

Physics instructors' acceptance and implementation of generative AI

Pornrat Wattanakasiwich^{1,*}, Kreetha Kaewkhong,² and Duanghathai Katwibun²

¹*Department of Physics and Material Sciences, Faculty of Science, Chiang Mai University, Chiang Mai, 50200 Thailand*

²*Department of Curriculum, Teaching & Learning, Faculty of Education, Chiang Mai University, Chiang Mai, 50200 Thailand*



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[This paper is part of the Focused Collection in Artificial Intelligence Tools in Physics Teaching and Physics Education Research.] This study investigates physics instructors' acceptance and implementation of generative AI (GenAI) in physics education, guided by Rogers' diffusion of innovation (DOI) theory, focusing on its five-stage innovation-decision process: knowledge, persuasion, decision, implementation, and confirmation. Two survey versions were developed—one for GenAI users and another for nonusers. Data were collected through an online survey featuring five-point Likert scale items and open-ended questions, yielding 320 responses from high school and university physics instructors. The persuasion stage was explored in depth using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). A mixed-method approach combining quantitative structural equation modeling (SEM) and qualitative content analysis was employed. We found instructors distributed across different adoption stages, with key barriers including insufficient technical knowledge (51.75% of nonusers) and language processing limitations (50.5% of users). Hedonic motivation ($\beta = 0.498$) was found to have a substantially stronger influence on adoption than performance expectancy ($\beta = 0.121$), with an effect size approximately 4 times greater. We identified significant differences between paid and free GenAI users, with paid users more likely to request prompt-writing guidance (30.56% vs 6.47%) despite using more advanced models. Support needs also varied substantially, as half of paid users requested budget support for GenAI services compared to only 17.65% of free users. Most physics instructors used GenAI primarily for assessment tasks, particularly for generating physics problems with solutions. Their primary concerns included incorrect physics information in GenAI responses, potential negative impacts on students' analytical thinking, language barriers, and challenges with prompt writing. These findings suggest that successful GenAI integration in physics education requires physics-specific training and differentiated support based on whether instructors use free or paid versions of GenAI tools.

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I. INTRODUCTION

Artificial intelligence (AI) is a rapidly developing field with practical applications across numerous areas, including education [1]. Generative AI (GenAI), a subset of AI, focuses on creating new content—such as text, images, and even music—based on existing data. Large language models (LLMs), a subset of generative AI that specializes in producing text-based outputs, are built using transformer technology [1]. This technology allows AI to concentrate on different parts of a sentence to better interpret meaning,

even across lengthy word sequences, thereby generating more coherent and precise responses [1–3].

The advancement in GenAI technology holds great promise for education, offering opportunities to personalize learning, automate tasks, and enhance instruction—ultimately benefiting both physics students and teachers [1,3]. A landmark development is ChatGPT, released by OpenAI in November 2022 [4]. In just 2 months, ChatGPT became the fastest-growing application in history, reaching 100 million active users by January 2023 [5,6]. Since then, numerous GenAI tools have emerged, each with the potential to revolutionize educational practices. Recently, OpenAI introduced the o1 model, which further advances AI's ability to handle complex reasoning in science, technology, engineering, and mathematics (STEM)-related domains, including physics and mathematics [4].

The effective integration of GenAI in education hinges on instructors' perceptions and willingness to adopt these tools [1,7]. While GenAI offers many opportunities, there

*Contact author: pornrat.w@cmu.ac.th

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are also several barriers, including ethical concerns, technical limitations, equity and accessibility issues, and practical and pedagogical challenges [1,2]. Instructors will be more likely to use GenAI if the perceived benefits for student learning outweigh these concerns [1].

Once instructors decide to adopt GenAI, how they implement it becomes equally important. To use GenAI effectively, instructors need to develop AI literacy [8], select tools that genuinely enhance their teaching [1,5], address the ethical and pedagogical challenges AI poses [2,8], and adapt their roles to prepare students for an AI-driven world [1]. Although GenAI holds potential for enhancing lesson planning, material creation, exams, and customized assessments [1], research on the readiness of physics instructors to adopt these tools remains limited, particularly in Thailand [2]. Most studies have focused on the use of GenAI among students [9,10] or English as a second language teachers [11].

