Integrating the FILA Framework with Generative AI to Support Independent Learning in Engineering Dynamics

Nik Syahrim Nik Anwar[1]*, Fadilah Abdul Azis[1], Satria Pinandita[2]

[1]Faculty of Electrical Technology and Engineering, Universiti Teknikal Malaysia Melaka, Malaysia

[2]Department of Electrical Engineering, Faculty of Engineering, Universitas Semarang, Indonesia

***Corresponding Author**

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ABSTRACT

This paper presents a pedagogical case study that integrates the FILA framework with generative artificial intelligence (AI) to support independent learning in Engineering Dynamics. The learning outcome (LO) requires students to analyze particle motion in planar systems by combining the Principle of Work and Energy, or the Conservation of Energy, with equations of curvilinear motion and projectile kinematics. The model was designed within Outcome-Based Education (OBE), constructive alignment, problem-based learning and self-regulated learning. In the learning task, students completed a handwritten quiz submission by applying FILA-Facts, Ideas, Learning Issues and Actions- to three selected Dynamics problems from the textbook. Generative AI is positioned as a bounded digital tutor that supports prompting, questioning, scaffolding, error checking and self-explanation, not as a source for copying final solutions. The paper describes the learning mechanism and assessment alignment. Qualitative findings were generated from an anonymized review of 51 student submissions assessed using readability, FILA accuracy and solution correctness. The class achieved a mean score of 79.9%, a median of 82.0%, and 31 of 51 submissions scored 80% or higher. The evidence suggests that FILA made problem representation visible, helped students separate facts from governing theories, and provided a pathway from conceptual planning to mathematical action. Weaker submissions revealed persistent difficulty in articulating specific learning issues and checking assumptions. The paper concludes that FILA supported by carefully guided generative AI can strengthen independent problem solving and provide visible evidence of LO attainment.

Keywords: Outcome-Based Education; FILA framework; generative AI; Engineering Dynamics; self-regulated learning.

INTRODUCTION

Engineering Dynamics often challenges students because the correct solution begins before algebra is written. In planar particle-motion problems, the learner must interpret a physical situation, recognize relevant quantities, select a suitable principle, construct equations and check whether the result has physical meaning. A student may remember individual formulas for work and energy, conservation of energy, projectile motion, or normal-tangential acceleration, but still struggle to decide which model applies at a particular instant. The learning difficulty is therefore conceptual and procedural. It concerns the ability to integrate ideas rather than merely substitute numbers.

The course task behind this paper required students to apply FILA to three selected problems. The template required four visible stages: Facts, Ideas, Learning Issues and Actions. The intended learning outcome (LO) was formulated as: to analyze motion of particles in planar systems by integrating the Principle of Work and Energy, or the Conservation of Energy, with the equations of curvilinear motion and projectile kinematics. This LO is suitable for OBE because it states an observable capability, embeds the content domain and describes the context of performance. It also demands evidence of reasoning, not only a final answer.

The emergence of generative AI creates both risk and opportunity. If used carelessly, AI may encourage answer copying and superficial completion (Maalek, 2024, Qadir, 2023). If designed pedagogically, however, AI can serve as a formative tutor that asks questions, prompts reflection and helps students check assumptions while preserving student accountability (Bravo, 2024). This paper proposes a FILA-plus-AI learning mechanism in which the student remains the author of the handwritten solution, the FILA table structures the thinking process, and the AI functions as a support system. The purpose is to show how such a method can help students work independently toward the stated LO while producing assessable evidence for continuous improvement.

Outcome-Based Education and Constructive Alignment

Outcome-Based Education begins with the question of what students should be able to demonstrate at the end of a learning experience. The stated LO is more than topic coverage; it requires students to integrate principles and make decisions in a problem context. OBE terms such as course learning outcome, performance indicator, assessment evidence and attainment are useful because they translate abstract learning into observable behavior. In this case, the desired behavior includes identifying known and unknown variables, selecting energy or kinematic principles, forming equations, executing a solution and evaluating the final result (Yaacob, 2021). This aligns with the idea of constructive alignment, in which the learning outcome, learning activity and assessment task deliberately require the same cognitive performance (Biggs, 1996).

The FILA task is constructively aligned with the LO. The selected Dynamics problems require application and analysis. The FILA template requires students to make their reasoning explicit. The assessment rubric evaluates readability, FILA accuracy and correctness of solution, so both communication process and technical product are valued. This is important in engineering education because a correct numerical answer without a traceable reasoning path provides weak evidence of learning. Conversely, a visible but imperfect solution can reveal the exact stage where learning support is needed.

