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Creativity and Critical Thinking as Mediators of Computational Thinking among Business Education Students

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ABSTRACT

Computational thinking is no longer confined to computer science departments, yet we still know little about how the broader set of twenty-first-century skills feeds into its growth among business students. Here we test whether collaboration and communication shape computational thinking directly, and whether creativity and critical thinking carry part of that influence. A cross-sectional survey of 215 business education students at an Indonesian public university provided the data, with 21 reflective indicators capturing five constructs. The proposed model was estimated with partial least squares structural equation modelling and 5,000 bootstrap subsamples, and the measurement model held up well on reliability and validity checks. Both collaboration and communication predicted computational thinking directly; collaboration was a particularly strong driver of creativity, while communication mainly shaped critical thinking, and each of these in turn predicted computational thinking. The indirect paths running through creativity and critical thinking were both significant, pointing to complementary partial mediation, and together the model accounted for 62.4% of the variance in computational thinking. In practice, collaborative and communicative learning seems to matter most when it is deliberately channelled into creative output and critical scrutiny. Business curricula would therefore do well to build in team-based problem solving, structured reflection, and algorithmic solution design, rather than teaching the 4Cs and computational thinking as unrelated outcomes.

Keywords: Collaboration, Communication, Computational thinking, Creativity, Critical thinking, PLS-SEM

1. INTRODUCTION

Graduates today are expected to handle complex, technology-saturated work where a single discipline rarely supplies the whole answer. The 4Cs (creativity, critical thinking, communication, and collaboration) are the competencies most often cited as underpinning innovation, adaptive decision making, and participation in digitally intensive settings (Ho & Le, 2026; Rapti et al., 2026; Tian & Zheng, 2025; van Laar et al., 2017, 2019). Business education students have a particular stake in this: day-to-day business practice already blends human interaction, data interpretation, process design, and technology-enabled problem solving. So curricula need to go beyond teaching students to operate digital tools. They also need to build the reasoning that lets students frame problems and work through them systematically.

Computational thinking (CT) offers a useful lens here. Wing (2006) described it as a way of solving problems, designing systems, and understanding behaviour, one that draws on core ideas from computer science: decomposition, abstraction, pattern recognition, algorithmic design, and systematic evaluation. CT started out as a computing concept. It is now widely treated as a transferable problem-solving skill that crosses disciplinary lines. For business students, this can mean breaking a customer problem into manageable parts, modelling an operational process,

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making sense of data, or building a decision procedure that can be repeated reliably. None of this reduces CT to programming ability.

How the 4Cs connect to CT makes theoretical sense, but the mechanics are not simple. Collaboration lets learners pool information, divide roles, weigh alternatives, and coordinate shared work, while communication gives them a way to state a problem, spell out assumptions, push back on reasoning, and explain a solution to others. Both can feed CT directly, since decomposing a problem and designing an algorithm usually depend on distributed knowledge being made explicit. There is also evidence tying collaborative learning to creative problem solving, and communication to reflection and critical evaluation (Ceballos et al., 2026; Laisema & Wannapiroon, 2014; Lin et al., 2026; Slof et al., 2016; Snyder et al., 2025; Tang et al., 2020; Yu et al., 2024). Communication allows them to articulate a problem, explain assumptions, challenge reasoning, and make a solution understandable to others. These social activities can directly facilitate CT because decomposition and algorithm design often require distributed knowledge and explicit representation. Collaborative learning has also been associated with creative problem solving, whereas communication supports reflection and critical evaluation.

Creativity is one plausible route from collaboration to CT. Generating alternatives, recombining existing ideas, and arriving at solutions that are both novel and useful are all creative acts, and collaboration widens the pool of perspectives a group can draw on and recombine. CT tasks, in turn, ask learners to reframe a problem, spot patterns, and design a workable procedure, all tasks that draw on creative exploration. Prior work has already found close ties between creative problem solving and computational activity (Çoban & Korkmaz, 2021; Israel-Fishelson & Hershkovitz, 2024; Korkmaz et al., 2017; Saad & Zainudin, 2022; J. Wang et al., 2025). That is why we expect collaboration to shape CT both directly and indirectly, through creativity.

