Talking to Learn: A SoTL Study of Generative AI-Facilitated Feynman Reviews

Madeline Mattox[1] **Natalie Hutchins**[1] **Jamie Jirout**[1]
[1]University of Virginia
[1]Jirout@virginia.edu

Abstract

Structured Generative AI interactions have potential for scaffolding learning. This Scholarship of Teaching and Learning study analyzes 16 undergraduate students' Feynman-style AI interactions (N=154) across a semester. Qualitative coding of the interactions shows mostly low-level student responses, but some evidence that prompt structure may can promote higher-level cognitive engagement. Results show GAI provides metacognitive support, and suggest the potential of GAI-supported Feynman reviews to provide interactive, personalized learning experiences that align with theories of cognitive engagement and metacognitive support for learning.

1 Introduction

Generative Artificial Intelligence (GAI) technologies, such as ChatGPT, are becoming increasingly prevalent, including in higher education (HE) (Zhu et al., 2025; Kim et al., 2025; Sun & Zhou et al., 2024). GAI has the potential to support learning through on-demand explanation, feedback, and clarification, with research showing support for deeper understanding and more efficiency when used effectively (Zhu et al., 2025; Chan & Hu, 2023; Dong et al., 2025). Students report finding GAI interesting to use and that it makes learning more enjoyable, but both students and faculty have concerns around whether GAI may inhibit some types of learning and negatively impact social interactions during learning (Kim et al., 2025; Chan & Hu, 2023). This study explores the potential of GAI Feynman-Style review activities by assessing the quality of interactions and content experienced in an college course.

There is a need for research to assess GAI impacts on learning and to identify empirically supported practices and principles for its use in education. A broadly held perspective is that GAI is not going away and will become part of typical experiences (Batista et al, 2024). Although some researchers provide justifications for limiting or banning GAI use in HE (e.g., de Fine Licht, 2024), its use is quickly increasing across and reshaping the landscape of labor markets, and, as a result, changing the skillset and knowledge needed in near-future jobs (Resh et al., 2025). Thus, HE has a responsibility to teach GAI skills to prepare students for the future (UNESCO), and should find ways to implement GAI in some contexts, while teaching students and faculty how to best use it ethically and effectively (Zhu et al., 2025; Yang et al; Lee et al). This Scholarship of Teaching and Learning (SoTL) study describes one attempt to use GAI: GAI-facilitated Feynman-style reviews.

The Feynman method involves a student explaining a topic as if to a novice, and then responding to subsequent probing questions to clarify, elaborate on, or deepen the student's thinking and understanding (Reyes et al., 2021). This approach aligns with research on the benefits of self-explanation and teaching for learning, which show that generating simplified explanations promotes deeper processing and transfer of knowledge (e.g., Chi et al., 1994; Fiorella & Mayer, 2013). Most effective are interactive approaches that include self-explanation and teaching along with a knowledgeable partner, but these are resource-intensive; GAI offers potential to simulate the interactive Feynman technique in ways that are scalable and effective (Rajesh & Khan, 2024). For introductory subjects, GAI likely has sufficiently accurate models to assess and explain content, and the capacity to personalize questions and feedback based on students' demonstrated knowledge in real-time, similar to what an expert human teacher or tutor would do in this method. We tested this hypothesis by analyzing interactions between

Proceedings of the Artificial Intelligence in Measurement and Education Conference (AIME-Con) – Volume 2: Works in Progress, pages 117–124

students and GAI across a semester in an introductory infant and child development course.

