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Fostering AI literacy in pre-service physics teachers: inputs from training and co-variables

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Background: While the transformative potential of artificial intelligence (AI) in education is widely recognized, the rapid evolution of these technologies necessitates a corresponding evolution in teacher education. This research sought to investigate the impact of a targeted training program on pre-service physics teachers' AI literacy levels and their subsequent attitudes and intentions toward AI adoption in their future teaching.

Methods: A pre-post-test control group quasi-experimental study was implemented among physics teacher education students. A 5 weeks long out-of-curriculum intervention was designed and implemented that combined theoretical grounding with practical, problem-based learning activities, with a focus on the use of various AI tools.

Results: There was a significant upswing in AI literacy performance post-intervention, showcasing that the training was effective in facilitating participants' understanding and application of AI in educational contexts. Additionally, perceived usefulness of AI was found to be a partial mediator in the link between literacy scores and behavioral intention to embed generative solutions into potential teaching.

Conclusion: The study concludes that incorporating comprehensive AI literacy programs into teacher education curricula is essential for fostering a technologically adept and pedagogically innovatively minded teaching workforce. Further research is needed to explore the long-term effects of AI literacy training on teacher practice and student learning outcomes.

KEYWORDS

AI literacy, behavioral control, behavioral intention, perceived usefulness, physics education, student-teachers

1 Introduction

Artificial intelligence (AI) has emerged as a transformative force that enables computer systems to perform tasks that traditionally required human intellect and behavior (Martin et al., 2024). Among the more sophisticated iterations of AI, generative AI (GenAI) stands out, leveraging deep learning models to produce intricate, human-like content in response to diverse prompts (Chiu, 2024; Groothuijsen et al., 2024). Since the launch of ChatGPT in November 2022, the rapid proliferation of GenAI tools has positioned it as the most impactful emerging technology, a status expected to persist over the next decade. Consequently, mastering GenAI has become a critical agenda for professionals across various fields, including education (Yuwono et al., 2024).

The integration of cutting-edge technologies into educational settings has historically posed a series of challenges, and AI is no exception. These challenges range from teacher adaptation to ethical considerations (Moya and Camacho, 2024). However, the swift development and adoption of GenAI have outpaced previous technological advancements, prompting unprecedented uptake among both students and educators (Moorhouse, 2024). The dynamic nature of GenAI and its potential to reshape the educational landscape necessitate that prospective teachers acquire the competencies required for its effective integration (Hong et al., 2024; Mnguni, 2024). As AI introduces new opportunities, it concurrently brings risks, such as learner dependency (Ye et al., 2025) and algorithmic discrimination (Cherner et al., 2024) that can exacerbate existing inequities in educational opportunities. This underscores the imperative for teachers to develop not only technical AI skills but also robust digital pedagogy, including the ability to craft effective prompts for tailored GenAI applications and foster positive attitudes and trust in AI technology for its productive utilization (Knoth et al., 2024).

Literature suggests that a profound grasp of AI can predict "positive outcomes in AI use, detection, ethics, creation, and problem-solving" (Ayanwale et al., 2024). Although the benefits of adopting AI in educational contexts have often been trumpeted by scholars, rather minimal evidence can be found regarding AI-informed training for pre-and in-service instructors. This lacuna highlights the need for targeted teacher education initiatives (Sanusi et al., 2024). Empirical studies emphasize the necessity of tailored support to develop teachers' AI teaching competencies, advocating for hands-on workshops and self-paced learning experiences (Kohnke et al., 2023; Zhang and Zhang, 2024). In response to the identified gap, our study focuses on the integration of AI-powered tools into science classrooms, particularly physics.

2 Conceptual framework

Integrating AI-powered instruments into science classrooms requires educators to possess a strong foundation in AI literacy, encompassing pedagogical knowledge, critical evaluation skills, and ethical considerations (Almasri, 2024). AI literacy implies the ability to understand the functionality of AI technologies and to use them responsibly (Chiu et al., 2024). While we recognize that there is a framework aimed broadly at AI literacy (Ng et al., 2021), a comprehensive framework specifically tailored to the needs of pre-service physics teachers remains lacking. Therefore, this study draws upon relevant literature in educational technology to propose a set of essential and truly applicable knowledge and skills for physics teacher education students as follows: (a) ability to assess if a problem can and should be solved with AI (Wang et al., 2023); (b) ability to prompt AI to develop engaging scenarios or thought experiments related to a physics concept (Ramos and Condotta, 2024); (c) ability to use AI to distill complex physics concepts into concise and understandable explanations for different age groups and learning levels (Chauncey and McKenna, 2023); (d) ability to prompt AI to generate lesson plans on the basis of specific educational frameworks, e.g., inquiry-based learning (Moundridou et al., 2024); (e) ability to use AI to develop engaging quizzes and assessments with varied question types aligned with learning objectives (Zhai and Nehm, 2023); (f) ability to critically assess the quality of AI output (Sperling et al., 2024); and (g) ability to weigh privacy and information security issues whenever using AI (Williams and Ingleby, 2024). Our AI literacy enhancement initiative was designed as addressing each of these capacities in order to cultivate teachers' fundamental understanding of the current AI instruments and integration practices.

The primary goal of this study was to answer the following research question: How did pre-service teachers' AI literacy change following the AI training initiative?

The secondary purpose was to test the hypotheses articulated in the next section.