Thus, our study investigates how Thai high school and university physics instructors perceive, accept, and implement GenAI, as well as the knowledge and support they require for effective integration. This focus on physics education is particularly important as the discipline involves complex conceptual understanding, problem solving, and visualization that GenAI could potentially enhance. Although centered on the Thai context, these findings may also inform physics educators elsewhere who are confronting similar challenges, helping them navigate the rapid integration of GenAI into their physics teaching and learning environments.

II. THEORETICAL FRAMEWORKS

This section presents the theoretical frameworks that guide this study on physics instructors' acceptance and usage of generative AI (GenAI). The research draws on two key models: Rogers' diffusion of innovation (DOI) theory and the unified theory of acceptance and use of technology 2 (UTAUT2). Rogers' DOI theory explains the process physics instructors undergo when deciding whether to adopt GenAI, while UTAUT2 identifies factors influencing their acceptance and continued use of the technology. Additionally, the section discusses potential implementations of GenAI in physics education and reviews potential barriers that may hinder its adoption.

A. Rogers' diffusion of innovation theory

The diffusion of innovation (DOI) theory [12] has been widely applied across various fields [13], including public health [14], massive open online courses (MOOCs) [15], and teacher education [16], to understand the adoption of innovations [13]. Rogers' diffusion of innovation theory serves as a suitable framework for exploring technology adoption in higher education and educational settings [13], particularly in understanding the adoption of GenAI in education [14].

1. Four elements in the diffusion

Rogers [12] defined diffusion as "the process by which an innovation is communicated through certain channels over time among the members of a social system." The four main elements of diffusion include:

Innovation. An idea, practice, or object that is considered new by those who adopt it. Its adoption rate can be predicted by five perceived attributes [12]: relative advantage (perceived improvement over existing solutions), compatibility (alignment with adopters' values and needs), complexity (ease of understanding and use), trialability (ability to test before full adoption), and observability (visibility of results to others) [13].

Communication channel. The pathways through which innovation messages spread between individuals. These include interpersonal (face-to-face), mass media (radio, TV, newspapers, and social media) [12,13], and hybrid platforms like social networks that combine mass reach with personal interaction. While mass media and social platforms effectively create awareness of innovations, interpersonal communication is more powerful in shaping attitudes and adoption decisions [13].

Time. A element in diffusion, encompassing three key aspects. First, the innovation-decision process describes how individuals progress from initial awareness to making a final adoption decision, which will be discussed in the next section. Second, innovativeness refers to how early an individual or group adopts new ideas compared to others within the system. Third, the adoption rate measures how quickly an innovation spreads throughout a social system [12].

Social system. A social system consists of connected individuals, groups, or organizations working toward common goals. Its structure and norms significantly influence innovation adoption through established networks and behavioral expectations [12,13]. In this study, the social system comprises physics instructors in Thailand, whose professional networks and teaching environments shape their acceptance of generative AI (GenAI) in education.

2. Innovation-decision process

This process is fundamentally an "information-seeking and information-processing activity" [12] where individuals work to reduce uncertainty about the advantages and disadvantages of an innovation. The process consists of five sequential stages [12]:

Knowledge. This stage initiates the process when an individual becomes aware of the innovation and seeks information. This includes awareness-knowledge (knowing it exists), how-to-knowledge (learning how to use it), and principles-knowledge (understanding how it works) [12]. In this study, physics instructors' initial exposure to GenAI reflects this stage.

Persuasion. This stage occurs when individuals develop either positive or negative attitudes toward an innovation

based on personal feelings and social influence [12]. Unlike the knowledge stage, which focuses on acquiring factual information, the persuasion stage is more emotion driven and influenced by social interactions.

Decision. This stage is where individuals choose to adopt or reject the innovation. Adoption involves full use, while rejection can be active (trying but discontinuing) or passive (never considering it) [13]. Trial opportunities, such as free trial versions of GenAI, can support positive adoption decisions.

Implementation. This stage is when users apply the innovation while dealing with challenges such as technical support needs or uncertainties. Reinvention, where users adjust the tool to fit their needs, often leads to higher adoption rates [12]. Physics instructors may adapt GenAI for personalized teaching, resource creation, and research-related tasks [1,3].