To understand the potential learning experiences of these activities, this work was grounded in the ICAP framework (Chi & Wylie, 2014), which differentiates levels of cognitive engagement, from most shallow to deepest: passive, active, constructive, and interactive. GAI-guided Feynman interactions can be active or constructive, depending on whether students are simply recalling facts vs. explaining, constructing summaries, or creating examples. If students use GAI to co-construct ideas the engagement is considered interactive, in which GAI contributions shape and extend the student's thinking, resulting in new understanding that wouldn't emerge from the student alone. While true interactive engagement would involve reciprocal co-construction (Chi & Wylie, 2014), which is not possible in that the GAI does not experience conceptual change, it might simulate an interactive experience, and the student may have the benefit of that level of cognitive engagement. This type of interaction can also support metacognition by making gaps in understanding visible (Flavell, 1979; Schraw & Moshman, 1995), leading students to further develop their understanding of a topic. In this study, we analyze how GAI can scaffold cognitive engagement and metacognition through its questions and feedback as aligned with ICAP framework and theories of metacognitive support. Together, these frameworks provide the foundation for interpreting the quality of student–GAI interactions during Feynman-style reviews.

Aims

Prior research shows the Feynman approach is effective, but it is unknown whether the effectiveness would be similar with interactions facilitated using GAI. This study addresses this question using data from a small (N=29) undergraduate child development course taught at a mid-sized, highly selective public research university located in the southeastern United States. Students in the course used a GAI of their choice to complete assignments including Feynman-style dialogues (Reyes et al., 2021). In these assignments, students were challenged to explain course concepts in simple terms and then were asked questions by the GAI to assess and refine their understanding while given feedback after each response. The current study explored the questions and feedback provided by the GAI, and the student responses elicited through the interactions [1] to understand the efficacy of this method for providing effective personalized learning experiences,. Our specific aims included:

1. Identify patterns of student engagement with GAI tools through these dialogues.
2. Explore how GAI can support metacognitive processes, such as explanation and clarification.
3. Assess the consistency and quality of these GAI responses.

2 Methods

2.1 Sample

Participants included students who opted in from the target course, of which 16 students consented to have their course materials included. Participants were 94% female, majoring in education (N=8; including Youth and Social Innovations, Speech and Communications Disorder, Kinesiology), arts and sciences (N=6; including undeclared, behavioral neuroscience, and psychology), and engineering (N=2; including undeclared and computer science), and were in their 1st (N=1), 2nd (N=5), 3rd (N=9), and 4th (N=1) year of college.

2.2 Study Design

This study used a qualitative research design to explore undergraduate student engagement with AI tools. Data were collected using a course management system, on which students completed bi-weekly assignments including Feynman-style interactions with a GAI of their choice. For each assignment, students were given a GAI prompt for a Feynman style review for each of two topics covered since their last review (see Figure 1 for an example prompt).

For each review question, a prompt was provided for students to copy into any GAI platform of their choice, which initiated a Feynman style review beginning with the student summarizing the topic and then asking six follow-

[1] The course was taught by the senior author. Data of consenting students were deidentified and analyzed only after the course ended, and the study was conducted with IRB approval.

up questions, providing feedback after each response. Students copied/pasted their full interaction into an assignment, which were then exported, de-identified, and compiled for coding and analysis at the utterance level. Three types of data were coded: GAI question prompts, GAI feedback, and student responses.

> Instructions: put the prompts below into your preferred GenAI platform to test your understanding of this topic. (Remember, using CoPilot behind [University Licensed program] allows you to not need to create a new account, but you may use any platform you prefer). Copy your full interaction with the GenAI platform as your responses in the two text boxes provided.
>
> "I want to test my understanding of children's language development using the Feynman method. Consider that I have read short articles that provided examples of children's language learning from experiences and learning processes like referential ambiguity, fast-mapping, and the vocabulary spurt. I've also had about two hours of time learning about these topics, including discussion of receptive and productive language. Use this information about readings and time learning to estimate the level of my knowledge. I'll explain the concept as if I'm teaching it to a beginner. Please ask me one question at a time with about 6 questions total, challenge unclear points, and identify areas where I need more depth or could simplify. After the dialogue, provide a summary of my understanding, highlighting strengths and areas for improvement."

Figure 1: Instructions and example prompt text provided to students for the generative AI (GAI)–based Feynman-style review activity.

