Linking Design Thinking and Computational Thinking to Mathematical Modelling Self-Efficacy and AI Pedagogical Role Preferences

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Abstract: *This study investigates the relationships between Design Thinking (DT), Computational Thinking (CT), and Mathematical Modelling Self-Efficacy (MMSE) in AI-enhanced education. Furthermore, it explores how students' levels of DT and CT influence their perceptions and preferences for different AI pedagogical roles during brief mathematical modelling attempts. An experimental design with 26 undergraduate participants was employed, where students completed initial problem-formulation tasks assisted by AI agents acting as Tutor, Teaching Assistant (TA), Peer, Struggling Student, and Excellent Student. Results indicate that both DT and CT are significant positive predictors of MMSE. Regarding AI roles, students with higher DT scores preferred the TA role significantly more than those with lower scores, whereas CT levels did not significantly bias preferences. The findings suggest that high-DT learners value the structured yet flexible guidance of a TA-style AI. This study provides preliminary insights into students' perceived preferences for AI personas and highlights the need for personalized AI agents, while acknowledging the need for future research on long-term performance outcomes.*

Keywords: Mathematical Modelling, Design Thinking, Computational Thinking, Artificial Intelligence in Education, Human-AI Collaboration

1. Introduction and Background

Mathematical Modelling (MM) education serves as a critical bridge between abstract mathematical concepts and real-world phenomena (Blomhoj, 2009). However, it imposes high cognitive demands, requiring students to engage in non-linear, iterative processes. To navigate these hurdles, integrating Design Thinking (DT) with Computational Thinking (CT) offers a promising cognitive framework. Specifically, DT emphasizes empathy, iterative prototyping, and navigating ambiguity (Brown, 2008), whereas CT focuses on abstraction and algorithmic logic (Wing, 2006). Both DT and CT have been identified as supportive of higher-order problem-solving in STEM (Maslihah et al., 2020), yet their specific impact on Mathematical Modelling Self-Efficacy (MMSE) remains under-explored.

Simultaneously, the rapid development of Generative AI offers new opportunities for personalized MM scaffolding. However, learners have diverse cognitive profiles. An AI role that acts as a directive "Tutor" might benefit one student but constrain the creativity of another. Existing literature lacks empirical evidence on how baseline competencies (DT and CT) influence students' preferences for different AI pedagogical personas.

To address this, we focus on two research questions:

RQ1: How do Design Thinking and Computational Thinking relate to students' Mathematical Modelling Self-efficacy?

RQ2: How do preferences for different Al roles differ among students with different levels of Design Thinking and Computational Thinking?

2. Methods

We employed a counterbalanced experimental design involving 26 non-STEM undergraduate students ($M_{age} = 22.0$ years) recruited via social media. Participants completed baseline assessments using validated scales: the 17-item MMSE Scale (Koyuncu et al., 2016), the 29-item CT Scale (Korkmaz et al., 2017), and the 9-item DT scale (Blizzard et al., 2015). Participants were divided into high- and low-scoring groups based on median splits of their CT and DT scores.

The experiment comprised six distinct mathematical modelling tasks. The first served as a non-AI baseline (a canteen queue problem), while the subsequent five featured AI assistance. These tasks required students to translate real-world scenarios into mathematical structures. For instance, in the "Beverage Can Optimization" task, students were asked to mathematically formulate how to minimize packaging material cost while maintaining a required volume. Given the brief four-minute duration per task, the objective was not to produce a complete mathematical calculation. Instead, the tasks were specifically designed to capture students' initial problem-formulation strategies and their intuitive, gut-reaction preferences for different AI interaction styles during the early conceptualization phase.

