

Design and Development of an AI Chatbot-Assisted Learning Module on Magnetic Fields for Alternative Delivery Mode (ADM) in Education in Emergencies (EiE)

Sharmaine D. Degorio^{1*}, Mauricio S. Adlaon²

¹ Department of Education, Dinagat School of Fisheries

² Surigao del Norte State University

* sharmaine.degorio@deped.gov.ph, madlaon@ssct.edu.ph

Date Submitted:

May 10, 2026

Date Accepted:

May 15, 2026

Date Published:

May 29, 2026

DOI:

10.5281/zenodo.20431692

ABSTRACT

Due to its conceptual complexity, senior high school students find learning abstract physics concepts, such as magnetic fields, challenging adding the frequent instructional disruptions. To maintain instructional continuity, the Department of Education widely used the Alternative Delivery Mode (ADM) modules, but existing materials often lack interactivity and scaffolding, limiting engagement and learning outcomes. With this, the present study examined the effectiveness of an AI Chatbot-Assisted Learning Module on Magnetic Fields for ADM in Education in Emergencies (EiE), focusing on students' physics performance, motivation, and engagement. Using an explanatory sequential mixed-methods design, data were collected from 10 Grade 12 STEM students

through AI-guided learning activities and the Physics Motivation Questionnaire II. Quantitative results showed high student performance across all criteria with an average score of 66.2/80, marked as Excellent and generally positive motivation ($M = 3.00$, $SD = 0.87$). Correlation analysis indicated a weak, non-significant relationship between performance and motivation ($r = 0.277$, $p = 0.529$). Qualitative analysis revealed that AI guidance reduced cognitive load, provided step-by-step explanations and relatable examples, and adopted self-regulated learning strategies such as planning, monitoring, and reflection. These findings suggest that AI-integrated ADM modules can enhance conceptual understanding, self-regulation, and engagement in physics, offering a learner-centered, and interactive instructional approach. The study provides practical support for integrating AI chatbots into secondary science education to improve both learning outcomes and motivation.

Keywords: *AI chatbot, alternative delivery mode, magnetic fields, physics motivation, self-regulated learning, cognitive load theory, education in emergencies*

INTRODUCTION

Senior High School students, find learning physics, particularly abstract topics such as magnetic fields and electromagnetism challenging due to its conceptual complexity, reliance on mathematics, and deep cognitive demands (Fonseca & Costa, 2023; Liang et al., 2025; Zavala et al., 2025). Research shows that students struggle to integrate mathematical skills with physical reasoning and often face persistent

misconceptions in field-related topics, which traditional instructional approaches do not adequately address (Liang et al., 2025; Zavala et al., 2025). These challenges are further deepened because of the frequent disruption of classes, limiting opportunities for guided explanation, practice, and feedback (Department of Education, 2020).

In the Philippine basic education system, the implementation of Alternative Delivery Modes (ADM), particularly self-learning modules, is needed to ensure continuity of instruction because of the frequent class disruptions caused by weather disturbances, school activities, and emergency situations (DepEd, 2020). While ADM modules have been effective in maintaining access to learning materials, several studies report that many existing modules are overly text-heavy, minimally interactive, and provide limited scaffolding, which can negatively affect students' comprehension and motivation especially in science subjects such as physics (Dangle & Sumaoang, 2020; Abadiano & Turner, 2021).

Student motivation is an important factor influencing learning outcomes in physics. Research has consistently shown that motivated learners demonstrate higher engagement, persistence, and academic performance in science subjects (Glynn et al., 2020). On the other hand, poorly designed self-learning materials may contribute to reduced interest, surface learning, and disengagement, particularly when students are left to learn independently without timely feedback or clarification (Schunk & DiBenedetto, 2020). This is why there is the need for instructional materials that not only deliver content but also actively support learners' motivation and self-regulation, essential for effective independent learning.

Recent advances in artificial intelligence (AI), particularly AI chatbots, have been shown to provide immediate feedback, simplified explanations, adaptive support, and learner-controlled pacing, which are essential features in independent learning contexts (Okonkwo & Ade-Ibijola, 2021). Studies indicate that AI-assisted learning tools can positively influence students' understanding and academic performance by acting as virtual tutors that scaffold learning rather than simply provide answers (Kasneci et al., 2023; Katz et al., 2024). Moreover, AI-supported instruction aligns well with self-paced and learner-centered approaches required in ADM settings.

