Journal of Education and Learning Research
Journal homepage: https://jelr.greadc.org/index.php/jelr

E-ISSN
3024-9589

An AI in the Triad: A Conceptual Model for Augmenting Collaborative Idea Construction with Generative AI

Siaw Hai Ng*

Bau Education Office, Sarawak, 94000, Malaysia

ARTICLE INFO

Article history:

Received: 24 Dec 2025
Revised: 02 January 2026
Accepted: 08 January 2026
Published online: 10 Feb 2026

Keywords:

Generative AI,
Collaborative writing,
Peer scaffolding,
Vygotsky,
Human-AI collaboration

* *Corresponding author.*

E-mail: ngsiawhai@gmail.com

Article Doi

Doi: https://doi.org/10.62208/jelr.3.2.p.64-71

A B S T R A C T

The integration of Generative AI (GenAI) into educational settings necessitates a paradigm shift for collaborative learning, as established frameworks remain undertheorized for non-human agents. Extending the empirically grounded Collaborative Idea Construction (CIC) model and its stable peer roles (MKP, PA, DP), this paper proposes the AI- Enhanced CIC (AI-CIC) framework. GenAI is conceptualized as a novel 'Peer Apprentice' rather than a simple tool. This intervention reshapes human social architecture, transforming the Peer Assistant into an 'AI Validator' and elevating the More Knowledgeable Peer to a 'Metacognitive Facilitator.' Consequently, the collaborative workflow is hypothesized to become more linear. The AI-CIC model offers a theory-driven framework with testable propositions regarding emergent socio-technical roles and workflow shifts. It provides a foundation for future empirical research and informs pedagogical strategies for facilitating critical human-AI interaction.

1. Introduction

The rapid integration of Generative Artificial Intelligence (GenAI) into education is not merely a technology update; it is a fundamental disruption to established pedagical models. (Yan et al., 2024). Within the landscape of collaborative writing, where learning has long been understood as a process driven by the nuanced interplay of social negotiation and cognitive effort GenAI tools present both unprecedented opportunities and profound challenges (Cress, 2023). The central problem is that the “black box” of online collaboration, once a challenge of observing human interaction has now become a complex socio-technical system. This system involves a non-human agent whose feedback, while instantaneous, may lack the nuanced “recognitive” capacity of human interaction (Corbin et al., 2025; Kim et al., 2025). As a wave of recent literature suggests, the uncritical adoption of these powerful

tools' risks fostering superficial engagement and encouraging cognitive offloading where the focus dangerously shifts from the learning process to the mere production of a polished output (Hodges, 2024; Lindsay et al., 2024; Skulmowski, 2024).

This new reality creates a significant theoretical gap. While foundational models of collaborative learning provide robust frameworks for understanding human-human interaction (Baker, 2024), they are ill-equipped to account for the introduction of a powerful, non-conscious agent. To address this, a clear baseline of the human system that is being disrupted must first be established. Previous research by the author sought to open this "black box" by developing the Collaborative Idea Construction (CIC) Model, an empirically grounded framework derived from extensive observation of primary school pupils (Author, 2021). The CIC model delineates two core components of effective peer collaboration: a five-phase cyclical workflow and a stable, interdependent social architecture of pupil roles-the More Knowledgeable Peer (MKP), the Peer Assistant (PA), and the Dependent Pupil (DP). This model provides a validated and granular baseline for understanding human-human collaborative dynamics (see Figure 1A for a visual representation).