FILA as a Problem-Based Learning Scaffold

FILA represents a compact form of problem-based learning. Facts require the student to extract givens, unknowns, constraints and conditions from the problem. Ideas require selection of theory, concepts and equations. Learning Issues require the student to name what remains unclear, such as whether a force is conservative, when projectile motion starts or how a normal acceleration term should be interpreted. Actions convert the plan into diagrams, equations, substitutions, numerical calculation and final interpretation. The framework therefore supports metacognition: students plan, monitor and evaluate their own thinking (Chan, 2024).

For Dynamics, the FILA sequence is pedagogically powerful because problem modelling is the heart of the LO. A student must decide whether work-energy is appropriate across a displacement, whether conservation of energy is valid when friction is absent or negligible, whether a trajectory segment should be treated as projectile motion, and whether curvilinear acceleration should be decomposed into tangential and normal components. FILA slows down the rush to calculation and makes these choices inspectable. It teaches students to ask, “What do I know?”, “What theory fits?”, “What do I still not understand?” and “What action will prove my answer?”

Generative AI as a Formative Tutor

Generative AI can be integrated into the FILA cycle as a formative support rather than an answer engine. In the Facts stage, students may ask AI to help identify what information should be extracted, without solving the problem. In the Ideas stage, students may ask AI to compare candidate principles and explain assumptions. In the Learning Issues stage, AI can generate questions that expose conceptual gaps. In the Actions stage, AI can check units, sign conventions and the logical sequence of a draft solution (Krupp, 2024). The boundary is that AI should not provide a complete answer for copying; students must submit their own handwritten reasoning (Lauren, 2023).

This boundary supports academic integrity and learning independence. A practical declaration can state that AI may be used for clarification, questioning and checking, but not for generating a final solution (Osunbunmi, 2025). The lecturer can require students to submit handwritten work, a short reflection or a prompt log. These

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practices preserve the value of human reasoning while acknowledging that AI can provide timely feedback. In this design, AI is aligned with assessment for learning: it provides formative cues during the learning process, while the final evidence remains the student's visible FILA work and solution (Sirnoorkar, 2024).

METHODOLOGY

Learning Task and Participants

The pedagogical model was illustrated using student work from the Engineering Dynamics course for first year undergraduate Mechatronics Engineering students. The task was a quiz activity based on selected problems from the textbook (Hibbeler, 2019). Students submitted individual handwritten work. The quiz instruction required them to apply the FILA framework to three problems. The assessment was designed to measure both process and product: readability of the handwritten solution, accuracy of FILA philosophy and correctness of the technical solution.

FILA plus AI Learning Mechanism

Figure 1 visualizes the proposed learning mechanism. The process begins with the LO and an authentic task. Students enter the FILA cycle by identifying facts, selecting ideas, articulating learning issues and completing actions. Generative AI surrounds the cycle as a support layer that offers prompting, scaffolding, questioning, error checking, feedback and self-explanation. The model also includes self-regulated learning actions: interpreting the problem, identifying known and unknown variables, selecting principles, drafting a solution, checking assumptions, revising the solution and reflecting on improvement. The OBE alignment is maintained by connecting the LO, task, learning process and assessment rubric.