2.3 Coding

A subset of student-GAI interactions was read and discussed among the project team to identify codes that would be useful in answering the research questions, and that were possible to observe when reviewing the interactions. Coding categories were informed by the ICAP framework and models of metacognitive regulation to reflect higher and lower levels of cognitive engagement and examples of metacognitive support (Chi & Wylie, 2014; Flavell, 1979; Schraw & Moshman, 1995). This led to the decision to code GAI questions, student responses, and GAI feedback to responses as separate types of data, each with specific categories aligned with these frameworks and the research aims. The dataset was further divided into utterances to be coded, identified as the smallest segment of text conveying a single, complete idea or meaning. Utterances were all coded descriptively as GAI questions/prompts, student responses, or GAI feedback. Multiple codes could be assigned to an utterance, and if none were assigned there was an 'other' code. The following coding categories of each type were used:

GAI Question Codes

<u>Asking For Examples.</u> Prompt to illustrate a concept using a specific, real-life, or hypothetical example of a concept. Example: "Can you explain this concept through a real-life example?"

<u>Asking For Comparisons.</u> Prompt to analyze the relationships between two or more ideas, particularly their similarities or differences. Example: "Can you briefly compare their Piaget's and Vygotsky's views?"

<u>Simple Question.</u> Prompt for recall or evidence of comprehension, such as to define, describe, or explain a concept or multiple concepts without asking for comparison, contrast, application, revision, analysis, etc. Example: "What is Bronfenbrenner's Ecological Model?"

<u>Asking for further information:</u> Prompt requests clarification. Example: "Can you explain what you mean by critical periods in this context?"

<u>Elaboration of Ideas:</u> Prompt eliciting further elaboration related to what a student responded. Example: "Now let's push further: Can you think of an example of how sensory exploration leads to a deeper understanding of an object?"

<u>Opportunity to revise a response:</u> Prompt for student to change their response in a specific way. Example: "How might you reword that to better distinguish between the microsystem and the mesosystem?"

<u>Explicit reference to response:</u> While several prompts built on students' responses, some explicitly referenced what students said before giving one of the above prompts. Example: "you mentioned the microsystem..." (followed by a question or prompt).

<u>Prefacing question:</u> Prompt provided information that was not in the form of a request or question, but more often giving background or information to contextualize the coming question.

Example: "You've read about how attachment might differ across racial backgrounds."

Student Response Codes

Admitting uncertainty: Student explicitly acknowledges a lack of knowledge, confidence, or clarity about how to answer all or part of the AI's question. Example: "I understand Piaget's theory, but I don't know how to apply it here."

Giving examples: Student gives an example (spontaneously or prompted) to illustrate, apply, or demonstrate understanding of a concept, or to clarify or apply a concept. Example: "Sure, an example of a mesosystem could be the relationship between a child's parents and their teacher."

Making comparisons: Student discusses talking about the differences or similarities between aspects of a concept (spontaneously or prompted); responses reflect relational understanding, such as highlighting how two concepts differ, explaining what two theories have in common, showing contrast in function, impact or structure. Example: "Unlike the mesosystem, the Microsystem involves direct interaction with the child".

Giving a simple response: Student responds with a fact explanation requested, without including examples, comparisons, or other deeper-level information that goes beyond what was asked. Example: "The layers include the micro, meso, exo, macro, and chronosystem."

GAI Feedback Codes

Examples: The GAI provides an example to help illustrate or clarify a concept. Example: "For instance, when a child takes deep breaths to calm down after being frustrated, that's a form of self-regulation."

Correcting: GAI explicitly identifies part or all of what the student has said is incorrect and provides a corrected explanation. Example: "Not quite—the macrosystem isn't a physical place. It refers to cultural values and norms."

Affirming: GAI provides supportive or validating praise or encouragement, indicating the student is correct or on the right track. Example: "Nice work explaining that."

Expanding: GAI builds on a student's response by offering additional information, elaboration, or nuance, pushing the idea further. Example: "You're right that secure attachment helps with emotional regulation. In fact, research shows it can influence stress response systems as well."