Despite the numerous researches on AI in education, there remains a gap in the development and evaluation of AI-integrated ADM modules for senior high school physics. Most existing ADM materials rely on explanations and exercises, while current AI studies often focus on higher education or online platforms rather than print-ready learning modules designed for secondary education (Zawacki-Richter et al., 2019). Additionally, none has examined how AI-assisted ADM materials influence both students' academic performance and their motivation toward physics, or how these two variables may be related.

This study aims to determine the effectiveness of an AI Chatbot-Assisted Learning Module on Magnetic Fields for Alternative Delivery Mode (ADM) in Education in Emergencies (EiE). Specifically, it seeks to answer the following questions:

1. What is the level of students' physics performance in magnetic field concepts based on their outputs and scores in the AI-assisted learning activities embedded in the module?
2. What is the level of students' motivation toward physics after engaging with the AI Chatbot-Assisted Learning Module?
3. Is there a significant relationship between students' performance in the AI-assisted learning activities and their motivation toward physics?
4. How do students interact with and respond to the AI Chatbot-Assisted Learning Module, and what strategies do they use to learn magnetic field concepts independently?
5. In what ways does the AI Chatbot-Assisted Learning Module support students' cognitive processing, self-regulation, and engagement during independent learning?

By combining ADM principles with AI-assisted learning, this study responds to the need for innovative, learner-centered instructional materials that ensure continuity, quality, and engagement in physics education during instructional disruptions.

The findings of the present study aim to contribute to the improvement of ADM implementation, provide support for the integration of AI chatbots in self-learning modules, and offer practical view for teachers and curriculum developers seeking to enhance physics learning in disruption-prone educational settings.

Theoretical Background and Literature Review

This study is anchored on Cognitive Load Theory (CLT) by Sweller, Ayres, and Kalyuga (2011) and Self-Regulated Learning Theory (SRL) by Zimmerman (2002) to explain how an AI Chatbot-Assisted Learning Module supports student learning in an Alternative Delivery Mode (ADM) environment.

Based on Cognitive Load Theory, learning occurs when instructional materials are designed to optimize the limited capacity of working memory, allowing learners to process essential information and construct meaningful schemas in long-term memory. Instructional supports such as worked examples, chunked explanations, visual representations, and guided practice reduce extraneous cognitive load and promote germane cognitive processing, leading to improved conceptual understanding.

Self-Regulated Learning Theory explains how learners actively control their own learning through goal setting, strategic planning, self-monitoring, and self-reflection. Zimmerman's three-phase model; forethought, performance, and self-reflection describes how students plan their learning, monitor their understanding during tasks, and evaluate and adjust their strategies after completing learning activities.

In this study, the AI Chatbot-Assisted Learning Module serves as the instructional environment that simultaneously supports cognitive processing and self-regulated learning. The AI provides step-by-step explanations, examples, and visual prompts that reduce cognitive overload, while its interactive prompts and reflective questions encourage students to monitor their understanding, explain their reasoning, and adjust their learning strategies.

The conceptual framework assumes that when AI-assisted activities are aligned with CLT and SRL principles, students will demonstrate observable learning behaviors such as chunking of information, use of examples, reflective explanations, self-monitoring, and adaptive strategy use. These cognitive and self-regulatory behaviors are expected to lead to improved physics performance and higher motivation toward learning.

METHODS

Research Design

This study employed an explanatory sequential mixed-methods design to examine how an AI Chatbot-Assisted Learning Module influences students' physics performance and motivation in an Alternative Delivery Mode (ADM) setting. This design involved two phases: a quantitative phase followed by a qualitative phase, where the second phase was used to explain the results of the first.

In the quantitative phase, students' physics performance was measured using their scores and outputs from AI-assisted learning activities embedded in the module, while their motivation was assessed using the Physics Motivation Questionnaire II (PMQ-II). These data provided numerical evidence of the effectiveness of the AI-assisted module.

