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Factors associated with computational thinking skills among colleges in the university

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Abstract: Computational Thinking (CT) skills are crucial for students in various academic disciplines. This study investigated the relationship between CT perspective, digital competence, and unplugged CT skills among college students. The study aimed to assess the influence of the CT perspective and digital competence onunplugged CT skills across different academic departments and programs. It also explored potential moderating effect of gender, grade level, study program, and GPA. The unplugged CT refers to practicing computational thinking skills without the use of Scratch applications. A cross-sectional survey design with a random sampling method was employed. Data was collected from 500 college students enrolled in bachelor's degree programs (science and non-science) at seven universities in Indonesia, from December 2023 to April 2024. The CT skills was collected through 25-item-multiple-choice questions test. CT perspective and digital competence were measured using separate 15-item and 20-item questionnares, respectively, all administered on a 5-point Likert scale that was distributed via Google Form. A structural model with a partial least squares approach was used tp analyze the relationship between the variables. The results indicated that there was a positive relationship between CT perspectives, digital competence, and CT skills. There were significant differences in CT skills based on study program, grade, and GPAs, but not gender. Students in science programs, upper grades, and with higher GPAs demonstrated higher CT skills. This study highlights the importance of fostering CT perspective and digital competence to enhance unplugged CT skills in various academic contexts.
Keywords: *College, Computational thinking, Digital competence, Moderating variable, Perspective.*

1. Introduction

Universities play a vital role in equipping young people, the future of society, with the most current professional knowledge. This knowledge is complemented by fostering adaptable 21st-century skills such as cognitive skills, collaborative teamwork, digital literacy and ICT skills, communication and media literacy, intercultural skillsadaptability, and resilience (Koyuncuoglu, 2022). Higher education institutions are particularly significant as they serve as both a major source of skilled personnel for knowledge production. Thus, analysing a country's higher education system in isolation from its science and technology system may result in incomplete or misleading assessments (Koyuncuoglu, 2022). In today's rapidly changing world, digital literacy and ICT skills have evolved into Computational Thinking (CT) as a problem-solving. This critical problem-solving skill equips students to navigate

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present complexities and future uncertainties (Adams et al., 2019). The advancement of information technologies has led to their widespread integration into education system. The integration of computers in education is fueled by four primary reasons, as outlined by Cavalier & Reeves (1993). These reasons include the need for computer literacy in technology-driven society, a necessity for individual career success, enhancing educational efficiency, and the potential of programming to foster cognitive skills.

The implementation of Computational Thinking (CT) can be divided into two activities: unplugged CT and plugged CT. First, unplugged CT focuses on teaching and learning CT concepts and skills without the use of computers or digital devices. Instead, it involves hands-on activities, puzzles, games, and exercises that help learners develop problem-solving abilities, algorithmic thinking, pattern recognition, and logical reasoning (El-Hamamsy et al., 2022; Wing, 2006). This approach is particularly useful for introducing CT concept to learners who may lack access to technology or for providing a foundation before transitioning to computer-based learning (El-Hamamsy et al., 2022). Plugged CT, on the other hand, utilizes computers, software, or digital devices to teach and practice CT skills. This approach often involves coding activities, programming exercises, and the use of software tools or programming languages to solve problems (Karen & Mitchel, 2012). This study assessed students' CT skills by using an unplugged activities test developed by El-Hamamsy et al. (2022).

Computational Thinking (CT) skills are essential for developing the CT perspective and digital competence, especially in tasks involving problem-solving, data analysis, and decision-making using digital tools. Previous studies shown that positive attitudes towards CT can lead to both better development of CT skills and improved academic performance, particularly among elementary school students and pre-service teachers (Cutumisu et al., 2022; Sun et al., 2021, 2022). The CT perspective, which provides the foundation for applying computational thinking skills in real-world contexts, is often fostered individuals with strong positive CT skills perspective (Junpho et al., 2022). These skills, such as problem decomposition, pattern recognition, algorithm design, and abstraction, provide a structured approach to problem-solving that can be applied across various digital contexts. Digital competence, encompassing a broader set of skills needed to interacting with and utilizing digital tools efficiently and responsibly, forms the foundation for successful engagement with computational thinking activities (Juškevičienė & Dagienė, 2018). Integrating CT into digital literacy curricula can further enrich this competence by equipping students with problem-solving strategies, specificallyapplicable to digital environments.

The previous research has investigated the relationship between gender and CT skills, with studies finding no significant differences between male and female pupils (Black & Wiliam, 1998; Brackmann et al., 2017). However, Djambong & Freiman (2016) identified a variation in CT skills based on educational level and access to technology. Nevertheless, the impact of factors such as attitude, field of study, grade level, and academic performance on CT development remains under-explored, with existing research often limited to spesific disciplines, such as computer science or engineering programs. Therefore, this study addresses this gap by investigating how CT skills are cultivated across diverse demographics, including gender, study program, GPA, grade level and explores the novel relationship between CT perspective, digital competence, and unplugged CT skills.