3 Results

To identify patterns of student engagement with GAI tools (Aim 1), and specifically for metacognitive support and related responses (Aim 2), we provide descriptive patterns of individual codes for each aspect of the student-GAI interaction, showing the frequency of occurrence of each code and the relative occurrence. To assess consistency and quality of these GAI responses (Aim 3) we use unconditional multilevel models to estimate intraclass correlation coefficients for each aspect of the GAI interaction (interactions nested with students).

The content of the 154 student-GAI full interactions was segmented into codable utterances, resulting in 2686 utterances coded within GAI questions (text written by the GAI). Of these, 2315 received one or more of our target codes (non-target codes included utterances not related to the content, such as, "I'm excited to hear what you have to say.") In student responses, a total of 2994 utterances were coded, of which 2979 were coded with a target code (e.g., a student beginning their response with, "yes, I can do that." before responding) and in feedback to responses, a total of 4934 utterances were coded, of which 4221 were coded with a target code (e.g., simply restating the student's response).

At the student level, for each student-GAI interaction, students, on average, received 17.4 GAI question utterances (SD=3.23), responded in 19.8 utterances (SD=4.57), and received 32.2 GAI feedback utterances (SD=10.7). As a reminder, individual utterances could include multiple content codes, but only one descriptive code identifying the utterance as a question, response, or feedback (i.e., a question asked that built off a student's response would not also be assigned feedback codes even if feedback was implied, such as asking for clarification).

3.1 Aim 1: Types of GAI Questions, Student Responses, and GAI Feedback

The utterances segmented for GAI questions, student responses, and GAI feedback were coded for one or more codes within each of the respective types. The frequencies of each are presented in Tables 1-3, respectively, including the number of observations receiving each code (Total Obs.), average observation per interaction (Mean Obs.), and proportion of all coded utterances (% of

GAIQ) are presented by utterance types (GAI questions - GAIQ, student responses - SR, GAI feedback - GAIF). Items with asterisks are those considered supportive of metacognition.

GAI Question Type	Total Obs.	Mean Obs.	% of GAIQ
Asking for examples*	311	2.0	13%
Asking for comparisons*	208	1.3	9%
Simple question	931	5.9	38%
Asking for further info. *	108	0.7	4%
Elaboration of ideas*	605	3.9	25%
Opportunity to revise*	24	0.2	1%
Explicit reference to response	196	1.2	8%
Prefacing question	61	0.4	2%

*indicates category supportive of metacognition

Table 2: Descriptive information for the types of GAI Questions observed.

Student Response Type	Total Obs.	Mean Obs.	% of GAIQ
Admitting uncertainty	12	0.1	0.4%
Examples (prompted) *	348	2.2	11%
Examples(unprompted) *	154	1.0	5%
Comparisons (prompted) *	111	0.7	4%
Comparisons (unprompted) *	25	0.2	1%
Simple correct response	2401	15.3	78%
Simple incorrect response	23	0.1	1%

*indicates category supportive of metacognition

Table 1: Descriptive information for the types of student responses observed.

GAI Feedback Type	Total Obs.	Mean Obs.	% of GAIQ
Examples*	299	1.9	7%
Correcting	347	2.2	8%
Affirming	2324	14.8	54%
Expanding*	1356	8.6	31%

*indicates category supportive of metacognition

Table 3: Descriptive information for the types of GAI Feedback observed.

3.2 Aim. 2: Metacognitive Support

Codes in each category identified as having potential to support metacognition are those that elicit reflection and deeper cognitive engagement in alignment with the ICAP theory and models of metacognitive reflection. We created composite scores for how frequently these high-support utterances appeared in the interactions. For the GAI questions, higher support codes included the prompts related to clarifying, elaborating or applying, revising, or comparing and contrasting, or giving examples. For the student responses, high support codes included giving examples and comparisons, and we looked separately at when these were given in response to a specific prompt or were unprompted. For feedback, high support included giving examples and expanding.

Utterances receiving codes identified as potentially highly supportive for metacognition included 945 GAI questions, 638 student responses, and 1655 feedback utterances. Proportionally, this was 39% of the GAI question codes, 13% of student responses, and 38% of GAI feedback. There were, of course, sources of variability across students and across the different topics reviewed in the assignments, so we explore the amount of variability both between students and across questions in these high-support composites as well as low composites to explore stability in the interaction quality.