Confirmation. This involves seeking reassurance after adoption. Positive experiences encourage continued use, while negative feedback can lead to discontinuance through replacement (switching to a better tool) or disenchantment (disappointment with results) [12]. This study examines how these stages influence GenAI adoption among physics instructors in Thailand.

By understanding the specific adoption stage that physics instructors in Thailand are experiencing, this study can identify critical points where support and resources are needed to facilitate the successful integration of GenAI in physics education. While the diffusion of innovation theory provides a useful framework, it assumes a linear adoption process that may not fully capture the complexities of technology adoption in diverse educational settings. For instance, cultural norms and institutional constraints in Thailand could influence the adoption of generative AI differently than the contexts originally examined by Rogers.

3. Adopter categories

After progressing through the stages of the innovation-decision process, individuals can be grouped into different adopter categories based on how quickly they decide to adopt an innovation. Rogers identifies five categories of adopters based on their willingness to adopt new innovations: innovators, early adopters, early majority, late majority, and laggards [12,13]. Innovators are adventurous risk-takers with advanced technical knowledge who are eager to try new technologies. Early adopters are influential opinion leaders whose acceptance encourages others to follow. The early majority is more cautious but open to new ideas after seeing proven success, often having above-average social status. The late majority is skeptical and adopts only after most others have done so. Finally, laggards are the last to adopt due to limited resources, resistance to change, or lack of knowledge.

B. Unified theory of acceptance and use of technology

This study explores the persuasion stage of Roger's innovation-decision process in depth by applying the unified theory of acceptance and use of technology 2 (UTAUT2), an extension of the original UTAUT model [17]. This is a widely adopted theoretical framework that explains how individuals accept and use technology in both organizational and personal contexts [3,18]. This model has been used to examine the acceptance of new technologies introduced into K-12 and higher education, such as the metaverse [19], MOOCs [20], augmented reality technology [21], learning management systems [22], and GenAI [18,23].

For this study, the UTAUT2 is particularly relevant for analyzing physics instructors' acceptance of GenAI during the persuasion stage of Rogers' innovation-decision process. Drawing on prior research that examines AI acceptance through UTAUT2, this study incorporates ten key constructs that influence behavioral intention and technology use [23–25].

Performance expectancy (PE). This construct is the degree to which physics instructors believe using GenAI will enhance their teaching effectiveness and help achieve desired outcomes. Research shows mixed findings on performance expectancy (PE) and GenAI acceptance [3,18,24,26]. Recent research studies indicate no direct influence of performance expectancy on teachers' GenAI acceptance, possibly because educators have difficulty understanding GenAI's potential benefits or integrating it into their existing teaching practices [26].

Effort expectancy (EE). This construct involves the ease of use associated with the technology and also impacts the intention to adopt GenAI. Instructors are more likely to adopt GenAI and AI tools if they find them easy to use and integrate into their existing workflows [27,28].

Social influence (SI). The impact of peers and social groups can affect the intention to use GenAI. For instance, if physics instructors see their colleagues successfully using GenAI in their teaching practices and receiving positive feedback, they might be more inclined to adopt it themselves. However, as generative AI is still relatively new in educational settings, social norms and widespread adoption patterns are still developing, and their influence might not yet be as strong compared to more established technologies [23,28].

Facilitating conditions (FC). The availability of adequate resources, infrastructure, training, and support is essential for successfully integrating generative AI in education [24,29]. If educators have access to reliable Internet connections, appropriate devices, technical support, and professional development opportunities that focus on using generative AI effectively, they are more likely to feel confident and comfortable incorporating these tools into their teaching [1,10,18].

Hedonic motivation (HM). The enjoyment, fun, and engagement that instructors derive from using GenAI can significantly influence their acceptance and continued use [24,26,29].

Habit (HT). The tendency to continue using GenAI once it becomes a part of one's routine is a powerful driver of long-term adoption [3,26]. The more educators use GenAI and integrate them into their daily workflows, the more likely they are to continue using them. However, this also highlights the importance of ensuring that early experiences with AI tools are positive and productive to encourage habit formation [26].

Price value (PV). Instructors' cognitive trade-off between perceived benefits and monetary costs of GenAI [23,30]. This construct acknowledges that individuals weigh the advantages they gain from using GenAI against the financial expenses involved in accessing and using it. Price value was not evaluated in a few study [18,24] because most GenAI was free during the study. However, pricing and value considerations could be more relevant as AI tools evolve and potentially transition to subscription-based models.

