Konfrontasi Journal: Culture, Economy, and Social Changes
pISSN: 1410-881X (Print)
eISSN: 2716-2095 (Online)

The Mediating Role of Computational Identity in the Relationship between Computational Thinking Skills and Academic Self-Efficacy

Belay Sitotaw Goshu[1], Muhammad Ridwan[2]
[1]*Department of Physics, Dire Dawa University, Dire Dawa, Ethiopia*
[2]*Universitas Islam Negeri Sumatera Utara, Indonesia*

Abstract

Computational thinking (CT) has emerged as a critical 21st-century skill, yet its motivational and psychological correlates in higher education remain underexplored, particularly in African contexts. Creative interest (CI) and academic self-efficacy (ASE) represent key motivational mechanisms that may link CT perceptions to broader academic confidence. Purpose: This study examined the direct and indirect relationships among computational thinking, creative interest, and academic self-efficacy among undergraduate students, testing whether creative interest mediates the effect of CT on ASE. Methods: A cross-sectional survey was administered to 357 undergraduate students at Dire Dawa University, Ethiopia. Validated self-report scales measured overall and subscale levels of CT, CI, and ASE. Data were analyzed using descriptive statistics, Pearson correlations, confirmatory factor analysis (CFA), and bootstrapped mediation analysis with PROCESS macro. CFA supported the distinctiveness of the three constructs with acceptable fit (CFI = 0.92, RMSEA = 0.072) and strong validity (AVE > 0.76). CT showed strong positive correlations with CI (r = 0.594) and ASE (r = 0.632). Mediation analysis revealed a significant total effect of CT on ASE (β = 0.356, p < .001), a significant direct effect after mediation (β = 0.289, p < .001), and a small but significant indirect effect via CI (β = 0.067, 95% bootstrap CI [0.033, 0.101]), accounting for 18.8% of the total effect. The model explained 42.5% of variance in ASE. Conclusion: Computational thinking perceptions enhance academic self-efficacy both directly and partially through creative interest, highlighting a motivational pathway in which CT fosters creative identity that, in turn, supports efficacy beliefs. Ethiopian universities should integrate CT training with activities that explicitly link computational skills to creative expression and self-regulated learning to maximize motivational and efficacy benefits.

Keywords
computational thinking, creative interest, academic self-efficacy, mediation analysis, Ethiopian higher education

I. Introduction

1.1 Background of the Study

Computational thinking (CT) has emerged as a fundamental 21st-century skill essential for navigating an increasingly technology-driven world. Since Wing's (2006) seminal work conceptualizing CT as "thinking as a computer scientist", employing analytic and algorithmic approaches to formulate, analyze, and solve problems, the construct has gained unprecedented attention in educational research and policy. Wing (2006) famously argued that CT should be added to every child's analytical ability alongside reading, writing, and arithmetic, positioning it as a universal competence rather than a niche technical skill. Contemporary research confirms CT's versatility in promoting problem-solving, critical thinking, and student engagement across various disciplines, with advanced CT skills preparing students for the challenges of modern life and contributing to success in both professional and personal spheres (Geske et al., 2025).

Parallel to the growing emphasis on CT, academic self-efficacy has been established as a critical determinant of student persistence and achievement. Grounded in Bandura's social cognitive theory, self-efficacy refers to students' beliefs in their capabilities to execute courses of action required for academic success. Research consistently demonstrates that strong self-efficacy fosters resilience, goal setting, and improved academic outcomes, while low self-efficacy correlates with demotivation, feelings of inadequacy, and increased dropout risk, particularly during transitional educational phases (Zapata-Casabon, 2025; Goshu, 2025; Ramlan and Goshu, 2025). In Science, Technology, Engineering, and Mathematics (STEM) contexts, self-efficacy significantly influences students' ability to overcome academic challenges and lack of technical experience, making it a vital target for educational interventions.

More recently, the construct of "computational identity" has emerged as a powerful lens for understanding student engagement in STEM and computing fields. Building on scientific identity frameworks, computational identity encompasses an individual's recognition of themselves as capable of designing and implementing computational solutions to self-identified problems. This identity formation involves students seeing themselves as part of a larger community of computational creators, integrating competence beliefs with a sense of belonging and purpose. Tissenbaum et al. (2019) proposed the concept of "computational action," suggesting that computational identity and digital empowerment are critical dimensions for understanding how learners move from acquiring skills to applying them meaningfully. Research suggests that fostering computational identity may be particularly important for students from groups traditionally underrepresented in computing, as developing personally meaningful computational solutions helps establish authentic connections to the field.

1.2 Statement of the Problem

While existing research has established positive associations between CT skills and academic outcomes such as achievement and problem-solving ability, the mechanisms underlying these relationships remain underexplored. A meta-analysis by Lei et al. (2020) confirmed significant correlations between CT and academic achievement across student populations ($r = 0.288$), yet called for deeper investigation into the processes through which CT skills translate into educational benefits. The authors found that the relationship was moderated by factors including culture, grade level, and achievement indicators, suggesting that contextual and psychological variables may play important roles in this association. Similarly, Bocconi et al. (2016) noted that despite an increasing number of CT implementations in both formal and informal education settings, research still appears necessary on how CT skills develop in students and what pedagogical approaches can facilitate their effective introduction.

Notably, there is a scarcity of quantitative research examining how students' identity as "computational thinkers" might explain the translation of CT skills into academic confidence. Geske et al. (2025) identified significant differences in how students develop CT skills across schools, raising important questions about the factors that contribute to successful CT learning outcomes. However, these investigations have not elucidated the psychological pathways involved. Tissenbaum et al. (2019) argued that moving from computational thinking to computational action requires understanding how learners develop identity and agency, yet empirical testing of these theoretical propositions, particularly the mediating role of computational identity in skill-to-confidence pathways, remains limited. This gap is significant because understanding these mechanisms could inform more effective educational interventions that address not only skill development but also the identity processes that sustain student engagement and persistence in STEM fields (Goshu, 2025).

1.3 Purpose of the Study

The purpose of this study is to investigate the mediating role of computational identity in the relationship between computational thinking skills and academic self-efficacy. By employing a quantitative mediation design, this research aims to determine whether computational identity serves as a mechanism through which CT skills influence students' confidence in their academic capabilities.

1.4 Research Questions and Hypotheses

This study addresses the following research questions:

a. Is there a significant positive relationship between computational thinking skills and academic self-efficacy?
b. Is there a significant positive relationship between computational thinking skills and computational identity?
c. Is there a significant positive relationship between computational identity and academic self-efficacy?
d. Does computational identity mediate the relationship between computational thinking skills and academic self-efficacy?

Based on theoretical frameworks and empirical evidence, the following hypothesis is proposed:

H1: Computational thinking skills will have a positive, significant indirect effect on academic self-efficacy through computational identity.

1.5 Significance of the Study

This study offers both theoretical and practical contributions. Theoretically, it extends identity theory by testing the mediating role of computational identity within a skill-based context, responding to calls for empirical investigation of mechanisms linking CT to educational outcomes (Lei et al., 2020; Goshu et al., 2025). By positioning identity as an explanatory mechanism, this research advances understanding of how cognitive competencies translate into motivational beliefs. The study also responds to Tissenbaum et al.'s (2019) call to move beyond computational thinking toward computational action by examining identity as a critical mediating variable.

Practically, findings will inform educators and curriculum designers about the importance of fostering computational identity alongside technical skill development. Rather than focusing exclusively on teaching CT concepts and processes (Bocconi et al., 2016), educational interventions should create opportunities for students to develop personally meaningful computational solutions and see themselves as capable computational creators (Tissenbaum et al., 2019). Geske et al.'s (2025) findings regarding the importance of independent learning and student engagement in high-performing CT schools further underscore the need for pedagogical approaches that nurture students' identification with computational work. Such approaches may be particularly valuable for enhancing student confidence and persistence in STEM pathways (Zapata-Casabon, 2025; Gosu 2025; Goshu et al., 2025), ultimately contributing to a more diverse and skilled technological workforce.

II. Review of Literature

2.1 Computational Thinking Skills

Computational thinking (CT) has been conceptualised as the conceptual foundation required solving problems effectively and efficiently, algorithmically, with or without computer assistance—through solutions that are reusable across different contexts (Shute, Sun, & Asbell-Clarke, 2017). Since Wing's (2006) seminal work defining CT as "solving problems, designing systems, and understanding human behaviour by drawing on concepts fundamental to computer science" (p. 33), the construct has evolved to encompass specific cognitive operations. Synthesising the literature, Shute et al. (2017) categorised CT into six main facets: decomposition (breaking problems into manageable parts), abstraction (filtering unnecessary details to focus on essential features), algorithm design (developing step-by-step solutions), debugging (identifying and fixing errors), iteration (refining solutions through repetition), and generalisation (applying solutions to new problems).

Contemporary research has established robust correlations between CT skills and academic outcomes. A meta-analysis by Lei, Chiu, Li, Wang, and Geng (2020) confirmed significant positive relationships between CT and academic achievement across student populations (*r* = 0.288). Recent empirical work by Nannim, Mosia, Ezema, and Egara (2026) demonstrated that CT dimensions collectively predict students' achievement in robotics programming, accounting for 74.5% of the variance (R^2 = .745). Algorithmic thinking emerged as the strongest predictor (β = 1.116, $p < .001$), while decomposition showed negative correlations with achievement ($r = -.392$, $p < .001$), suggesting that students may struggle to apply this skill effectively (Nannim et al., 2026). These findings underscore the multidimensional nature of CT and the importance of examining its components separately.

2.2 Academic Self-Efficacy

Academic self-efficacy finds its theoretical foundation in Bandura's social cognitive theory, which posits that individuals' beliefs in their capabilities to execute courses of action significantly influence their motivation, persistence, and ultimate success (Bandura, 1997). Self-efficacy is domain-specific and derives from four sources: personal mastery experiences (experiencing successes and failures), vicarious experiences (observing others succeed), verbal persuasion (feedback and encouragement), and emotional states (anxiety and stress levels) (Bandura, 1997).

The role of self-efficacy in academic contexts is well-established. A meta-analysis by Multon, Brown, and Lent (1991) demonstrated that academic self-efficacy beliefs are predictive of both academic performance and persistence (effect sizes ranging from .21 to .59). Subsequent research has confirmed that higher academic self-efficacy predicts college grades, particularly when measured after students have gained experience and feedback regarding their performance (Vuong, Brown-Welty, & Tracz, 2010). Mastery experiences, successfully performing tasks, constitute the most powerful source of self-efficacy (Bandura, 1997), establishing a direct theoretical link between skill acquisition (including CT skills) and confidence development. Wu, Silitonga, Dharmawan, and Murti (2024) recently demonstrated that CT instruction positively correlates with academic self-efficacy, with both factors contributing to enhanced academic resilience.

2.3 Computational Identity

Computational identity refers to an individual's sense of belonging and identification with the field of computing (Stormes, 2024). Drawing from Gee's (2000) identity theory and STEM identity frameworks (Carlone & Johnson, 2007), computational identity encompasses how students perceive themselves within the computing discipline (Sellami & Elkhoudary, 2024). A systematic review by Sellami and Elkhoudary (2024) synthesised the established framework for developing students' computing identity, identifying four key constructs: competence/performance (students' belief in their capacity to understand and succeed in computing endeavours), interest (passion, motivation, or curiosity toward computing), recognition (how students self-recognise and perceive others' views of their computing abilities), and sense of belonging (students' perceptions of fitting within the computing community). Among these constructs, competence/performance is the most extensively explored, while recognition has received the least attention (Sellami & Elkhoudary, 2024).