Research on CT skills development has primarily focused on K-12 education, with fewer studies examining CT skills development at the higher education level and across different study program. Moreover, the findings of this study can serve as valuable reference points for educators seeking to innovate learning methods aimed at fostering the development of CT skills through unplugged activities. In order to achieve the aims of this study, this research raises six main research questions:
RQ1: Does the CT perspective influence CT skills?
RQ2: Does digital competence influence CT skills?
RQ3: Do the CT perspective and digital competence have a relationship with CT skills?
RQ4: Do the CT skills differ according to the gender?
RQ5: Do the CT skills differ according to the GPAs?

RQ6: Do the CT skills differ according to the grade?
RQ7: Do the CT skills differ according to the study program?

Based on these research questions, understanding the factors contributing to computational thinking skills is critical to developing targeted interventions.

2. Literature Review

2.1. Unplugged CT Skills

Unplugged computational thinking (CT) skills test assess an individual's ability to think computationally without relying on digital tools, such as Scratch application. This approach offers significant advantages in educational setting with limited resources or where educators prioritize fostering a conceptual understanding od CT over proficiency in specific programming languages. These assessments offer several advantages. First, they align with the definition of "unplugged" established by Agbo et al. (2024) & Brackmann et al. (2017). This allows for straightforward deployment in diverse settings and at a large scale because they do not necessitate the use of computers or screen. Second, unlike traditional programming assessments, unplugged CT tests eliminate the barrier of prior coding knowledge or familiarity with specific programming languages (Jou et al., 2023; Román-González et al., 2017). Instead, it typically involves hands-on, offline activities that challenge individuals to demonstrate their understanding of computational concepts and problem-solving strategies in a physical or tangible manner. This present study adopts the unplugged CT test developed by El-Hamamsy et al. (2022), with focuses on evaluating six CT indicators namely sequences, simple loops, complex loops, conditional statements, while statements, and combinations.

2.2. CT Perspectives

The CT skills identified in this study closely align with and are organized according to the themes outlined in the framework proposed by Brennan & Resnick (2012) and Karen & Mitchel (2012). These themes include computational concepts, practices, and perspectives (Korkmaz & Bai, 2019). Among these, the computational thinking perspective is particularly relevant. It refers to a spesific approach to problems and tasks, leveraging principles and techniques from computer science and computational methods. This perspective emphasizes breaking down complex problems into smaller, more manageable parts (decomposition), and developing solutions using step-by-step procedures (algorithmic thinking). It also encourages focusing on essential aspects of a problem while disregarding irrelevant details (abstraction), and applying logical rules and patterns to solve problems (logical reasoning). This study adopts the CT perspectives scale developed by Karen & Mitchel (2012), which focuses on three aspects: expressing, connecting and questioning. From an educational standpoint, fostering a computational thinking perspective involves teaching and encouraging individuals to apply these skills across various domains and disciplines. This fosters their development as effective problem solvers, critical thinkers, and innovators in an increasingly technology-driven world.

2.3. Digital Competence

The conceptual model of digital competence from a sociocultural perspective (Conde-Jiménez, 2018) is constituted by transferring different constructs of this approach: Command, Privileging, Appropriation and Reintegration (Vygotsky, 2000). The digital competence includes a set of basic instrumental skills and abilities related to the access and management of Information and Communication Technologies (ICT) at a basic user level. These skills demonstrate knowledge and the technical application of ICT tools. It extend beyond mere technical proficiency, also incorporating knowledge, skills, values and attitudes. This includes prioritizing ICTs as valuable tools for problem-solving and personal development, potentially favoring them over other resources.

Critically, digital competence facilitates a deeper understanding of computational concepts. Through hands-on experiences with digital tools individuals can grasp fundamental concepts such as algorithms, data structures, and automation. This practical engagement with technology fosters a stronger understanding of how these concepts are applied in computational thinking practices in various contexts (Nouri et al., 2020).

2.4. Related Literature

Several studies suggest a connection between weaker CT skills and less positive CT perspective. Individuals with lower CT skills may have a less positive computational thinking perspective, feel less confident in their ability to apply CT techniques, and underestimate the relevance of CT skills. This highlights the importance of both CT skills and CT perspective, as they work together to empower individuals to navigate the digital landscape with confidence, creativity, and critical thinking. This combined ability allows them to thrive in various academic, professional, and personal settings (Barr & Stephenson, 2011; Grover & Pea, 2018; Wing, 2006). Building on this notion, Esteve-Mon et al. (2020) emphasize the interrelated nature of digital competence and CT They argue that navigating the digital world effectively requires proficiency in using digital tools and software, which often involves understanding basic computational concepts. For instance, being able to create a spreadsheet requires understanding how to use formulas and functions, which inherently involves CT skills like algorithmic design and logical reasoning.