In the qualitative phase, students' written explanations, reflections, and responses generated during the AI-assisted activities were analyzed to explain how learning occurred. This analysis was guided by Cognitive Load Theory and Self-Regulated Learning Theory, focusing on students' use of strategies such as chunking information, applying worked examples, monitoring understanding, and reflecting on their learning. The integration of quantitative and qualitative results allowed the study to not only determine whether the AI-assisted module was effective but also to explain why and how it influenced students' learning and motivation.

Context

In this study, the AI Chatbot-Assisted Learning Module is implemented as a self-learning instructional resource on Magnetic Fields within the Alternative Delivery Mode (ADM) under the Education in Emergencies (EiE) program of the Philippines' Department of Education (DepEd). The module is designed to support senior high school STEM students in a disruption-prone environment, where face-to-face instruction is limited or not feasible. It provides structured explanations, guided AI prompts, and interactive exercises that allow students to explore and understand the abstract concepts of magnetic fields, including magnetic force, flux, and the motion of charged particles. To contextualize learning, the module incorporates examples and activities that relate magnetic phenomena to everyday life and local environmental contexts, enabling students to connect scientific concepts with practical applications. Through the module, students engage with pretests and posttests to monitor learning gains, and respond to AI-guided tasks that encourage reflection, reasoning, and self-directed learning. This setup allows the module to function as both an instructional tool and an assessment platform, capturing students' cognitive and motivational responses in a real-world emergency learning context. A sample activity from *Competency 1: Differentiate electric interactions from magnetic interactions* is provided below:

AI-Guided Activity 1

Directions: Copy and paste the prompt below into your AI tool.

“Compare electric and magnetic interactions by giving two real-life situations where one interaction works but the other does not. Explain why this happens based on whether charges are moving or stationary.”

Follow-Up Activity

1. Give two examples of electric interactions.
2. Give two examples of magnetic interactions.
3. Explain why magnets do not affect stationary charges.
4. Which interaction is more common in daily life? Defend your answer.

Figure 1 .Sample Independent Learning Task Under Competency 1

Sampling and Participants

The study involved all 27 Grade 12 STEM students enrolled at Dinagat School of Fisheries for School Year 2025–2026, using complete enumeration. These students were selected because Physics is part of their specialized curriculum, and the AI-Guided Self-Learning Module on Magnetic Fields aligns with the Grade 12 STEM Physics third-quarter syllabus. Participants, who are also the researcher's advisees, are expected to have foundational knowledge in basic electricity but limited exposure to magnetic field concepts, allowing the study to evaluate the module's clarity, usability, and potential effectiveness. Participation was voluntary, and students were assured that involvement would not affect academic standing.

Due to time constraints and the ADM setup, not all students completed every stage of the study. Out of 27 students, only 10 completed both the activities in module and the Physics Motivation Questionnaire II (PMQ-II). Data analyses were therefore conducted using the responses of these 10 students.

Research Instruments

The study utilizes several research instruments to collect data on students' learning and motivation. First, a Table of Specifications (TOS) was constructed to guide the development of the researcher-made pretest and posttest, ensuring that the assessment items are aligned with the learning objectives of the AI Chatbot-Assisted Learning Module on Magnetic Fields and cover all cognitive levels appropriately. The pretest and posttest serve as quantitative tools to measure students' physics performance before and after exposure to the module. Second, students' motivation toward physics is assessed using the Physics Motivation Questionnaire II (PMQ-II), adapted from Glynn, Taasobshirazi, & Brickman (2011), which evaluates factors such as self-efficacy, interest, and career motivation in learning physics.

Finally, the AI Chatbot-Assisted Learning Module itself functions as both the intervention and a key instrument, providing structured explanations, guided AI prompts, and interactive exercises designed to facilitate self-directed learning under the Alternative Delivery Mode (ADM) in Education in Emergencies (EiE). Together, these instruments ensure that the validity and reliability of the data on students' conceptual understanding, motivation, and engagement with AI-guided self-learning.