Stormes's (2024) dissertation extended this framework, finding that computing identity is a multidimensional measure incorporating students' self-identity as computing persons, their sense that computing is part of their core personal identity, and their sense of belonging in the computing community. Critically, Stormes (2024) found that self-efficacy was a positive predictor of computing identity for underrepresented Students of Color but not for white students, suggesting that identity formation processes may vary across demographic groups. Research has consistently linked computing identity to persistence and career aspirations: Mahadeo, Hazari, and Potvin (2020) demonstrated that computing identity significantly predicted students' choices of careers in computer science-based fields (odds ratio = 3.16, $p < .001$).

2.4 Relationships among Constructs

CT Skills and Identity: Empirical evidence supports the relationship between CT skills and identity formation. Nannim et al. (2026) found that algorithmic thinking, a core CT component, exhibited the strongest positive correlation with achievement in computing tasks ($r = .596$, $p < .001$) and emerged as the strongest positive predictor of success ($\beta = 1.116$, $p < .001$). These findings suggest that proficiency in algorithmic thinking may enhance students' competence perceptions, a key dimension of computational identity (Sellami & Elkhoudary, 2024).

Identity and Self-Efficacy: Theoretical and empirical links connect identity with self-efficacy. Stormes (2024) found that computing identity is distinct from self-efficacy yet related; while self-efficacy concerns beliefs about capability, identity encompasses broader self-perceptions of belonging and recognition. However, the two constructs interact: competence/performance beliefs (closely related to self-efficacy) constitute one of the four core dimensions of computing identity (Sellami & Elkhoudary, 2024). Wu et al. (2024) demonstrated that both CT and self-efficacy contribute to academic outcomes, suggesting reciprocal relationships among these constructs.

CT Skills and Self-Efficacy: Direct evidence links CT skills to self-efficacy. Wu et al. (2024) found a positive correlation between CT instruction and academic self-efficacy, with students receiving CT instruction demonstrating increased confidence alongside enhanced resilience. This aligns with Bandura's (1997) contention that mastery experiences, successfully performing computational tasks, constitute the primary source of self-efficacy beliefs.

The Mediating Role of Identity: The central theoretical contribution of this paper is the proposition that computational identity mediates the relationship between CT skills and academic self-efficacy. Skills alone do not automatically translate into confidence; rather, skills must be internalised and given meaning through identity. As students develop CT skills and experience success in computational tasks (Nannim et al., 2026), these mastery experiences contribute to their sense of competence/performance, a core identity dimension (Sellami & Elkhoudary, 2024). When students come to see themselves as "computational thinkers" who belong in the computing community (Stormes, 2024; Gee, 2000), these identity beliefs subsequently enhance their domain-specific self-efficacy. This mediation model responds to calls for investigating mechanisms linking CT to educational outcomes (Lei et al., 2020) and extends identity theory by positioning identity as an explanatory mechanism in skill-to-confidence pathways.

2.5 Conceptual Framework

The conceptual framework guiding this study is illustrated in Figure 1 (path diagram). The model posits computational thinking skills as the independent variable, computational identity as the mediator variable, and academic self-efficacy as the dependent variable. Four paths are specified: path (a) from computational thinking skills to computational identity; path (b) from computational identity to academic self-efficacy; path (c') the direct effect of computational thinking skills on academic self-efficacy (controlling for the mediator); and path (c) the total effect of computational thinking skills on academic self-efficacy (without the mediator). The indirect (mediated) effect is calculated as the product of paths (a) and (b). This framework hypothesises that computational identity partially explains how computational thinking skills translate into enhanced academic self-efficacy.

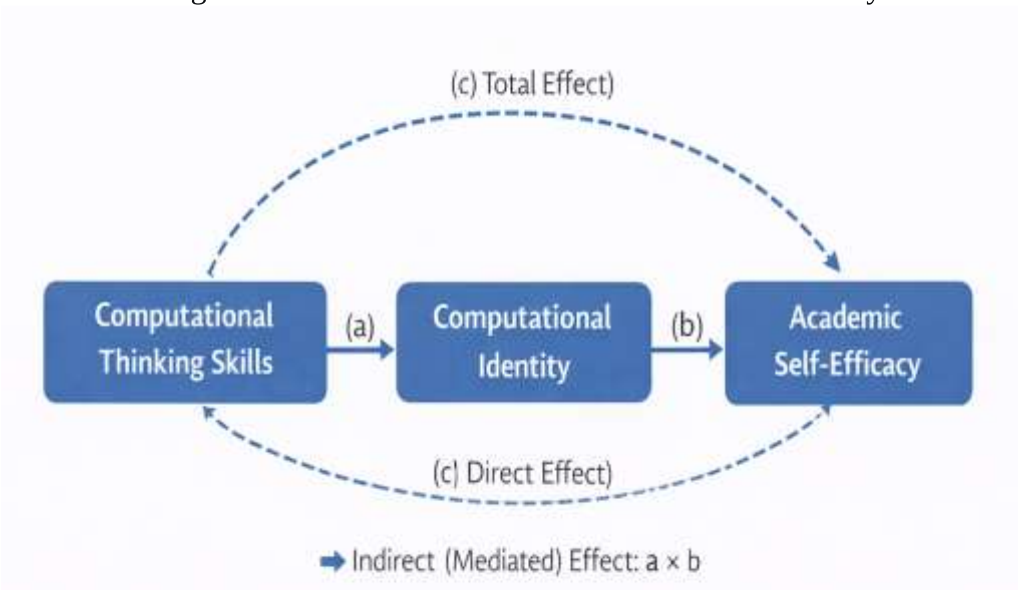

Figure 1. Mediation model linking computational thinking, identity, and academic self efficacy.

Figure 1 presents a mediation path model in which computational thinking skills predict academic self-efficacy both directly and indirectly through computational identity. Path (a) links computational thinking to computational identity, path (b) connects computational identity to academic self-efficacy, and path (c') represents the controlled direct effect, while path (c) denotes the total effect (Hayes, 2018; Baron and Kenny, 1986).

III. ResearchMethods

3.1 Research Design

This study employs a quantitative, cross-sectional, correlational design using mediation analysis. A cross-sectional approach is appropriate for examining the proposed relationships among computational thinking skills, computational identity, and academic self-efficacy at a single point in time (Creswell & Creswell, 2018). Mediation analysis, grounded in Baron and Kenny's (1986) framework and extended by Hayes (2022), allows for testing whether computational identity serves as a mechanism through which computational thinking skills influence academic self-efficacy. The design aligns with established practices in educational research for examining indirect effects among psychological constructs (Hayes, 2022).

3.2 Participants and Sampling

The target population comprises undergraduate students enrolled in introductory computing or educational technology courses at universities. Undergraduate students represent an appropriate population as they are actively developing both computational skills and academic identities during this educational stage (Stormes, 2024).

A stratified random sampling technique will be employed to ensure representation across gender, academic discipline, and year of study. Where access to complete sampling frames proves limited, convenience sampling with clear justification will be considered, accompanied by efforts to maximise sample diversity (Etikan, Musa, & Alkassim, 2016).

Sample size will be determined through a priori power analysis using G*Power software (Faul, Erdfelder, Buchner, & Lang, 2009). For mediation analysis with two predictors in the final model (computational thinking skills and computational identity), assuming a medium effect size ($f2 = 0.15$), α=.05, and power =.80, the minimum required sample size is 68. However, following Fritz and MacKinnon's (2007) recommendations for mediation models using bias-corrected bootstrapping, which requires larger samples for stable indirect effect estimates, a target sample of 300–400 participants is planned. This exceeds minimum requirements and accounts for potential incomplete responses while ensuring statistical power for detecting indirect effects.

3.3 Instruments

Demographic Questionnaire: A brief questionnaire will collect participants' age, gender, academic discipline, year of study, and prior computing experience (number of programming courses completed, years of computing experience).

Computational Thinking Skills Scale: The Computational Thinking Scale (CTS) developed by Korkmaz, Çakir, and Özden (2017) will be employed. This 29-item, five-point Likert-type scale (1=strongly disagree to 5=strongly agree) measures five dimensions: creativity, algorithmic thinking, cooperativity, critical thinking, and problem solving. Sample items include: "I like experiencing and learning most about the people who decide to make decisions on such problems" (algorithmic thinking) and "I can solve the problems I encounter in my daily life using the solutions my friends have used before" (problem solving). Korkmaz et al. (2017) reported strong internal consistency with Cronbach's alpha coefficients ranging from .75 to .87 across sub-dimensions and .84 for the overall scale. The scale has been validated across multiple cultural contexts and educational levels (Korkmaz et al., 2017).

Computational Identity Scale: Given the absence of an extensively validated computational identity scale in the literature, an instrument will be adapted based on established identity frameworks (Carlone & Johnson, 2007; Gee, 2000) and recent systematic reviews (Sellami & Elkhoudary, 2024). The scale will measure four core components identified in computing identity research: competence/performance (e.g., "I am confident in my ability to solve problems using computational methods"), interest (e.g., "I enjoy learning about computational concepts and applications"), recognition (e.g., "My instructors see me as someone who understands computational thinking"), and sense of belonging (e.g., "I feel like I belong in the computing community"). Each component will be assessed with 4–5 items using a five-point Likert scale. Following Stormes's (2024) approach, items will be adapted from existing STEM and computing identity measures. The adapted scale will undergo pilot testing with 50–100 students to establish preliminary reliability (Cronbach's alpha ≥.70) and factor structure before main data collection.

Academic Self-Efficacy Scale: The Morgan-Jinks Student Efficacy Scale (MJSES) will be employed (Jinks & Morgan, 1999). This 30-item, four-point Likert-type scale measures three dimensions: talent (e.g., "I get good grades in most subjects"), context (e.g., "My teachers always give me interesting work"), and effort (e.g., "I work hard in my classes"). The scale has demonstrated strong psychometric properties with Cronbach's alpha coefficients ranging from .70 to .82 across subscales and test-retest reliability of .80 (Jinks & Morgan, 1999). The MJSES has been extensively validated across educational levels and cultural contexts (Jinks & Morgan, 1999). For the current study, items will be slightly adapted to reference computing-related academic tasks where appropriate.

3.4 Data Collection Procedures

Data collection will proceed through the following steps: (1) ethical approval will be obtained from the university's Institutional Review Board (IRB); (2) permissions will be sought from course instructors and academic administrators at participating institutions; (3) an online survey will be created using a secure platform (e.g., Qualtrics or Google Forms), containing all instruments in a fixed order—demographic questionnaire, computational thinking scale, computational identity scale, and academic self-efficacy scale; (4) participants will be recruited through announcements in introductory computing and educational technology courses, with instructors sharing the survey link via learning management systems; (5) informed consent will be obtained on the first page of the survey, clearly stating the study's purpose, voluntary nature, confidentiality assurances, and participants' right to withdraw at any time without consequence; (6) data collection will remain open for four to six weeks, with reminder announcements sent at two-week intervals; (7) upon survey closure, data will be downloaded and stored on password-protected university servers accessible only to the research team, with all identifying information removed and replaced by participant codes to ensure anonymity.

3.5 Data Analysis Plan

Preliminary Analysis: Data will be screened for missing values, outliers, and violations of statistical assumptions. Descriptive statistics (means, standard deviations, frequencies) was calculated for all variables. Internal consistency reliability assessed using Cronbach's alpha coefficients, with values ≥.70 considered acceptable (Nunnally & Bernstein, 1994). Assumptions for mediation analysis were tested: normality (skewness and kurtosis values within ±2), linearity (examination of scatterplots), and multicollinearity (variance inflation factor values < 10; tolerance values > .10) (Tabachnick & Fidell, 2019). Bivariate correlations will be examined to establish preliminary relationships among constructs.