The relationship between computational thinking (CT) skills and various factors like GPA, gender, study program, grade level, is a complex interplay influenced by individual characteristics, educational experiences, and societal factors. This section ecplores each variable and its potential influence on CT skills. Higher GPAs may indicatie stronger analytical and problem-solving abilities, foundational skills for CT. Research by John Lemay et al. (2021) supports this notion, finding a positive correlation between academic performance and CT skills among university students in computer education programs. Gender disparities in CT are not universal. A study by Espino & González (2016) found no significant gender-based differences in CT skills among university students. Cultural norms, educational opportunities, and individual interests likely play a role in these disparities. The chosen study program can significantly influence the CT development. STEM programs often provide more opportunities for students to engage in activities that foster CT, such as programming, data analysis, and problem-solving. This is reflected in research by Grover & Pea (2018), which foundthat students in computer science and engineering programs tend to have higher levels of CT skills compared to those in non-STEM programs. Grades in specific courses, such as mathematics, computer science, or logic, may correlate with CT skills. Higher grades in these courses may indicate a stronger foundation in the concepts and skills relevant to CT. A study by Fessakis et al. (2013) investigated the relationship between students' grades in mathematics and their computational thinking skills and found a positive correlation between the two variables.

3. Methodology

3.1. Research Design and Hypothesis

This study investigated the effect of computational thinking perspective (CTP) and digital competence on the college students' CT skills. It also explored the relationships between colleges' CT skills with four factors: gender, study program, grade level, and GPA. These relationships were depicted in a research model diagram (Figure 1). It therefore followed the correlational research design with cross-sectional survey conducted from December 2023 to April 2024.

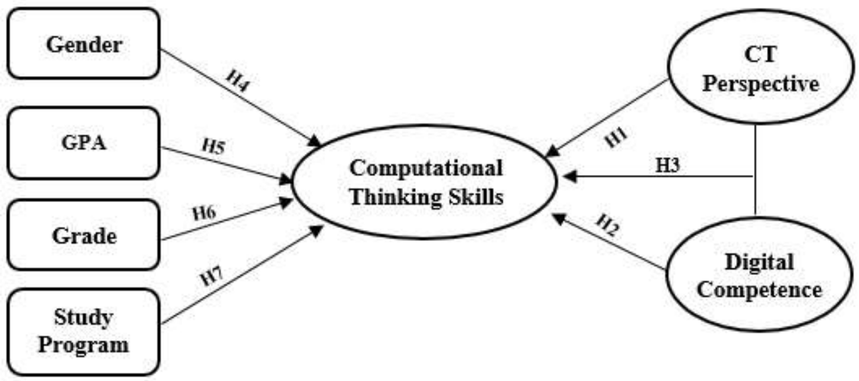

Figure 1.
Research diagram.

To examine the direct effects on CT skills, the following hypotheses were proposed:
H_1: The CT perspective significantly influence the CT skills.
H_2: The digital competence significantly influences the CT skills.
H_3: The CT perspective and digital competence signifcantly have a relationship with CT skills.
Additionally, hypotheses were formulated to explore potential moderating effects:
H_4: The CT skills did not differ according to the gender.
H_5: The CT skills significantly differ according to the GPA.
H_6: The CT skills significantly differ according to the grade level.
H_7: The CT skills significantly differ according to the study program.

3.2. Participants

This study involved 500 college students enrolled in various undergraduate bachelor's study programs (science and non-science) across seven universities. The universities consisted of three private and four public institutions, all with relatively similar technological capabilities. Participants were selected using a random sampling method.

To ensure a representative sample, inclusion criteria required all participants to have demonstrable experience using technology and to be enrolled in semesters one through eightof their academic programs. The sample encompassed a diverse range of students as shown in Table 1. This diversity included gender (female and male), study program (science and social), grade level (lower and upper grades), GPA (lower and higher) Specifically, the research sample comprised students from the Faculty of Mathematics and Natural Science, Faculty of Social and Political Science, Faculty of Economic and Administrative, Faculty of Vocational, Faculty of Primary Education and Faculty of Health Services. Participation in this study was voluntary, free, and anonymous. All participants answered the test and questionnaire on this basis.

Table 1.
Description of participants.

Variable	Category	N	%
Gender	Female	252	50.4
	Male	248	49.6
GPAs	2.00-3.00	255	51
	3.01-4.00	245	49
Grade	Lower (Semester 1-4)	253	50.6
	Upper (Semester 5-8)	247	49.4
Study program	Natural science	246	49.2

Variable	Category	N	%
	Social science	254	50.8

3.2. Data Collections and Research Procedure

In line with the purpose and problems of the research, the survey model was used in this study. Participation in the study was entirely voluntary. At first, the colleges were requested to complete a participant information form to gather descriptive data, and subsequently, they filled out data collection instruments. The administration of these instruments took approximately 90 minutes. The authors collected the data in December 2023 until April 2024. The research procedure of this study involved the following steps:

(i) Google Form questionnaires were designed to collect data relevant to the study's hypotheses
(ii) Questionnaires were administered to participants during their class periodsunder the direct supervision of the researcher to ensure proper completion and minimize distruption.
(iii) Data collected was carefully reviewed for verification and analysis of results.

3.3. Research Instruments

The section details the research instruments employed for data collection, all administered through close-ended questionnares.

3.4. CT Perspective (15 items, 5 scale)

To measure participan's perspectives and experiences related to computational thinking activities, a validated instrument developed by Korkmaz & Bai (2019) was used. This questionnaire assessed three aspects of computational thinking perspective (CTP): expressing (4 items), questioning (3 items), and connecting (8 items) as presented in Table 2. Each item was rated on a 5-point Likert scale, ranging from strongly disagree, disagree, neutral, agree, and strongly agree. The instrument demonstrated good internal consistency with a Cronbach's alpha reliability coefficient of 0.9 for this study and 0.822 for each aspect in the original study. Prior to full-scale administration, the questionnaire was piloted on a sample of 200 participants.