Personal innovativeness (PI). An individual's willingness to adopt and use new technologies. It reflects instructors' inherent inclination to embrace technological advancements and integrate them into their practices [18].

Self-efficacy (SE). An individual's belief in their ability to successfully perform specific tasks or behaviors [25,26]. University instructors with higher self-efficacy are more inclined to embrace GenAI and persevere in the face of challenges [26]. Conversely, GenAI tools like ChatGPT have the potential to positively influence self-efficacy. By providing personalized support, real-time feedback, and access to vast knowledge bases, GenAI can empower users and foster a sense of competence [25].

Behavioral intention. The likelihood that instructors will adopt and continue using GenAI.

Several studies emphasize that habit, performance expectancy, and hedonic motivation are among the most impactful factors influencing behavioral intention [3,18,21–30]. Other factors like effort expectancy, social influence, price value, facilitating conditions, and personal innovativeness also play significant roles [21–30]. The relative strength of these factors can vary depending on the specific context, technology, and user characteristics. Understanding these factors is crucial for promoting the successful adoption and integration of technologies, particularly GenAI and AI tools in education [3].

C. Generative AI in physics education

As generative AI (GenAI) continues to evolve, the role of instructors and the required competencies are changing. The integration of AI in education raises critical questions about instructors' control and their ability to decide how and when to use this technology effectively. Thus,

instructors must be empowered with a strong understanding of the technical, ethical, and pedagogical aspects of AI [8].

For physics instructors, AI literacy is increasingly essential as AI-powered tools become more prevalent in both society and physics education [31]. Generative AI offers significant potential to support instructors across various professional tasks. Based on recent studies [1,3,5], the implementation of GenAI in teaching can be categorized into the following six main areas.

1. Content creation

GenAI has transformed content creation in physics education by offering versatile support across multiple aspects of teaching materials [3]. Physics instructors can create clear explanations of complex concepts, generate diverse practice problems with worked solutions, and develop scaffolded materials for different student abilities—applications directly demonstrated in research by de Souza *et al.* [32]. In their study, high school students used Bing AI to visualize relativistic concepts through carefully crafted prompts. Students with stronger conceptual understanding formulated prompts like “I imagine a sheet representing the space with massive stars bending the space and changing the light trajectory,” which successfully produced images showing spacetime deformation with light rays bending around massive objects. Higher-scoring students consistently created visualizations focused on key physics concepts like curved spacetime and gravity. The implementation required students to iteratively refine their prompts, highlighting that effective AI utilization depends not only on physics knowledge but also on prompt-writing skills [33], a finding particularly relevant for physics educators seeking to implement GenAI tools in their teaching.

2. Instructional design

GenAI serves as a powerful tool for instructional design in physics education by helping teachers develop structured and effective learning experiences [1,3]. It can assist in crafting detailed lesson plans that incorporate various teaching strategies, suggesting appropriate sequencing of topics, and designing engaging learning activities that align with specific learning objectives.

Küchemann *et al.* [33] demonstrated this potential by showing how prospective physics teachers used ChatGPT 3.5 to develop assessment tasks. The process involved iterative prompting—starting with general requests (e.g., “Create a question about velocity-acceleration relationships”) and refining them for specificity (e.g., “Create a 10th-grade calculation problem about acceleration with constant velocity change over time”). This approach enabled teachers with minimal task development experience to generate high-quality physics assessments.

Similarly, Ben-Zion *et al.* [34] showcased how instructors could create custom educational simulations without

programming expertise. Instructors used prompts like “Write an HTML file that simulates a simple pendulum with sliders to adjust mass (0.1–10 kg), length (0.5–5 m), and initial angle (−0.7–0.7 radians)” to build interactive simulations for concepts like pendulum motion and Ising models. The resulting HTML code could be copied into a text editor, saved with a .html extension, and opened in any browser—giving educators customized teaching tools without requiring technical skills typically needed for simulation development.

3. Assessment and evaluation

GenAI significantly enhances assessment and evaluation practices in physics education by supporting both formative and summative assessment strategies [1,3]. It can generate diverse question banks with varying difficulty levels, create detailed rubrics for evaluating complex physics problems, and provide customized feedback on student work.