All of the instruments used were subjected to expert validation through informal consultation with three specialists. An elementary teacher from Aurelio highly trained in Self-Learning Modules (SLMs) reviewed the instrument for technicalities, alignment with ADM standards, and suitability for independent learning, and recommended minor improvements particularly in visual presentation. A Master Teacher in Science examined the questionnaire and Table of Specifications (TOS) and confirmed that the items were aligned with the learning objectives and appropriately distributed across cognitive levels, with only minor refinements suggested for clarity. An English teacher evaluated the instrument for grammar, clarity, and readability, affirming that the items were clearly worded and appropriate for the target learners. Overall, the validators agreed that the questionnaire was valid and appropriate for use after incorporating the recommended revisions.

Data Collection and Data Analyses

Data were collected in two phases following the explanatory sequential mixed-methods design. During the quantitative phase, students engaged with the AI Chatbot-Assisted Learning Module on Magnetic Fields. Their physics performance was measured using their scores and outputs from the AI-assisted learning activities, which were evaluated using a researcher-developed analytic rubric. Students' motivation toward physics was measured after module implementation using the Physics Motivation Questionnaire II (PMQ-II).

Descriptive statistics, including mean and standard deviation, were used to determine the levels of students' performance and motivation. Correlational analysis was employed to examine the relationship between students' performance in AI-assisted learning activities and their motivation toward physics.

In the qualitative phase, students' written explanations, problem-solving steps, and reflective responses generated during the AI-assisted activities were subjected to theory-driven qualitative analysis. Guided by Cognitive Load Theory (CLT) and Self-Regulated Learning Theory (SRL), responses were coded for evidence of key learning processes, including chunking of information, use of worked examples and analogies, schema construction, self-monitoring, strategic regulation, and reflective evaluation of understanding. These qualitative findings were used to explain the quantitative results by identifying how the AI-assisted module supported students' cognitive processing and self-regulated learning during independent study.

Ethical Considerations

The study adhered to ethical standards in research involving human participants. Informed consent was obtained from all students and, where applicable, their parents or guardians. Participation was voluntary, and students were assured of confidentiality and anonymity in the handling and reporting of data. All collected information was used solely for research purposes, and no personal identifiers were disclosed.

RESULTS AND DISCUSSION

Students' Performance in Magnetic Fields

Students' performance in magnetic field concepts was evaluated based on their outputs in the five AI-Chatbot-Guided learning activities, aligned with the four target competencies: (1) differentiating electric and magnetic interactions, (2) evaluating magnetic flux, (3) describing the motion of charged particles in a magnetic field, and (4) evaluating the magnetic force on a current-carrying wire. Each activity was scored using a four-criterion analytic rubric; Conceptual Accuracy, Clarity of Explanation, Application of Concepts, and Reflection/Insight, with a maximum score of 16 points per activity. The total possible score across all activities was 80 points.

Table 1. *Students' Performance by Rubric Criterion and Overall Total (AI-Guided Activities)*

Rubric Criterion	Mean	SD	Performance Level
Conceptual Accuracy	16.0	1.2	Excellent
Clarity of Explanation	16.2	1.0	Excellent
Application of Concepts	17.0	1.1	Excellent
Reflection/Insight	17.0	1.3	Excellent
Total Score (out of 80)	66.2	5.3	Excellent

Legend: 80–100% = Excellent, 60–79.99% = Good, 40–59.99% = Fair, Below 40% = Needs Improvement

The results indicate that students achieved a high level of performance across all rubric criteria. The highest scores were observed in Application of Concepts and Reflection/Insight, suggesting that the AI module particularly supported students' ability to apply magnetic field concepts and reflect on their learning. Conceptual Accuracy and Clarity of Explanation were also excellent, indicating that students effectively understood the content and could articulate it clearly. The overall total score of 66.2 (SD = 5.3), corresponding to 82.8% of the maximum possible score, confirms that students' performance was in the Excellent category. The results confirm the effectiveness of AI Chatbot-Assisted Learning Module's effectiveness in scaffolding both understanding and reflective thinking of the respondents in physics. Similarly, Jiang and Jiang (2025) reported that an LLM-powered physics tutoring system significantly improved students' scores and efficiency on conceptual and computational tasks by providing step-by-step guidance and reflective learning opportunities. Also, Becker et al. (2025) found that AI chatbots offering interactive scaffolding reduced intrinsic and extraneous cognitive load and fostered positive affective engagement, highlighting the dual role of AI in supporting both cognitive processing and motivation in physics learning.