3 Literature review and hypothesis development

Research related to absorbing new concepts is commonly underpinned by the assumptions of the Innovation Diffusion Theory (Rogers, 1983) which, simply put, can be umbrellaed under the notion that an individual's willingness to adopt and implement an innovation depends on their perceived balance between its pros and cons (Ayanwale and Ndlovu, 2024). In this context, higher AI literacy can be seen as enhancing potential teachers' understanding of AI compatibility with their teaching ideals and the observability of its benefits (i.e., how apparent the advantages of the innovation are to potential users). This, in turn, may make them more comfortable with the idea of incorporating AI into their future instructional practices. Empirically, Ma and Lei (2024) pinpointed AI literacy as a determinant that impacts student-teachers' behavioral intention to utilize AI technologies. Similarly, Yao and Wang (2024) tested a structural model linking pre-service special education teachers' digital literacy to their behavioral intention to integrate AI in education. However, this link was found to be insignificant. Building on these findings, it becomes pertinent to further investigate how AI literacy influences behavioral intentions in different teaching disciplines. Given the unique cognitive demands and technological applications in physics education, pre-service physics teachers may perceive AI technologies as more aligned with their teaching objectives. Therefore, the following hypothesis was proposed:

> H1. Post-test AI literacy positively predicts behavioral intention toward AI.

As indicated above, understanding AI's capabilities is supposed to go hand-in-hand with recognizing its relative advantages over other teaching methods, thus increasing the perceived practicality of AI. When teachers are well versed in AI, they are better positioned to identify specific applications where AI can address pedagogical challenges. Hence, we hypothesize the following:

> H2. Post-test AI literacy positively predicts perceived usefulness of AI.

One of the most influential models of technology acceptance has been the Technology Acceptance Model (TAM; Davis, 1989), which draws upon the belief that one's intention to use a technology is driven by their perception of the technology's usefulness and ease-of-use. However, the latter was not included in our hypothetical model since the primary driving force behind a person's willingness to harness new technology lies in their assessment of its practical value, rather than how easy it is to exploit (Kelly et al., 2023). Moreover, high AI literacy itself is likely to imply that the technology has become relatively accessible and comprehensible for that individual, potentially diminishing concerns about ease of use. Earlier evidence advocates that the AI practicability expressed by pre-service teachers is positively associated with their desire to further dive into AI and utilize it (e.g., Sun et al., 2024; Zhang et al., 2023). Concurrently, pre-service biology teachers' beliefs about the serviceability of AI were found to be unrelated to their intent to deploy it later for teaching genetics (Adelana et al., 2024). Given these mixed findings in the literature and the potential importance of perceived usefulness in technology adoption, particularly for AI, it is crucial to examine this relationship specifically within the context of tomorrow's physics educators. This leads us to our third hypothesis:

> H3. Perceived usefulness of AI positively predicts behavioral intention toward AI.

While H1-H3 delineate direct relationships between AI literacy, perceived usefulness, and behavioral intention, the interplay between these variables may not be merely direct. The TAM suggests that the perception of a technology's usefulness can mediate the relationship between external variables (in this case, AI literacy) and behavioral intention to use that technology (Jimenez et al., 2021). This mediating effect has been observed in various technological contexts, including educational settings (e.g., Humida et al., 2022; Pan et al., 2024; Shahzad et al., 2024). In the context of AI in physics education, it is plausible that AI literacy affects behavioral intention not only directly but also indirectly through perceived usefulness. In other words, as student-teachers become more literate in AI, they may better appreciate its potential benefits and thus perceive it as more useful, which, in turn, could strengthen their inclination to incorporate AI into their future teaching practices. To examine this potential underlying mechanism, we assume the following:

> H4. Perceived usefulness of AI mediates the relationship between AI literacy and behavioral intention toward AI.

Perceived behavioral control is a concept closely related to self-efficacy. While both concepts concern an individual's belief in their ability to perform behaviors, self-efficacy is more specific, concentrating solely on inherent capabilities. In contrast, perceived behavioral control encompasses a broader range of beliefs, including external factors (such as administrative support) that could influence the behavior (Lim and Weissmann, 2023; Liu and Wang, 2024). In theoretical words, greater AI literacy empowers student-teachers with a better understanding of AI concepts, applications, and pedagogical strategies, enabling them to navigate the intricacies of generative technologies and confidently design captivating learning experiences that leverage AI tools. This confidence stems not just from their comprehension of AI itself but also from their awareness of available resources, potential support networks, and the feasibility of implementing AI-driven teaching strategies within educational contexts. Consequently, as preservice teachers gain greater AI literacy, they are more likely to perceive greater control over their ability to adopt AI-supported educational approaches, even when potential extraneous barriers are considered. This path can be substantiated through the lens of the Theory of Planned Behavior (TPB; Ajzen, 1991), which premises that behavioral beliefs formed through information (e.g., knowledge about LLMs acquired during AI training) can alter perceptions of behavioral control (Ajzen, 2020). To our knowledge, the link between AI literacy and perceived behavioral control has not yet been examined among teacher education students. Nonetheless, AI literacy reportedly had a positive effect on perceived behavioral control among cross-disciplinary students (Wang et al., 2024). It is, therefore, reasonable to hypothecate:

> H5. Post-test AI literacy positively predicts perceived behavioral control.

Research favors the idea that individuals tend to adopt behaviors they perceive as likely to yield positive outcomes and that are within their grasp (Sanusi et al., 2024). When extrapolating the principles of the TPB (Li et al., 2022) to the context of the present study, it is reasonable to anticipate that as pre-service teachers perceive a greater level of control over their ability to manage AI, they will be more inclined to develop a strong intention to construct AI-informed teaching environments. Overall, the association between control perceptions and intention levels has seldom been addressed in empirical research, particularly among prospective teachers. A recent study (Jo, 2023) failed to reveal a significant relationship between university students' perceived behavioral control over ChatGPT and their intent to employ the chatbot. Given this context, the following hypothesis was generated:

> H6. Perceived behavioral control positively predicts behavioral intention toward AI.

Drawing upon the TPB framework, we also suggest that rather than being only a direct precursor of behavioral intention, behavioral control also serves as a conduit through which AI literacy impacts this intention. This conceptualization engenders the following hypothesis:

> H7. Perceived behavioral control mediates the relationship between AI literacy and behavioral intention toward AI.

The hypotheses are summarized in Figure 1. Through these hypotheses and previous research, we sought to explore how the knowledge, skills, and perceptions of prospective teachers regarding today's generative technology influence their willingness to apply it. This approach is expected to contribute to the discourse on AI-saturated education, shedding light on the attitudes of student-teachers as they navigate this burgeoning phenomenon.