Critical thinking is a second candidate mechanism. It involves purposeful analysis, evaluation, inference, and judgement. Communication gives learners room to clarify a claim, ask for evidence, weigh competing views, and revise a conclusion, and these habits sharpen critical thinking in exactly the ways CT needs: judging whether a decomposition makes sense, whether an algorithm holds together logically, and whether a solution actually does what it is meant to. Critical thinking, then, works as an evaluative backbone for CT, and communication supplies the dialogue through which that evaluation happens (de Bruin & van Merriënboer, 2017; Liu et al., 2026; Tang et al., 2020; F. Wang et al., 2025).

Most prior research has looked at correlations between CT and learner characteristics, tested specific instructional interventions, or lumped the twenty-first-century skills together (Durak & Saritepeci, 2018; Sun et al., 2021). Far less attention has gone to the specific pathways by which social competencies turn into computational problem-solving ability, especially outside computing programmes. Modelling the 4Cs as parallel, undifferentiated predictors risks hiding creativity's generative role and critical thinking's evaluative one. Business education students are also underrepresented in this literature, even though their work increasingly demands digital processes and data-driven decisions.

We build on this gap by testing a mediated model in which collaboration predicts CT both directly and indirectly through creativity, and communication predicts CT both directly and indirectly through critical thinking. Six direct hypotheses follow: collaboration positively affects CT (H1); collaboration positively affects creativity (H2); communication positively affects CT (H3); communication positively affects critical thinking (H4); creativity positively affects CT (H5); critical thinking positively affects CT (H6). Two mediation hypotheses come with them: creativity mediates the effect of collaboration on CT (H7), and critical thinking mediates the effect of communication on CT (H8). Separating these generative and evaluative mechanisms gives a sharper account of how the 4Cs actually work within CT development in business education.

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2. METHOD

We used a quantitative, cross-sectional explanatory design. Participants were 215 students in a business education programme at Universitas Negeri Malang, Indonesia, recruited through stratified sampling to better represent different student subgroups. Participation was voluntary, respondents knew the academic purpose of the study, and their responses were analysed in aggregate with no identifying information retained in the dataset.

We collected data with a structured questionnaire made up of 21 reflective indicators: four each for collaboration, communication, creativity, and critical thinking, and five for CT. Constructs and indicators were adapted from established work on twenty-first-century and computational thinking competencies (Korkmaz et al., 2017; van Laar et al., 2017), and items asked students to rate their typical learning-related behaviours and capabilities. Before administration, the instrument went through a content-relevance review,

We analysed the hypothesised model with partial least squares structural equation modelling (PLS-SEM) in SmartPLS 3, which suits this study because it predicts CT while simultaneously estimating several direct and indirect relationships among latent variables (Hair et al., 2019). The analysis ran in two stages. The first evaluated the reflective measurement model through indicator loadings, Cronbach's alpha, rho_A, composite reliability, average variance extracted (AVE), the Fornell–Larcker criterion, cross-loadings, the heterotrait–monotrait ratio (HTMT), and variance inflation factors (VIF). The second assessed the structural model using path coefficients, bootstrap t statistics and p values, confidence intervals, coefficient of determination (R^2), effect size (f^2), and model fit indices.

Significance was evaluated with 5,000 bootstrap subsamples and two-tailed tests at the 5% level; an effect counted as significant when $p < .05$ and its 95% bootstrap confidence interval excluded zero. We classified mediation by weighing the significance and direction of both the direct and indirect effects together.

3. RESULTS AND DISCUSSION

3.1. Measurement Model

All indicator loadings cleared .70, ranging from .725 to .926, which points to adequate indicator reliability. As Table 1 shows, Cronbach's alpha and rho_A stayed above .80 for every construct, composite reliability ranged from .890 to .942, and AVE values ran from .624 to .803, comfortably above the recommended .50 cut-off. Together these results back up internal consistency and convergent validity.

Table 1. Construct reliability and convergent validity

Construct	Cronbach's α	rho_A	CR	AVE
Collaboration	.881	.884	.918	.737
Communication	.918	.921	.942	.803
Computational thinking	.849	.850	.892	.624
Creativity	.862	.864	.906	.708
Critical thinking	.835	.849	.890	.671

Every reliability coefficient in Table 1 cleared .70 and every AVE cleared .50. Communication came out highest on both composite reliability and AVE, CT lowest on AVE, but all five constructs still met the accepted thresholds, so we moved on to discriminant validity.