The primary contribution of this paper is to bridge the theoretical gap between established models of human collaboration and the new reality of human-AI partnership. This is accomplished by proposing a conceptual extension of a previously validated empirical framework. This is not another descriptive overview of AI's potential, of which there are many (Albadarin et al., 2024), but a specific, theory-driven argument about how a known, stable learning system might adapt. A theoretical argument is built that moves beyond a technocentric implementation towards one grounded in the learning sciences (Makransky et al., 2024). The paper theorizes how a GenAI tool alters the established roles of the MKP, PA, and DP; how its presence reshapes the recursive nature of the CIC model's workflow, and the subsequent implications for pedagogical scaffolding. In doing so, this paper offers a theoretically sound model, the AI-enhanced CIC (AI-CIC) Model, to guide future empirical research and inform pedagogical practice in the age of AI. Crucially, the novelty lies not merely in incorporating AI, but in theorizing the emergent socio-technical roles (Peer Apprentice, AI Validator, Metacognitive Facilitator) and the resultant workflow shifts within a validated collaborative framework, offering a more nuanced and testable vision than generic human-AI partnership concepts.

Unlike existing models that often view AI as an external 'resource' or a superior 'tutor,' the AI-CIC model provides a distinct socio-technical architecture. It specifically theorizes how the presence of a 'Peer Apprentice' forces a structural redistribution of human agency, moving beyond a simple user-tool interaction to a stable, interdependent triad of specialized roles.

To theorize the potential impact of AI, it is essential to first understand the system it is entering. The CIC model is build on foundational learning theories, including Vygotsky (1978) Sociocultural Theory, Stahl (2006) model of Group Cognition, and the principles of Knowledge Building by Scardamalia (2005). Its central argument is that collaborative idea construction is not a linear event but a dynamic, recursive prpcess propelled by a specific social structure. The creative process unfolds across a preparatory Pre-Cycle (Task Distribution) and four iterative cycles: Cycle 1 (Information Gathering), Cycle 2 (Idea Formation), Cycle 3 (Idea Revision), and Cycle 4 (Idea Finalization). The revision cycle is the engine of deep learning, where text is reviewed, critiqued, and improved through peer feedback. Disagreement at this stage often force the group to loop back to a previous cycle, reflecting a process of generative sense-making that is crucial for robust knowledge construction (Lubbe et al., 2025).

This workflow is driven by a stable triad of emergent peer roles. The More Knowledgeable Peer (MKP) acts as the group leader and primary scaffolder, guiding the collaborative process. The Peer Assistant (PA) functions as a critical intermediary who operates between the MKP and the DP. Finally, the Dependent Pupil (DP) is the primary learner who relies heavily on the PA and MKP to participate meaningfully.

This social architecture is deeply rooted in Vygotsky (1978) sociocultural theory, with each role defined by its function within the Zone of Proximal Development (ZPD). The MKP and PA operate as scaffolders for the DP. The PA's function is particularly critical, creating a "cascade of support" by operating within their own ZPD relative to the MKP, receiving support from the MKP while providing direct, more relatable scaffolding to the DP. This human-human system is characterized by its recursive nature and its layered, synergistic social support. It represents a delicate, self-organizing ecosystem of learning. The introduction of a GenAI agent is a profound intervention that promises to reconfigure this entire system, challenging the field to revitalize these foundational concepts for a new era (Baker, 2024).

2. Methodology

This paper employs a conceptual framework development methodology based on principles of theoretical synthesis (Jaakkola, 2020; MacInnis, 2011). As a conceptual work, it does not present new empirical data but instead develops a novel, testable framework by logically integrating two distinct and previously disconnected bodies of knowledge the socio-cognitive dynamics of peer collaboration and the technical affordances of generative AI. The process involves three rigorous steps.

First, the paper establishes the theoretical baseline by adopting the existing, empirically grounded CIC Model (Author, 2021). This step is methodologically crucial, as any robust theory of change must first define the stable, validated system being changed. This provides a granular and validated baseline of the social architecture and workflow that the new agent will disrupt.

Second, it integrates the new agent by conducting a targeted synthesis of the burgeoning literature on GenAI in education. This analysis move beyond genera surveys (Albadarin et al., 2024) to focus on specific functionalities that define GenAI as a collaborative partner and cognitive tool for co-constructing knowledge (Cress, 2023; Hu et al., 2025). This step conceptualizes the AI not as a passive tool, but as an active agent with specific, non-human affordances.