The AI agents were powered by GPT models, with behaviors dictated by strictly defined system prompts (100–150 words each) to ensure distinct pedagogical personas. The Tutor was instructed to act authoritatively and systematically: "Explain core concepts and problem-solving approaches in detail. Provide the final answer after ensuring student understanding." Conversely, the Teaching Assistant (TA) was strictly forbidden from providing direct solutions: "Never directly give the final answer. Use open-ended questions, hints, and guidance to help students think through problems." The remaining three roles included a Peer Student (programmed for equal, collaborative exploration using phrases like "let's try"), a Struggling Student (instructed to make logical errors and express uncertainty), and an Excellent Student (instructed to provide direct, correct answers without explaining the process).

After interacting with each AI role, participants ranked their preferences from 1 (most preferred) to 5 (least preferred). To address RQ1, Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to evaluate the relationships among MMSE, CT, and DT. For RQ2, Mann-Whitney U tests were conducted to assess differences in role preferences. Since the study aimed to compare the ordinal ranking preferences between two independent samples (the high-scoring and low-scoring groups), this non-parametric test served as the most appropriate statistical approach.

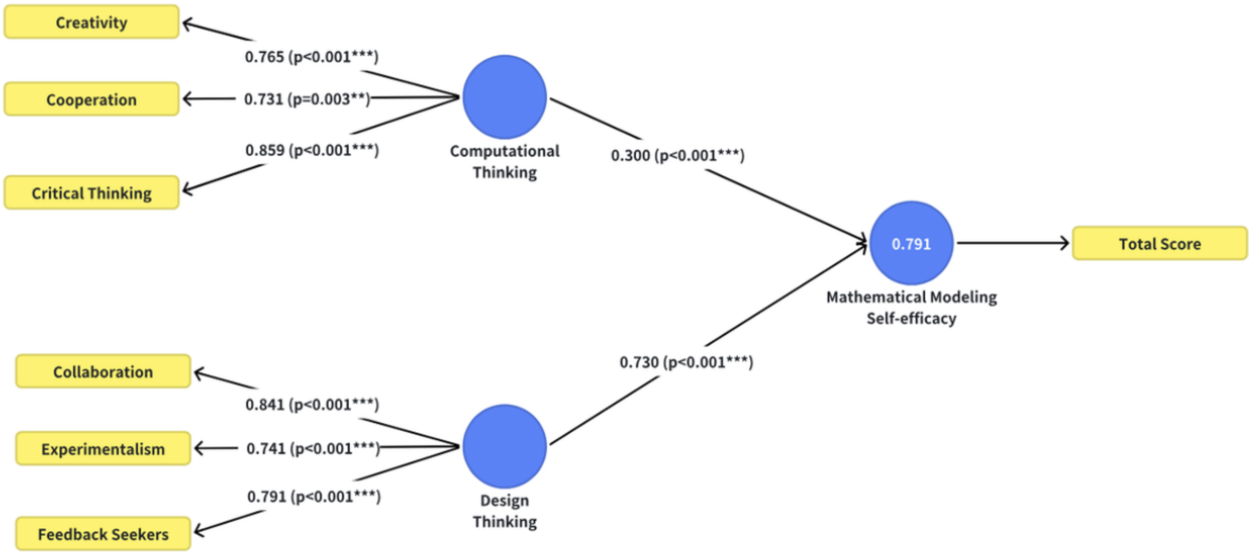
3. Results

3.1. Mathematical Modelling Self-efficacy, Computational Thinking and Design Thinking

The measurement model demonstrated satisfactory reliability and validity (outer loadings > 0.70; CR > 0.60; AVE > 0.50). The PLS-SEM revealed that both DT ($\beta = 0.730$, $p < .001$) and CT ($\beta = 0.300$, $p < .001$) were significant positive predictors of MMSE. The model explained a substantial proportion of variance in MMSE ($R^2 = 0.808$). Effect sizes (f^2) indicated that DT had a very large effect (2.288), while CT had a medium-to-large effect (0.387).

Figure 1

Structural equation model illustrating the relationships between CT, DT, and MMSE.



Note: The Standardized path coefficients. *$p < .05$, **$p < .01$, ***$p < .001$.