Discriminant validity held up as well. Under the Fornell–Larcker criterion, each construct's AVE square root exceeded its correlations with the other constructs, and HTMT values stayed within .539 to .841, below the .85 ceiling. Every indicator loaded most strongly on its intended construct,

and VIF values (1.505–3.859 outer, 1.000–2.257 inner) suggest collinearity was not distorting the estimates.
Table 2 breaks this down further, reporting the loading and bootstrap significance of every item retained in the measurement model.

Table 2. Indicator reliability and bootstrap significance

Indicator	Construct	Loading	t	p
KM1	Collaboration	.849	41.441	<.001
KM2	Collaboration	.887	42.771	<.001
KM3	Collaboration	.851	32.634	<.001
KM4	Collaboration	.846	34.126	<.001
KO1	Communication	.878	37.505	<.001
KO2	Communication	.899	49.773	<.001
KO3	Communication	.881	35.239	<.001
KO4	Communication	.926	66.609	<.001
KR1	Creativity	.846	39.373	<.001
KR2	Creativity	.864	42.181	<.001
KR3	Creativity	.857	36.148	<.001
KR4	Creativity	.797	24.129	<.001
BK1	Critical thinking	.725	16.366	<.001
BK2	Critical thinking	.797	25.867	<.001
BK3	Critical thinking	.885	55.495	<.001
BK4	Critical thinking	.861	44.242	<.001
CT1	Computational thinking	.789	23.666	<.001
CT2	Computational thinking	.785	27.494	<.001
CT3	Computational thinking	.759	22.053	<.001
CT4	Computational thinking	.857	45.869	<.001
CT5	Computational thinking	.757	22.791	<.001

All 21 indicators loaded strongly and significantly on their intended constructs, with the lowest loading at .725 and every bootstrap t value clearing the critical value, so none needed to be dropped. With indicator reliability established, we turned to discriminant validity at the construct level.
Table 3 presents the Fornell–Larcker matrix, in which the diagonal values represent the square roots of AVE and the off-diagonal values represent correlations among constructs.

Table 3. Fornell–Larcker criterion

Construct	1	2	3	4	5
1. Collaboration	.858				
2. Communication	.519	.896			
3. Computational thinking	.623	.603	.790		
4. Creativity	.703	.482	.622	.841	
5. Critical thinking	.583	.514	.711	.606	.819

Note: Diagonal values are the square roots of AVE; off-diagonal values are latent-variable correlations.

In every row and column, the diagonal value beat all its correlations, which supports discriminant validity under the Fornell–Larcker criterion. Since this criterion can miss some validity problems, we also ran the more sensitive HTMT check.
Table 4 reports the HTMT ratios for all pairs of constructs.

Table 4. Heterotrait–monotrait ratios (HTMT)

Construct pair	HTMT	Construct pair	HTMT
Communication–Collaboration	.576	Creativity–Collaboration	.800

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Construct pair	HTMT	Construct pair	HTMT
CT–Collaboration	.719	Creativity–Communication	.539
CT–Communication	.681	Creativity–CT	.724
Critical thinking–Collaboration	.674	Critical thinking–Communication	.580
Critical thinking–CT	.841	Critical thinking–Creativity	.711

Every HTMT ratio stayed below .85, from a high of .841 (critical thinking–CT) to a low of .539 (creativity–communication). The five constructs, in other words, remained empirically distinct even though they are theoretically related.

Before moving to the structural relationships, we checked collinearity at both the indicator and predictor levels; Table 5 summarises the VIF ranges.

Table 5. Collinearity statistics

Assessment	Minimum VIF	Maximum VIF	Interpretation
Outer-model indicators	1.505	3.859	No critical indicator collinearity
Inner-model predictors	1.000	2.257	No critical structural collinearity

The maximum outer VIF (3.859) and inner VIF (2.257) suggest neither indicator redundancy nor predictor collinearity was severe enough to bias the estimates, which cleared the way to evaluate the full structural model.

Figure 1 shows the complete bootstrapped model, with t statistics on the structural paths and indicator arrows confirming that every hypothesised relationship and every outer loading was significant.