Recent research shows that GPT-3.5 and GPT-4 models combined with optical character recognition (OCR) tools like MathPix [35] can support physics assessment by grading handwritten solutions and providing tailored feedback on conceptual responses [35]. Students have found GPT-generated feedback more useful than human-written comments, and a GenAI assistant can notably reduce the time instructors spend grading [36].

However, challenges persist, such as limited OCR accuracy, difficulty handling complex multicriteria rubrics, and problems with interpreting diagrams [35,37]. Despite these issues, GenAI shows potential for streamlining assessment processes, particularly for formative feedback and solution presorting. Overall, GenAI shows promise in physics assessment but still requires human oversight, especially for high-stakes evaluations [35–37].

4. Personalized learning tools

The integration of generative AI with educational technologies has expanded the possibilities for personalized learning. These systems can generate customized educational content, provide immediate feedback, and engage in natural language interactions that support student learning [1]. However, researchers emphasize that these tools should complement rather than replace human instruction, particularly in science education, where conceptual understanding and experimental skills are crucial [3].

A Harvard University study found that classroom engagement doubled when an AI tutor was tailored to a physics course for life science majors. This approach supported students with varying levels of physics proficiency, and they reported significantly higher engagement and motivation [38]. In another example, LEAP provides physics teachers with a user-friendly platform to create physics tasks and integrate ChatGPT into their teaching [39]. The platform allows teachers to provide specific prompts and correct answers, ensuring that ChatGPT

generates accurate and targeted feedback to help students better understand physics concepts [39]. GenAI is used to provide personalized and structured support for problem solving, these AI tools can help students develop a deeper understanding of physics concepts and improve their problem-solving skills [40]. As AI technology continues to advance, further research and development in this area hold great potential for transforming the way physics is taught and learned [1,3,38,39].

5. Administrative and academic tasks

AI can assist instructors with routine administrative responsibilities, such as drafting and responding to emails, creating essential documents like syllabi and announcements, and managing scheduling and organizational duties [1,3–5]. These tasks, though essential, are often time-consuming and can be streamlined through AI-powered tools, allowing instructors to focus more on teaching and research.

GenAI offers practical advantages for conducting physics education research. It can be used for research and data analysis [40], idea generation [3], and writing and editing research papers [1,3,41]. It can generate synthetic student responses for concept inventories, helping researchers test and refine assessment instruments while exploring psychometric properties [6]. In qualitative research, GenAI aids large-scale data analysis through computational grounded theory, uncovering patterns in student responses, interviews, and classroom discussions [41]. While its potential in interpreting visual data like kinematics graphs is promising [42], research and development of tools using this technology could help students with visual impairments learn physics more effectively. However, researchers should be aware of its limitations in processing visual details accurately [42]. Effective use of GenAI in physics education research requires understanding its strengths and constraints. It should complement, not replace, researcher judgment and theoretical insight, ensuring rigorous and valid research outcomes [41–43].

6. Professional development

Developing AI literacy is essential for physics instructors as AI becomes increasingly integrated into education [8]. Students increasingly expect universities to incorporate AI into their curricula and provide relevant training for both themselves and faculty [44]. Many already use AI in their studies and anticipate more AI-focused courses [44], reflecting the growing demand for AI-driven learning environments.

Meeting these expectations requires physics instructors to master AI tools, particularly the ability to craft effective AI prompts [45]. This skill enables instructors to create personalized learning materials, design adaptive assessments, and ensure reliable AI-generated content that supports diverse student needs. Beyond classroom applications,

generative AI enhances instructors' professional development. It assesses readiness for AI integration, identifies areas for improvement, and recommends customized training resources, peer collaborations, and relevant content [1,7]. AI-driven platforms can create individualized development plans, build professional communities, and facilitate data-driven instructional adjustments [46].

Moreover, AI-powered simulations offer instructors opportunities to practice classroom scenarios and receive real-time feedback. Educators can also design custom AI tools [1,43], promoting both personal growth and broader educational innovation. By analyzing large datasets, AI helps uncover learning patterns [46], enabling instructors to refine teaching strategies and deliver more effective, personalized learning experiences [1].