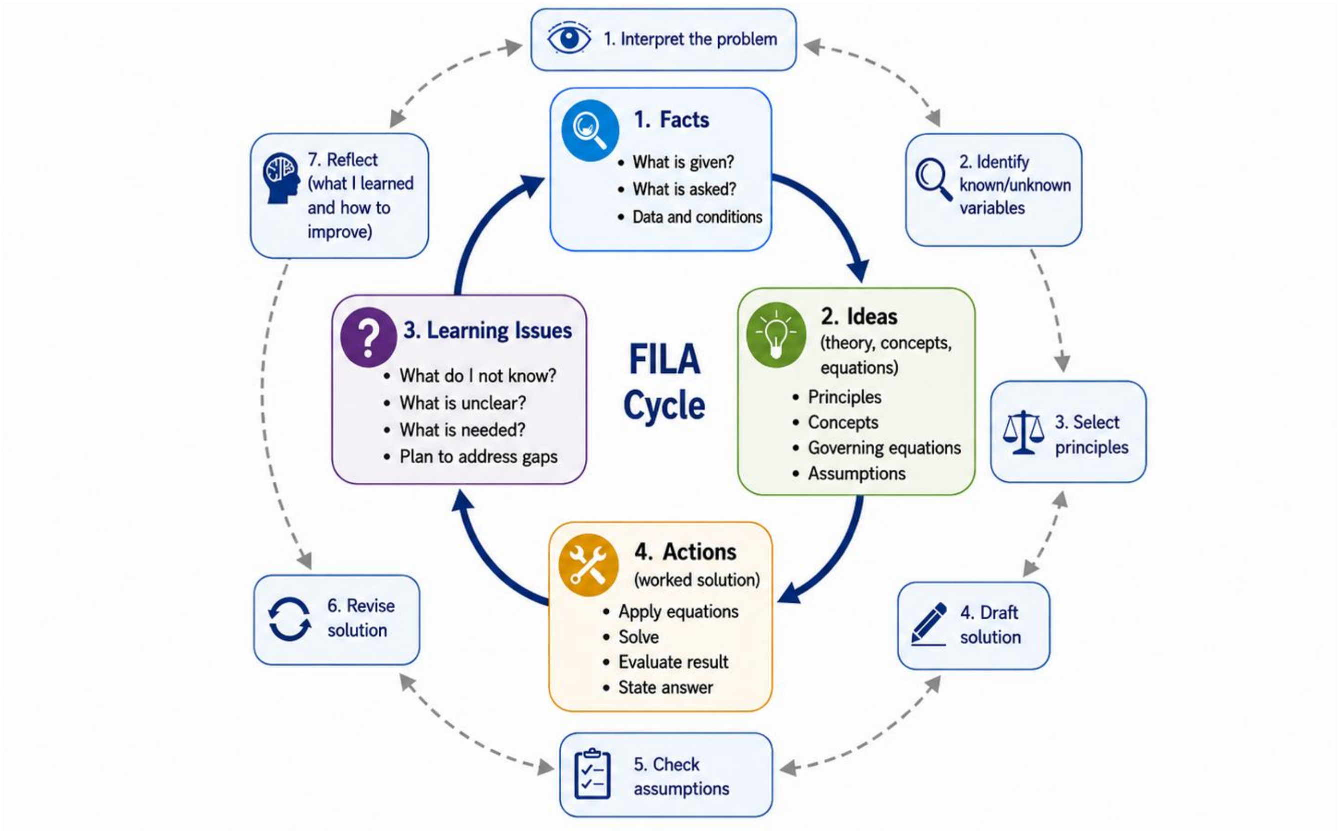

Figure 1. FILA plus generative AI learning mechanism

The learning mechanism can be implemented in four phases. First, the lecturer explains the LO and demonstrates how FILA maps to a Dynamics problem. Second, students attempt selected problems using FILA before completing final calculations. Third, students use AI only for support, such as generating questions, clarifying assumptions or checking the logic of a draft. Fourth, students submit handwritten work that shows both the FILA

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reasoning process and the final mathematical solution. This design keeps students cognitively active and allows the lecturer to evaluate whether the LO has been achieved.

Table 1. Alignment of FILA stages, generative AI support and OBE evidence.

FILA stage	Student learning purpose	Permitted generative AI support	OBE evidence
Facts	Identify givens, unknowns, diagrams, conditions and constraints.	Ask AI what information should be extracted and what variables may be missing.	Problem representation is visible and auditable.
Ideas	Select principles such as work-energy, conservation of energy, curvilinear motion and projectile kinematics.	Ask AI to compare principles, explain assumptions and generate concept checks.	Theory selection matches the intended LO.
Learning Issues	State specific conceptual gaps or uncertainties before solving.	Ask AI to pose Socratic questions or explain a confusing concept without solving.	Students show awareness of what must be learned.
Actions	Execute diagrams, equations, substitution, calculation, units and final statement.	Ask AI to check units, signs, assumptions and logic in a student-drafted solution.	Final answer and reasoning process can be assessed.

Assessment Method

The evaluation used three criteria totaling 100 marks: readability of the handwritten solution (20%), FILA philosophy accuracy (50%) and solution correctness (30%). Readability captured whether the lecturer could follow the student's text, symbols and scan quality. FILA accuracy captured whether the student correctly separated facts, ideas, learning issues and actions instead of treating FILA as a decorative heading. Solution correctness captured the appropriateness of equations, substitutions, units and final answers. The same criteria can be used in future implementations with a larger weighting for AI reflection if prompt logs are collected.