4 Materials and methods

This research adopted a pre-test/post-test controlled quasi-experimental study design. The investigation involved self-allocation and quantitative data collection.

4.1 Sample and data collection

Given that path analysis was needed to test our hypotheses, the *a priori* sample size was calculated by means of the Monte Carlo

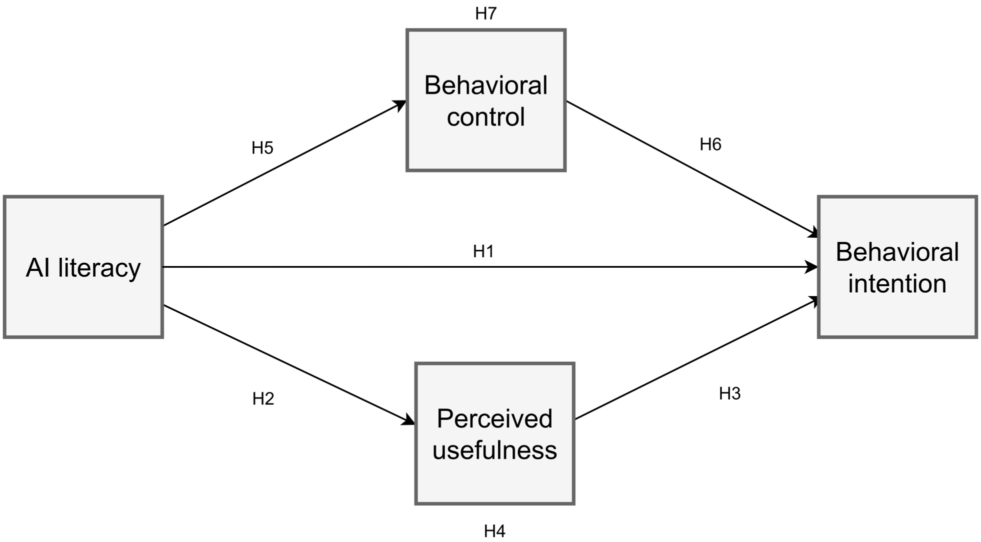

FIGURE 1
Hypotheses of this study.

simulation-based application (Schoemann et al., 2017). We inputted 0.60 r indices (strong correlation lower bound) into the correlation matrix underlying the model with two parallel mediators. This returned that approximately 110 subjects needed to achieve a cutoff of 80% statistical power for identifying the expected indirect effects. The institutional ethics board at Zhetysu University approved this study in November 2023 (protocol no 1807). The research team then contacted science faculty deans at nine universities in the authors' country of institutional affiliation. The researchers negotiated the implementation of the enrollment and examination procedures with science faculty deans at nine universities in the authors' country of institutional affiliation. Potential participants were approached for recruitment by university staff face-to-face and electronically. The only two criteria to qualify for the study were (a) being enrolled in a physics teacher undergraduate program in the country and (b) owning a device for completing the intervention-related procedures. The objectives of the investigation were briefed to potential participants. They were invited to join the study on a voluntary basis, and individuals were enrolled only after providing their informed consent. All data collected during the research process were kept anonymous, with random letter-number identifiers enabling the analyst to match individual baseline and post-experimentation responses. Students self-selected on the basis of whether they opted to engage in the AI training condition or belong to a non-participating reference group.

The final sample of this study included a total of 136 undergraduate students at various stages of their physics teacher education programs across the nine universities. They were on average 19.6 years old [standard deviation (SD) = 1.17], and 89.7% were female. As for the course year, 22.1% were in the 1st year, 25.7% in the 2nd year, 36.0% in the 3rd year, and 16.2% in the 4th year. Prior to the research, the majority of participants reported occasional use of GenAI (72.1%), followed by frequent use, i.e., 4–7 times a week, use (22.8%) and no use (5.1%). Separate group statistics are listed in Table 1.

Questionnaires were filled out distantly through an online form including questions on basic demographics. An open-response form was administered and supervised as a paper-pencil after-lecture assessment by a faculty member at the corresponding university. The objective tool was designed by the researchers in Russian. The questionnaires were independently translated into Russian and back-translated by two certified translators. The face validity and content validity of the measures was ensured prior to administration. Details on the flow of this research are available in Figure 2.

4.2 Intervention

Our research team, which includes educators with backgrounds in physics education and AI integration, developed an out-of-curricular AI literacy training module for pre-service physics teachers. The program aimed to equip them with the skills to integrate AI tools into physics education effectively, ensuring that they could critically assess and utilize these tools in their future teaching. This initiative constituted the intervention enacted in the treated group (n = 59). The module (see Figure 3) spanned 5 weeks during the spring semester in 2024, with each weekly session combining asynchronous and synchronous learning through Google Classroom and Google Meet, respectively. Each synchronous meeting, lasting approximately 60 min, was facilitated by a researcher team member, who showcased AI implementations, led discussions and guided the partakers. Throughout the module, each session, except for the introductory one, featured a problem-based scenario focused on teaching a specific physics topic. Student-teachers were tasked with solving these scenarios via various AI tools that were selected based on several criteria: relevance to educational tasks, user-friendliness, integration capabilities with educational platforms, and the availability of a free plan to ensure accessibility for all participants. For instance, ChatGPT was chosen for its conversational AI capabilities, whereas eduaide.ai was selected for its lesson planning features, both offering free tiers suitable for educational use. The synchronous activities served to introduce the problem scenarios, discuss the relevant AI tools, demonstrate problem-solving using these tools, and explain how prompts should be posed and refined. Following each live session, the

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TABLE 1 Overview of demographics.