Third, it derives logical propositions through theoretical induction. The final step theorizes the consequences of introducing the GenAI agent (from Step 2) into the CIC model's social architecture and workflow (from Step 1). By analyzing the collision of these two systems, the paper inductively derives a series of logical, testable propositions about the resulting transformations. This process generates the novel AI-CIC Model. Providing a clear and urgently needed roadmap for future empirical investigation.

3. Results and Discussion

The proposed AI-enhanced CIC (AI-CIC) model: core propositions

The proposition is that GenAI does not act as a passive tool but enters the triad as an active, non-human agent. Figure 1 visually contrasts the original CIC model (Figure 1A) with the proposed AI-CIC model (Figure 1B), illustrating the theoretical shifts in roles and workflow discussed in the following propositions. The proposition is that GenAI does not act as a passive tool but enters the triad as an active, non-human agent. Wile Vygotsky's framework invites a conception of AI as a new form of "More Knowledgeable Other," capable of providing instant feedback and generating diverse ideas (Song, 2023; Zhou, 2024), this view is dangerously incomplete. An AI, unlike a human peer, lack genuine understanding, social awareness, and pedagogical intuition (Cress, 2023). Its strengths and weaknesses are unique, leading to the core propositions of this model. Therefore, this paper moves beyond the general 'AI as MKO' analogy to propose a distinct, functionally defined role, the Peer Apprentice, situate within the established social dynamics of the peer triad.

Proposition 1: the emergence of AI as the "peer apprentice"

It is argued that GenAI does not replace the human MKP but instead functions as a Peer Apprentice. This novel role is defined by a paradoxical set of attributes. It possesses high knowledge but low wisdom, meaning it has access to a vast repository of information but lacks the contextual understanding to make nuanced judgements about tone, style, or narrative cohesion (Pallant et al., 2025). Its output is instantaneous but uncritical; it can generate text or provide feedback immediately, but it cannot self-evaluate the quality, accuracy, or appropriateness of its own output, often producing plausible-sounding but factually incorrect "hallucinations" (Ahmad et al., 2023; Corbin et al., 2025). Finally, it demonstrates a profound dependence on human direction. Its utility is entirely contingent on the quality of prompts and the critical oversight provided by the human students, underscoring the emerging consensus that effective prompt engineering is a critical skill for leveraging these tools (Kim et al., 2025; Lee et al., 2024). Empirically, this dependence is marked by prompt iteration frequency and the ratio of human-edited text to AI-generated content, where a lack of human intervention indicates a failure of the apprentice role and a slide toward passive output consumption.

Proposition 2: the reshaping of human peer roles

The second proposition is that the presence of the powerful but flawed AI Peer Apprentice fundamentally reshapes the functions of the human triad, pushing the group toward an augmentation, not a replacement, perspective (Lindsay et al., 2024). The PA evolves into AI Validator, a crucial new role focused on mediating the interaction between the DP and the AI. Instead of generating ideas themselves, the PA now helps formulate effective prompts and, most

importantly, critically evaluates the AI's output. They become the first line of defense against misinformation and superficial suggestions, guiding the DP on how to use the AI's output responsibly (Francis et al., 2025). The MKP is elevated to the Metacognitive Facilitator. Freed from the burden of providing constant, low-level support like vocabulary definitions or grammar correction, the MKP's role shifts to a higher cognitive plane. This role now involves leading a metacognitive dialogue about the overall strategy of human-AI collaboration, asking questions like, "Is the AI's suggestion actually helping our story?" and ensuring the group maintains its intellectual agency rather than succumbing to cognitive offloading (Jose et al., 2025; Skulmowski, 2024). The AI Validator role can be operationalized through verification discourse (e.g., 'Is this source real?' or 'Let's check this fact'), while the Metacognitive Facilitator is distinguished by strategic planning and monitoring talk (e.g., 'How should we prompt the AI to fix this paragraph?' or 'We need to ensure our voice isn't lost here'). Finally, the DP remains the Scaffolded Learner, but now requires a new layer of social scaffolding from the PA and MKP to learn how to interact with this powerful new tool effectively and critically, fostering a balanced human-AI symbiosis rather than a parasitical reliance (Khan, 2025; Shibani et al., 2024).