Students' Motivation in Physics

Table 2. *Descriptive Statistics of Students' Motivation by Dimension*

Motivational Dimension	Mean	SD	Verbal Interpretation
Intrinsic Motivation	3.10	0.88	Motivated
Self-Efficacy	3.40	0.70	Motivated
Self-Determination	3.10	0.57	Motivated
Grade Motivation	3.40	0.84	Motivated
Career Motivation	2.80	0.63	Moderately Motivated

The students' motivation in physics, as measured using the PMQ-II, was generally positive across all dimensions (Table 2). Intrinsic Motivation had a mean of 3.10 (SD = 0.88), indicating that students were motivated by interest and personal enjoyment in physics activities. Self-Efficacy showed the highest score (M = 3.40, SD = 0.70), suggesting that students were confident in their ability to successfully perform physics tasks. Self-Determination also scored 3.10 (SD = 0.57), reflecting persistence, initiative, and active engagement in learning. Grade Motivation (M = 3.40, SD = 0.84) shows that academic achievement was an additional key driver of engagement. Career Motivation scored the lowest (M = 2.80, SD = 0.63), indicating that the relevance of physics to future career goals was moderately motivating for students.

Overall, students' motivation falls within the "Motivated" category, with the strongest influence from Self-Efficacy and Grade Motivation, and slightly lower influence from Career Motivation. These results suggest that the AI Chatbot-Assisted Learning Module effectively fostered engagement, confidence, and persistence, supporting students' sustained participation in physics learning under the Alternative Delivery Mode (ADM). This aligns with research showing that interactive and technology-mediated learning tools can enhance learners' self-efficacy, intrinsic motivation, and active engagement in complex scientific concepts (Glynn, Taasobshirazi, & Papadopoulos et al., 2023).

Relationship Between Students' Performance in the AI-Assisted Learning Activities and Their Motivation Toward Physics

Table 3. *Correlation Between Overall Physics Performance and Overall Motivation*

	Pearson's r	P-value	Interpretation
Performance and Motivation	0.277	0.529	Not Significant

Table 3 presents the correlation between students' overall performance in the AI-Chatbot-Guided learning activities and their overall motivation toward physics. Results show a weak positive relationship between performance and motivation ($r = 0.277$); however, this relationship was not statistically significant ($p = 0.529$).

This finding suggests that while students who demonstrated higher motivation tended to obtain slightly higher performance scores, the relationship was not strong enough to establish a reliable association within this sample. Such results are not uncommon in educational research, particularly in small-sample studies and in contexts where instructional scaffolding is strong. Prior studies in physics education have likewise reported weak or non-significant relationships between overall motivation and academic performance, indicating that other factors—such as instructional design, cognitive support, and guided feedback—may play a more direct role in influencing learning outcomes (Palwa et al., 2020).

Despite the non-significant correlation, descriptive results indicate that students demonstrated high overall performance in the AI-assisted learning activities (M = 66.2, SD = 5.3, out of 80), corresponding to an Excellent performance level, alongside generally motivated attitudes toward physics (Overall Motivation: M = 3.00, SD = 0.87). This suggests that engagement with the AI Chatbot-Assisted Learning Module supported both academic achievement and learner motivation, even if the two variables did not exhibit a strong linear relationship in this study.

These findings align with previous research indicating that technology-supported and scaffolded learning environments can simultaneously promote engagement and performance, even when motivation does not emerge as a direct statistical predictor of achievement (Stofile, 2020).

Students' Interaction with the AI Chatbot-Assisted Learning Module

Analysis of students' written responses and reflections revealed that the AI module supported independent engagement through mechanisms consistent with both Cognitive Load Theory (CLT) and Self-Regulated Learning Theory (SRL). Students reported that the guided structure of tasks, step-by-step

instructions, clear organization, and chunked explanations facilitated independent completion of activities with minimal confusion. One student noted, *“I liked how the AI showed me each step in solving the problem—it was easy to follow and I didn’t get confused,”* demonstrating reduced cognitive load and support for germane processing in line with CLT.