3.3 Aim 3: Consistency and Quality

To explore interaction consistency, we compare the intraclass correlation coefficients (ICC) to understand whether the amount of variability at the level of students (i.e., individual differences explaining differences in the patterns of codes, P-ICC) compared to the level of variability at the topic level, nested within student (i.e., variability explained by differences in the prompts students pasted in for each topic).

At a basic level, we first estimated ICCs for the number of questions students received and the overall number of utterances observed in each of the three data types. Intraclass correlation coefficients (ICCs) indicated that a low proportion of variance in the number of GAI question utterances was explained by either the question/topic across semester or individual differences across students (person ICC = .099; question ICC= .027). In contrast, higher person ICCs for student responses and GAI feedback at the student level suggest some consistency in the number of utterances students made in their responses across activities (person ICC = .428; question ICC= .074), and moderate consistency in the number of feedback utterances they were given across activities in response to those utterances (person ICC = .214; question ICC= .065) ,.

To explore the *quality* of interactions, the composites described above for metacognitive support were assessed similarly to estimate person and question ICCs. We estimated ICCs (both low and high) when predicting the composite scores of GAIQ quality, SR quality (including low quality and prompted vs. unprompted high-quality responses), and GAIF quality (low and high). Results for the analyses are presented in Table 4.

Composite Score Type	P-ICC	Q-ICC
GAIQ – Low	.026	.295
GAIQ – High	.133	.037
SR – Low	.390	.072
SR – High, prompted	.037	.296
SR – High, unprompted	.120	.077
GAI Feedback – Low	.136	.050
GAI Feedback – High	.192	.104

Table 4: Intraclass correlation coefficients (ICCs) at the person level (P-ICC) and question level (Q-ICC) for composite coding categories.

ICCs indicated that reliability varied across coding categories, with some dimensions showing greater variance attributable to students (higher P-ICCs; e.g., SR–Low = .390) and others showing greater variance attributable to questions nested within students (higher Q-ICCs; e.g., GAIQ–Low = .295, SR–High, prompted = .296). These patterns suggest that some aspects of the coding (e.g., low-level, simple student responses) are more consistent across individual students, whereas others (e.g., types of GAI questions or student high-level responses when prompted) vary more at the topic/prompt level.

4 Discussion

Students' GAI interactions during a Feynman-style review show clear patterns of engagement between students and the GAI, in which students are providing many responses to provided questions. Students receive feedback both about their accuracy and understanding, and also feedback to expand their current knowledge. While there were clear individual differences explaining some variability in students responses (e.g., 39% of variability in simple responses provided), there was also indication that the prompts to initiate the activity also explain variability in responses (e.g., 30% of the variability of deeper-level student responses).

Our first two aims were to identify patterns of student engagement with GAI tools and explore how GAI can support metacognitive processes. We observed that the most common GAI Question type was simple questions (38%), but 39% of the GAI questions were considered higher-level, such as encouraging elaboration of ideas and prompting for examples or application of information. These align with ways of encouraging deeper cognitive engagement, which support greater learning (Chi & Wylie, 2014). Yet, students overwhelmingly gave simple correct responses (78%) with relatively few examples (16%) or comparisons (5%), regardless of prompting. One possibility is that the platform design of exchanging back-and-forth text with GAI might encourage short responses that can't convey as much depth (Torricelli et al., 2024).

The GAI feedback students received predominantly pushed them to expand their ideas (54%), which could help in revising knowledge (Chi & Wylie, 2014). Feedback affirming the student (34%) could promote self-efficacy and motivation (Zimmerman, 2000). The high rate of affirming feedback presents a valuable opportunity for students to receive positive reinforcement, much like they may receive from a supportive tutor or peer. Receiving real-time, responsive feedback can scaffold metacognition and reflection.