RESULTS

Submission Samples

Figure 2 shows two samples from the FILA table submitted by a good scoring (left) and moderately scoring (right) student. Here only the Facts, Ideas and Learning Issues are shown. As apparent in the sample, the good scoring student demonstrates more critical points in the FILA table.

Descriptive Evidence of Learning Performance

Meanwhile, Table 2 presents the analysis obtained from the exercise. An anonymized review of 51 Quiz 2 submissions was used to generate qualitative evidence of the method. The class mean was 79.9%, the median was 82.0%, the highest score was 94% and the lowest score was 15%. Thirty-one submissions scored 80% or higher, 18 submissions fell between 60% and 79%, and two submissions scored below 60%. Because there was no pre-test, control group or AI-use log, the results should not be interpreted as causal proof. Instead, they provide classroom evidence that the FILA task created visible traces of how students approached the LO.

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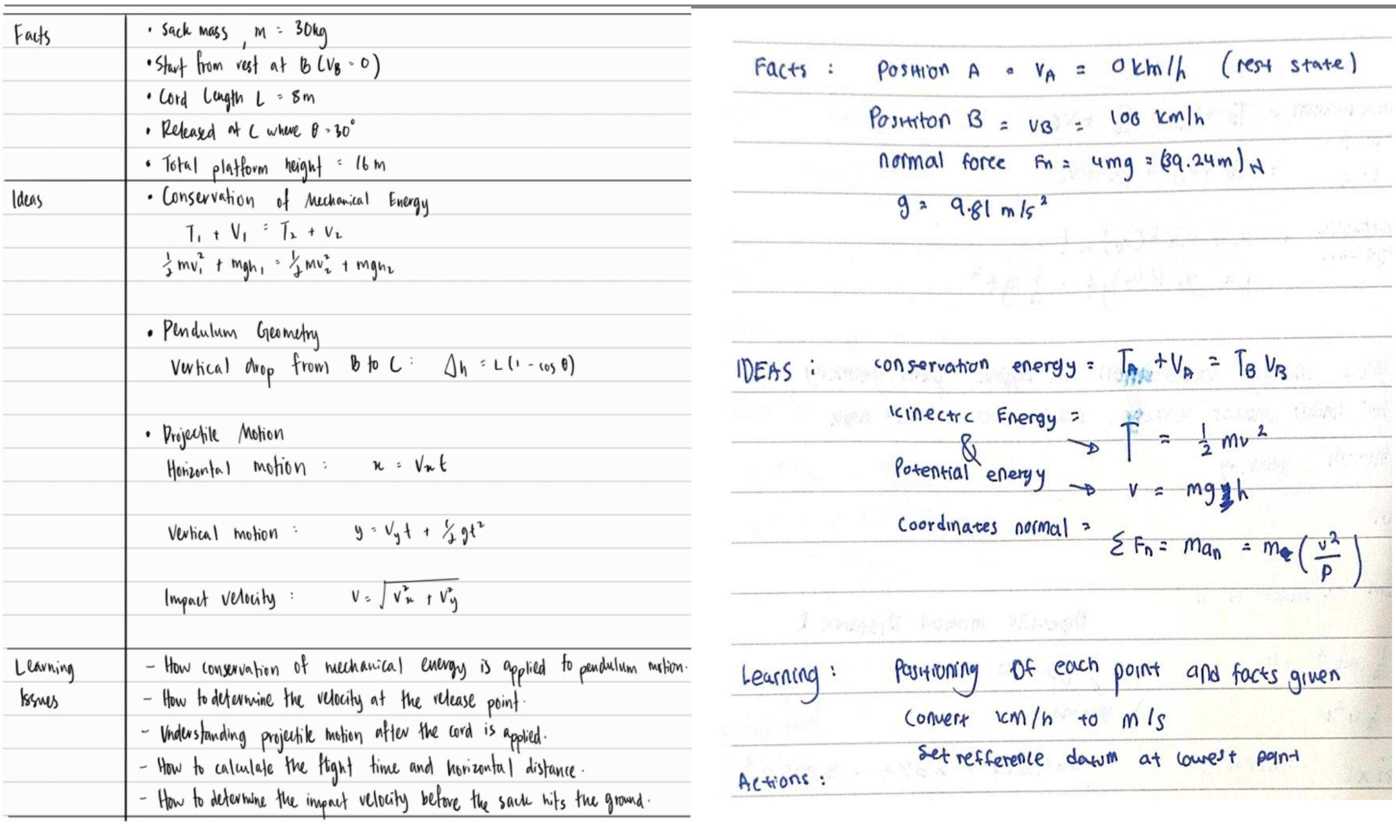

Figure 2. Two submission samples from a good (left) and moderately (right) scoring students

Table 2. Summary of assessed learning evidence from 51 student submissions.