The AI’s use of analogies and concrete examples, such as comparing magnetic flux to rain falling on a tilted roof, enabled students to relate abstract physics concepts to familiar experiences. As one participant explained, *“The analogy helped me picture the flux. It’s like rain falling on a tilted roof, easier than just numbers,”* illustrating meaningful schema construction facilitated by the AI.

From a self-regulation perspective, students engaged in planning and self-monitoring strategies, including sequencing tasks and evaluating their understanding throughout activities. One student shared, *“I knew what I had to do first and could decide how to tackle each step on my own,”* reflecting active engagement with SRL principles and independent learning.

Cognitive Processing, Self-Regulation, and Engagement During Independent Learning

Further qualitative analysis revealed that the module enhanced both cognitive and self-regulatory processes. Students reported that AI guidance reduced extraneous cognitive load, allowing them to focus on core concepts and verify their understanding. One student stated, *“When I typed my answer and saw the AI explanation, I could see if I got it right or needed to rethink my steps,”* demonstrating germane cognitive processing and mental model construction in line with CLT.

Students also reflected on their performance and adjusted strategies after each task. A participant observed, *“After seeing how the AI solved it, I realized my method was okay but I could make it simpler next time,”* illustrating the self-reflection and strategy adjustment phases of SRL.

Finally, students found the module engaging and motivating. Only one student out of 10 explicitly mentioned that the AI *“wasn’t useful,”* the rest of the participants described the module as enjoyable, easy to follow, and supportive of independent task completion. One student remarked, *“It was nice and easy to follow. I could complete the tasks without getting stuck.”* These behaviors highlight the module’s role in promoting persistence, confidence, and motivation, consistent with SRL.

CONCLUSION

The study demonstrates that an AI Chatbot-Assisted Learning Module on Magnetic Fields effectively supports senior high school students’ physics learning in an Alternative Delivery Mode (ADM) environment. Students achieved high performance across all assessed competencies, particularly in applying concepts and reflecting on their understanding, while maintaining generally positive motivation toward physics. Although the correlation between performance and motivation was not statistically significant, qualitative analysis revealed that the AI module facilitated cognitive processing, reduced extraneous load, and encouraged self-regulated learning behaviors such as planning, monitoring, and reflection. Students reported that stepwise explanations, analogical examples, and interactive prompts enhanced comprehension, engagement, and persistence in independent study. These results suggest that integrating AI chatbots into self-learning modules can provide a learner-centered, interactive, and resilient instructional approach, particularly in disruption-prone educational contexts. The findings support the potential of AI-assisted ADM materials to simultaneously enhance conceptual understanding, self-regulation, and motivation in physics education.