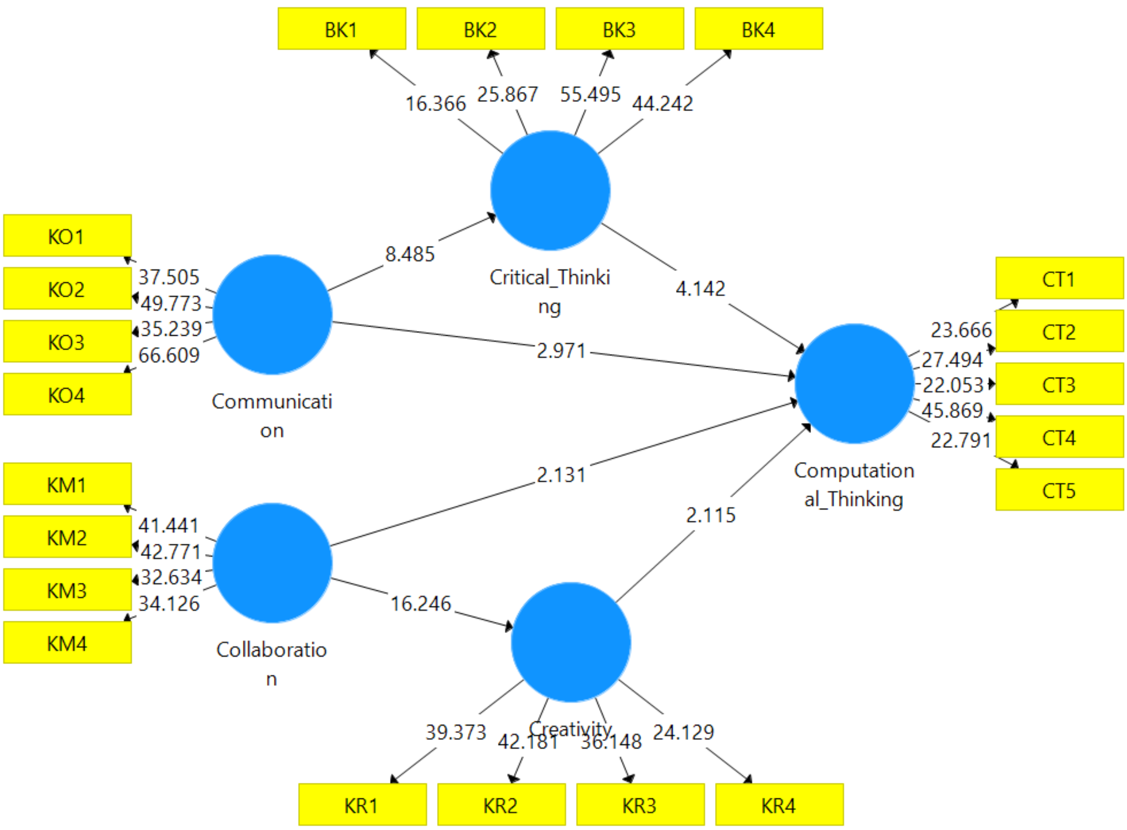

Figure 1. Bootstrapped PLS-SEM model

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The figure lays out the two proposed mechanisms side by side: collaboration reaches CT directly and through creativity, communication reaches CT directly and through critical thinking. All the t statistics shown exceed 1.96, an early visual sign that the hypothesised relationships and indicators would hold up statistically.

3.2. Structural Model and Hypothesis Testing

The structural model accounted for 62.4% of the variance in CT (adjusted R^2 = .617), 49.4% in creativity (adjusted R^2 = .492), and 26.4% in critical thinking (adjusted R^2 = .260). The saturated-model SRMR came in at .061, but the estimated-model SRMR was higher at .125, which calls for some caution about absolute fit. Even so, the predictive performance, reliability, validity, and bootstrapped structural effects together give enough grounds to evaluate the proposed relationships.

Table 6 brings the explained-variance statistics and the available global fit indices together, so predictive performance and approximate fit can be weighed side by side.

Table 6. Explained variance and model fit

Criterion	Saturated model	Estimated model	Interpretation
R^2: Computational thinking	—	.624 (adj. .617)	Moderate explanatory power
R^2: Creativity	—	.494 (adj. .492)	Moderate explanatory power
R^2: Critical thinking	—	.264 (adj. .260)	Weak-to-moderate explanatory power
SRMR	.061	.125	Saturated acceptable; estimated elevated
d_ULS	.867	3.605	Reported descriptively
d_G	.410	.486	Reported descriptively
Chi-square	518.779	568.151	Reported descriptively
NFI	.834	.819	Below conventional .90 guideline

Table 6 shows the model explains CT best, followed by creativity and then critical thinking. The saturated SRMR meets the conventional guideline, though the estimated SRMR and NFI suggest absolute fit needs a cautious read. We therefore based hypothesis decisions mainly on the bootstrapped coefficients and confidence intervals reported next.