Table 2.
The aspects of CT perspectives.

Aspect	Sub aspect	No.	Indicator
Expressing	Communication & cooperativity	1	Exchange of ideas among group members.
		2	Expression of ideas and debating them.
	Algorithmic thinking	3,4	Thinking procedurally and systematically.
Questioning	Collaboration & community building	5	Helps peer group.
		6	Individual contributions make the group advance.
		7	Different work roles/task diversity.
Connecting	Context creation & problem solving	8	Activity follows a designed structure.
		9	Analysis of errors in the process.
		10	Justification of the solution.
		11	Writes the process of the solution to the challenge.
	Creativity & critical thinking	12	Holds initiative to make further steps in programs.
		13	Holds initiative to make further steps in programs.
		14	Use of various elements outside environment of platform.
		15	Application of concepts from other discipline.

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3.5. Digital Competence (20 items, 5 scale)

Digital competence was assessed using a validated instrument scale developed by Conde-Jiménez (2018).Validation of a theoretical model using PLS. This scale encompasses four aspects namely command (5 items), privileging (6 items), appropriation (5 items) and reintegration (4 items) as presented in Table 3. Each item was again rated on a 5-point Likert scale, ranging from "Strongly Disagree" to "Strongly Agree". This instrument demonstrated good internal consistency with a Cronbach's alpha reliability coefficient of 0.9 for the present study, indicating strong relationships within the model. Similar to the CTP instrument, this questionnaire was piloted on a sample of 200 participants before full-scale administration.

Table 3.
The aspects of digital competence.

Aspect	No.	Indicator
Command	1	Knowing and using the basic digital equipment.
	2	Knowing and handling the different programs to do specific tasks.
	3	Accessing and using the different digital platforms.
	4	Creating and store digital content.
	5	Knowing the legal and ethical issues about digital media.
Privileging	6	Analyzing and searching for content on the internet.
	7	Caring about the source from which the content come.
	8	Finding the relevant options for your personal learning.
	9	Recognizing the value of diversity offered by internet.
	10	Using the computer to d things you couldn't do with any other means.
	11	Recognizing the value that both digital and traditional tools bring.
Appropriation	12	Treating people in the same way when you are on the internet as in real life.
	13	Don't interact with people who do not know.
	14	Don't share data or passwords with anyone.
	15	Creating new things with computers.
	16	Using the computer to learn by yourself.
Reintegration	17	Creating the accounts in some digital platforms.
	18	Participating and /or collaborate in a network.
	19	Exchanging and download the things that you like online.
	20	Communicating and express yourself through the media.

Unplugged CT Test (25 items, multipe choice test)

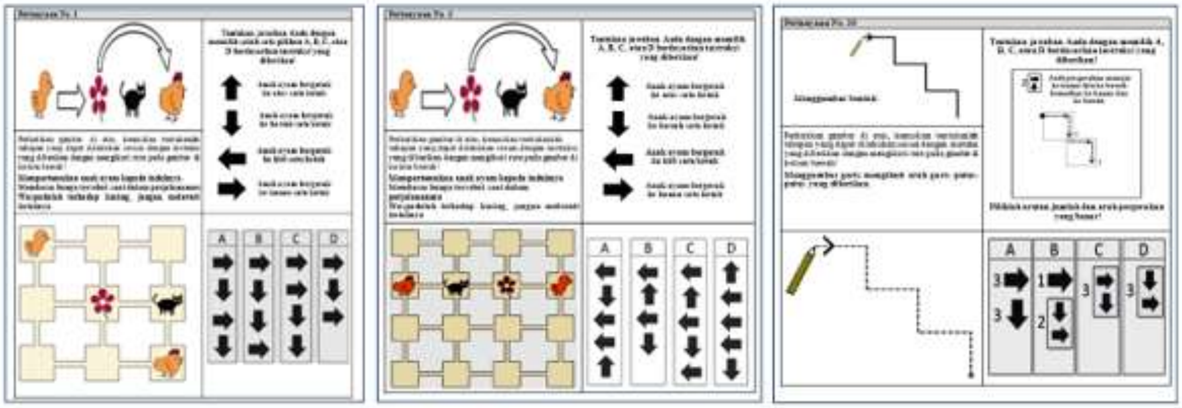

Figure 2.
Type of questions (a) 3x3 grid, (b) 4x4 grid, (c) canvas-type question.

Finally, an unplugged CT test developed by El-Hamamsy et al. (2022) was used to assess participants' CT skills. The test, translated into Indonesian for this study, measured six CT aspects: sequences (4 items), simple loops (4 items), complex loops (7 items), conditional statements (4 items), while statements (4 items), and combinations (2 items). Some items were revised based on pilot feedback regarding question instructions. The test was re-evaluated for reliability, with an average Cronbach's alpha reliability coefficient of 0.9 for each aspect. The test comprised 21 questions presented in 3×3 and 4×4 grids, and 4 open-ended "canvas-type" questions where participants replicated drawing patterns. Each correct answer received four pointsand incorrect answers received zero points.