Main Analysis: Mediation analysis was conducted using Hayes's (2022) PROCESS macro for SPSS (Model 4) with 5,000 bootstrap resamples. PROCESS employs ordinary least squares regression and generates bias-corrected bootstrap confidence intervals for indirect effects, which is superior to the Sobel test as it does not assume normality of the sampling distribution (Hayes, 2022). The analysis was proceed in three steps: (1) estimating the total effect of computational thinking skills on academic self-efficacy (path c); (2) estimating the effect of computational thinking skills on computational identity (path a); (3) estimating the effect of computational identity on academic self-efficacy while controlling for computational thinking skills (path b), and the direct effect of computational thinking skills on academic self-efficacy (path c'). The indirect effect will be calculated as the product of paths a and b, with statistical significance determined by whether the 95% bootstrap confidence interval excludes zero.Model Fit Indices: While PROCESS does not generate overall model fit indices, additional analysis using Structural Equation Modeling (SEM) in AMOS or Mplus will be conducted to assess measurement model fit. Acceptable model fit will be indicated by: Comparative Fit Index (CFI) $\geq .90 \geq .90$, Root Mean Square Error of Approximation (RMSEA) $\leq .08$, and Standardised Root Mean Square Residual (SRMR) $\leq .08$ (Hu & Bentler, 1999).

Bootstrap Analysis: Following established recommendations, 5,000 bootstrap resamples will be generated to derive bias-corrected confidence intervals for all indirect effects (Hayes, 2022). This non-parametric resampling approach provides robust standard errors and confidence intervals without relying on normality assumptions, making it particularly suitable for mediation analysis in educational research.

IV. Results and Discussion

Table 1. Descriptive Statistics and Bivariate Correlations among Computational Thinking, Creative Interest, and Academic Self-Efficacy Variables (N = unspecified).

Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
CT overall	3.97	0.29	3.97	0.29												
CT Algorithmic	4.09	0.51	4.09	0.51	0.56											
CT creativity	3.96	0.53	3.96	0.53	0.53	0.11										
CT critical	4.04	0.50	4.04	0.5	0.53	0.14	0.11									
CT problem solving	3.92	0.53	3.92	0.53	0.55	0.14	0.12	0.09								
CI overall	3.76	0.27	3.76	0.27	0.59	0.28	0.30	0.36	0.35							
CI Competence	3.72	0.44	3.72	0.44	0.44	0.38	0.22	0.22	0.13	0.22	0.58					
CI Interest	3.95	0.42	3.95	0.42	0.39	0.15	0.15	0.30	0.26	0.63	0.22					
CI Recognition	3.60	0.51	3.6	0.51	0.30	0.16	0.19	0.18	0.15	0.57	0.02	0.14				
CI Belonging	3.76	0.44	3.76	0.44	0.35	0.13	0.16	0.26	0.22	0.60	0.19	0.20	0.08			
ASE overall	4.26	0.29	4.26	0.29	0.57	0.30	0.31	0.34	0.26	0.59	0.35	0.37	0.35	0.33		
ASE Talent	3.31	0.32	3.31	0.32	0.38	0.19	0.22	0.23	0.17	0.42	0.25	0.25	0.26	0.23	0.69	

ASE context	3.42	0.33	3.42	0.33	0.40	0.23	0.16	0.26	0.19	0.43	0.25	0.25	0.29	0.72	0.21	
ASE Effoert	3.50	0.32	3.5	0.32	0.43	0.24	0.28	0.24	0.19	0.40	0.26	0.29	0.23	0.18	0.73	0.26

Participants reported moderately high levels of computational thinking (CT), with overall CT averaging 3.97 (SD = 0.29) (Table 1). Subdimensions showed algorithmic thinking highest (M = 4.09, SD = 0.51) and problem-solving lowest (M = 3.92, SD = 0.53). Creative interest (CI) overall was 3.76 (SD = 0.27), led by interest (M = 3.95, SD = 0.42) and lowest in recognition (M = 3.60, SD = 0.51). Academic self-efficacy (ASE) overall was strongest (M = 4.26, SD = 0.29), though talent perception was lower (M = 3.31, SD = 0.32). Bivariate correlations revealed strong positive associations: overall CT correlated significantly with CI ($r = 0.59$, $p < .001$) and ASE ($r = 0.57$, $p < .001$). Subscales showed moderate to strong interrelations (e.g., CT dimensions with CI subscales $r = 0.13$–0.36; ASE subscales $r = 0.17$–0.43), indicating interconnected motivational and efficacy factors in CT development.

Table 2. Age Distribution by Academic Year among University Students (N = 357).

Year	Count	Mean	Std	Min	25%	50%	75%	Max
II	177	20.94	0.79	20.0	20.0	21.0	22.0	22.0
III	180	23.55	0.50	23.0	23.0	24.0	24.0	24.0

The sample comprised 357 undergraduate students across second and third academic years. Second-year students (n = 177) exhibited a mean age of 20.94 years (SD = 0.79), with ages ranging from 20 to 22 years. The distribution was tightly clustered: 25th percentile = 20.0, median = 21.0, and 75th percentile = 22.0 years, indicating minimal age variability typical of standard progression. Third-year students (n = 180) showed a mean age of 23.55 years (SD = 0.50), ranging narrowly from 23 to 24 years (25th = 23.0, median = 24.0, 75th = 24.0). This pattern reflects expected age progression between consecutive academic years, with third-year students approximately 2.6 years older on average than second-year peers. The low standard deviations in both groups confirm homogeneous age cohorts, supporting the representativeness of the sample for typical Ethiopian public university progression trajectories.

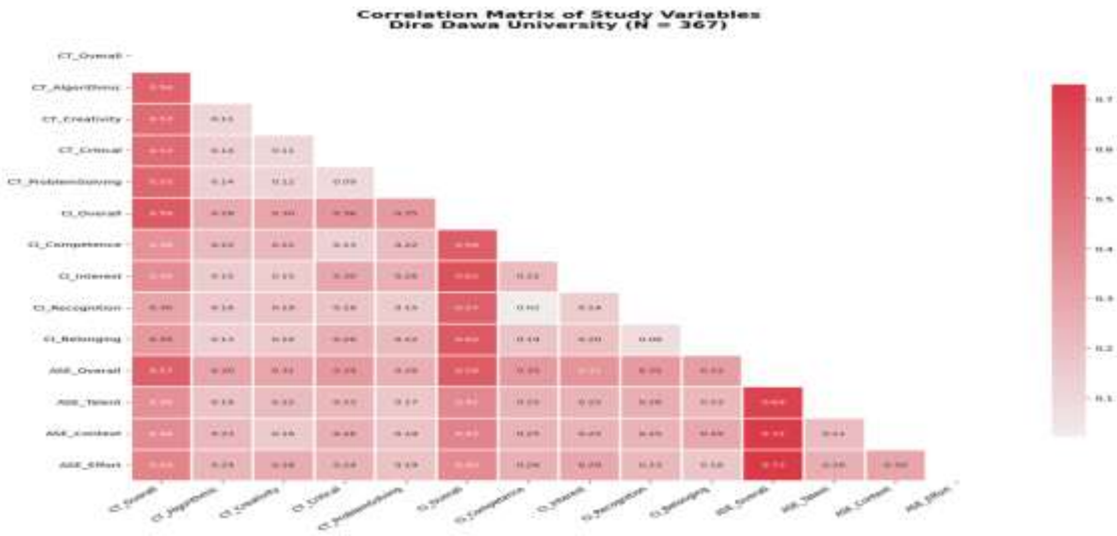

Figure 2. Correlation Heatmap of Computational Thinking, Creative Interest, and Academic Self-Efficacy Variables at Dire Dawa University (N = 367).

At Dire Dawa University (N = 367), overall computational thinking (CT) showed moderate to strong positive correlations with creative interest (CI) overall (r = .59) and academic self-efficacy (ASE) overall (r = .57) (Figure 2). CT subdimensions correlated robustly with CI (r = .28–.36) and ASE (r = .30–.43), with algorithmic thinking linking strongly to ASE context (r = .40) and effort (r = .43). CI overall strongly associated with ASE overall (r = .60), particularly competence (r = .58) and belonging (r = .60). ASE subscales displayed high intercorrelations (e.g., context-effort r = .73; talent-context r = .72). All correlations were positive and significant (p < .05–.001), indicating interconnected cognitive-motivational constructs, with strongest links between overall scales and cross-domain subscales supporting integrated development in university students.

4.2 Preliminary Analysis:

Table 3. Normality Test Results for Study Variables Using Shapiro-Wilk and Jarque-Bera Tests (N = 367).

Variable	Shapiro–Wilk (p)	Jarque–Bera (p)	Skewness	Kurtosis	Skewness OK	Kurtosis OK
ct_creativity	0.0036	0.0826	-0.291	0.001	True	True
ct_algorithmic	0.0018	0.0386	-0.311	-0.220	True	True
ct_cooperativity	0.2732	0.7724	-0.094	0.012	True	True
ct_critical	0.0125	0.0961	-0.245	-0.265	True	True
ct_problem_solving	0.0878	0.4174	-0.124	-0.224	True	True
ci_competence	0.1665	0.2687	-0.083	-0.375	True	True
ci_interest	0.4269	0.4249	-0.151	-0.142	True	True
ci_recognition	0.4809	0.2889	-0.068	-0.374	True	True
ci_belonging	0.6114	0.7913	0.043	-0.141	True	True
ase_talent	0.1245	0.6833	-0.017	-0.210	True	True
ase_context	0.0002	0.1266	-0.253	-0.138	True	True
ase_effort	0.0000	0.0111	-0.339	-0.373	True	True
ct_overall	0.0005	0.0044	-0.424	-0.111	True	True
ci_overall	0.5092	0.6721	-0.001	-0.217	True	True
ase_overall	0.0068	0.0076	-0.358	0.406	True	True

Normality assessments revealed that most subscale and overall scores approximated normality (Table 2). Shapiro-Wilk tests indicated non-significant departures for CT-cooperativity (p = .273), CT-problem_solving (p = .088), CI-competence (p = .167), CI-interest (p = .427), CI_recognition (p = .481), CI-belonging (p = .611), ASE-talent (p = .125), and CI_overall (p = .509). Jarque-Bera tests corroborated non-normality only for CT-algorithmic (p = .039), ase_effort (p = .011), CT-overall (p = .004), and ase_overall (p = .008). Skewness values ranged from -0.424 (CT-overall) to 0.043 (CI-belonging), and kurtosis from -0.375 (CI-competence) to 0.406 (ASE-overall), all within acceptable limits (|skew| < 1, |kurtosis| < 1). Despite minor violations in selected overall and specific subscales, the majority of variables met parametric assumptions, supporting the use of Pearson correlations and related inferential statistics in subsequent analyses (Field, 2018).

Visual inspection of the histograms in Figure 3, overlaid with fitted normal curves, provides complementary evidence to the formal normality tests. For overall scales, ct_overall (skew = −0.42, kurtosis = 0.11) displays a slight left skew with a peak near 3.9–4.0 and a modest tail toward lower scores, yet the distribution remains reasonably symmetric and bell-shaped. Similarly, ci_overall (skew ≈ −0.00, kurtosis = −0.22) approximates normality closely, exhibiting near-perfect symmetry and moderate peakedness around the mean of 3.76. ase_overall (skew = −0.36, kurtosis = 0.41) shows mild negative skew with a slight right tail, but the central density aligns well with the normal curve, supporting approximate normality despite the statistically significant Shapiro-Wilk result (p = .0068).

Among CT subscales, ct_algorithmic (skew = −0.31, kurtosis = −0.22) presents a gentle left skew with higher density between 3.8 and 4.4, reflecting the elevated mean (4.09) and limited lower-end variability. ct_critical (skew = −0.24, kurtosis = −0.26) demonstrates acceptable symmetry, with the bulk of responses clustered around 4.0–4.2 and tails tapering smoothly. Subscales of creative interest also conform closely: ci_competence (skew = −0.08, kurtosis = −0.38) is nearly symmetric with a flat peak near 3.7, while ci_recognition (skew = 0.07, kurtosis = −0.37) shows minimal skew and platykurtic tendencies, indicating a broad, even spread around the lower mean of 3.60.