Characteristics	Intervention group	Control group
Age: mean (SD)	19.73 (1.24)	19.49 (1.11)
Gender		
Female	54	68
Male	5	9
Year of study		
1st	13	17
2nd	13	22
3rd	22	27
4th	11	11
Use of GenAI		
None	4	3
Occasional	39	59
Frequent	16	15

participants received detailed instructions via Google Classroom to complete hands-on activities during the week. These activities were designed to reinforce the application of AI tools in educational settings and to enhance participants' prompt engineering skills. The participants were reminded to submit assignments through Google Classroom, promoting continuous engagement and application of the learned AI tools. Corrective feedback was provided to the participants through Google Classroom, which was intended to identify areas for improvement and refine their understanding of AI tools in education. All the data collected through Google Classroom and Meet were securely stored. Prior to implementation with the main study cohort, the module underwent a pilot study with four physics teaching undergraduates (outside the final sample) representing varied levels of AI experience. Through informal interviews, the pilot participants provided qualitative feedback, which focused on the clarity of instructions and the relevance of the chosen AI tools. This feedback was instrumental in refining the module.

The introductory session, titled Introduction to AI in Education, provided a foundational understanding of AI, including machine learning, LLMs, and their potential applications in teaching physics. Simple interactions with ChatGPT were performed to illustrate AI capabilities, without delving into complex matters. Subsequent sessions centered around problem case scenarios related to specific physics topics, integrating relevant generative AI tools to address each scenario. The participants were informed about the potential variability in AI tool performance due to updates or changes in the models, emphasizing the importance of critical evaluation of AI outputs. Ethical considerations, including data privacy and security, were also discussed, highlighting the importance of responsible AI use and data protection in educational settings.

The second session, Using AI to Develop Engaging Physics Scenarios, focused on generating thought experiments and scenarios with AI. The participants explored how ChatGPT, an LLM, could assist a high school physics teacher in making Newton's first law more engaging through thought experiments. During the synchronous Google Meet session, the participants were introduced to ChatGPT and basic prompt engineering techniques, which were demonstrated and practiced through interactive exercises. The student-teachers learned how to use prompts to generate engaging thought experiments related to Newton's first law and how to refine the AI-generated responses. The evaluation criteria for thought experiments included creativity, alignment with learning objectives, and age-appropriate content. The discussions covered the potential use cases for different student groups. Asynchronous activities implied generating their own thought experiments for various grade levels using ChatGPT, refining the outputs as necessary. The participants learned strategies for phrasing prompts to elicit relevant and creative responses from the AI, including iterative prompt refinement to enhance content quality.

The third session, Simplifying Complex Physics Concepts with AI, addressed the use of AI to distill complex concepts. The participants examined how Gemini, another LLM, could help a middle school teacher explain wave–particle duality in simple terms for a mixed-ability class. The transition from ChatGPT to Gemini was made to explore differences in their functionalities, such as the character input limit. The simplification of complex physics concepts via Gemini was demonstrated, followed by discussions on modifying AI-generated explanations for different student groups. The validation of AI-generated explanations encompassed peer review and alignment with established physics principles. Asynchronous tasks required participants to generate simplified explanations of wave–particle duality for various grade levels, practicing prompt adjustments to tailor explanations to students with varying levels of understanding. By specifying the desired complexity level and target audience, this training focused on creating prompts that generated scientifically accurate and accessible explanations.

In the fourth session, AI for Lesson Plan Development, the participants learned how to generate lesson plans with AI. The problem scenario involved designing a project-based learning (PBL) lesson on electromagnetism. Using a lesson plan generator on eduaide.ai, participants were shown how to create lesson plans aligned with specific educational standards such as the Next Generation Science Standards. During the synchronous session, they discussed aligning AI-generated lesson plans with educational standards. Discussions included the limitations of AI in understanding contextual nuances, which might affect lesson plan quality. Asynchronous activities implied generating their own lesson plans using eduaide.ai, focusing on inquiry-based and project-based learning approaches, and modifying the AI-generated plans to meet specific educational standards. Training included creating detailed prompts to generate lesson plans that incorporated elements such as learning objectives, hands-on activities, and assessments, tailored to pedagogical frameworks like PBL.

The fifth and final session, Creating AI-generated Quizzes and Assessments, focused on developing physics assessments with AI. The participants explored how a quiz and assessment generator on magicschool.ai could help a teacher create diverse assessments on thermodynamics, including multiple-choice, short-answer, and problem-solving questions. During the synchronous session, the instructor demonstrated the use of magicschool.ai to generate varied quizzes and discussed strategies for ensuring that the assessments aligned with specific learning objectives. The session included a critique on the AI's ability to understand complex physics concepts, potentially impacting question quality. Asynchronous tasks involved generating their own quizzes on thermodynamics using magicschool.ai and adjusting the AI-generated questions to align with specific