Evidence indicator	Observed pattern	Pedagogical interpretation	Improvement action
Overall attainment	Mean 79.9%, median 82.0%, 31/51 submissions at 80% or above.	Most students demonstrated competent attainment of the LO.	Maintain FILA as a visible reasoning scaffold.
Problem representation	Stronger submissions separated givens, unknowns and equations before calculation.	FILA supported translation from problem statement to model.	Demonstrate more examples of good Facts and Ideas entries.
FILA accuracy	Many submissions used the four FILA sections, but quality varied.	Students understood the structure but not always the depth of each section.	Provide annotated exemplars and a checklist.
Learning Issues	Weaker submissions often wrote generic or incomplete learning issues.	Students need support in naming conceptual uncertainty.	Use AI-generated Socratic questions during practice.
Solution correctness	Most medium and high scorers had coherent equations and units; weak scorers lacked solution continuity.	Planning improved execution when Ideas and Actions were connected.	Require final physical checks and unit verification.
Presentation	Readability and neatness affected confidence in marking and interpretation.	Engineering reasoning must be communicated clearly.	Use scan-quality and layout requirements.

Qualitative Trends

Three qualitative trends emerged from the submissions. First, FILA improved problem representation. Stronger students did not begin directly with equations; they showed a transition from facts to concepts and then to calculation. This suggests that the framework encouraged students to slow down and interpret the physical situation before solving. Second, FILA acted as a bridge between textbook theory and independent action. The Ideas section prompted students to name the Principle of Work and Energy, Conservation of Energy, curvilinear motion or projectile kinematics before using equations. Third, the Learning Issues section was the least mature stage. Some students wrote broad phrases such as "understand the formula" instead of a specific uncertainty. This is where generative AI can be most useful, because AI can generate probing questions that help students convert vague confusion into targeted learning needs.

The qualitative results therefore support the pedagogical value of combining FILA with AI. FILA provides the structure, while AI can strengthen the weak links through formative questioning. For example, when a student writes a generic learning issue, AI can ask: "Which force does work along the path?", "Is mechanical energy conserved here?", "Which component of acceleration is normal to the path?", or "At what point does projectile motion begin?" These questions do not solve the problem, but they direct attention to the LO. The method is effective when students use AI to refine thinking and then document their own reasoning by hand.

DISCUSSION

Contribution to Independent Learning

The proposed model shifts the student from answer-seeking to understanding-seeking process. In a conventional solution, a learner may focus on reaching the same numerical answer as a textbook or peer. In an OBE system, however, the central question is whether the student can demonstrate the intended capability. FILA supports this by requiring students to display their facts, theories, uncertainties and actions. Generative AI can extend the support by giving immediate prompts and feedback when the lecturer is not present. The combination is especially useful for independent study because students receive a structure for thinking and a source of formative questioning, while still being responsible for the final solution.

OBE Implications for Assessment and CQI

The model supports continuous quality improvement (CQI) because each FILA section can be mapped to a performance indicator. Facts show whether the problem is understood. Ideas show whether theory selection is correct. Learning Issues show self-awareness and conceptual monitoring. Actions show technical execution. Marks and qualitative comments can therefore be analyzed to identify which part of the LO needs instructional improvement. In the current evidence, most students could complete the structure, but some needed help with Learning Issues and assumption checking. The next teaching cycle can respond by adding prompt templates, worked examples and reflection requirements. This closes the OBE loop from planning to delivery, assessment, evaluation and improvement.

CONCLUSION

This paper has presented a pedagogical case-study for integrating the FILA framework with generative AI to support independent learning of particle motion in Engineering Dynamics. The approach is aligned with Outcome-Based Education because it begins with a clear LO, uses an authentic task from the textbook, provides a structured learning mechanism and evaluates visible evidence of reasoning and correctness. The classroom evidence suggests that FILA is a promising scaffold for making engineering problem-solving reasoning visible, while the proposed bounded-AI layer offers a plausible mechanism for supporting questioning, clarification, and error checking. Stronger empirical designs are required to determine the specific contribution of generative AI.