Proposition 3: the transformation of the collaborative workflow

This new socio-technical architecture, which can be termed a "human-AI partnership" (Amrullah, 2025) or a "socio-cognitive teammate" system (Yan, 2025), in turn, alters the workflow of the CIC model. The hypothesis is a linearization of the process, where the workflow becomes less recursive. The instant availability of "good enough" text from the AI may reduce the perceived need for the intensive, iterative feedback loops that characterize the all-important Idea Revision Cycle (Costello et al., 2024). Workflow linearization can be concretely measured by a reduction in the frequency of recursive 'loop-backs' to earlier information-gathering or idea-formation cycles, as students may bypass the intensive human-to-human negotiation characteristic of the original CIC model. This leads to a profound shift in the locus of criticality. The most cognitively demanding work no longer occurs during the initial drafting but shifts to the evaluation of AI-generated content and the craft of prompt engineering. This demands a pedagogical focus on the learning process over the final product, a challenge that requires rethinking assessment itself (Akbar, 2025; Kadel et al., 2025). The resulting AI-CIC Model thus conceptualizes a more efficient but potentially less deeply engaged collaborative process.

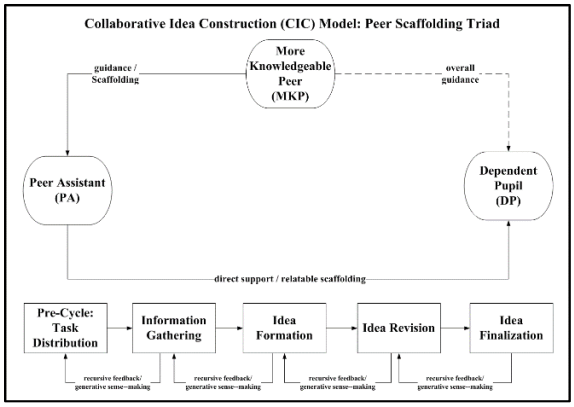

Figure 1A. The Original Collaborative Idea Construction (CIC) Model, Illustrating the Human Peer Traid (MKP, PA, DP) and the Recursive Workflow Driven by Peer Scaffolding.

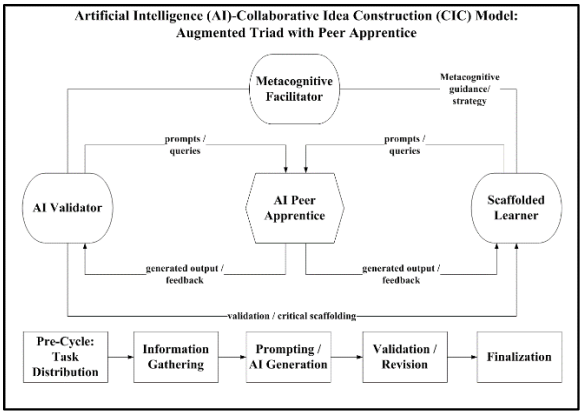

Figure 1B. The Proposed AI-Enhanced CIC (AI-CIC) Model, Showing the Introduction of the AI Peer Apprentice, the Transformation of Human Roles, and the Hypothesized Shift Towards a More Linear Workflow.

Discussion

Boundary conditions and context sensitivity

While the AI-CIC model theorizes a structural reconfiguration of the triad, several boundary conditions may impede these role transformations. For example, the transition of the MKP into a Metacognitive Facilitator assumes a level of metacognitive maturity that may not be present in very young learners or students with lower linguistic ability. In such contexts, the MKP may struggle to mediate the AI's output, leading to cognitive

offloading where the AI Peer Apprentice effectively replaces human cognitive effort rather than augmenting it.