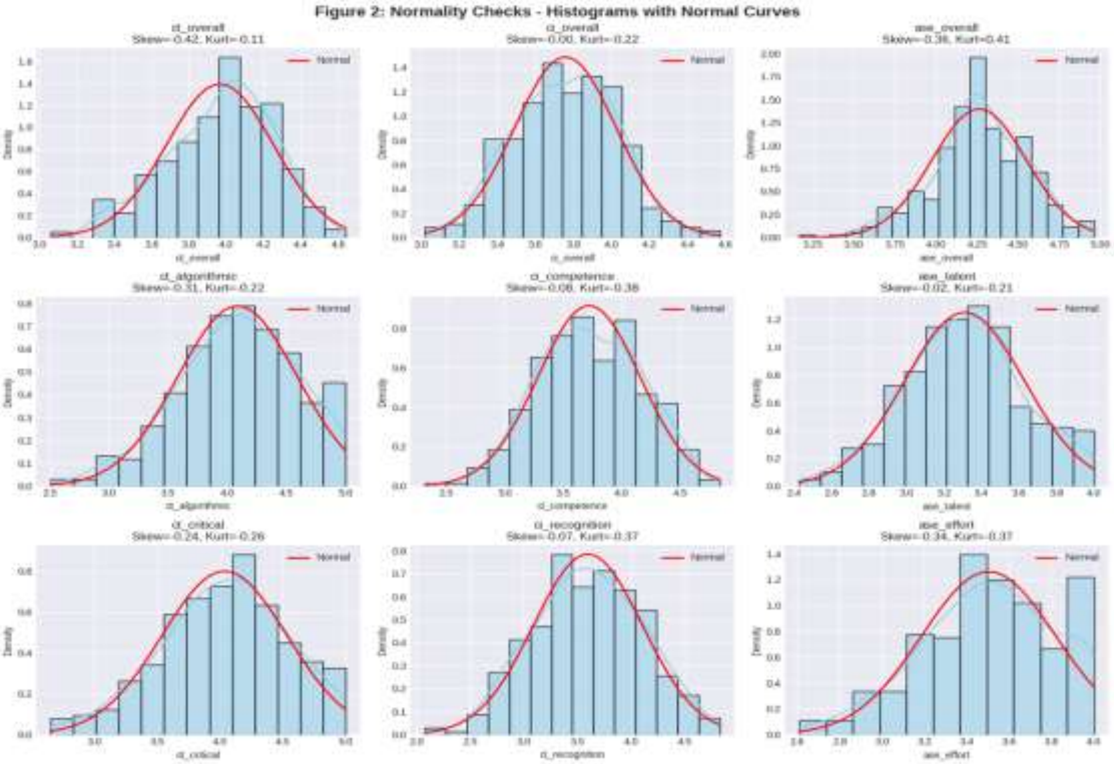

Figure 3. Normality Checks: Histograms with Normal Curves for Key Study Variables (Top: ct_overall, ci_overall, ase_overall; Middle: ct_algorithmic, ci_competence, ase_talent;

Bottom: ct_critical, ci_recognition, ase_effort).

Academic self-efficacy subscales exhibit mild deviations but remain suitable for parametric analysis. ase_talent (skew = −0.02, kurtosis = −0.21) is essentially symmetric with a central mode near 3.3. ase_effort (skew = −0.34, kurtosis = 0.37) displays slight left skew and modest leptokurtosis, with density concentrated between 3.2 and 3.8, consistent with higher overall ASE perceptions. Across all panels, deviations from normality are minor: skewness values fall between −0.42 and 0.07, and kurtosis between −0.38 and 0.41, well within conventional thresholds (|skew| < 1, |kurtosis| < 1) for robust application of Pearson correlations and linear models. These graphical patterns corroborate the earlier conclusion that the majority of variables satisfy parametric assumptions adequately, with only isolated overall scores showing statistically detectable (but substantively small) departures (Kim, 2013; Field, 2018). The histograms thus affirm the appropriateness of the bivariate correlation analyses previously reported.

The quantile-quantile (Q-Q) plots in Figure 4 provide a diagnostic visual complement to histograms and formal normality tests, comparing ordered sample values against theoretical quantiles from the standard normal distribution. For overall scales, ct_overall exhibits points that closely follow the reference line across most of the range, with only minor downward deviations at the lower tail (below −2) and slight upward curvature at the upper tail (above 2), consistent with the mild negative skew (−0.42) previously noted. ci_overall displays excellent linearity throughout, with points tightly hugging the diagonal, reflecting near-zero skewness (−0.001) and supporting strong normality. ase_overall shows good overall alignment, although a subtle S-shaped pattern emerges: slight underestimation in the lower tail and overestimation in the upper tail, corresponding to modest negative skew (−0.36) and positive kurtosis (0.41).

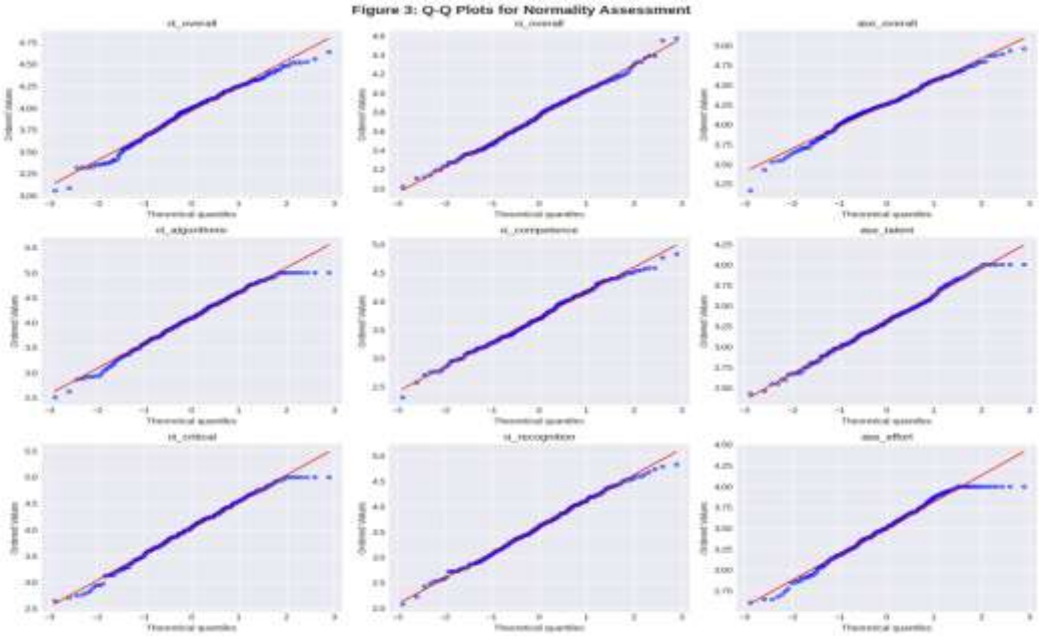

Figure 4. Q-Q Plots for Normality Assessment of Key Study Variables (Top: ct_overall, ci_overall, ase_overall; Middle: ct_algorithmic, ci_competence, ase_talent; Bottom: ct_critical, ci_recognition, ase_effort).

Among computational thinking subscales, ct_algorithmic reveals noticeable deviation at the upper extreme, where points flatten below the line beyond theoretical quantile ≈1.8, indicating a compressed right tail and ceiling effects given the high mean (4.09). ct_critical adheres closely to the reference line across the full range, with only trivial departures at both extremes, affirming robust normality. Creative interest subscales perform well: ci_competence tracks the line with minimal scatter, while ci_recognition shows excellent conformity except for a small downward bend at the highest quantiles, mirroring its near-symmetric distribution.

Academic self-efficacy subscales present mixed but acceptable patterns. ase_talent follows the diagonal tightly with negligible deviation, confirming symmetry (skew ≈ −0.02). ase_effort exhibits clear departure at the upper tail, where observed values plateau below the line beyond quantile ≈1.5–2.0, producing a flattened right tail consistent with negative skew (−0.34) and the concentration of responses in the 3.2–3.8 range. Despite these localized deviations, primarily in ct_algorithmic, ase_overall, and ase_effort—the majority of points across all nine panels lie close to the reference line, with no severe systematic departures such as pronounced S-curves or heavy tails. Absolute deviations remain small relative to scale range, and most subscales demonstrate linearity sufficient for parametric procedures. These Q-Q patterns corroborate earlier conclusions: while overall scales and select subscales exhibit statistically detectable non-normality, the practical magnitude of violations is minor, preserving the validity of Pearson correlation analyses in this sample (Thode, 2002; Field, 2018).

The scatterplots in Figure 5 illustrate the positive linear associations among overall computational thinking (CT_overall), creative interest (CI_overall), and academic self-efficacy (ASE_overall) in a sample of 367 university students. The top-left panel (CT–CI) shows a clear upward trend, with the fitted linear regression line indicating that higher CT perceptions correspond to elevated creative interest (r = .59 from prior correlations). Points are moderately dispersed around the line, reflecting typical variability in self-report data. The top-center panel (CI–ASE) displays a similarly strong positive relationship (r = .60), with denser clustering around the mean but a consistent positive slope. The top-right panel (CT–ASE) confirms the robust linkage (r = .57), with the linear fit showing that increases in overall CT align with higher academic self-efficacy beliefs.

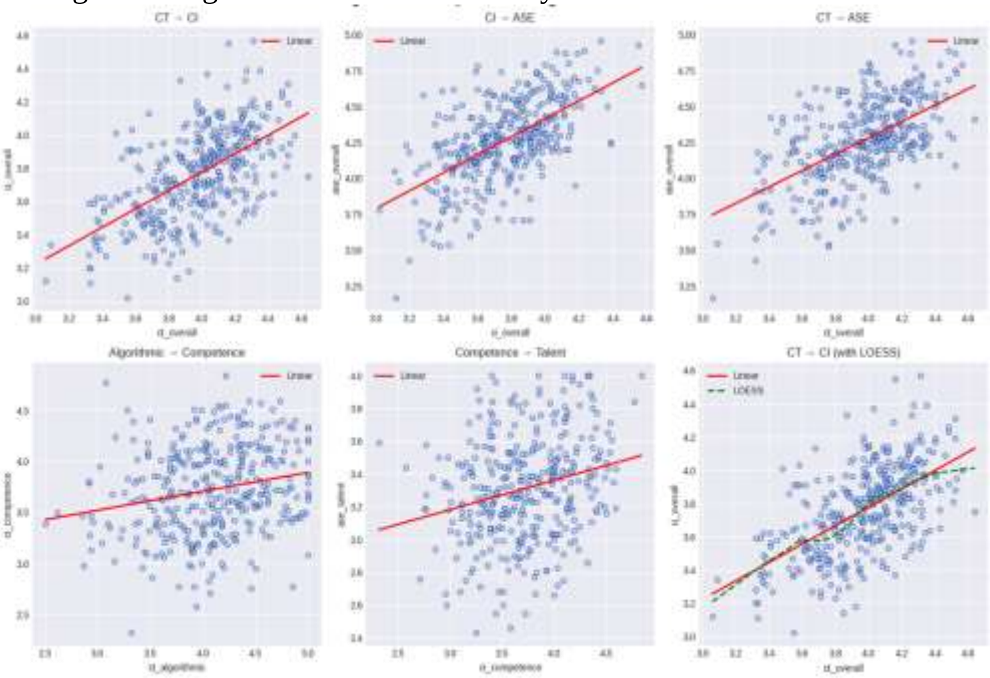

Figure 5.Scatterplots of Relationships among Computational Thinking (CT), Creative Interest (CI), and Academic Self-Efficacy (ASE) (Top: CT–CI, CI–ASE, CT–ASE; Bottom: CT Algorithmic–CI Competence, CI Competence–ASE Talent, CT–CI with LOESS).