The qualitative evidence from 51 submissions suggests that the method is promising. Most students achieved competent or high marks and produced visible FILA structures. The strongest evidence appeared in clearer problem representation and more deliberate theory selection. The weakest evidence appeared in generic learning-issue statements and inconsistent checking of assumptions. For future implementation, lecturers should provide explicit AI-use boundaries, annotated FILA exemplars, prompt templates and reflective checks. Used in this way, generative AI can support rather than weaken engineering education, because the student remains responsible for demonstrating the LO through handwritten reasoning and technically sound solution work.

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Limitations and Future Work

This paper is a pedagogical design and classroom evidence report, not a controlled experimental study. The available data were based on assessed submissions and lecturer interpretation. There were no AI-usage logs, pre/post measures, or comparison groups. Therefore, the results cannot isolate the effect of generative AI from the effect of FILA, lecturer instruction or student ability. A future study should collect prompt histories, student reflections, pre/post LO tests and interview data. It should also compare groups using conventional solutions, FILA only, and FILA plus bounded AI support. Such evidence would allow stronger claims about effectiveness while preserving the classroom practicality of the method.

REFERENCES

1. Maalek, R. (2024). Integrating generative artificial intelligence and problem-based learning into the digitization in construction curriculum. Buildings, 14(11), 3642. https://doi.org/10.3390/buildings14113642
2. Qadir, J. (2023). Engineering Education in the Era of ChatGPT: Promise and pitfalls of generative AI for education. In 2023 IEEE Global Engineering Education Conference (EDUCON) (pp. 1–9). IEEE. https://doi.org/10.1109/EDUCON54358.2023.10125121
3. Bravo, F. A., & Cruz-Bohorquez, J. M. (2024). Engineering Education in the Age of AI: Analysis of the impact of chatbots on learning in engineering. Education Sciences, 14(5), 484. https://doi.org/10.3390/educsci14050484
4. Yaacob, M. R., & Velte, C. M. (2021). Students perception towards the implementation of asynchronous video lectures and video-based instructions in experimental fluid mechanics course. Evergreen, 8(2), 374-378. https://doi.org/10.5109/4480719
5. Biggs, J. (1996). Enhancing teaching through constructive alignment. Higher Education, 32, 347-364.
6. Hibbeler, R. C. (2019). Engineering Mechanics: Dynamics (15th ed. in SI units). Pearson.
7. Chan, R. Y.-Y., Chan, C. K. Y., Jong, M. S.-Y., Hu, Z., & Zhang, Y. (2024). WIP: Engineering class students' epistemic cognition when interacting with generative AI. In 2024 IEEE Frontiers in Education Conference, FIE 2024—Proceedings. IEEE. https://doi.org/10.1109/FIE61694.2024.10893501
8. Krupp, L., Steinert, S., Kiefer-Emmanouilidis, M., Avila, K. E., Lukowicz, P., Kuhn, J., Küchemann, S., & Karolus, J. (2024). Unreflected acceptance—Investigating the negative consequences of ChatGPT-assisted problem solving in physics education. In HHAI 2024: Hybrid Human AI Systems for the Social Good: Proceedings of the Third International Conference on Hybrid Human-Artificial Intelligence (Frontiers in Artificial Intelligence and Applications, Vol. 386). IOS Press. https://doi.org/10.3233/FAIA240195
9. Lauren, P., & Watta, P. (2023). Work-in-Progress: Integrating generative AI with evidence-based learning strategies in computer science and engineering education. In 2023 IEEE Frontiers in Education Conference (FIE) (pp. 1–5). IEEE. https://doi.org/10.1109/FIE58773.2023.10342970
10. Osunbunmi, I., Shih, B. P. J., Cutler, S., & Perez, C. (2025). WIP: Developing a generative AI literacy module for engineering graduate teaching assistants: A model for engineering education. In 55th IEEE Annual Frontiers in Education Conference, FIE 2025—Conference Proceedings. IEEE. https://doi.org/10.1109/FIE63693.2025.11328161
11. Sirnoorkar, A., Zollman, D., Laverty, J. T., Magana, A. J., Rebello, N. S., & Bryan, L. A. (2024). Student and AI responses to physics problems examined through the lenses of sensemaking and mechanistic reasoning. Computers and Education: Artificial Intelligence, 7, 100318. https://doi.org/10.1016/j.caeai.2024.100318
12. Pham, T., Nguyen, B. T., Ha, S., & Nguyen Ngoc, T. (2023). Digital transformation in engineering education: Exploring the potential of AI-assisted learning. Australasian Journal of Educational Technology, 39(5), 1–19. https://doi.org/10.14742/ajet.8825