Furthermore, the hypothesized linearization of the workflow carries the unintended consequence of eroding generative sense-making. If the AI Validator fails to critically evaluate output, the group may prioritize efficiency over deep learning, resulting in a polished final product that lacks the robust knowledge construction inherent in the recursive cycles of the original CIC model. Therefore, the AI-CIC framework should be viewed as context-sensitive, with its success heavily dependent on the students' pre-existing collaborative skills and the teacher's active scaffolding of critical AI literacy.

Pedagogical Implications and Scaffolding

The proposed AI-CIC model has profound implications for teaching and learning. If AI, acting as the 'Peer Apprentice,' reconfigures the natural peer-scaffolding system by necessitating new human roles like the AI Validator and Metacognitive Facilitator, then pedagogical scaffolding must also adapt. Simple technical training is insufficient; educators must actively scaffold the interaction within this new socio-technical triad. The teacher's role must evolve from the "sage on the stage" or "guide on the side" to a new, more complex role: the facilitator of critical human-AI interaction. This shift aligns with emerging concepts like "Generativism," which recognizes the future of education in the synergistic collaboration between human intelligence and generative AI (Pratschke, 2023).

This new role is not about teaching students to use a tool; it is about cultivating a new set of essential literacies (Tzirides et al., 2024). First and foremost is Critical AI Literacy. Educators must move beyond simplistic warnings about academic integrity (Cannity, 2024; Rasul et al., 2024) and actively teach students to view AI not as an oracle but as a flawed, biased, and non-conscious tool. This involves direct instruction on identifying "hallucinations" (Ahmad et al., 2023), understanding the implications of algorithmic biases, and developing a sophisticated ethical framework for its use (Cardon et al., 2023; Swindell et al., 2024; Wang, 2025).

Second, Prompt Engineering Skills become fundamental. Effective collaboration with an AI requires knowing how to ask the right questions. Teachers must scaffold the skill of crafting precise, context-rich prompts that elicit high-quality, relevant outputs, transforming the act of questioning into a core academic skill (Deep, 2025; Salhab, 2024). Finally, Metacognitive Regulation is essential. Students must be taught to continuously reflect on their collaborative process with prompts like, "When should we use the AI?" and "How do we know if our final product is truly our own work?". In an AI-augmented classroom, the ultimate goal of scaffolding is to ensure that students remain the primary cognitive agents in their own learning, using AI as a powerful apprentice, not a replacement for thought (Kim et al., 2025).

4. Conclusion

This paper has argued for the AI-Enhanced Collaborative Idea Construction (AI-CIC) Model, a conceptual framework for understanding how GenAI may reshape the dynamics of peer collaboration. The core argument is that AI enters the collaborative ecosystem as a "Peer Apprentice," an agent that transforms the established social architecture and alters the collaborative workflow. This model provides a necessary theoretical lens to move beyond the simplistic dichotomy of AI as either a "cheating tool" or a panacea. The propositions put forth require rigorous empirical validation, and the paper concludes by offering a clear agenda for future research. By grounding the integration of GenAI within a specific, empirically-derived model of human collaboration and theorizing concrete transformations in roles and workflow, the AI-CIC model offers a crucial foundation for building more effective and pedagogically sound human-AI learning partnerships.

Future work must focus on the empirical testing of this model. Mixed-methods studies (Combrinck, 2024) are needed to directly compare peer-only triads with human-AI triads, testing the hypotheses regarding role changes and workflow shifts. Here, learning analytics methods like multimodal analysis (Xu et al., 2023) and sequence analysis (Ouyang et al., 2022) will be invaluable for quantifying these complex interactions. Longitudinal studies are also urgently needed to investigate the long-term effects on AI-assisted collaboration on students' writing development, critical thinking, and their ability to collaborate without AI support (Jose et al., 2025). Finally, research into pedagogical interventions is necessary to design and test different scaffolding strategies for teaching critical AI literacy and prompt engineering, moving from theory to practice (Memon, 2025). By pursuing this agenda, researchers can refine the AI-CIC model and provide educators with the evidence-based guidance needed to harness the transformative potential of AI while preserving the core human values

of deep learning, critical thought, and meaningful collaboration.