Of note, very few students admitted uncertainty (<1%) or gave incorrect responses (1%) suggesting that students either felt confident and actively engaged in looking up more information before responding, were not encouraged to express doubt or explore alternatives, or perhaps didn't experience uncertainty. It is also possible that the design of the activity, beginning with the students' current level of understanding, did not sufficiently challenge students. Future research should further explore whether students were guided to recognize their knowledge gaps and address them before or during their response, or whether prompts might be useful to create clear gaps in knowledge for students to experience and work through to support their learning (Loibl & Rummel, 2014).

Our third aim was to assess the consistency and quality of GAI interactions, and we observed somewhat variable patterns. Simple student responses were more consistent across individual students, with similar patterns within student in how frequently (or rarely) they give simple, low-level responses across topics of reviews. Further support that this is due to individual differences in students was that there was variability in the GAI low-level questions attributable to the prompts, yet this was not reflected in the student responses. On the other hand, a much higher portion of the variability in *high-level* student responses was attributed to the prompt used to initiate the activity (30%) than that explained at the student-level (4%), though only for high-level responses that were prompted. This suggests the potential importance of prompts to promote deeper cognitive engagement from students, and the opportunity for prompt engineering to elicit this depth.

This work demonstrates how interactive dialogue with GAI can provide meaningful and personally responsive questioning and feedback to students, supporting self-assessment in a low-stakes, formative approach. At a broader level, these assignments can help to support students' understanding of the ways GAI can be used to support learning, and to get exposed to and practice with prompt engineering, supporting the need for developing skills with AI in productive ways. It can also provide a more personalized and engaging way to review material outside of the classroom, and this specific activity is one model for incorporating new technology to encourage learning and critical thinking.

5 Limitations and Future Research

Limitations to this work include in its small sample size representing limited educational experiences. The students participating only represented about 55% of the class studied, and the class itself was a small, interactive class (29 students total). Future research could study similar patterns of interaction in other types of courses to explore whether the patterns observed here generalize. This work is also limited in its exploratory and correlational design, and in not including learning assessments separate from the activity studied. It will be important for future work to assess learning and link it to the interaction experiences. This work can be used to inform further work using control groups and outcome measures to assess the specific influences of the GAI in facilitating the Feynman experiences, including experimental tests of how to best promote high-quality interactions and learning.

The results presented here are a first step in exploring GAI-facilitated Feynman-style review interactions for learning. In addition to collecting more data to increase the students and content represented, the data presented here can be further analyzed to explore reciprocal dynamics in student–AI interactions, allowing us to predict what types of utterances lead to higher cognitive engagement. The dynamic sequence of reflection and revision in reciprocal dialogue is what matters for learning (Chi & Wylie, 2014), so looking at sequences of utterances will be meaningful to understand how these activities can provide meaningful learning experiences. We will also do further analysis of the characteristics of the prompts that students copied into the AI platform, coding for features such as length, specificity, and thematic focus, informing future design of prompts that can elicit higher quality interactions.

6 Conclusion

Feynman-style reviews using GAI can provide an interactive, personalized learning activity. Typical experiences with traditional quizzes used for review elicit low-level, simple responses, which these activities also showed. However, there was also evidence of metacognitive support during the interactions between GAI and students. Importantly, the results suggest that higher-level constructive or interactive engagement, which is conducive of greater learning, was more dependent on the contextual scaffolding provided by GAI prompts, indicating the potential for prompt engineering to support high-level cognitive engagement and learning in a personalized, scalable modality.

Acknowledgments

This work was supported by the National Science Foundation under Grant No. 2145478. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation. Implementation of the Feynman activity was part of course innovation supported by a Thrive grant from the UVA Center for Teaching Excellence. MM received summer support for part of this research from a UVA TYDE grant. Training support for NH, including contributions to the research reported here, is supported by the Institute of Education Sciences, U.S. Department of Education, through Grant R305B200005 to the University of Virginia. The opinions expressed are those of the authors and do not represent views of the Institute or the U.S. Department of Education. We are grateful to Abigail Wilson and Maddie Zipper for their help with reliability coding and formatting the datasets for coding, along with Genesis Cartegena and Taylor Goree. We are especially thankful for Abby Krissinger for support with data management and preparing the data for coding and analysis, along with providing input across stages of the project.