Table 7 lists the six direct structural effects along with their bootstrap statistics, confidence intervals, and hypothesis decisions.

Table 7. Direct effects and hypothesis decisions

Hypothesised relationship	β	t	p	95% CI	Decision
H1 Collaboration → CT	.155	2.131	.033	[.007, .294]	Supported
H2 Collaboration → Creativity	.703	16.246	<.001	[.616, .784]	Supported
H3 Communication → CT	.241	2.971	.003	[.081, .400]	Supported
H4 Communication → Critical thinking	.514	8.485	<.001	[.393, .629]	Supported
H5 Creativity → CT	.152	2.115	.034	[.013, .295]	Supported
H6 Critical thinking → CT	.404	4.142	<.001	[.216, .594]	Supported

All six direct effects in Table 7 were positive and significant. Collaboration predicted CT (β = .155, p = .033) and, more strongly, creativity (β = .703, p < .001); communication predicted CT (β = .241, p = .003) and critical thinking (β = .514, p < .001); and both creativity (β = .152, p = .034) and

critical thinking (β = .404, p < .001) fed forward into CT. Of all these paths, critical thinking was the strongest direct predictor of CT.
Effect sizes add some texture here. Collaboration's effect on creativity was large (f^2 = .978), and communication's effect on critical thinking moderate-to-large (f^2 = .358). Critical thinking's effect on CT was moderate (f^2 = .237), while communication's direct effect on CT was small (f^2 = .102), as were the direct effects of collaboration (f^2 = .028) and creativity (f^2 = .027) on CT. Collaboration, then, looks especially important for setting up creative activity, while critical thinking sits closer to actually executing and evaluating a computational solution.
Table 8 classifies the f^2 value of every structural relationship, making the practical contribution of each path easier to compare.

Table 8. Effect sizes for endogenous constructs

Predictor → Outcome	f^2	Magnitude
Collaboration → CT	.028	Small
Collaboration → Creativity	.978	Large
Communication → CT	.102	Small
Communication → Critical thinking	.358	Large
Creativity → CT	.027	Small
Critical thinking → CT	.237	Medium

Collaboration's contribution to creativity was the strongest of all, followed by communication's contribution to critical thinking. The effects on CT itself were more spread out. Critical thinking made a medium contribution, while collaboration, communication, and creativity each made only a small one. That spread is reason enough to check whether some of the social skills' influence was actually being carried through the proposed mediators.

3.3. Mediation Analysis

We tested the mediation hypotheses using specific indirect effects and percentile bootstrap confidence intervals; Table 9 reports the two indirect pathways specified by theory.

Table 9. Specific indirect effects

Mediated relationship	β	t	p	95% CI	Decision
H7 Collaboration → Creativity → CT	.107	2.080	.038	[.009, .210]	Supported
H8 Communication → Critical thinking → CT	.208	3.598	<.001	[.104, .329]	Supported

Collaboration's indirect effect on CT through creativity was significant (β = .107, p = .038, 95% CI [.009, .210]), and so was communication's indirect effect through critical thinking (β = .208, p < .001, 95% CI [.104, .329]). Since the direct effects stayed significant alongside these indirect ones, and everything pointed in the same positive direction, both count as complementary partial mediation. Collaboration's total effect on CT came to .262, communication's to .449.
Table 10 pulls the direct and mediated components together, comparing the direct, indirect, and total effects on CT along with the bootstrap evidence behind each total effect.

Table 10. Direct, indirect, and total effects on computational thinking

Antecedent	Direct	Indirect	Total	t (total)	p (total)	95% CI total	Mediation
Collaboration	.155	.107	.262	3.322	.001	[.103, .410]	Complementary partial
Communication	.241	.208	.449	6.889	<.001	[.324, .584]	Complementary partial
Creativity	.152	—	.152	2.115	.034	[.013, .295]	Not applicable
Critical thinking	.404	—	.404	4.142	<.001	[.216, .594]	Not applicable

Communication's total effect on CT (.449) was the largest, ahead of critical thinking (.404), collaboration (.262), and creativity (.152). Because collaboration's and communication's direct and indirect components were both significant and pointed the same way, both qualify as complementary partial mediation. These results form the empirical basis for the discussion that follows.