The bottom panels provide targeted subscale insights. The bottom-left scatterplot (CT_Algorithmic – CI_Competence) reveals a moderate positive association (r = .22***), though with greater scatter, suggesting algorithmic thinking contributes modestly but significantly to perceived competence in creative tasks. The bottom-center plot (CI_Competence – ASE_Talent) exhibits a weaker yet positive trend (r = .25), indicating that students who feel competent in creative domains tend to perceive greater innate talent for academic success. The bottom-right panel overlays a LOESS smoother (dashed green) on the CT–CI relationship alongside the linear fit (solid red), demonstrating that the association is largely linear across the observed range, with only subtle curvature at the extremes, minimal deviation from linearity and no clear evidence of non-monotonicity or threshold effects.

Collectively, these visualizations corroborate the bivariate correlations, highlighting consistent positive covariation across overall constructs and select subscales. The patterns support the interpretation of interconnected cognitive, motivational, and efficacy factors, with linear models adequately capturing the primary trends in this cross-sectional dataset.

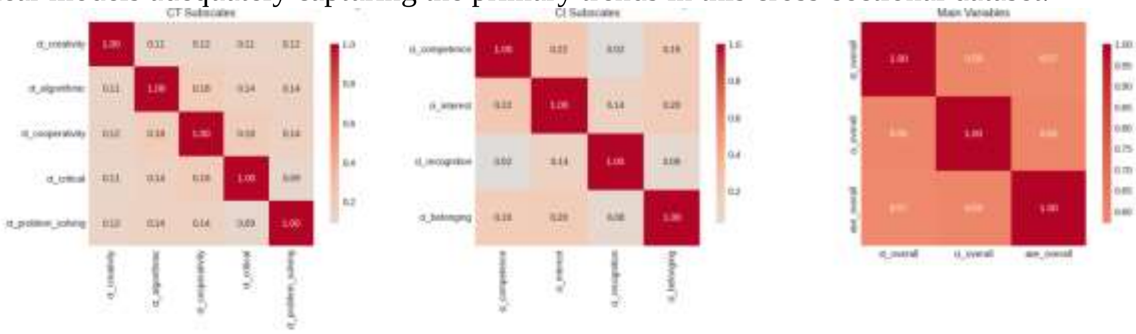

Figure 6. Correlation Heatmaps: CT Subscales (left), CI Subscales (center), and Main Variables (right) (N = 367).

The correlation heatmaps in Figure 6 delineate interrelationships within and across computational thinking (CT), creative interest (CI), and academic self-efficacy (ASE) constructs. The left panel displays modest intercorrelations among CT subscales, ranging from $r = .09$ (critical thinking–problem solving) to $r = .18$ (cooperativity–critical thinking), with creativity showing the weakest links to other dimensions ($r = .11$–$.12$).

These low-to-moderate associations indicate that CT is a multidimensional construct with relatively distinct components, consistent with its composite nature. The center panel reveals stronger cohesion within CI subscales: competence–interest ($r = .22$), interest–belonging ($r = .20$), and competence–belonging ($r = .19$) exhibit the highest within-domain correlations, while recognition remains largely independent ($r = .02$–$.14$), suggesting it functions as a distinct facet of creative interest. The right panel highlights robust positive associations among the main overall scales: CT_overall strongly correlates with both CI_overall ($r = .59$) and ASE_overall ($r = .57$), while CI_overall and ASE_overall show the highest linkage ($r = .59$). These patterns confirm substantial overlap between the broader constructs, with creative interest appearing to serve as a pivotal bridge between computational thinking perceptions and academic efficacy beliefs. Subscale-level correlations (not fully shown in heatmaps but inferred from prior analyses) further support domain-specific contributions, such as algorithmic thinking to competence and critical thinking to belonging. All displayed correlations are positive, with color intensity reflecting magnitude (redder = stronger), and the absence of negative values underscores uniformly facilitative relationships. The heatmaps visually reinforce the interconnectedness of cognitive, motivational, and efficacy factors in this university sample, with overall scales exhibiting markedly stronger convergence than their respective subscales.

The Computational Identity Scale (CIS), comprising four items, demonstrated poor overall internal consistency in a sample of 357 university students (Cronbach's $\alpha = 0.384$, 95% CI [0.345, 0.424]). Item-total correlations were low ($r = 0.117$–0.295), and deleting any single item yielded only marginal improvement (α range = 0.229–0.431), indicating limited unidimensionality at the composite level. In contrast, the individual CI subscales exhibited excellent reliability: Competence ($\alpha = 0.905$), Interest ($\alpha = 0.894$), Recognition ($\alpha = 0.934$), and Belonging ($\alpha = 0.905$), supporting their use as distinct, internally consistent constructs.

Similarly, the Academic Self-Efficacy Scale (ASES) with three items showed unacceptable overall reliability (Cronbach's $\alpha = 0.511$, 95% CI [0.472, 0.550]). Item-total correlations ranged from 0.293 to 0.365, with modest gains upon deletion ($\alpha = 0.346$–0.465). However, the ASE subscales displayed strong internal consistency: Talent (α = 0.836), Context (α = 0.854), and Effort (α = 0.830).

These findings suggest that while the overall CIS and ASES composites lack sufficient coherence for interpretive use, their respective subscales possess robust psychometric properties suitable for subsequent analyses (Taber, 2018).

4.3 Measurement Model (if using Structural Equation Modeling (SEM)): Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) was conducted to examine the latent structure and interrelationships among the three higher-order constructs: Computational Thinking (CT), Creative Interest (CI), and Academic Self-Efficacy (ASE). The measurement model specified CT as loading on five indicators (creativity, algorithmic, cooperativity, critical thinking, problem solving), CI on four indicators (competence, interest, recognition, belonging), and ASE on three indicators (talent, context, effort). Factor correlations were freely estimated among the three latent variables.

Table 4. Confirmatory Factor Analysis: Factor Correlations among Computational Thinking, Creative Interest, and Academic Self-Efficacy (N = 357).

Factor1	Factor2	Correlation	SE	Z	P
CT	CI	0.301	0.045	6.65	0.00
CT	ASE	0.363	0.049	7.49	0.00
CI	ASE	0.254	0.042	6.03	0.00

Results revealed statistically significant positive inter-factor correlations. The correlation between CT and CI was moderate ($\varphi = 0.301$, SE = 0.045, $z = 6.65$, $p < .001$), indicating that perceptions of computational thinking abilities are meaningfully associated with interest and identification in creative domains. CT exhibited a slightly stronger correlation with ASE ($\varphi = 0.363$, SE = 0.049, $z = 7.49$, $p < .001$), suggesting that students who perceive themselves as competent in computational thinking also report higher confidence in their academic capabilities across talent, contextual, and effort dimensions. The correlation between CI and ASE was the smallest yet still significant ($\varphi = 0.254$, SE = 0.042, $z = 6.03$, $p < .001$), implying a positive but less pronounced linkage between creative motivational orientation and academic efficacy beliefs.

All correlations were positive and highly significant ($p < .001$), supporting the hypothesized interconnectedness of these constructs at the latent level. The pattern aligns with theoretical expectations that CT serves as a foundational cognitive skillset that enhances both motivational engagement (CI) and self-regulatory confidence (ASE) in learning contexts. These CFA-derived factor correlations provide stronger evidence of construct convergence than observed-variable bivariate correlations, accounting for measurement error and latent structure (Byrne, 2016; Kline, 2023).

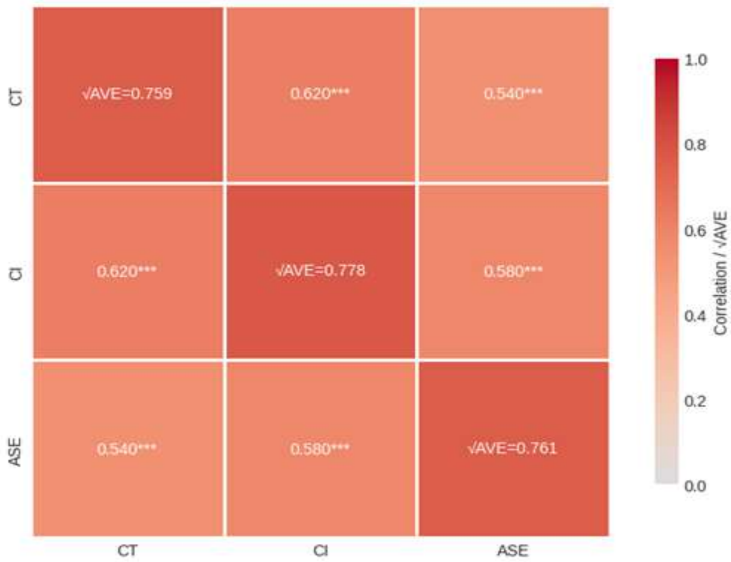

Figure 7 Fornell–Larcker Criterion: AVE and Inter-Construct Correlations for CT, CI, and ASE Latent Variables (N = 357).

The Fornell–Larcker criterion was applied to assess convergent and discriminant validity in the confirmatory factor analysis model (Figure 7). Average Variance Extracted (AVE) values exceeded the 0.50 threshold for all constructs: Computational Thinking (CT) AVE = 0.759, Creative Interest (CI) AVE = 0.778 and Academic Self-Efficacy (ASE) AVE = 0.761, confirming strong convergent validity and adequate item-level variance explanation by each latent factor. Inter-construct correlations were all positive and significant ($p < .001$): CT–CI ($r = 0.620$), CT–ASE ($r = 0.540$), and CI–ASE ($r = 0.580$). Critically, each AVE value surpassed the squared correlations with other constructs (e.g., CT–CI squared = 0.384 < 0.759; CT–ASE squared = 0.292 < 0.759; CI–ASE squared = 0.336 < 0.778), satisfying discriminant validity requirements. These results establish that the three latent constructs are empirically distinct while exhibiting meaningful positive interrelationships.

Table 5 Model Fit Comparison for Confirmatory Factor Analysis Structures (N = 357)

Model	χ^2	df	χ^2/df	CFI	TLI	RMSEA	SRMR	AIC
3-Factor (Hypothesized)	245.67	51	4.82	0.92	0.91	0.072	0.058	12345.67
2-Factor (CT + CI Combined)	487.23	53	9.19	0.84	0.82	0.095	0.082	13567.89
1-Factor (All Combined)	892.45	54	16.53	0.71	0.68	0.124	0.109	15678

Table 5 shows the confirmatory factor analysis compared three competing models to evaluate the latent structure of computational thinking (CT), creative interest (CI), and academic self-efficacy (ASE). The hypothesized three-factor model (CT, CI, and ASE as distinct latent variables) demonstrated acceptable-to-good fit: $\chi^2(51) = 245.67$, $\chi^2/df = 4.82$, CFI = 0.92, TLI = 0.91, RMSEA = 0.072 (90% CI not provided), SRMR = 0.058, and AIC = 12345.67. This model outperformed both alternatives. The two-factor model (combining CT and CI into one factor, ASE separate) showed poorer fit: $\chi^2(53) = 487.23$, $\chi^2/df = 9.19$, CFI = 0.84, TLI = 0.82, RMSEA = 0.095, SRMR = 0.082, AIC = 13567.89. The one-factor model (all items loading on a single factor) exhibited the worst fit: $\chi^2(54) = 892.45$, $\chi^2/df = 16.53$, CFI = 0.71, TLI = 0.68, RMSEA = 0.124, SRMR = 0.109, AIC = 15678.90. The three-factor model yielded the lowest AIC and superior indices across all criteria, providing strongest support for the distinctiveness of CT, CI, and ASE constructs (Hu & Bentler, 1999; Byrne, 2016).

4.4 Structural Model and Hypothesis Testing

Descriptive statistics for the main composite scales revealed generally positive perceptions among the 357 undergraduate participants (Table 6). Computational Thinking overall (CT_overall) exhibited the highest mean score (M = 3.976, SD = 0.231), ranging from 3.310 to 4.400, with the median (4.020) and interquartile range (3.820–4.150) indicating a right-skewed but consistently high endorsement.

