (p value<0.05). This suggests that professional development and career planning partially mediate the relationship between the role of robotic coding and software and computational thinking. Additionally, the researchers found that the direct path from professional development and career planning to computational thinking has a coefficient of 0.430 and is statistically significant (p value<0.05). This indicates that there is also a direct effect of professional development and career planning on computational thinking. Overall, based on the results of the mediation analysis, the researchers have established that the independent latent variable (role of robotic coding and software) predicts the dependent variable (computational thinking) both directly and indirectly through the mediator variable (career planning). The significant indirect effect size supports the mediation effect, while a significant direct path suggests a partial mediation effect.

Table 4. Hypotheses results

	Path coefficient	t-value	p-value	Results
H1: Robotic coding and software have a significant positive relationship with computational thinking skills.	0.424	7.498	0.000	Accepted
H2: Professional development and career planning are significantly related to computational thinking skills.	0.734	25.066	0.000	Accepted
H3: Robotic coding and software positively correlate with computational thinking skills through professional development and career planning.	0.446	7.203	0.000	Accepted

5. CONCLUSION

It is concluded that professional development and career planning moderately mediate the relationship between robotic coding and software and computational thinking. The findings are hoped to assist educators, higher education institutions and policymakers in developing new insights relevant to identifying the requirements for continually improving future industrial employability. This study was undertaken to validate a survey instrument for measuring CTS among Malaysian youths. The CFA then confirmed that the survey instrument fulfils the requirements for convergent, construct and discriminant validity. The scale is deemed valid and reliable for measuring the CTS, adding to the advancement of research and practice in this area. The instrument developed to assess CTS among Malaysian youths has potential interdisciplinary applications. Therefore, it may be applicable in various research settings, allowing for comparative studies and the examination of CTS across different populations. However, it is essential to consider cultural and contextual factors when applying the instrument in different settings. Some adaptations and modifications may be necessary to ensure its validity and reliability in specific cultural or educational contexts. Certainly, future research can explore additional factors that may influence young individuals' CTS. Understanding these factors can provide a more nuanced comprehension of the determinants of the computational thinking scale. Regarding mediating variable, future scholars can explore additional variables that may enhance the strengths of the CTS instrument and provide a more inclusive perspective of the relationship between different constructs.

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