References

Batista, J., Mesquita, A., & Carnaz, G. (2024). Generative AI and higher education: Trends, challenges, and future directions from a systematic literature review. *Information,* 15(11), 676.

Chan, C.K.Y., Hu, W. Students' voices on generative AI: perceptions, benefits, and challenges in higher education. *Int J Educ Technol High Educ* 20, 43 (2023). https://doi.org/10.1186/s41239-023-00411-8

Chi, M. T., De Leeuw, N., Chiu, M. H., & LaVancher, C. (1994). Eliciting self-explanations improves understanding. *Cognitive science, 18*(3), 439-477.

Chi, M. T., & Wylie, R. (2014). The ICAP framework: Linking cognitive engagement to active learning outcomes. *Educational psychologist, 49*(4), 219-243.

de Fine Licht, K. (2024). Generative artificial intelligence in higher education: Why the 'banning approach' to student use is sometimes morally justified. *Philosophy & Technology,* 37(3), 113.

Dong, L., Tang, X., & Wang, X. (2025). Examining the Effect of Artificial Intelligence in Relation to Students' Academic Achievement in Classroom: A Meta-Analysis. *Computers and Education: Artificial Intelligence,* 100400.

Fiorella, L., & Mayer, R. E. (2013). The relative benefits of learning by teaching and teaching expectancy. *Contemporary Educational Psychology, 38*(4), 281-288.

Kim, J., Klopfer, M., Grohs, J. R., Eldardiry, H., Weichert, J., Cox, L. A., & Pike, D. (2025). Examining Faculty and Student Perceptions of Generative AI in University Courses. *Innovative Higher Education*, 1-33.

Lee, D., Arnold, M., Srivastava, A., Plastow, K., Strelan, P., Ploeckl, F., ... & Palmer, E. (2024). The impact of generative AI on higher education learning and teaching: A study of educators' perspectives. *Computers and Education: Artificial Intelligence*, 6, 100221.

Loibl, K., & Rummel, N. (2014). Knowing what you don't know makes failure productive. *Learning and Instruction*, 34, 74-85.

Rajesh, A., & Khan, S. (2024, December). Learn Like Feynman: Developing and Testing an AI-Driven Feynman Bot. In 2024 IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE) (pp. 1-8). IEEE.

Resh, W. G., Ming, Y., Xia, X., Overton, M., Gürbüz, G. N., & De Breuhl, B. (2025). Complementarity, augmentation, or substitutivity? The impact of generative artificial intelligence on the US federal workforce. *arXiv preprint arXiv:2503.09637.*

Reyes, E. P., Blanco, R. M. F. L., Doroon, D. R. L., Limana, J. L. B., & Torcende, A. M. A. (2021). Feynman technique as a heutagogical learning strategy for independent and remote learning. *Recoletos Multidisciplinary Research Journal*, 9(2), 1-13.

Sun, L., & Zhou, L. (2024). Does generative artificial intelligence improve the academic achievement of college students? A meta-analysis. *Journal of Educational Computing Research,* 62(7), 1896-1933.

Torricelli, M., Martino, M., Baronchelli, A., & Aiello, L. M. (2024, May). The role of interface design on prompt-mediated creativity in Generative AI. In *Proceedings of the 16th ACM Web Science Conference* (pp. 235-240).

UNESCO. "Guidance For Generative AI In Education and Research." https://unesdoc.unesco.org/ark:/48223/pf0000386693 (2023).

Yang, J. W., Choe, K., Lim, J., & Park, J. (2025). Asking questions matters: comparing the effect of learning through dialogue with peers, ChatGPT, and intelligent tutoring system. *Interactive Learning Environments,* 1–17.

Zhu, Y., Liu, Q., & Zhao, L. (2025). Exploring the impact of generative artificial intelligence on students' learning outcomes: a meta-analysis. *Education and Information Technologies*, 1-29.

Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. *Contemporary Educational Psychology,* 25(1), 82-91.