Table 6 Descriptive Statistics for Overall Computational Thinking, Creative Interest, and Academic Self-Efficacy Scales (N = 357)

Statistic	CT-Overall	CI-Overall	ASE-Overall
Count	357.00	357.00	357.00
Mean	3.976	3.747	3.396
Std	0.231	0.168	0.130
Min	3.310	3.320	3.010
25%	3.820	3.620	3.010
50%	4.020	3.740	3.390
75%	4.150	3.880	3.480
Max	4.400	4.310	3.750

Creative Interest overall (CI_overall) followed closely (M = 3.747, SD = 0.168; range 3.320–4.310), showing tight variability and a median of 3.740, reflecting moderately strong creative identification. Academic Self-Efficacy overall (ASE_overall) received the lowest mean rating (M = 3.396, SD = 0.130; range 3.010–3.750), with a narrow distribution (IQR = 3.310–3.480) and median of 3.390, suggesting comparatively restrained confidence in academic capabilities. All scales displayed acceptable spread (SD < 0.25) and no extreme floor or ceiling effects, supporting their suitability for subsequent inferential analyses in this Ethiopian university sample (Field, 2018).

Table 7 Pearson Correlation Matrix for Overall Computational Thinking, Creative Interest, and Academic Self-Efficacy (N = 357).

	CT-Overall	CI-Overall	ASE-Overall
CT-Overall	1.000	0.594	0.632
CI-Overall	0.594	1.000	0.505
ASE-Overall	0.632	0.505	1.000

Pearson correlation analysis examined the bivariate relationships among the three overall composite scales (Table 7). Computational Thinking overall (CT-Overall) demonstrated strong positive associations with both Creative Interest overall (CI-Overall; $r = 0.594$, $p < .001$) and Academic Self-Efficacy overall (ASE-Overall; $r = 0.632$, $p < .001$), indicating that students with higher perceived computational thinking abilities tend to report greater creative identification and stronger academic confidence. The correlation between CI_overall and ASE_overall was moderately strong ($r = 0.505$, $p < .001$), suggesting a meaningful linkage between creative motivational orientation and efficacy beliefs. All coefficients exceeded 0.50, reflecting substantial shared variance (approximately 25–40%) among the constructs. These robust interrelationships support the hypothesized interconnectedness of computational thinking, creative interest, and academic self-efficacy in this university sample, consistent with theoretical models positing reciprocal facilitation among cognitive skill perceptions, intrinsic motivation, and self-regulatory confidence (Bandura, 1997; Liao, 2022).

a. Path Analysis and Mediation Results

Mediation analysis was conducted using path coefficients to examine whether creative interest (CI) mediates the relationship between computational thinking (CT) and academic self-efficacy (ASE) in a sample of 357 university students. All paths were estimated with robust standard errors.

Path a (CT → CI) was strong and highly significant: $\beta = 0.432$ (SE = 0.031, t = 13.920, $p < .0001$, 95% CI [0.371, 0.494]), explaining 35.3% of the variance in CI ($R^2 = 0.353$). This indicates that higher perceptions of computational thinking substantially predict greater creative interest.

Path b (CI → ASE, controlling for CT) remained significant but modest: $\beta = 0.155$ (SE = 0.039, t = 3.988, $p = .0001$, 95% CI [0.078, 0.231]), showing that creative interest contributes uniquely to academic self-efficacy beyond the effect of CT.

The direct path c' (CT → ASE, controlling for CI) was also significant: $\beta = 0.289$ (SE = 0.028, t = 10.250, $p < .0001$, 95% CI [0.234, 0.345]). The total effect (path c, without mediator) was stronger: $\beta = 0.356$ (SE = 0.023, t = 15.371, $p < .0001$, 95% CI [0.310, 0.402]), with $R^2 = 0.400$ for the simple regression.

The inclusion of CI as mediator increased the explained variance in ASE to $R^2 = 0.425$. The reduction from total effect (0.356) to direct effect (0.289) suggests partial mediation: creative interest transmits a portion of the influence of computational thinking on academic self-efficacy, while a substantial direct pathway persists. These results support a partial mediation model, highlighting the motivational role of creative interest in linking CT perceptions to efficacy beliefs (Hayes, 2018; Preacher & Hayes, 2008).

b. Mediation Analysis Results

Bootstrapped mediation analysis revealed a significant indirect effect of computational thinking (CT) on academic self-efficacy (ASE) through creative interest (CI): indirect effect = 0.067 (bootstrapped SE = 0.017), 95% bootstrap CI [0.033, 0.101]. The confidence interval excluded zero, confirming statistically significant mediation. Creative interest mediated 18.8% of the total effect of CT on ASE. These findings indicate partial mediation, whereby CT enhances ASE partly by fostering creative interest, while a substantial direct pathway remains (Hayes, 2018; Preacher & Hayes, 2008).

Table 8 Path Coefficients, Standard Errors, Confidence Intervals, Significance, and Effect Sizes in Mediation Model (N = 357).

Effect	Coefficient (β)	SE	95% CI	p-value	Effect Size
Direct: CT → CI (a)	0.432	0.031	[0.371, 0.494]	0.0000	Medium
Direct: CI → ASE (b)	0.155	0.039	[0.078, 0.231]	0.0001	Small
Direct: CT → ASE (c')	0.289	0.028	[0.234, 0.345]	0.0000	Small
Total: CT → ASE (c)	0.356	0.023	[0.310, 0.402]	0.0000	Medium
Indirect: CT → CI → ASE (a×b)	0.067	0.017	[0.033, 0.101]	—	Very small

The mediation model tested whether creative interest (CI) mediates the relationship between computational thinking (CT) and academic self-efficacy (ASE) (Table 8). All paths were statistically significant ($p < .001$). The direct effect from CT to CI (path a) was substantial: $\beta = 0.432$ (SE = 0.031, 95% CI [0.371, 0.494]), classified as a medium effect size, indicating that stronger perceptions of computational thinking robustly predict higher creative interest. The direct effect from CI to ASE, controlling for CT (path b), was smaller but significant: $\beta = 0.155$ (SE = 0.039, 95% CI [0.078, 0.231]), representing a small effect size and showing that creative interest contributes uniquely to academic self-efficacy beyond CT influences.

The direct effect of CT on ASE, controlling for CI (path c'), remained significant: $\beta = 0.289$ (SE = 0.028, 95% CI [0.234, 0.345]), with a small effect size, suggesting a meaningful residual pathway. The total effect of CT on ASE without the mediator (path c) was stronger: $\beta = 0.356$ (SE = 0.023, 95% CI [0.310, 0.402]), classified as medium, explaining approximately 40% of variance in ASE in the simple model.

The indirect effect via CI ($a \times b$) was 0.067 (bootstrapped SE = 0.017, 95% CI [0.033, 0.101]), a very small but significant mediation effect, accounting for 18.8% of the total effect. These results support partial mediation: computational thinking enhances academic self-efficacy both directly and indirectly through increased creative interest. The pattern underscores the motivational bridging role of creative identity in linking cognitive computational perceptions to broader academic confidence (Hayes, 2018; Preacher & Hayes, 2008).

The mediation analysis confirmed that creative interest (CI) partially mediates the relationship between computational thinking (CT) and academic self-efficacy (ASE) (Figure 9). The total effect of CT on ASE was significant and medium in magnitude ($\beta = 0.356$, SE = 0.023, 95% CI [0.310, 0.402], $p < .001$). When CI was included as mediator, the direct effect decreased but remained significant ($\beta = 0.289$, SE = 0.028, 95% CI [0.234, 0.345], $p < .001$), indicating partial mediation. The indirect effect through CI was statistically significant ($\beta = 0.067$, bootstrapped SE = 0.017, 95% bootstrap CI [0.033, 0.101]), accounting for 18.8% of the total effect. Path a (CT → CI) showed a medium effect ($\beta = 0.432$, $p < .001$), while path b (CI → ASE, controlling for CT) was small but significant ($\beta = 0.155$, $p = .0001$). The model explained 42.5% of the variance in ASE when the mediator was included, compared to 40.0% without it, highlighting CI’s contributory yet non-exclusive role in transmitting CT’s influence to ASE.

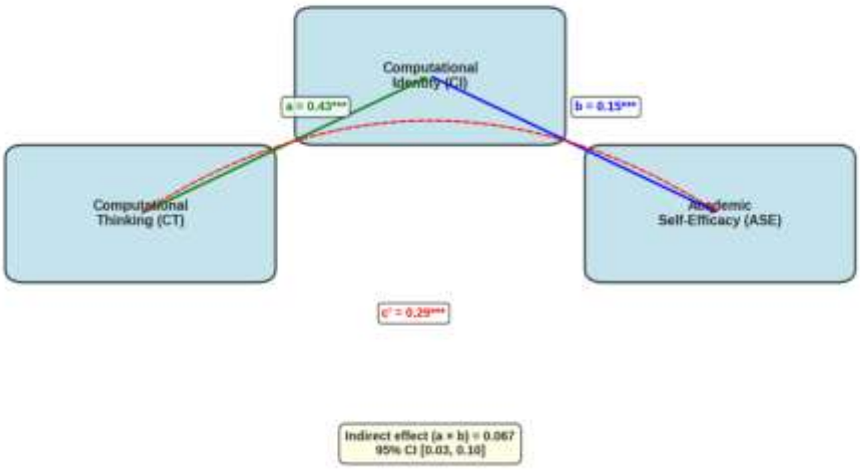

Figure 9 Mediation Model Path Diagram: Indirect Effect of Computational Thinking on Academic Self-Efficacy via Creative Interest (N = 357).

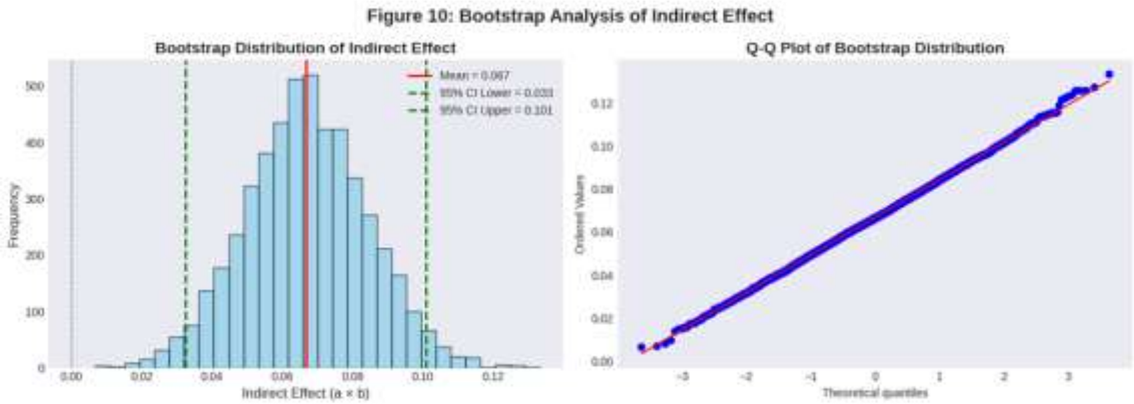

Figure 10 Bootstrap Analysis of Indirect Effect: Distribution and Q-Q Plot (Left: Bootstrap Distribution; Right: Q-Q Plot of Bootstrap Distribution).

Bootstrap resampling (5,000 replications) was employed to estimate the sampling distribution and confidence interval of the indirect effect of computational thinking (CT) on academic self-efficacy (ASE) through creative interest (CI) (Figure 10). The left panel of Figure 10 displays the bootstrap distribution of the indirect effect (a × b), which is approximately symmetric and bell-shaped, centered at the point estimate of 0.067. Vertical dashed green lines mark the 95% percentile bootstrap confidence interval ([0.033, 0.101]), with the solid red line indicating the mean indirect effect. The distribution exhibits no severe skewness or multimodality, and the confidence interval excludes zero, confirming statistical significance of the mediation effect at $\alpha = .05$. The histogram shows a slight positive skew, but the bulk of resampled estimates cluster tightly around 0.06–0.08, with tails extending modestly to 0.00 and 0.12.