References

Ahmad, Z., Kaiser, W., & Rahim, S. (2023). Hallucinations in ChatGPT: An Unreliable Tool for Learning. *Rupkatha Journal on Interdisciplinary Studies in Humanities*, *15*(4). https://doi.org/10.21659/rupkatha.v15n4.17

Akbar, M. S. (2025). *Beyond Detection: Designing AI-Resilient Assessments with Automated Feedback Tool to Foster Critical Thinking* (No. arXiv:2503.23622). arXiv. https://doi.org/10.48550/arXiv.2503.23622

Albadarin, Y., Saqr, M., Pope, N., & Tukiainen, M. (2024). A systematic literature review of empirical research on ChatGPT in education. *Discover Education*, *3*(1), 60. https://doi.org/10.1007/s44217-024-00138-2

Amrullah, M. F. N. (2025). Human-AI Collaboration in Education: Designing Effective Teacher-AI Partnerships for Enhanced Learning. *Communications on Applied Nonlinear Analysis*, *32*(9s), 1865–1869. https://doi.org/10.52783/cana.v32.4357

Author. (2021). *[Details withheld for blind review]*.

Baker, M., & Reimann, P. (2024). Editorial Notes: Revitalising foundational concepts. *International Journal of Computer-Supported Collaborative Learning*, *19*(4), 395–400. https://doi.org/10.1007/s11412-024-09440-5

Cannity, D. (2024). Generative AI: A New Frontier with Familiar Challenges. *Medical Science Educator*, *34*(1), 9–10. https://doi.org/10.1007/s40670-024-02237-z

Cardon, P., Fleischmann, C., Aritz, J., Logemann, M., & Heidewald, J. (2023). The Challenges and Opportunities of AI-Assisted Writing: Developing AI Literacy for the AI Age. *Business and Professional Communication Quarterly*, *86*(3), 257–295. https://doi.org/10.1177/23294906231176517

Combrinck, C. (2024). A tutorial for integrating generative AI in mixed methods data analysis. *Discover Education*, *3*(1), 116. https://doi.org/10.1007/s44217-024-00214-7

Corbin, T., Tai, J., & Flenady, G. (2025). Understanding the place and value of GenAI feedback: A recognition-based framework. *Assessment & Evaluation in Higher Education*, *50*(5), 718–731. https://doi.org/10.1080/02602938.2025.2459641

Costello, E., Brunton, J., Otrel-Cass, K., Lyngdorf, N. E. R., & Brown, M. (2024). Hacking Happier Futures: An AI-augmented student hackathon to address affective and ethical digital learning challenges. *EDEN Annual Conference Proceedings: Learning in the Age of AI: Towards Imaginative Futures*, 9.

Cress, U., & Kimmerle, J. (2023). Co-constructing knowledge with generative AI tools: Reflections from a CSCL perspective. *International Journal of Computer-Supported Collaborative Learning*, *18*(4), 607–614. https://doi.org/10.1007/s11412-023-09409-w

Deep, P. D., & Chen, Y. (2025). The Role of AI in Academic Writing: Impacts on Writing Skills, Critical Thinking, and Integrity in Higher Education. *Societies*, *15*(9), 247. https://doi.org/10.3390/soc15090247

Francis, N. J., Jones, S., & Smith, D. P. (2025). Generative AI in Higher Education: Balancing Innovation and Integrity. *British Journal of Biomedical Science*, *81*, 14048. https://doi.org/10.3389/bjbs.2024.14048

Hodges, C. B., & Kirschner, P. A. (2024). Innovation of Instructional Design and Assessment in the Age of Generative Artificial Intelligence. *TechTrends*, *68*(1), 195–199. https://doi.org/10.1007/s11528-023-00926-x