3.4. Discussion

Taken together, these findings suggest social interaction and individual reasoning are not rival explanations for CT so much as connected layers of it. Both collaboration and communication had significant direct effects on CT, which fits the idea that computational problem solving improves when students coordinate what they know and make their reasoning explicit. That squares with a view of CT as a situated practice built on shared problem formulation, negotiation, and explanation, rather than a purely individual technical skill. It also echoes earlier work linking collaboration to problem solving in technology-rich learning environments (Shin et al., 2025; Slof et al., 2016; Snyder et al., 2025; Sun et al., 2021).

The strongest path in the whole model ran from collaboration to creativity, which suggests peer interaction substantially widens the space students have for generating and combining ideas. It exposes them to alternative representations, spreads the cognitive load, and gives quick feedback on emerging possibilities. Yet creativity's own direct effect on CT was comparatively small, which points to creative ideation being necessary but not sufficient on its own: ideas still have to be turned into decomposed, abstracted, algorithmic form. Recent work similarly treats creativity and CT as closely interdependent capabilities (Israel-Fishelson & Hershkovitz, 2024; J. Wang et al., 2025). That may be why structured project- and problem-based learning can be more effective than unstructured group activity (Saad & Zainudin, 2022).

Communication was a strong predictor of critical thinking, and critical thinking in turn was the most influential direct predictor of CT in the model. That tracks with what a computational solution actually demands: not just an answer, but checked assumptions, tested logic, caught errors, and a judgement about whether the solution generalises. Dialogue is what makes this reasoning visible and open to challenge. Explaining a procedure, fielding questions, or defending a choice all push students to monitor and revise their own thinking. The findings back up the theoretical claim that critical evaluation sits at the centre of abstraction, algorithm design, and debugging (Lin et al., 2026; Liu et al., 2026; F. Wang et al., 2025).

The mediation results are, we think, this study's main contribution. Collaboration shaped CT partly by way of creativity, and communication shaped it partly by way of critical thinking. The communication-to-critical-thinking path, though, was nearly twice the size of the collaboration-to-creativity one. That split points to two complementary mechanisms at work: a generative one that widens the pool of possible solutions, and an evaluative one that selects, refines, and validates them. Lump the 4Cs together as a single bundle and these different functions disappear from view.

For business education, this points toward embedding CT in real business problems rather than isolating it in stand-alone technology exercises. Teams could decompose a customer, marketing, logistics, or entrepreneurial problem, generate alternative process or data solutions, turn the chosen one into an ordered procedure, and test it against explicit criteria. Instructors can support this by assigning interdependent roles, using structured questioning, asking students to explain their algorithms in plain language, and building in reflection on errors and revisions. Assessment, in turn, should capture not just the quality of the final solution but the collaborative, creative, communicative, and critical work that produced it (Ho & Le, 2026; Rapti et al., 2026; Safahi et al., 2026).

There are implications for the instrument itself, too. The 21 indicators held up well on reliability and on convergent and discriminant validity in this sample, which supports using them to study these five constructs in a business education setting. That validation, though, is contextual rather

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than universal. Later work should test measurement invariance across programmes, institutions, gender groups, and levels of prior digital experience.

A constructionist reading helps explain why collaboration and communication matter as much as they do here: CT develops as learners externalise ideas into artefacts that can be inspected, discussed, and revised (Papert & Harel, 1991). Team members are not just dividing labour; they are turning tacit ideas into shared representations that let the group compare patterns, spot missing steps, and improve a solution over successive rounds. Anderson (2016) made a related point: that CT matters beyond computer science because it gives undergraduates a disciplined language for problem solving. Our evidence extends that claim to business education, showing socially organised learning can serve as an entry point into computational reasoning.

The collaboration–creativity pathway also fits with evidence that authentic, project-oriented tasks build higher-order capabilities: project-based learning pairs open-ended exploration with a concrete outcome (Bakhru & Mehta, 2020; Parrado-Martínez & Sánchez-Andújar, 2020), and fact-checking projects, design jams, and creative problem-solving environments show novelty becomes educationally useful once students have to justify and operationalise their ideas (Ceballos et al., 2026; Pérez-Escolar et al., 2021; Tang et al., 2020). So the small creativity-to-CT effect found here does not mean creativity matters less; it means instructors need to scaffold the step from divergent ideas to decomposition, abstraction, and executable sequences.