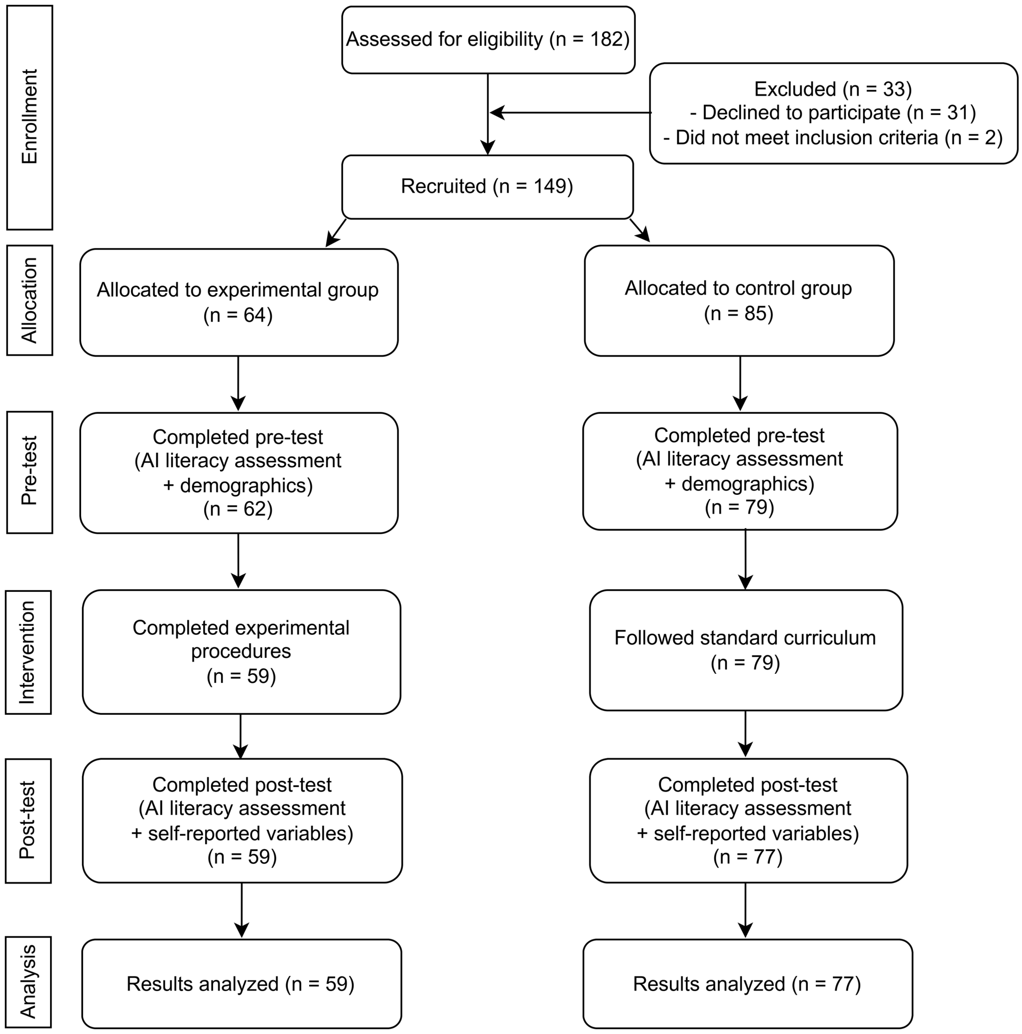

FIGURE 2
Study sequence.

learning objectives. Training emphasized creating detailed prompts to generate assessments with varied question types, ensuring alignment with learning objectives and appropriate levels of difficulty.

4.3 Data collection and instruments

4.3.1 AI literacy

To quantify students' fundamental understanding of the current AI instruments and integration practices, an open-ended 7-item AI literacy assessment was designed by the researchers. Three science didactics experts were invited, each with at least a master's degree and experience in modeling assessments in science teacher education, to validate the instrument. These experts were initially approached via email, introducing the research project and the need for their expertise. They were then provided with a draft of the assessment, including the scoring scheme, and asked to review it for (a) alignment with the AI literacy framework, (b) clarity and comprehensibility of the questions, (c) appropriateness of the scoring rubric, and (d) overall suitability for evaluating pre-service physics teachers' AI literacy. Following their feedback, we held a virtual meeting to discuss their suggestions and refine the assessment. This iterative process resulted in a final version of the inventory. A pilot study then took place. Specifically, we were interested in a heterogeneous sample to keep account of the floor and ceiling of the 3-point scoring scheme. Seven student-teachers consented to take the pre-final test and then review the scoring rubric. In the invitation stage, four of them claimed that they employ generative AI models fragmentally and for superficial ends (e.g., to compose an e-mail to a teacher). On the other hand, three of the seven reported deep usage (e.g., crafting context-specific prompts to model engineering simulations). Based on the students' recommendations, some items were rephrased. None of the pilot participants scored above 16. However, we refused the idea of simplifying the measure to leave room for potential respondent excellence that should not be blurred by the lowered plank.

The post-experimental version of the assessment differs from the pre-test one to minimize the risk of participants memorizing questions from the first measurement and crafting pre-written responses for the second evaluation. This approach helps ensure that the responses at time 2 are spontaneous and reflect the true impact of the intervention.

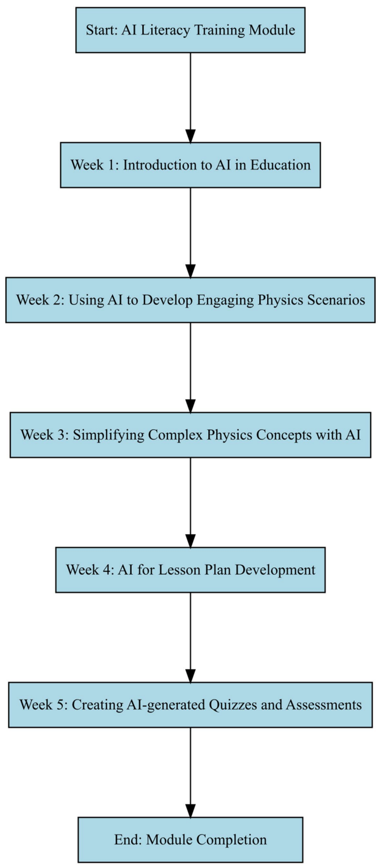

FIGURE 3
Content of the intervention.

A sample item from the post-intervention form including the coding scheme can be found in Appendix.

Separate overall scores for pre-test and post-test were derived by summing the points earned for the seven questions. The possible overall score thus ranged from zero to 21. In the main study, the instrument proved to be reliable (random split-half reliability of 0.78 pre-test and 0.83 post-test). The scoring rubric yielded substantial inter-rater agreement (kappa of 0.74 pre-test and 0.65 post-test).

4.3.2 Perceived usefulness of AI

This variable was measured via three self-constructed items: "Teaching physics using AI will improve my performance while in-service"; "Using AI will enable me to make my physics classrooms more engaging while in-service"; and "Teaching physics using AI will enable me to accomplish tasks more quickly while in-service." The survey yielded random split-half reliability of 0.88 at time 1 and 0.81 at time 2.