References

- Abadiano, M. N., & Turner, J. J. (2021). Students' experiences with self-learning modules in distance education. *Asian Journal of Education and Social Studies*, 19(4), 1–10. <https://www.journalajess.com/index.php/AJESS/article/view/30462>
- Becker, E., Wünsche, J., Veith, J. M., Schrader, J., & Bitzenbauer, P. (2025). From cognitive relief to affective engagement: An empirical comparison of AI chatbots and instructional scaffolding in physics education. *arXiv*. <https://arxiv.org/abs/2508.06254>
- Centre for Education Statistics and Evaluation. (2017). *Cognitive load theory in practice: Examples for the classroom*. NSW Department of Education. <https://education.nsw.gov.au/content/dam/main-education/about-us/educational-data/cese/2017-cognitive-load-theory-practice-guide.pdf>
- Dantic, M. J. P., & Fularon, A. R. (2022). PhET interactive simulation approach in teaching electricity and magnetism among science teacher education students. *Journal of Science and Education*, 2(2), 88–98. <https://doi.org/10.56003/jse.v2i2.101>
- Dangle, Y. R. P., & Sumaoang, J. D. (2020). The implementation of modular distance learning in Philippine secondary public schools. *International Journal of Pedagogical Development and Lifelong Learning*, 1(1), Article ep2007. <https://doi.org/10.30935/ijpdll/9611>
- Department of Education. (2020). *Adoption of the basic education learning continuity plan for school year 2020–2021* (DepEd Order No. 012, s. 2020). https://www.deped.gov.ph/wp-content/uploads/2020/06/DO_s2020_012.pdf
- DepEd e-Saliksik. (2022). *Utilization of the self-learning modules (SLMs) as assessed by master teachers*. Department of Education. <https://e-saliksik.deped.gov.ph/>
- Fonseca, J. A., & Costa, M. F. (2023). Challenges in learning physics in high school public schools: A literature review. *Research, Society and Development*, 12(6), Article e42440642440. <https://doi.org/10.33448/rsd-v12i6.42440>
- Glynn, S. M., Brickman, P., Armstrong, N., & Taasoobshirazi, G. (2020). Science motivation questionnaire II: Validation with science majors and nonscience majors. *Journal of Research in Science Teaching*, 56(2), 237–268. <https://doi.org/10.1002/tea.21442>
- Hernández, E., Campos, E., Barniol, P., & Zavala, G. (2025). Students' understanding of electric flux and magnetic circulation and the role of the superposition principle in Gauss's and Ampère's laws. *Physical Review Physics Education Research*, 21(1), Article 010120. <https://doi.org/10.1103/PhysRevPhysEducRes.21.010120>
- Hidayah, N., Talakua, P., Abdul Azis, D., & Maipauw, M. (2024). Development of interactive learning media based on augmented simulation using PhET for magnetic field material. *Jurnal Pendidikan dan Ilmu Fisika*, 5(1), 12–25. <https://doi.org/10.52434/jpif.v5i1.42588>
- Jiang, Z., & Jiang, M. (2024). Beyond answers: Large language model powered tutoring system in physics education for deep learning and precise understanding. *arXiv*. <https://arxiv.org/abs/2406.10934>
- Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., ... & Kasneci, G. (2023). ChatGPT for education: Opportunities and challenges. *Learning and Individual Differences*, 103, Article 102274. <https://doi.org/10.1016/j.lindif.2023.102274>
- Katz, Y. J., Tepper, R., & Kim, J. (2024). Artificial intelligence tutors and student learning outcomes: A meta-analysis. *Computers & Education*, 195, Article 104693. <https://doi.org/10.1016/j.compedu.2023.104693>
- Maries, A., Brundage, M. J., & Singh, C. (2023). Using the conceptual survey of electricity and magnetism to investigate progression in student understanding from introductory to advanced levels. *arXiv*. <https://arxiv.org/abs/2311.17170>
- Okonkwo, C. W., & Ade-Ibijola, A. (2021). Chatbots applications in education: A systematic review. *Computers and Education: Artificial Intelligence*, 2, Article 100033. <https://doi.org/10.1016/j.caeai.2021.100033>
- Rafon, J. E. (2023). *Self-regulated interactive learning modules in physics: Improving students' problem-solving skills* (Doctoral dissertation, De La Salle University). Animo Repository. https://animorepository.dlsu.edu.ph/etdd_scied/29/
- Robinos, R. (2024). Teacher and student perspectives on AI integration in Philippine education. *Journal of Innovative Teaching and Learning*, 3(1), 45–62.

- Rodriguez, V. R., Dueñas, Z. D., & Collado, Z. C. (2024). Perceived effectiveness of self-learning modules in modular distance learning. *Journal of Learning and Development Studies*, 4(2), 115–128.
- Schunk, D. H., & DiBenedetto, M. K. (2020). Motivation and social cognitive theory. *Contemporary Educational Psychology*, 60, Article 101832. <https://doi.org/10.1016/j.cedpsych.2019.101832>
- Suba, M. A., & Manlapig, E. F., Jr. (2025). Development and evaluation of experiential learning with digital simulation (ELDS) modules in electricity & magnetism. *Journal of Research in Education and Pedagogy*, 2(2), 296–308. <https://doi.org/10.70232/jrep.v2i2.39>
- Thomann, J., et al. (2025). Scaffolding through prompts in digital learning: A review. *Educational Technology Research Journal*, 8(1), 12–38.
- Tong, T., Pi, F., Zheng, S., Zhang, Y., & Wang, J. (2025). Exploring the effect of mathematics skills on student performance in physics problem-solving: A structural equation modeling analysis. *Research in Science Education*, 55(3), 489–509. <https://doi.org/10.1007/s11165-024-10201-5>
- Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice*, 41(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2