Hu, W., Tian, J., & Li, Y. (2025). Enhancing student engagement in online collaborative writing through a generative AI-based conversational agent. *The Internet and Higher Education*, *65*, 100979. https://doi.org/10.1016/j.iheduc.2024.100979

Jaakkola, E. (2020). Designing conceptual articles: Four approaches. *AMS Review*, *10*(1), 18–26. https://doi.org/10.1007/s13162-020-00161-0

Jose, B., Cherian, J., Verghis, A. M., Varghise, S. M., S, M., & Joseph, S. (2025). The cognitive paradox of AI in education: Between enhancement and erosion. *Frontiers in Psychology*, *16*. https://doi.org/10.3389/fpsyg.2025.1550621

Kadel, R., Shailendra, S., & Saxena, U. R. (2025). *Navigating the New Landscape: A Conceptual Model for Project-Based Assessment (PBA) in the Age of GenAI* (No. arXiv:2508.11709). arXiv. https://doi.org/10.48550/arXiv.2508.11709

Khan, K. (2025). *Automated but Atrophied? Student Over-Reliance vs Expert Augmentation of AI in Learning and Cybersecurity* (No.

arXiv:2507.21062). arXiv. https://doi.org/10.48550/arXiv.2507.21062

Kim, J., Yu, S., Detrick, R., & Li, N. (2025). Exploring students' perspectives on Generative AI-assisted academic writing. *Education and Information Technologies*, *30*(1), 1265–1300. https://doi.org/10.1007/s10639-024-12878-7

Lee, A. V. Y., Teo, C. L., & Tan, S. C. (2024). Prompt Engineering for Knowledge Creation: Using Chain-of-Thought to Support Students' Improvable Ideas. *AI*, *5*(3), 1446–1461. https://doi.org/10.3390/ai5030069

Lindsay, E. D., Otto, S., & Ejsing-Duun, S. (2024). Three Frameworks to Support Engineering Education to Develop with Generative AI. *Proceedings of the 35th Australasian Association for Engineering Education (AAEE) Annual Conference AAEE*. Australasian Association for Engineering Education.

Lubbe, A., Marais, E., & Kruger, D. (2025). Cultivating independent thinkers: The triad of artificial intelligence, Bloom's taxonomy and critical thinking in assessment pedagogy. *Education and Information Technologies*, *30*(12), 17589–17622. https://doi.org/10.1007/s10639-025-13476-x

MacInnis, D. J. (2011). A Framework for Conceptual Contributions in Marketing. *Journal of Marketing*, *75*(4), 136–154. https://doi.org/10.1509/jmkg.75.4.136

Makransky, G., Shiwalia, B. M., Herlau, T., & Blurton, S. (2024). *Beyond the 'Wow' factor: Using Generative AI for Increasing Generative Sense-Making*. Research Square. https://doi.org/10.21203/rs.3.rs-5622133/v1

Memon, T. D., & Kwan, P. (2025). A Collaborative Model for Integrating Teacher and GenAI into Future Education. *TechTrends*, *69*, 1192–1206. https://doi.org/10.1007/s11528-025-01105-w

Ouyang, F., Xu, W., & Cukurova, M. (2022). *An Artificial Intelligence driven Learning Analytics Method to Examine the Collaborative Problem solving Process from a Complex Adaptive Systems Perspective* (No. arXiv:2210.16059). arXiv. https://doi.org/10.48550/arXiv.2210.16059

Pallant, J. L., Blijlevens, J., Campbell, A., & Jopp, R. (2025). Mastering knowledge: The impact of generative AI on student learning outcomes. *Studies in Higher Education*, 1–22. https://doi.org/10.1080/03075079.2025.2487570

Pratschke, B. M. (2023). *Generativism: The new hybrid* (No. arXiv:2309.12468). arXiv. https://doi.org/10.48550/arXiv.2309.12468