4.3.3 Perceived behavioral control

The participants' behavioral control beliefs regarding AI adoption in their future classrooms were evaluated through four items adapted from Watson and Rockinson-Szapkiw (2021) (authors reported Cronbach's $\alpha = 0.88$). The resultant four items were as follows: "I will have the knowledge (e.g., future professional development) to use AI-enabled learning in my future classrooms"; "I will have access to the tools for AI-enabled teaching in my future classrooms"; "I will have the time to use AI-enabled learning in my future classrooms"; and "I will have the support (e.g., technology support staff and/or administrative support) to use AI-enabled learning in my future classrooms." Prior to the experimentation, a random split-half coefficient for the item responses was 0.84, while upon the research conclusion it was 0.91.

4.3.4 Behavioral intention toward AI

It was gauged using items BI2, BI3 and BI5 from the five-item instrument (Ayanwale et al., 2022), with a reported Cronbach's alpha of 0.929. The random split-half test resulted in a score of 0.86 at baseline and 0.79 at follow-up.

The responses to all the questionnaires were scored on a six-point Likert scale. Specifically, 1 represented strong disagreement and 6 represented strong agreement.

4.4 Data analysis

To examine group differences in post-intervention AI literacy, a Bayesian repeated-measures analysis of covariance (RM ANCOVA) was computed in JASP. The AI literacy assessment score was a within-subjects factor, whereas group (experimental vs. control) was a between-subjects factor. The covariates were baseline AI literacy and frequency of GenAI use (no use was coded as 0, seldom use was coded as 1, and frequent use was coded as 2). Prior model probabilities were assigned uniformly.

The hypotheses specified for this research were tested via mediation analysis in R package *process*. Significance was conventionally set at p below 0.05.

5 Results

5.1 Effect of the intervention on AI literacy

At time 1, the AI literacy level was nearly equal in the non-training group (mean = 7.29, SD = 0.58) and the experimental group (mean = 7.42, SD = 0.53). At time 2, the treated undergraduates completed the open-ended test, with a total score (mean = 10.20, SD = 1.19) almost three points higher than that of the busy-as-usual subjects (mean = 7.34, SD = 0.62). The data for AI literacy passed neither Shapiro–Wilk test ($W = 0.891$, $p = 0.001$) nor Levene's test [$F(1,134) = 15.400$, $p = 0.001$]. Given this, the logarithm of the Bayes factor was used to test a null hypothesis (zero effectiveness of the intervention) via model probability distribution within RM ANCOVA. To that end, eight possible models were compared (Table 2). The overall model explained 78.0% of the variation in the outcome (model averaged $R^2 = 0.783$). The $\text{Log}(BF_{10})$ column in Table 2 reveals that relative to the null model, the remaining models (except the one including frequency alone) received discernable support from the collected data. However, only the model entailing the effects of condition, pre-existing performance and GenAI utilization frequency showed positive odds [$\text{Log}(BFm = 4.141)$], suggesting that the observed data is about 4 times more probable under the alternative model, which assumes the superiority of the intervention. Moreover, the group + baseline + AI frequency use

TABLE 2 Bayesian analysis of covariance, model comparison.

Models	P(M)	P(M|data)	Log(BF_M)	Log(BF_{10})
Null model	0.125	1.925×10^{-42}	−94.108	0.000
Group + AI literacy pre-test + GenAI use frequency	0.125	0.900	4.141	95.948
Group + AI literacy pre-test	0.125	0.100	−0.249	93.753
Group + GenAI use frequency	0.125	3.935×10^{-7}	−12.802	81.306
Group	0.125	6.134×10^{-8}	−14.661	79.447
AI literacy pre-test + GenAI use frequency	0.125	1.797×10^{-39}	−87.269	6.839
AI literacy pre-test	0.125	1.690×10^{-39}	−87.330	6.777
GenAI use frequency	0.125	2.020×10^{-42}	−94.059	0.048

TABLE 3 Model fit data.

Criterion	Observed	Recommended
χ^2/df	1.94	<5.0
CFI	1.0	>0.90
TLI	0.98	>0.90
SRMR	0.02	<0.10
RMSEA	0.08	<0.10
GFI	0.99	>0.90
AGFI	0.96	>0.90

χ^2/df = the ratio of chi-squared to the degree of freedom. CFI, comparative fit index; TLI, Tucker-Lewis index; SRMR, standardized root mean square residual; RMSEA, root mean square error of approximation; GFI, goodness-of-fit index; AGFI, adjusted goodness-of-fit index.

model yielded the highest Bayes factor [Log(BF_{10}) = 95.948], with a probability of 90.0% [P(M|data) = 0.900], indicating strong evidence in favor of the alternative over null hypothesis. Hence, upon adjusting for the error variance attributable to how often the student-teachers employed generative tools and how adept in AI they were before this research, there was still strong evidence for the beneficial impact of the experimental procedures on the focal outcome.

5.2 Interconnections

The data for hypothetically interlinked factors had skewness values between −0.05 and 0.95, whereas kurtosis values ranged from −0.34 to 1.45. Some goodness-of-fit values, such as χ^2/df and root mean square error of approximation, exceeded reference values due to outliers in the AI literacy scores. To address this issue, the explanatory variable was winsorized using built-in functions of R. This adjustment resulted in model fit values (as shown in Table 3) suggesting that the mediation model is congruous with the gathered data. The parallel mediating model is graphed in Figure 4.