3.6. Data Analysis

The data collected from the instruments were analyzed to examine the relationships between dependent and independent variables, dependent variables with some factors such as gender, grade, study program, and GPAs. The high values of Cronbach's alpha suggested that the instruments have a good reliability level and a good internal consistency of the scales. This means that the items within each scale was closely related and consistently measure the same construct. For investigating the influence of CT perspective, digital competence, and moderating factors were analysed using path coefficient. Furthermore, the inter-item correlation matrix provided insights into the relationships between the variables. A partial least square (PLS) approach was employed due to the exploratory nature of the present study. All data analyses were conducted using the Smart PLS Version 3.0 software (Hair et al., 2022). In the subsections below, the researchers reported the results for both the measurement and structural models. The measurement model provided statistics to establish the reliability and validity of the data and model. The structural model determined the strength and significance of the model relationships. The model fit demonstrated a good fit between the model and data, as presented in Table 4.

Table 4.
Good criteria of model fit.

Category	Measure	Recommended criterion
Goodness of fit model	SRMR	Acceptable if < 0.1
	NFI	Acceptable if < 1 The closer the NFI to 1, the better the fit
Outer model	Outer loading	Acceptable if > 0.7
	AVE construct reflective	Acceptable if > 0.5
	Cronbach's alpha	Acceptable if > 0.7

Inner model	Path coefficient	Acceptable if p< 0.05
	R-adjusted	Acceptable if original sample > 0.6
	t-value	Acceptable if > 1.96

4. Results

The descriptive analysis was performed on the college's CT skills and perspective on digital competence, as presented in Table 5. In summary, Table 5 provided a helpful numerical overview of model fit, where the equation models have fulfilled the standard requirement, which applied to the recommended criterion. A strong positive correlation with an adjusted R of 0.822 between CT perspective and digital competence is presented in Table 4. It indicated that individuals with greater CT perspective and digital skills also tend to increase the score of CT skills. Based on the path analysis, study programs, GPAs, and grades have a significant direct relationship with CT skills. Path coefficient showed no direct effect of the gender variable on the CT skills. The detailed descriptive statistics can be seen in Table 5.

Table 5.
Descriptive statistics.

Variable	Predictor	Mean	Std. dev.	Std.err	Cronbach's alpha
CT Skills	Sequences	52.48	5.08	0.22	0.995
	Simple loops	52.40	5.19	0.23	
	Complex loops	52.46	5.12	0.22	
	Conditional statements	52.46	5.25	0.23	
	While statements	52.47	5.24	0.23	
	Combinations	52.59	5.07	0.22	
CT perspective	Expression	66.85	7.80	0.34	0.996
	Questioning	66.98	7.54	0.33	
	Connecting	74.79	7.78	0.34	
Digital competence	Command	66.85	7.83	0.35	0.978
	Privileging	74.53	7.57	0.33	
	Appropriation	74.84	7.66	0.34	
	Reintegration	74.59	7.84	0.35	
Gender	Female	52.39	5.61	0.35	0.976
	Male	52.57	4.52	0.28	
GPAs	2.00-3.00	53.37	4.86	0.31	0.986
	3.01-4.00	51.62	5.18	0.32	
Grade	Lower (Semester 1-4)	49.26	3.64	0.22	0.985
	Upper (Semester 5-8)	55.77	4.19	0.26	
Study program	Science program	53.67	5.38	0.34	0.987
	Social program	51.32	4.52	0.28	

Table 5 was SRMR (standardized root mean square residual) as the structural equation model used in the study, and a value close to 0.02 indicated a good fit for both the saturated and estimated models. d_ULS and d_G, with lower values, indicated a better fit. Chi-Square was higher for the estimated model (1373.976) compared than the saturated model (1082.384). NFI (Normed Fit Index) values (0.942 for saturated and 0.926 for estimated, near to 1) indicated a good fit model.

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Table 6.
Result of model fit.

Measure	Saturated model	Estimated model
SRMR	0.020	0.021
d_ULS	0.063	0.064
d_G	0.371	0.426
Chi-Square	1082.384	1373.976
NFI	0.942	0.926

The R-square adjusted value (0.816) of CT skills indicated that 81.6% of the variance in CT skills was explained by the model, demonstrating strong explanatory power. The p-value (0.000) confirms the statistical significance presented in Table 7.

Table 7.
R-square adjusted.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	p -values
CT Skills	0.816	0.821	0.024	34.486	0.000

Table 8 showed the relationships between various predictors and CT skills. CT perspective (0.585, p = 0.000) and digital competence (0.615, p = 0.000) have a positive and significant effect on CT skills. Path analysis revealed significant relationships between CT skills and various predictors. Study programs, GPAs, and grades have a significant direct impact on CT skills, while gender does not directly affect CT skills (0.075, p = 0.276). However, interaction effects between GPA and digital competence, as well as gender with CT perspective, suggest that these combined factors significantly influence CT skills. Gender alone did not have a direct effect, its interaction with other variables played a role in shaping CT skills. The combinations of factors enhance CT skills more effectively than individual factors alone, as presented in Figure 3.