The communication–critical thinking pathway reads well through a metacognitive-regulation lens: communication forces students to state what they know, separate evidence from assumption, and answer objections, and critical thinking then helps them weigh alternatives and catch weaknesses before committing to a procedure. Authentic assessment is particularly relevant because it makes reasoning and revision observable rather than rewarding only a final answer (Sokhanvar et al., 2021). Likewise, collaborative learning outcomes depend on interpersonal perceptions and the quality of interaction, not simply on placing students in groups (Slof et al., 2016). Structured dialogue protocols, peer review, and reflective prompts are therefore likely to strengthen the pathway identified in this study (Lin et al., 2026; Liu et al., 2026).

The relative size of these effects has some pedagogical payoff. Collaboration explained close to half the variance in creativity through a very large effect, communication had a substantial effect on critical thinking, and by comparison the direct effects of collaboration and creativity on CT were small. Read together, they suggest a sequence: let collaboration broaden participation and generate alternatives first, let communication drive scrutiny, selection, and refinement next, and let CT practices formalise the chosen solution last. Work on educational robotics and unplugged activities points the same way, showing tangible or embodied tasks can link exploration to systematic reasoning (Diago et al., 2022; Rapti et al., 2026; Sun et al., 2021).

There is a measurement-practice contribution too. The factor loadings, reliability coefficients, AVE values, Fornell–Larcker comparisons, and HTMT ratios all backed the distinction among the five constructs, which matters because creativity and critical thinking are sometimes folded into CT as subdimensions rather than modelled as related but distinct capabilities (Korkmaz et al., 2017). Keeping them separate here is what makes their mediating roles testable in the first place. Future validation work should still pair self-report indicators with performance tasks, behavioural traces, and expert ratings. Performance-based CT platforms and carefully validated digital-competence questionnaires offer useful precedents (Çoban & Korkmaz, 2021; Mengual-Andrés et al., 2016).

A few contextual factors could qualify these findings. Digital experience, attitudes toward technology, gender, and educational level have all been linked to differences in CT (F. Wang et al., 2025), motivation may shape whether students stick with computational tasks and benefit from technology-supported learning (Martín-Núñez et al., 2023), and communication itself is shaped by role clarity, group climate, and access to the right learning media (Hwang & Kim, 2022). The significant paths reported here, then, are average relationships within one sampled programme, not fixed effects guaranteed in every classroom, and they deserve testing across other institutions and learning designs.

The model-fit results, finally, call for a balanced reading. The saturated SRMR of .061 suggests acceptable correspondence once construct correlations are freely estimated, but the estimated SRMR of .125 and the NFI of .819 show the exact structural configuration does not reproduce every observed association optimally. That is a reminder that PLS-SEM assessment should not lean on a single global index, particularly when prediction is the goal (Hair et al., 2019). The substantial R^2 for CT, the significant bootstrap confidence intervals, the sound measurement quality, and the absence of serious collinearity all support the model's explanatory value, even as the elevated estimated SRMR makes a case for testing plausible alternatives in future work, including reciprocal relationships, extra paths among the 4Cs, and higher-order specifications.

4. CONCLUSIONS AND SUGGESTION

Collaboration and communication, this study shows, feed into computational thinking both directly and through separate psychological mechanisms: collaboration by way of creativity generating alternatives, communication by way of critical thinking evaluating reasoning. Both indirect effects were significant and worked alongside, not instead of, the direct effects, and together the model explained 62.4% of the variance in computational thinking, with a measurement model that held up on reliability and validity. That supports an integrated pedagogical approach where social interaction, creative production, critical evaluation, and computational problem solving are deliberately sequenced within business education tasks. The study is limited by its cross-sectional, self-report design and its focus on one programme, so causal claims are best avoided, and the higher estimated-model SRMR is worth keeping in mind when generalising the structural configuration. Future work should turn to longitudinal or experimental designs, bring in performance-based CT measures, test alternative model specifications, and check measurement invariance across educational contexts. In the meantime, business education instructors might consider building authentic team projects around problem decomposition, idea generation, reasoned dialogue, algorithmic representation, testing, and revision.

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