Despite the promising applications of generative AI in physics education, recent research by Polverini *et al.* [47] reveals significant technological constraints that demand careful consideration. Their comprehensive study demonstrated that even advanced models like ChatGPT-4o struggle with fundamental physics education challenges. While these models can correctly state physics principles in 95% of cases, they apply those principles accurately only 70% of the time. More critically, the research uncovered substantial weaknesses in spatial reasoning, with the AI misinterpreting spatial relationships in 32% of analyzed responses and performing dismally in three-dimensional reasoning tasks, achieving accuracy rates as low as 3%–20%. These findings underscore a critical point: GenAI should be viewed as a supportive tool, not a replacement for expert instruction. Physics educators must remain vigilant, carefully verifying and contextualizing AI-generated content to maintain rigorous academic standards while simultaneously exploring the innovative potential of these emerging technological approaches. The gap between GenAI's capabilities and the needs of comprehensive physics education contributes to various forms of resistance toward its adoption, which we explore in the following section.

D. Resistance to GenAI adoption

Resistance to the GenAI adoption in teaching is a multifaceted issue influenced by various social, ethical, and practical concerns [1–3,5,7,43]. Some instructors do not trust AI-generated content or worry about losing control over their teaching. Others are unsure whether GenAI is truly helpful for student learning. Ethical concerns, such as academic honesty, data privacy, and bias in AI tools, also contribute to their reluctance. Practical issues, such as a lack of training, poor Internet access, subscription costs, and difficulty using English-based tools, make adoption even harder. Together, these concerns create a complicated situation that requires careful attention. In the sections that follow, we look more closely at the main reasons for resistance: fear of change, ethical concerns, lack of support, and wider system-level problems.

1. Resistance to change

Adopting new technologies in educational settings is rarely straightforward. Some instructors prefer traditional teaching methods, resisting the adoption of GenAI due to skepticism about its effectiveness [1] and fears of losing control over instructional delivery [46]. This resistance is often influenced by a lack of familiarity with emerging technologies, discomfort with changing established teaching routines, and concerns about the reliability of AI-generated content in subject-specific contexts like physics. Instructors may also question the pedagogical alignment of GenAI with their teaching goals or worry that AI tools may oversimplify complex concepts.

According to diffusion of innovation theory, resistance is strongest among late adopters and laggards, who are often cautious and influenced by institutional norms [12,13]. This can be reduced by showing successful examples, offering hands-on training, and addressing misconceptions through targeted professional development.

2. Trust and ethical concerns

Adopting GenAI in physics education introduces complex ethical challenges that extend beyond technological capabilities. These concerns fundamentally question the reliability, fairness, and educational impact of AI-powered tools.

Bias and fairness. AI models trained on large datasets can inherit and amplify biases present in the data [1,5,45]. Instructors are concerned that these biases could perpetuate inequalities in education [1,7]. For instance, an AI grading tool influenced by biased training data might unfairly penalize students from certain demographics, exacerbating existing disparities [1,7].

Accuracy and reliability. Despite advances, AI models are not always reliable, particularly in complex fields like physics. They can produce incorrect or nonsensical outputs, a phenomenon known as “hallucination” [5], which requires instructors to carefully evaluate AI-generated content before using it in teaching or assessments [1,45].

Academic integrity and plagiarism. GenAI's ability to produce high-quality text raises concerns about cheating and plagiarism [1,48,49]. Students might misuse AI to generate work they submit as their own [46], complicating traditional performance assessments [50]. Furthermore, some AI-generated content can evade detection by plagiarism-checking tools, prompting a need to reassess assessment models to maintain academic integrity [50].

Overreliance and critical thinking. The accessibility of AI tools like ChatGPT may encourage students [1,5,44] and even instructors to overrely on these technologies [1,5] potentially hindering their development of critical thinking and problem-solving skills [5,42]. Instructors worry that students might use AI to complete assignments without understanding the underlying concepts, undermining the educational process [5,46].

3. Institutional and operational barriers

This emphasizes systemic issues related to skills, time, and resources that inhibit GenAI adoption.