Table 8.
Path coefficient from smartPLS.

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	p-values
CT perspective -> CT skills	0.585	0.580	0.055	10.699	0.000
Digital competence -> CT skills	0.615	0.615	0.060	10.701	0.000
CT perspective*Digital competence -> CT skills	0.526	0.571	0.051	10.589	0.000
GPAs -> CT skills	0.267	0.267	0.042	6.376	0.000
GPAs*Digital competence -> CT skills	0.435	0.432	0.123	3.523	0.000
GPAs*CT perspective -> CT skills	0.447	0.451	0.107	4.160	0.000
Gender -> CT Skills	0.075	0.076	0.069	1.089	0.276
Gender*CT perspective -> CT skills	0.166	0.167	0.081	2.042	0.042
Gender*Digital competence -> CT skills	0.156	0.157	0.075	2.083	0.038
Grade -> CT skills	0.309	0.307	0.030	10.255	0.000
Grade*CT perspective -> CT skills	0.176	0.177	0.064	2.736	0.006
Grade*Digital competence -> CT skills	0.175	0.176	0.054	3.250	0.001
Study program -> CT skills	0.267	0.271	0.072	3.735	0.000
Study program*CT perspective -> CT skills	0.278	0.280	0.103	2.713	0.007

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	p-values
Study program*Digital competence -> CT skills	0.305	0.312	0.084	3.651	0.000

Green outer circles represent the moderating variables integrated with independent variables (gender, GPAs, semester, study program). Blue circles represent the variables (digital competence, CT perspective, grade/semester, study program, and GPAs). The yellow rectangle represents the indicators of variables. The p-values across the lines indicate the statistical significance of the relationships between these variables.

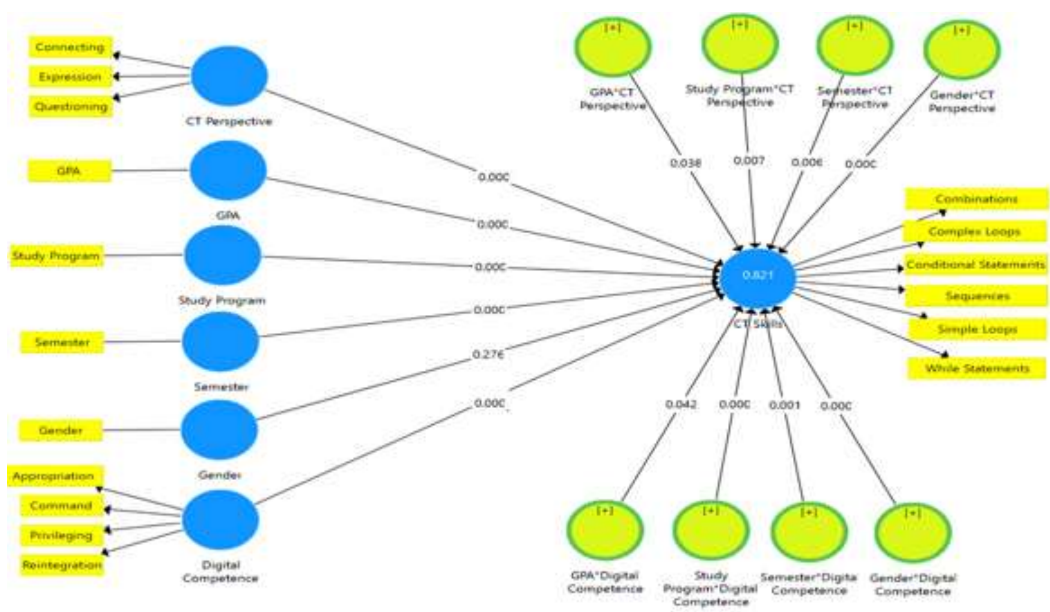

Figure 3.
P-value of structural equation model.

The point in the blue circle of the CT skills (0.821, >0.6) is the value of the R-adjusted square, which means there is a strong relationship between the independent and dependent variables. Result findings above suggest that:

H_1 stated that the colleges' CT perspective significantly influenced their CT skills accepted (p=0.000). In general, the college with higher CT perspective have higher CT skills than those with a lower CT perspective.

H_2 stated that colleges' digital competence significantly influenced their CT skills accepted (p=0.000). Thus, it can be expected that individuals with higher digital competence have higher CT skills than those with lower digital competence.

H_3 stated that CT perspective and digital competence significantly have a relationship with CT skills was accepted (R=0.82, p=0.000). Therefore, a significant and positive relationship between the CT perspective and digital competence with colleges' CT skills has been shown to exist.

H_4 stated that colleges' CT skills did not differ according to the gender accepted (p=0.276). In general, gender does not positively predict CT skills.

H_5 stated that colleges' CT skills significantly differ according to the GPAs accepted (p=0.000). GPAs can be said to positively predict their CT skills.

H_6 stated that colleges' CT skills significantly differ according to the grade/semester accepted (p=0.000). In general, a grade or semester positively predicts their CT skills.