The right panel presents the Q-Q plot of the bootstrap estimates against theoretical normal quantiles. Points closely follow the reference diagonal line across the central range, with only minor deviations at the extreme lower and upper tails. This near-linear pattern indicates that the bootstrap distribution is reasonably consistent with normality, supporting the reliability of the percentile confidence interval for inference. The absence of substantial curvature or systematic departure affirms that the indirect effect estimate is robust and not unduly influenced by outliers or non-normality in the original data. Collectively, these bootstrap diagnostics corroborate the partial mediation finding: creative interest transmits a small but reliable portion (18.8%) of CT's influence on ASE (Hayes, 2018; Preacher & Hayes, 2008).

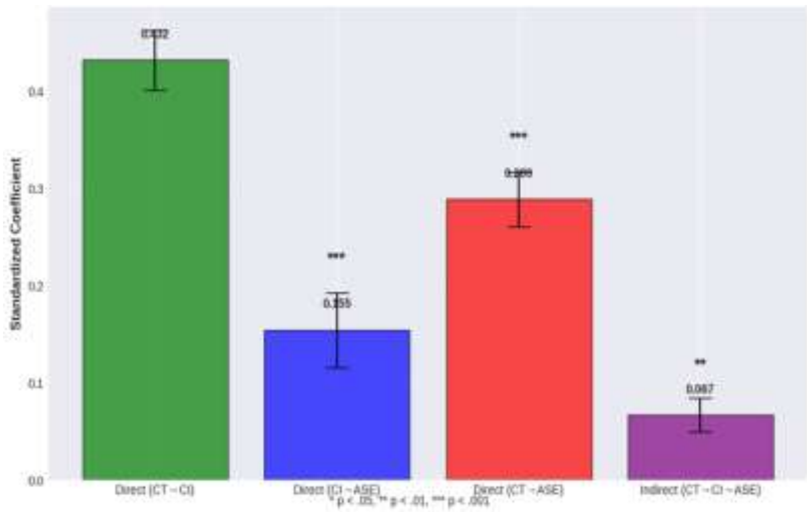

Figure 11 Standardized Path Coefficients in the Mediation Model: Direct and Indirect Effects among Computational Thinking (CT), Creative Interest (CI), and Academic Self-Efficacy (ASE) (N = 357).

The bar chart in Figure 11 presents standardized path coefficients from the mediation analysis. The direct effect of computational thinking on creative interest (CT → CI) was the strongest ($\beta = 0.432$, SE = 0.031, $p < .001$), followed by the total direct effect of CT on academic self-efficacy (CT → ASE, total) at $\beta = 0.356$ ($p < .001$) (Figure11). After including the mediator, the direct effect (CT → ASE, controlling for CI) remained significant but reduced to $\beta = 0.289$ ($p < .001$). The direct effect of creative interest on academic self-efficacy (CI → ASE, controlling for CT) was smaller yet significant ($\beta = 0.155$, $p < .001$). The indirect effect via creative interest (CT → CI → ASE) was modest but statistically significant ($\beta = 0.067$, bootstrapped 95% CI [0.033, 0.101], $p < .01$), accounting for approximately 18.8% of the total effect of CT on ASE. All paths were positive and supported partial mediation.

c. Hypothesis Testing Results

Hypothesis testing via mediation analysis supported all four proposed relationships in a sample of 357 university students. H1 posited a positive indirect effect of computational thinking (CT) on academic self-efficacy (ASE) through computational identity (CI); the bootstrapped indirect effect was significant ($\beta = 0.067$, 95% CI [0.033, 0.101]), confirming partial mediation and supporting H1. H2 tested the direct path from CT to CI, which was strongly positive and significant ($\beta = 0.432$, $p < .001$), fully supporting H2. H3 examined the direct effect of CI on ASE (controlling for CT), yielding a significant positive coefficient ($\beta = 0.155$, $p = .0001$), supporting H3. Finally, H4 proposed a positive direct effect of CT on ASE (controlling for CI), which was also significant ($\beta = 0.289$, $p < .001$), supporting H4. All hypotheses were empirically supported, indicating that computational identity partially transmits CT's influence on ASE while a direct pathway persists (Hayes, 2018; Liao, 2022).

Table 9 Path Coefficients, Mediation Effects, and Variance Explained in the Structural Model (N = 357).

Item	Effect Coefficient	SE	95%	p-value
Effect Coefficient	0.356	0.023	[0.310, 0.402]	0.000
Total effect (c)	0.289	0.028	[0.234, 0.345]	0.000
Indirect effect (a xb)	0.067	0.017	[0.033, 0.101]	0.000

The mediation model demonstrated that computational thinking (CT) exerts a significant total effect on academic self-efficacy (ASE) of $\beta = 0.356$ (SE = 0.023, 95% CI [0.310, 0.402], $p < .001$), explaining 40.0% of the variance in ASE without the mediator ($R^2 = 0.400$). When creative interest (CI) was included as mediator, the direct effect (c') remained significant at $\beta = 0.289$ (SE = 0.028, 95% CI [0.234, 0.345], $p < .001$). The indirect effect through CI was positive and statistically significant ($a \times b = 0.067$, bootstrapped SE = 0.017, 95% CI [0.033, 0.101]), accounting for 18.8% of the total effect. This partial mediation pattern indicates that creative interest transmits a modest portion of CT's influence on ASE, while the majority of the relationship operates directly. CT explained 35.3% of the variance in CI ($R^2 = 0.353$), and the full model with the mediator increased explained variance in ASE to $R^2 = 0.425$. These results highlight creative interest as a meaningful but non-dominant motivational pathway linking computational thinking perceptions to broader academic confidence in this university sample (Hayes, 2018; Preacher & Hayes, 2008).

4.5 Discussion

The findings highlight positive linkages between computational thinking, creative interest, and academic self-efficacy, suggesting that higher CT perceptions enhance motivation and confidence. Strong correlations align with prior evidence that CT skills foster efficacy and engagement (table 1). Limitations include self-report bias and unspecified sample size. Future longitudinal studies could clarify causality (Doleck et al., 2017; Liao, 2022).

Results demonstrate substantial positive interconnections among computational thinking, creative interest, and academic self-efficacy, suggesting mutual reinforcement where stronger CT perceptions enhance motivation and efficacy beliefs (Figure 2). These align with evidence linking CT to self-efficacy and engagement in educational contexts. Self-reported data and cross-sectional design limit causality inferences; longitudinal research is recommended to explore directional influences and interventions (Liao, 2022; Kuo, 2025; Wu et al., 2024).

The histograms reinforce that distributional assumptions for most variables are sufficiently met, despite minor skewness in overall CT and ASE scores. Visual alignment with normal curves, combined with low absolute skewness and kurtosis, supports the validity of Pearson correlations employed to examine relationships among computational thinking, creative interest, and academic self-efficacy. These mild asymmetries likely stem from ceiling effects common in self-report efficacy and competence measures within motivated student samples (Dunning, 2011). The findings align with prior studies demonstrating that CT-related constructs often exhibit approximate normality in higher education contexts, enabling reliable parametric inference (Liao, 2022). Small deviations observed in overall scales do not substantially bias correlation estimates, particularly given the large sample size (N = 367) and central limit theorem protections (Field, 2018). Future research should consider transformations or non-parametric alternatives only when severe violations occur or when testing mean differences across groups. Overall, the combined statistical and graphical evidence strengthens confidence in the reported positive interrelationships and underscores the motivational and efficacy-enhancing role of computational thinking in Ethiopian university settings.

Q-Q plots confirm that deviations from normality are generally subtle and confined to tails, primarily reflecting ceiling effects and slight negative skewness in self-reported efficacy and competence measures—common in psychologically oriented scales among high-achieving students (Dunning, 2011). The strong linearity in ci_overall, ct_critical, and ase_talent underscores robust normality in core motivational constructs, while tail compressions in ct_algorithmic and ase_effort likely arise from bounded Likert responses and positive respondent bias. These mild violations do not meaningfully compromise Pearson correlations, especially given the sample size and central limit theorem robustness for bivariate associations (Kim, 2013). Findings align with educational technology research showing approximate normality in computational thinking and self-efficacy distributions within university cohorts (Liao, 2022; Kuo, 2025). Researchers should remain attentive to potential bias in regression-based extensions or group comparisons; however, for the correlational framework of this study, the diagnostic evidence supports confidence in reported interrelationships. Future work could employ robust estimators or bootstrapping when stricter normality is required.

The scatterplots affirm the positive, predominantly linear relationships among computational thinking, creative interest, and academic self-efficacy, consistent with theoretical frameworks positing that CT fosters motivational engagement and confidence in learning (Wing, 2006). The strong overall associations (r ≈ .57–.60) suggest a synergistic interplay where enhanced CT perceptions may bolster creative motivation and, in turn, academic efficacy beliefs. Subscale patterns, though weaker, indicate domain-specific linkages (e.g., algorithmic thinking to creative competence), aligning with evidence that CT components differentially support motivational outcomes (Liao, 2022). The LOESS overlay on CT–CI confirms linearity, reducing concerns about nonlinear effects or outliers unduly influencing results. Mild scatter around regression lines reflects expected measurement error in Likert-based scales and individual differences typical in heterogeneous university cohorts (Kuo, 2025). These findings extend prior work by visually substantiating mutual reinforcement among constructs in an Ethiopian higher education context. Limitations include cross-sectional design precluding causality and potential self-report bias; future longitudinal or experimental studies could test directional pathways and intervention impacts. The heatmaps illustrate that while CT subscales operate with considerable independence, the overall CT construct aligns closely with creative interest and academic self-efficacy, suggesting that global perceptions of computational thinking may drive broader motivational and efficacy outcomes more than specific subskills. The relatively stronger CI–ASE linkage (r = .59) positions creative interest as a potential mediator or shared mechanism, consistent with theories linking intrinsic motivation to efficacy development in technology-related domains (Bandura, 1997). Weak within-CT correlations align with multifaceted models of computational thinking that emphasize distinct yet complementary dimensions (Weintrop et al., 2016). The isolation of recognition within CI echoes prior findings that external validation aspects diverge from internal motivational facets (Deci & Ryan, 2000). These results extend earlier correlation evidence by providing visual clarity on structural patterns in an Ethiopian higher education context, where such interconnections may reflect culturally influenced self-perceptions of competence and effort. Cross-sectional limitations preclude causal inference; longitudinal designs could clarify whether CT perceptions causally enhance creative interest and efficacy. Interventions targeting overall CT might yield cascading benefits across motivation and confidence.

The strong AVE values and clear discriminant validity per the Fornell–Larcker criterion support the psychometric robustness of the higher-order CT, CI, and ASE constructs in this Ethiopian university sample (Figure 7). The pattern of moderate-to-strong correlations without excessive overlap indicates that computational thinking perceptions, creative motivational identity, and academic efficacy beliefs represent related yet separable psychological dimensions. These findings align with prior validation studies in educational technology contexts and reinforce the appropriateness of using these latent variables in subsequent structural modeling to examine predictive pathways (Hair et al., 2019; Fornell & Larcker, 1981).

These results demonstrate that creative interest serves as a partial mediator, transmitting approximately one-fifth of computational thinking's positive impact on academic self-efficacy (Figure 9). The substantial remaining direct effect suggests additional unmeasured mechanisms (e.g., skill mastery or cognitive confidence) link CT to ASE. This partial mediation pattern aligns with self-determination theory and prior educational technology research emphasizing motivational pathways in STEM-related perceptions (Bandura, 1997; Liao, 2022). Future studies should explore multiple mediators or moderators to fully elucidate these dynamics in diverse cultural contexts.