Lack of AI literacy and training. A central obstacle to GenAI adoption is the widespread deficit in AI-related knowledge among physics instructors. Many educators lack sufficient understanding of AI concepts, tools, and applications specific to physics education [1,8,45]. This includes difficulties in formulating effective AI prompts and interpreting AI-generated output [45], which hinders their ability to leverage GenAI in instructional settings. Addressing this barrier requires comprehensive, targeted professional development programs. These initiatives must be carefully designed to enhance instructors' AI proficiency, build confidence in AI tool utilization, and provide practical, discipline-specific training [8].

Time constraints and increased workload. Integrating GenAI tools into teaching requires a significant time investment [5,49], which conflicts with instructors' already demanding workloads [8]. The process of learning and adapting to new AI technologies can be overwhelming without dedicated time for professional development [5,8]. Institutional strategies such as structured workshops and support for streamlined AI implementation could ease these constraints [8].

Lack of infrastructure and institutional support. The successful deployment of GenAI in physics education depends on adequate technological infrastructure, including robust Internet access, advanced computing resources, and specialized software [1,49]. Financial limitations in underfunded institutions further exacerbate this barrier [1]. Institutional investments in necessary infrastructure and equitable access to AI tools and training are essential for overcoming this challenge [8].

Lack of budget. The cost of subscription-based GenAI tools is a significant barrier for physics instructors [1], as advanced features often come with recurring fees that can strain personal or departmental budgets. This challenge is even greater for those in resource-limited settings [1,49]. To address this, instructors can turn to pretrained open-source models, and institutions can support by providing shared subscriptions or access to AI tools [1].

4. Further concerns

Beyond immediate pedagogical challenges, integrating GenAI into education raises profound ethical, accessibility, and environmental considerations that demand careful scrutiny.

Data privacy and security. The adoption of GenAI tools introduces significant data management challenges [1,48]. These tools often need access to sensitive information, such as student records and institutional data, which raises fears about data breaches or misuse [1,8]. Many instructors and

institutions are also unsure how AI providers handle, store, or use their data, especially with third-party services. To address these issues, it is important to have strong security measures, clear rules for managing data, and ensure AI tools follow privacy regulations to build trust among educators and institutions [1,45].

Multilingualism and fair access. Language represents a critical barrier in GenAI implementation. Most large language models are predominantly designed for English, creating systemic disadvantages for non-English speaking educators and students [1,45]. Kortemeyer *et al.* [51] provided alarming evidence of linguistic performance disparities, showing that GPT-4o's performance on physics concept inventories in Thai was only 47% accurate compared to 72% in English, with particularly poor results (35%–40%) on mechanical wave conceptual assessments in Thai. The study also revealed severe performance gaps for several other languages, with GPT-4o achieving only 20% accuracy for Punjabi (equivalent to random guessing), 22% for Tamil, 27% for Persian, and around 40% for Hebrew, Hindi, and Turkish [51].

Efforts to improve multilingual support in AI tools are ongoing, but there is still much work to be done [1]. Additionally, the high costs of training and maintaining AI models often limit access to well-funded institutions, widening the gap for underfunded schools and countries [1].

High energy consumption. Training and operating large language models require significant computational resources and energy. This raises questions about environmental sustainability as AI becomes more common in education [1]. Research by Nøland *et al.* [50] suggests AI data centers may increase electricity demand. Their projections indicate that by 2027, new AI server deliveries could potentially use up to 210.6 TWh of electricity annually if run at full capacity. This high energy consumption raises important questions about the environmental sustainability of widespread AI integration in education [1].

III. RESEARCH QUESTIONS

To investigate physics instructors' acceptance and implementation of GenAI in physics education, the study aims to address the following four research questions.

RQ1: What are the barriers preventing physics instructors from adopting GenAI?

RQ2: What factors influence high school and university physics instructors' acceptance of GenAI in their teaching practices?

RQ3: How are physics instructors currently implementing GenAI in their classroom practices?

RQ4: What challenges do physics instructors encounter when integrating GenAI into their teaching, and what support do they need?

IV. METHODS

A. Participants and data collection

We conducted a survey in September 2024 to examine factors influencing the acceptance and usage of GenAI in physics education. Participants were recruited through convenience and snowball sampling via professional social media networks, including Line and Facebook groups. The online survey link was distributed through established physics education communities such as the Thai Young Physicists' Tournament (TYPT), the Thailand Physics Olympiad, and the Physics Education Network of Thailand (PENThai). Although the exact reach of the survey is indeterminable due to the nature of social media sharing, these communities collectively comprise approximately 1000 members, with some overlap likely among the groups.