3.2. Differences in AI Role Preferences Based on Computational and Design Thinking Levels

Participants were divided into high (n=13) and low (n=13) groups based on median splits of their CT and DT scores. Mann-Whitney U tests revealed no significant differences in AI role preferences based on CT levels across all five AI roles (all ps > .288). However, for Design Thinking, a significant difference emerged specifically for the TA role (p = .049). The high-DT group ranked the TA role significantly more favorably (M = 2.38, SD = 1.04) than the low-DT group (M = 3.46, SD = 1.56). No other AI roles showed significant differences between DT groups.

Table 1.

Comparison of AI role evaluations between high-scoring and low-scoring design thinking groups.

AI Role	High Group (n=13)		Low Group (n=13)		*p*
	M	*SD*	*M*	*SD*	
Tutor	2.62	1.12	2.08	0.86	0.188
Excellent	2.62	1.45	2.31	1.18	0.633
Peer	2.62	1.33	3.08	1.04	0.326
TA	2.38	1.04	3.46	1.56	0.049*
Struggling	4.77	0.6	4.08	1.5	0.178

Note: Groups were formed by median split (N = 26) on design thinking questionnaire scores. Rankings ranged from 1 (most preferred) to 5 (least preferred). Mann-Whitney U tests were conducted. * p < .05.

4. Discussion

4.1. The positive associations between DT, CT, and Mathematical Modelling

Our findings confirm that both CT and DT positively predict MMSE. While CT equips students with the logical abstraction needed for mathematical structures, DT's emphasis on experimentalism and feedback-seeking appears to be an even stronger driver of students' confidence in navigating the ambiguous nature of modelling problems. This suggests that cultivating self-efficacy requires scaffolding that encourages active inquiry rather than just algorithmic calculation.

4.2. The Specific Link Between DT and TA Preference

The isolated finding that high-DT students significantly prefer the TA role over other personas provides valuable insight into human-AI interactions. Design thinking heavily relies on divergent thinking and self-directed exploration (Cross, 2023). The TA role, as operationalized in our prompts, offered guiding questions and hints rather than deterministic answers. This aligns with the cognitive style of high-DT learners: it preserves their autonomy and does not restrict their personalized thinking methods, providing a "sounding board" rather than a rigid instructional constraint. Conversely, CT abilities (focused on deterministic problem-solving) did not dictate a strong preference for specific pedagogical personas in these brief tasks.

4.3. Limitations and Future Work

We acknowledge several limitations. First, the 4-minute tasks primarily captured students' gut reactions and initial problem-formulation strategies rather than deep, iterative mathematical modelling. Therefore, the findings reflect perceived preferences rather than proven collaborative learning gains. Second, the sample consisted of a convenience group of non-STEM students, limiting generalizability. Future studies should employ longer, rubric-evaluated modelling tasks to measure actual modelling quality and performance outcomes, and investigate whether these AI role preferences remain stable over extended interventions.

5. Conclusion

This study explored the interplay between students' Design Thinking (DT), Computational Thinking (CT), and Mathematical Modeling Self-efficacy (MMSE) in AI-enhanced environments. Our results confirm that both DT and CT are significant positive predictors of MMSE. Crucially, the study reveals that learner profiles influence preferences for AI partners: students with higher DT abilities demonstrated a distinct preference for the Teaching Assistant (TA) role. This suggests that high-DT learners value the structured yet flexible guidance a TA provides, which supports their iterative problem-solving style without constraining creativity. Conversely, CT levels did not significantly bias role preferences. These findings contribute to the theoretical framework of human-AI collaboration by highlighting the need for personalized AI agents. For educators and designers, this implies that "one-size-fits-all" AI tools may be insufficient; instead, AI roles should be adaptive, scaffolding feedback-seeking behavior to match students' cognitive strengths. Future research should expand on these findings to develop adaptive AI systems that dynamically adjust their pedagogical roles.

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