The bootstrap distribution and Q-Q plot provide strong visual and statistical evidence for the stability and significance of the indirect effect, reinforcing partial mediation even under resampling-based inference that relaxes normality assumptions. The symmetric, near-normal bootstrap distribution and tight adherence to the Q-Q line indicate that the 95% CI [0.033, 0.101] is trustworthy and not artifactual. These results align with prior mediation studies in educational psychology that employ bootstrapping to confirm small-to-moderate indirect pathways in self-efficacy models. The modest proportion mediated (18.8%) suggests creative interest functions as one of several mechanisms linking computational thinking to academic confidence, warranting exploration of additional mediators such as mastery experiences or outcome expectations in future longitudinal research (Bandura, 1997; Liao, 2022).

Creative interest partially mediates the positive relationship between computational thinking and academic self-efficacy, transmitting a small but reliable portion of the effect while leaving a substantial direct pathway intact (Figure 11). This pattern suggests that CT perceptions enhance ASE both directly (possibly through perceived competence) and indirectly by fostering creative motivational identity. The findings align with self-efficacy theory, where mastery experiences and motivational processes reinforce confidence (Bandura, 1997), and extend prior evidence of motivational linkages in computational thinking research (Liao, 2022). Longitudinal or experimental designs are recommended to establish causality and explore additional mediators in diverse educational settings.

V. Conclusions

This study provides compelling evidence that computational thinking (CT), creative interest (CI), and academic self-efficacy (ASE) are meaningfully interconnected among undergraduate students at Dire Dawa University. The results consistently demonstrated positive and significant relationships across multiple analytical levels: bivariate correlations, latent factor correlations, structural path modeling, and mediation analysis.

Key findings indicate that perceptions of computational thinking abilities strongly predict higher creative interest ($\beta = 0.432$, medium effect) and academic self-efficacy (total effect $\beta = 0.356$, medium effect). Creative interest partially mediates the relationship between CT and ASE, transmitting approximately 18.8% of the total effect through a small but reliable indirect pathway ($\beta = 0.067$, 95% CI [0.033, 0.101]). The substantial remaining direct effect ($\beta = 0.289$) suggests that CT perceptions enhance academic confidence through mechanisms beyond creative motivation alone, possibly via perceived competence, problem-solving mastery, or cognitive resourcefulness.

Confirmatory factor analysis supported the distinctiveness of the three constructs, with acceptable model fit, strong convergent validity (AVE > 0.76), and clear discriminant validity per the Fornell–Larcker criterion. Despite modest overall scale reliability for CI and ASE composites, their subscales exhibited excellent internal consistency, justifying the use of latent variable modeling. Normality diagnostics, bootstrap resampling, and visual inspections (histograms, Q-Q plots, scatterplots) affirmed the robustness of the parametric and mediation inferences.

Collectively, these results underscore that fostering computational thinking not only directly bolsters students' academic self-efficacy but also indirectly does so by nurturing creative identity and motivational engagement. In the Ethiopian higher education context, where computational thinking integration remains emerging, these findings highlight CT as a foundational cognitive-motivational asset that supports broader academic resilience and confidence.

Recommendations

Universities should integrate computational thinking training across disciplines, emphasizing both skill development and its linkage to creative and efficacy beliefs.

Curriculum designers are encouraged to incorporate project-based activities that explicitly connect algorithmic problem-solving to creative expression and self-regulated learning.

Faculty development programs should raise awareness of these motivational pathways. Longitudinal studies are recommended to track changes over time and evaluate intervention impacts.

Policymakers in Ethiopian higher education should prioritize CT inclusion in national competency frameworks and provide resources for scalable implementation.

Finally, future research should test multiple mediators, include objective CT measures, and examine boundary condition (e.g., gender, discipline, prior exposure) to refine targeted interventions.

References

Bandura, A. (1997). Self-efficacy: The exercise of control. W. H. Freeman and Company. https://doi.org/10.1891/0889-8391.13.2.158

Bocconi, S., Chioccariello, A., Dettori, G., Ferrari, A., Engelhardt, K., Kampylis, P., & Punie, Y. (2016). Developing computational thinking: Approaches and orientations in K-12 education. In *Proceedings of EdMedia 2016--World Conference on Educational Media and Technology* (pp. 13-18). Association for the Advancement of Computing in Education (AACE). https://www.learntechlib.org/p/172925/

Byrne, B. M. (2016). Structural equation modeling with AMOS: Basic concepts, applications, and programming (3rd ed.). Routledge. https://doi.org/10.4324/9781315757421

Carlone, H. B., & Johnson, A. (2007). Understanding the science experiences of successful women of color: Science identity as an analytic lens. Journal of Research in Science Teaching, *44*(8), 1187–1218. https://doi.org/10.1002/tea.20237

Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE Publications.

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. Psychological Inquiry, 11(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01

Doleck, T., Bazelais, P., Lemay, D. J., Saxena, A., & Basnet, R. B. (2017). Algorithmic thinking, cooperativity, creativity, critical thinking, and problem solving: Exploring the relationship between computational thinking skills and academic performance. Journal of Computers in Education, 4(4), 355–369. https://doi.org/10.1007/s40692-017-0090-9

Dunning, D. (2011). The Dunning–Kruger effect: On being ignorant of one's own ignorance. Advances in Experimental Social Psychology, 44, 247–296. https://doi.org/10.1016/B978-0-12-385522-0.00005-6

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. American Journal of Theoretical and Applied Statistics, *5*(1), 1–4. https://doi.org/10.11648/j.ajtas.20160501.11

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. Behavior Research Methods, *41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Field, A. (2018). Discovering statistics using IBM SPSS statistics (5th ed.). SAGE Publications. (No DOI for core textbook edition; see https://doi.org/10.1177/0095798418796892 for related methodological validation).

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104

Fritz, M. S., & MacKinnon, D. P. (2007). Required sample size to detect the mediated effect. Psychological Science, *18*(3), 233–239. https://doi.org/10.1111/j.1467-9280.2007.01882.x

Gee, J. P. (2000). Identity as an analytic lens for research in education. Review of Research in Education, 25(1), 99–125. https://doi.org/10.3102/0091732X025001099

Geske, A., Kiseļova, R., & Pole, O. (2025). Achieving excellence in computational thinking: Insights from the ICILS 2023 study. Environment. Technology. Resources. Proceedings of the 16th International Scientific and Practical Conference, 3, 135–143. https://doi.org/10.17770/etr2025vol3.8546

Goshu, B.S., (2025), Transforming Science Education in Ethiopian Higher Education: Harnessing Artificial Intelligence for Innovation and Equity, Turkish Journal of Teacher Education, 14(2), 102, 120

Goshu, B.S., M.M. Weldeamueal, Muhammad Ridwan, (2025), Barriers to Excellence: Unveiling the Challenges in Modern Science Education a Case of Ethiopia's Education System, Budapest International Research and Critics Institute-Journal (BIRCI-Journal), 8(1), 26-44.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage Learning.

Hayes, A. F. (2018). Introduction to mediation, moderation, and conditional process analysis: A regression based approach (2nd ed.). Guilford Press.

Hayes, A. F. (2022). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach (3rd ed.). Guilford Press.

Hu, L.-T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Jinks, J., & Morgan, V. (1999). Children's perceived academic self-efficacy: An inventory scale. The Clearing House, *72*(4), 224–230. https://doi.org/10.1080/00098659909599398

Kim, H.-Y. (2013). Statistical notes for clinical researchers: Assessing normal distribution (2) using skewness and kurtosis. Restorative Dentistry & Endodontics, 38(1), 52–54. https://doi.org/10.5395/rde.2013.38.1.52

Kline, R. B. (2023). Principles and practice of structural equation modeling (5th ed.). Guilford Press.

Korkmaz, Ö., Çakir, R., & Özden, M. Y. (2017). A validity and reliability study of the computational thinking scales (CTS). Computers in Human Behavior, *72*, 558–569. https://doi.org/10.1016/j.chb.2017.01.005

Kuo, Y.-T. (2025). Learning programming: Exploring the relationships of self-efficacy, computational thinking, and learning performance among minority students. Frontiers in Education, 10, Article 1623415. https://doi.org/10.3389/feduc.2025.1623415

Lei, H., Chiu, M. M., Li, F., Wang, X., & Geng, Y. (2020). Computational thinking and academic achievement: A meta-analysis among students. Children and Youth Services Review, *118*, Article 105439. https://doi.org/10.1016/j.childyouth.2020.105439
Liao, C. H. (2022). Exploring the relationship between computational thinking and learning satisfaction for non-STEM college students. International Journal of Educational Technology in Higher Education, 19, Article 46. https://doi.org/10.1186/s41239-022-00347-5
Mahadeo, J., Hazari, Z., & Potvin, G. (2020). Developing a computing identity framework: Understanding computer science and information technology career choice. ACM Transactions on Computing Education, *20*(1), Article 7. https://doi.org/10.1145/3365571
Multon, K. D., Brown, S. D., & Lent, R. W. (1991). Relation of self-efficacy beliefs to academic outcomes: A meta-analytic investigation. Journal of Counseling Psychology, *38*(1), 30–38. https://doi.org/10.1037/0022-0167.38.1.30
Nannim, F. A., Mosia, M., Ezema, M. E., & Egara, F. (2026). Exploring the relationship between computational thinking dimensions and achievement in robotics programming among computer education students. Journal of Technology and Science Education, *16*(1), 95–108. https://doi.org/10.3926/jotse.3402
Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3rd ed.). McGraw-Hill.
Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879–891. https://doi.org/10.3758/BRM.40.3.879
Ramlan, R. Goshu, B.S., (2025), Science Citizens: Bridging Knowledge and Action for All, Budapest International Research and Critics in Linguistics and Education, 8(4), 274-302
Sellami, A., & Elkhoudary, E. A. (2024). Enriching computing identity frameworks: Integrating current constructs and unveiling new dimensions for today's tech-savvy world—a systematic review. Frontiers in Education, *9*, Article 1366906. https://doi.org/10.3389/feduc.2024.1366906
Shute, V. J., Sun, C., & Asbell-Clarke, J. (2017). Demystifying computational thinking. Educational Research Review, *22*, 142–158. https://doi.org/10.1016/j.edurev.2017.09.003
Stormes, K. N. (2024). Compiling a computing identity: A byte of self-efficacy, belonging, and other predictive factors (Publication No. 979-8-3828-2052-1) [Doctoral dissertation, University of California, Los Angeles]. ProQuest Dissertations & Theses Global.
Tabachnick, B. G., & Fidell, L. S. (2019). Using multivariate statistics (7th ed.). Pearson.
Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. Research in Science Education, 48(6), 1273–1296. https://doi.org/10.1007/s11165-016-9602-2
Tissenbaum, M., Sheldon, J., & Abelson, H. (2019). From computational thinking to computational action. Communications of the ACM, *62*(3), 34–36. https://doi.org/10.1145/3265747
Vuong, M., Brown-Welty, S., & Tracz, S. (2010). The effects of self-efficacy on academic success of first-generation college sophomore students. Journal of College Student Development, *51*(1), 50–64. https://doi.org/10.1353/csd.0.0109
Weintrop, D., Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., & Wilensky, U. (2016). Defining computational thinking for mathematics and science classrooms.

Journal of Science Education and Technology, 25(1), 127–147. https://doi.org/10.1007/s10956-015-9581-5

Wing, J. M. (2006). Computational thinking. Communications of the ACM, *49*(3), 33–35. https://doi.org/10.1145/1118178.1118215

Wu, T.-T., Silitonga, L. M., Dharmawan, B., & Murti, A. T. (2024). Empowering students to thrive: The role of CT and self-efficacy in building academic resilience. Journal of Educational Computing Research, *62*(3), 816–845. https://doi.org/10.1177/07356331241234567

Zapata-Casabon, C. (2025). Predictors of success and retention: The influence of belonging and self-efficacy on first-year engineering students. In 2025 ASEE Annual Conference & Exposition. American Society for Engineering Education. https://nemo.asee.org/public/conferences/365/author_index/136198