The mediation analysis revealed several significant relationships among the variables of interest. AI literacy exerted a positive significant effect on the intention to utilize AI-integrated solutions (b = 0.348, 95% CI [0.202, 0.496]; z = 4.723; p = 0.001), denoting a medium effect size. Similarly, the influence of AI literacy on perceived usefulness was statistically discernable (b = 0.306, 95% CI [0.214, 0.423]; z = 5.930; p = 0.001), also suggesting a medium positive effect. However, the association between perceived usefulness and behavioral intention was significantly positive but small in magnitude (b = 0.202, 95% CI [0.011, 0.346]; z = 2.194; p = 0.028). The path from AI literacy to behavioral control over the technology was significant and small-to-medium (b = 0.238, 95% CI [0.200, 0.277]; z = 11.666; p = 0.001). Conversely, the subsequent impact of behavioral control on the intention was medium but insignificant (b = 0.373, 95% CI [−0.035, 0.833]; z = 1.996; p = 0.050). Perceived usefulness emerged as a marginally significant mediator in the relationship between AI literacy and behavioral intention (b = 0.089, 95% CI [−0.018, 0.178]; z = 2.009; p = 0.045). This finding suggests that perceived usefulness partially mediates the relationship between AI literacy and the behavioral intention to integrate AI tools, as the direct path from AI literacy to behavioral intention remained significant even after accounting for perceived usefulness. However, the indirect effect through behavioral control was negligible and insignificant (b = 0.062, 95% CI [−0.005, 0.120]; z = 1.930; p = 0.054).

6 Discussion

This study sought to determine whether the intervention bolstered AI literacy and how this literacy influenced other variables, such as perceived usefulness and behavioral intention toward generative tools. The findings indicate a significant enhancement in AI literacy post-intervention, demonstrating that the training was effective in facilitating participants' understanding and application of AI in educational contexts. The observed increase in AI literacy following the intervention can be attributed to the module's design, which combines theoretical grounding with practical, problem-based learning activities. The use of diverse AI tools and the emphasis on prompt engineering likely contributed to participants developing a more robust understanding of AI capabilities and limitations. The integration of asynchronous and synchronous learning provided a balanced approach, allowing participants to practice and refine their skills in a supportive environment.

The research described herein appears to be the first to target AI literacy enhancement for pre-service teachers, thereby setting the stage for future studies. Given this, contrasting our revelations to existing literature is challenging due to the scarcity of studies focusing on AI-specific literacy enhancement interventions for student-teachers. This, in turn, stems from the too recent flourish of user-friendly generative AI tools and the embryonic stage of educational

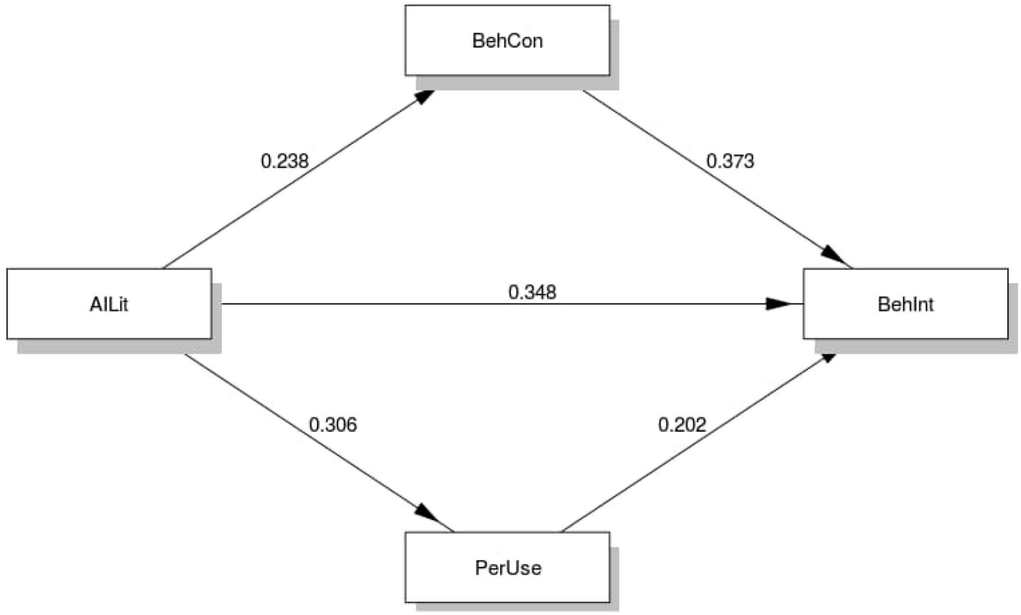

FIGURE 4
Unstandardized path coefficients of the statistical model.

research focused on these technologies. Literally, the only similar and relevant work that could be found at the time of writing is the paper (Ding et al., 2024), which reported improvements in in-service school science teachers' AI literacy through case-based professional development. The present investigation corroborates the potential of targeted AI training programs.

Furthermore, the results reported here largely uphold our initial hypotheses. H1, positing a positive relationship between post-training AI literacy and behavioral intention toward AI, was supported. Similarly, H2 and H3, suggesting positive links between AI literacy and perceived usefulness, and between perceived usefulness and behavioral intention, respectively, were confirmed. This alignment suggests a clear pathway: enhanced AI literacy leads to greater perceived usefulness of the technology, which in turn fosters stronger intentions to use it. H4, proposing a mediating role of perceived usefulness between AI literacy and behavioral intention, was supported, indicating that the perceived benefits of AI partially explain the positive impact of AI literacy on intended use. While H5, predicting a positive association between AI literacy and perceived behavioral control, was confirmed, H6, which posits a positive connection between perceived behavioral control and behavioral intention, was not supported. This unexpected outcome suggests that while the training increased participants' confidence in their ability to manage AI tools, this confidence did not translate into a stronger intention to actually use them. Consequently, H7, suggesting a mediating role for perceived behavioral control, was also unsupported. The lack of support for H7 suggests that perceived behavioral control may not play a critical role in linking AI literacy to the intention to integrate AI tools in education. This finding may reflect the unique context of pre-service physics teachers, where gaining AI literacy and recognizing the usefulness of AI are more influential drivers of behavioral intention than their perceived control over using the technology. It is possible that the participants already felt confident or neutral about their ability to use AI tools due to their familiarity with technology, as evidenced by the high percentage (94.9%) reporting occasional or frequent use of generative AI tools prior to the study.