Rasul, T., Nair, S., Kalendra, D., Balaji, M. S., Santini, F. de O., Ladeira, W. J., Rather, R. A., Yasin, N., Rodriguez, R. V., Kokkalis, P., Murad, M. W., & Hossain, M. U. (2024). Enhancing academic integrity among students in GenAI Era:A holistic framework. *The International Journal of Management Education*, *22*(3), 101041. https://doi.org/10.1016/j.ijme.2024.101041

Salhab, R. (2024). AI Literacy across Curriculum Design: Investigating College Instructor's Perspectives. *Online Learning*, *28*(2). https://doi.org/10.24059/olj.v28i2.4426

Scardamalia, M., & Bereiter, C. (2005). Knowledge Building: Theory, Pedagogy, and Technology. In R. K. Sawyer (Ed.), *The Cambridge Handbook of the Learning Sciences* (1st edn, pp. 97–116). Cambridge University Press. https://doi.org/10.1017/CBO9780511816833.008

Shibani, A., Knight, S., Kitto, K., Karunanayake, A., & Buckingham Shum, S. (2024). Untangling Critical Interaction with AI in Students' Written Assessment. *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*, 1–6. https://doi.org/10.1145/3613905.3651083

Skulmowski, A. (2024). Placebo or Assistant? Generative AI Between Externalization and Anthropomorphization. *Educational Psychology Review*, *36*(2), 58. https://doi.org/10.1007/s10648-024-09894-x

Song, C., & Song, Y. (2023). Enhancing academic writing skills and motivation: Assessing the efficacy of ChatGPT in AI-assisted language learning for EFL students. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1260843

Stahl, G. (2006). *Group Cognition: Computer Support for Building Collaborative Knowledge*. The MIT Press. https://doi.org/10.7551/mitpress/3372.001.0001

Swindell, A., Greeley, L., Farag, A., & Verdone, B. (2024). Against Artificial Education: Towards an Ethical Framework for Generative Artificial Intelligence (AI) Use in Education. *Online Learning*, *28*(2). https://doi.org/10.24059/olj.v28i2.4438

Tzirides, A. O. (Olnancy), Zapata, G., Kastania, N. P., Saini, A. K., Castro, V., Ismael, S. A., You, Y., Santos, T. A. dos, Searsmith, D., O'Brien,

C., Cope, B., & Kalantzis, M. (2024). Combining human and artificial intelligence for enhanced AI literacy in higher education. *Computers and Education Open*, *6*, 100184. https://doi.org/10.1016/j.caeo.2024.100184

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.

Wang, C. (2025). Exploring Students' Generative AI-Assisted Writing Processes: Perceptions and Experiences from Native and Nonnative English Speakers. *Technology, Knowledge and Learning*, *30*(3), 1825–1846. https://doi.org/10.1007/s10758-024-09744-3

Xu, W., Wu, Y., & Ouyang, F. (2023). Multimodal learning analytics of collaborative patterns during pair programming in higher education. *International Journal of Educational Technology in Higher Education*, *20*(1), 8. https://doi.org/10.1186/s41239-022-00377-z

Yan, L. (2025). *From Passive Tool to Socio-cognitive Teammate: A Conceptual Framework for Agentic AI in Human-AI Collaborative Learning* (No. arXiv:2508.14825). arXiv. https://doi.org/10.48550/arXiv.2508.14825

Yan, L., Greiff, S., Teuber, Z., & Gašević, D. (2024). Promises and challenges of generative artificial intelligence for human learning. *Nature Human Behaviour*, *8*(10), 1839–1850. https://doi.org/10.1038/s41562-024-02004-5

Zhou, X., & Schofield, L. (2024). Using social learning theories to explore the role of generative Artificial Intelligence (AI) in collaborative learning. *Journal of Learning Development in Higher Education*, *30*. https://doi.org/10.47408/jldhe.vi30.1031

.

How to cite this article:

Ng, S. H. (2026). An AI in the Triad: A Conceptual Model for Augmenting Collaborative Idea Construction with Generative AI. *Journal of Education and Learning Research*, *3(2)*, 64-71.