H_7 stated that colleges' CT skills significantly differ according to the study program accepted (p=0.000). It can be said that, in general, the study program (science and nonscience major) positively predicts their CT skills.

5. Discussion

5.1. The Influence of CT Perspective on the CT Skills ($p=0.000$, $\alpha=0.05$)

This discovery aligns with previous studies, indicating a significant influence between CT perspective and CT skills (Cutumisu et al., 2022; Hava & Koyunlu Ünlü, 2021). CT perspective, encompassing traits like creativity, algorithmic thinking, cooperation, and critical thinking, demonstrates close ties to CT skills (Korkmaz & Bai, 2019). Over recent years, CT skills have been shown to flourish through project-based and problem-based learning approaches, yielding positive outcomes (Cahdriyana et al., 2019; Hava & Koyunlu Ünlü, 2021; Richardo et al., 2019). Consequently, creativity, critical thinking, and cooperative learning can be fostered through these methods. Colleges with a positive CT perspective are more motivated and engaged in learning activities related to computational thinking. This increased engagement leads to more consistent practice and a deeper understanding of CT concepts. Research has shown that motivation and a positive attitude toward learning are critical for skill acquisition and mastery (Birgili, 2015; Perdana et al., 2021). A CT perspective fosters an environment where students are encouraged to think critically and solve problems creatively. This is crucial for developing CT skills, which are inherently problem-solving oriented. When colleges perceive computational thinking as valuable and interesting, they are more likely to tackle complex problems and persist through challenges. A positive CT perspective includes a focus on algorithmic thinking, which is essential for breaking down problems into manageable steps and developing solutions. This skill is critical in programming and other CT-related tasks (Kannadass et al., 2023).

5.2. The Influence of Digital Competence on the CT Skills ($p=0.000$, $\alpha=0.05$)

Digital competence provides individuals access to a wide range of digital tools and resources. This exposure enables them to practice computational thinking skills using programming languages, online coding platforms, and software applications to facilitate algorithmic thinking and problem-solving. Digital competence allows individuals to apply computational thinking skills in various contexts. For example, someone proficient in spreadsheet software can apply algorithmic thinking to analyze data, identify patterns, and develop formulas to automate tasks. Digital competence fosters critical thinking and problem-solving skills, which are essential components of computational thinking. When individuals engage with digital technologies, they encounter challenges that require them to analyze problems, think creatively, and develop innovative solutions. Over time, this iterative process strengthens their computational thinking abilities. Digital competence facilitates collaboration and communication among individuals with diverse backgrounds and perspectives. Collaborative problem-solving exercises, online forums, and virtual communities provide opportunities for individuals to exchange ideas, share strategies, and collectively tackle complex problems (Esteve-Mon et al., 2020; Juškevičienė & Dagienė, 2018).

5.3. The Relationship Between CT Perspective and Digital Competence with CT Skills ($R=0.821$, $\alpha=0.05$)

The relationship between CT perspective, digital competence, and CT skills is intertwined, with each component influencing and enhancing the others in various ways. The CT perspective encompasses students' attitudes towards computational thinking, including their interest, motivation, and value placed in CT. A positive CT perspective leads to higher engagement in learning activities, which is crucial for the development of CT skills. When students value CT, they are more likely to

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invest time and effort into learning and practicing these skills. The CT perspective includes creativity, algorithmic thinking, and critical thinking. These attitudes foster an environment where students are encouraged to think outside the box, approach problems methodically, and critically evaluate solutions. These enhance their ability to develop and apply CT skills effectively. On the other hand, digital competence involves the ability to use digital tools and technologies effectively. Proficiency with digital tools allows colleges to better engage with CT activities, such as coding, data analysis, and digital simulations. Mastery of these tools is often a prerequisite for developing higher-level CT skills (Chan et al., 2023; Kannadass et al., 2023). Digital competence includes the ability to find, evaluate, and use information effectively. Information literacy supports CT skills by enabling colleges to gather and analyze relevant data, draw informed conclusions, and solve problems based on evidence. When colleges have both a positive CT perspective and strong digital competence, they are more likely to excel in CT skills. For instance, a college that values CT and is proficient in using digital tools will be more adept at engaging in complex problem-solving tasks. CT perspective and digital competence reinforce each other. As colleges develop digital competence, they may become more interested in CT, enhancing their perspective. Conversely, a strong CT perspective can motivate students to improve their digital skills (Cutumisu et al., 2022).

5.4. The CT Skills According to the Gender ($p=0.276$, $\alpha=0.05$)

Previous studies have also revealed no significant difference in CT skills between female and male colleges. Despite male students exhibiting a higher mean score than female students, inferential testing indicates that this disparity lacks statistical significance. This is supported by a study conducted by (Demir-Kaymak et al., 2021) found that both men and women demonstrated similar levels of interest and aptitude in computer science when provided with equal opportunities and encouragement. The potential reason why CT skills may not differ significantly between female and male students is the increasing efforts to promote gender equity in education, particularly in STEM fields. Educational initiatives to foster CT skills may be designed to be inclusive and accessible to all students, regardless of gender (Birgili, 2015). Advancements in teaching methods and curriculum development may focus on address gender biases and stereotypes, ensuring that learning environments are supportive and conducive developing CT skills for female and male students. The growing recognition of the importance of diversity and inclusion in STEM education may lead to implementing interventions designed to engage and empower underrepresented groups, including females, in CT learning (Espino & González, 2016).