The significant link between AI literacy and perceived usefulness suggests that as pre-service teachers become more knowledgeable about AI, they begin to recognize its potential to enhance their teaching practices. The results suggest that AI literacy influences behavioral intention primarily through perceived usefulness rather than through perceived behavioral control. One possible mechanism behind this finding is that pre-service teachers may be less concerned with control issues (e.g., access to top-performing LLM models) because they are more focused on the immediate benefits of AI, such as time saving. Conversely, the lack of a significant relationship between behavioral control and intention may reflect the fact that participants have yet to experience the logistical and institutional challenges that in-service teachers face when integrating AI into their classrooms.

6.1 Contribution and recommendations

This study makes several key contributions to both research and practice. The outcomes of this investigation illuminate the potential of targeted training programs to augment prospective teachers' capability to evaluate and utilize AI tools. They underscore the importance of not only equipping future educators with technical skills but also fostering a clear understanding of AI's pedagogical applications and its potential to enhance student learning. This aligns with the idea that the use of AI systems should be guided by educational goals rather than confined to what is technologically possible (Velli and Zafiropoulos, 2024). The findings also highlight the crucial role of perceived usefulness in driving AI adoption, suggesting that professional development efforts should emphasize the practical benefits of integrating AI into teaching. To our knowledge, this is the first study to propose and empirically test a model encapsulating AI literacy, the behavioral intention to employ AI, perceived usefulness of AI, and behavioral control over AI in the context of pre-service teacher education. This work provides a foundation for future research on AI literacy in teacher education.

As Alamäki et al. (2024) noted, AI literacy should be viewed as an educational goal that empowers students to critically assess AI's features and implications, thereby fostering a more informed and capable teaching force. Based on our findings, it is recommended that teacher education programs, especially in the science field, integrate AI literacy training into their curricula, ultimately enriching the learning experience. Such training should focus on practical applications of AI, including generating lesson plans and simplifying complex concepts. Additionally, teacher educators should emphasize the importance of prompt engineering, as this skill appears to be core in enabling potential educators to effectively deploy generative AI products (Ma et al., 2024). Practitioners should focus on developing both the technical skills and the critical evaluation capabilities necessary for effective AI integration. Professional development initiatives should combine direct instruction with case-based learning to enhance AI literacy comprehensively.

6.2 Limitations and directions for future research

Like any other study, this one suffers from some limitations. In particular, the intervention spanned only 5 weeks, which may not be sufficient for long-term retention of AI skills or for addressing the full range of challenges that teachers may face when integrating AI in real classrooms. Moreover, the reliance on a limited number of specific AI tools might not reflect the broader landscape of available technologies. One might add that the study's focus on physics education and a single country may limit the transferability of the findings to other educational contexts or subject areas. Additionally, the sample was predominantly female, limiting the generalizability of the findings to male pre-service teachers.

Given the limited body of research on AI-focused literacy interventions for pre-service teachers, it is essential to acknowledge that this is an emerging field. The integration of AI into education is still in its early stages, and as generative AI tools become more accessible, we anticipate a surge in educational research exploring their potential. Further studies could explore the long-term impacts of AI training on teaching practices, possibly through longitudinal studies that follow pre-service teachers into their professional careers to see whether the gains in AI adroitness and positive attitudes toward AI integration are sustained over time. What also seems promising is examining AI literacy interventions across different subject areas and educational contexts to determine whether the findings extrapolate beyond physics education.

More research is needed to understand the disconnect between perceived control and use intent, exploring potential barriers to AI integration despite external resource expectations and self-efficacy. In other words, it is possible that despite feeling adept at handling AI tools, participants may still harbor concerns about other things influencing their future use. Investigating the role of contextual factors, such as school resources, could provide deeper insights into the barriers to and facilitators of AI integration in education. Learning effectiveness and cognitive style are also the factors that can influence intention to engage with a web-based technology (Ye et al., 2022; Zhang et al., 2025). Furthermore, following the example of Ye et al. (2023), entering variables like expectancy belief and online learning attitudes as predictors of perceived usefulness of the tool could potentially bring about more information on causal mechanisms.

Lastly, the feature of our analysis is the exclusive use of a quantitative approach. Subsequent research incorporating qualitative methods within a mixed-methods framework would enable a more complete understanding of student-teachers' perspectives on the pedagogical applications of AI in physics.

In sum, this study provides preliminary evidence for the potential of generative technology-based training in enhancing both the capabilities and intentions of pre-service physics teachers to integrate AI into their future educational practices. By fostering a deeper understanding and appreciation of AI technologies, such initiatives not only prepare future educators to better exploit these tools but also contribute to the broader goal of modernizing educational environments to harness the benefits of technological advancements. However, further research is needed to fully understand the efficacy and long-term effects of AI literacy training. As AI continues to transform various aspects of society, equipping future educators with the necessary AI literacy is paramount for preparing them to effectively leverage this technology for the benefit of their students.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by Ethics board at Zhetysu University. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

AA: Conceptualization, Investigation, Writing – original draft. NZ: Methodology, Supervision, Writing – original draft. YA: Formal analysis, Investigation, Writing – original draft. FB: Formal analysis, Investigation, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that Gen AI was used in the creation of this manuscript. During the preparation of this work, the authors used Claude 3.5 Sonnet to proofread and improve the readability of individual sentences. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Appendix

An exemplary item from the AI literacy assessment.

Task

Imagine you are teaching an 11th-grade class about electric circuits. Write an AI prompt that would generate three different assessment items to evaluate student understanding of series and parallel circuits. For each assessment type, provide an example of a question you anticipate the AI might generate, along with the correct answer and a justification for your choice of assessment format.

Scoring

0 points: No response or irrelevant response that does not address the task.

1 point: Partial response that includes an AI prompt and at least one assessment item with an answer, but lacks variety in assessment types or justifications.

2 points: Adequate response that includes an AI prompt and two or three assessment items with answers and some justification, but may lack depth or clarity in explanations.

3 points: Comprehensive response that includes a well-crafted AI prompt, three distinct assessment items (e.g., a computational problem, a conceptual question, and a real-world application scenario) with correct answers and clear justifications for each assessment format.