5.5. The CT Skills According to the GPAs ($p=0.000$, $\alpha=0.05$)

The academic success, as reflected in higher GPAs, typically indicates superior problem-solving skills. Computational thinking involves breaking down complex problems into smaller, manageable parts and devising systematic solutions, a skill set that aligns closely with the analytical and problem-solving abilities cultivated through academic achievement. Colleges with high GPAs often require students to think critically, analyze, and synthesize information across various subjects and disciplines. These cognitive abilities are transferrable to CT, where individuals must critically evaluate problems, identify patterns, and develop logical solutions. High GPAs often require persistence, diligence, and a strong work ethic. CT requires patience and perseverance in the face of complex problems, as well as the dedication to iterate on solutions until they are optimized. Individuals with a track record of academic success are more likely to facilitate the development of CT skills (John Lemay et al., 2021; Lei et al., 2020).

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5.6. The CT Skills According to the Grade (p=0.000, α=0.05)

One potential reason for differences in CT skills according to the grade variable is the developmental progression of cognitive abilities and problem-solving skills as students advance through different grade levels. Younger students in lower grades may still be developing foundational skills related to logical reasoning, algorithmic thinking, and abstraction, which are essential components of CT. As a result, their performance on unplugged CT tasks may vary compared to older students in higher grades who have more exposure to CT concepts and opportunities for practice (Çiftçi & Baykan, 2013; Demir-Kaymak et al., 2021). Additionally, competency standards and learning objectives may vary across grade levels, influencing the emphasis on CT skills learning activities. For example, lower-grade curricula may prioritize basic concepts of sequencing, patterns, and logical reasoning, while higher-grade curricula may incorporate more advanced CT concepts such as algorithm design, abstraction, and problem-solving strategies. These differences in curricular focus and instructional approaches could contribute to variations in unplugged CT skills among students at different grade levels (Piedade & Dorotea, 2022).

5.7. The CT Skills According to the Study Program (p=0.000, α=0.05)

The differences in CT skills according to study programs could be the varying emphasis on CT-related concepts and skills within different fields of study. For example, students in STEM (Science, Technology, Engineering, and Mathematics) disciplines may receive more explicit instruction and practice in CT concepts than students in non-STEM fields. STEM programs often integrate computational thinking into their curricula through computer science, engineering, and mathematics courses, providing students with opportunities to develop CT skills through hands-on projects, problem-solving activities, and coding experiences. Conversely, students in non-STEM programs may have less exposure to CT concepts or encounter them in a less structured or explicit manner within their coursework (Aria & Yulianto, 2019). Furthermore, differences in students' backgrounds, interests, and career aspirations within different study programs may also influence their motivation to engage with CT-related activities and their perceived relevance to their academic and professional goals (Demir-Kaymak et al., 2021). For example, students in STEM fields may be more intrinsically motivated to develop CT skills due to their alignment with career pathways in technology, engineering, and related fields, whereas students in non-STEM fields may perceive CT skills as less relevant or necessary for their chosen career paths. Overall, the varying curricular emphases, instructional approaches, and student motivations within different study programs may contribute to differences in unplugged CT skills among students across different disciplines (Karen & Mitchel, 2012).

6. Conclusion

This research comprehensively analyzed colleges' computational thinking (CT) skills with interaction by some factors. The study found a strong positive correlation between CT perspective and digital competence, indicating that students with higher CT perspectives and digital skills also tend to have higher CT skills. CT skills in college students were significantly influenced by their CT perspective, digital competence, GPA, grades, and study programs. It was caused by the developmental progression of cognitive abilities, problem-solving skills, and varying curricular focuses and instructional approaches. Students in science fields receive more explicit instruction and practice in CT concepts, while students in social fields have less exposure to CT concepts. The differences in students' backgrounds and interests can also influence their motivation to engage in CT-related activities. However, gender alone did not have a direct effect, its interaction with other variables played a role in shaping CT skills because of equal educational opportunities and inherent abilities across genders. In summary, the interaction with other variables how socio-cultural factors, educational interventions, and individual competencies can shape CT skills differently across genders.

6.1. Recommendation

Background factors might affect CT skills. Therefore, it is necessary to study background factors to explain the potential factors that influence college computational thinking skills. Learning strategies that foster computational thinking and digital competence are also needed to enhance overall CT skills among colleges. Educators are encouraged to devise innovative approaches like project-based and problem-based learning to foster CT skills and perspectives. Integrating CT concepts across the curriculum and embedding digital competence within various subjects can help develop these skills holistically.

6.2. Limitation

This study focused on two independent variables to predict a college's CT skills: CT perspective and digital competence. It also considered four moderating variabels: gender, GPA, study program, and grade level. However, the study relied solely on self-reported data, which can be biased due to social desirability. Incorporating qualitative and quantitative data would provide a deeper understanding of the observed relationships to strengthen future research.

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