From the distributed online survey, we received 320 complete responses from physics instructors. The sample comprised 206 GenAI users (64.4%) and 114 nonusers (35.6%). Table I presents participant demographics separated by GenAI usage status. The sample represented diverse educational institutions, with 72.4% teaching at secondary schools and 27.6% at universities.

B. Survey

The survey on the acceptance and usage of generative AI in teaching physics was designed to gather data across five stages: knowledge, persuasion, decision, implementation,

TABLE I. Participants' profile ($N = 320$). There are 206 responses from GenAI users and 114 responses of nonuser, with their data shown in parentheses. ^aNote: Percentages were calculated within each demographic subgroup (e.g., male and female under gender) by dividing the number of GenAI users or nonusers by the total number of respondents in that subgroup.

Demographic		N	% ^a
Gender	Male	118 (46)	72.0 (28.0)
	Female	88 (68)	56.4 (43.6)
Age (years)	< 30	46 (14)	76.7 (23.3)
	30–40	79 (31)	71.8 (28.2)
	40–50	70 (46)	60.3 (39.7)
	50–60	11 (23)	32.3 (67.6)
Role	Teacher	146 (98)	60.0 (40.0)
	Lecturers	60 (16)	78.9 (21.0)
Education level	Bachelor	61 (44)	58.1 (41.9)
	Master	87 (57)	60.4 (39.6)
	Ph.D.	58 (13)	81.7 (18.3)
Teaching experience (years)	< 2	23 (8)	74.2 (25.8)
	3–5	29 (13)	69.0 (31.0)
	6–10	50 (26)	65.8 (34.2)
	11–20	77 (37)	67.5 (32.5)
	> 20	27 (30)	47.4 (52.6)

and confirmation. Two parallel versions of the survey were created—one for users and another for nonusers of GenAI.

Instructors begin by indicating whether they use generative AI. Based on their response, they are directed to either the user or nonuser version of the survey. The user version is provided in the Appendix, containing four main parts.

Part 1: Demographics. This section collected participants' profile information, including gender, age, role (high school or university instructor), education level, and teaching experience. This section is included in both the user and nonuser versions.

Part 2: GenAI acceptance in physics teaching. This section contains 28 Likert-scale items (ranging from 1 = strongly disagree to 5 = strongly agree) based on the UTAUT2 model, measuring ten key factors:

- (1) Performance expectancy (PE)
- (2) Effort expectancy (EE)
- (3) Social influence (SI)
- (4) Facilitating conditions (FC)
- (5) Hedonic motivation (HM)
- (6) Habit (HT): routine usage patterns
- (7) Price value (PV)
- (8) Personal innovativeness (PI)
- (9) Self-efficacy (SE)
- (10) Behavioral intention (BI)

The codes for each item are provided in the Appendix for use when reporting the results and discussion.

Part 3: GenAI usage. This part examined instructors' GenAI usage patterns, collecting data on experience duration, usage frequency, and access methods (free vs paid subscriptions). We investigated specific usage patterns across four domains:

- (1) teaching tasks (e.g., lesson planning, content creation),
- (2) assessment and evaluation (e.g., problem generation, rubric development),
- (3) research and professional development (e.g., literature review, research tools), and
- (4) advanced teaching technologies (e.g., adaptive learning systems, automated feedback).

For each domain, respondents rated their usage frequency on a five-point scale from (1) never used and do not plan to use, (2) never used but interested, to (5) regularly.

Part 4: Effective implementation, impact, and support needs. This section combined quantitative and qualitative approaches to examine:

- Instructors' policies on student GenAI use (allow, allow with restrictions, or prohibit)
- Examples of effective GenAI implementation through open-ended responses
- Implementation barriers through eight predefined obstacles corresponding to resistance to GenAI adoption
- Support needs for effective GenAI implementation through open-ended responses

The survey instrument was validated by a panel of three experts in physics and education research to ensure content validity. Additionally, five high school physics teachers and three university physics instructors participated in a trial run of the survey and were subsequently interviewed. Feedback from the pilot study and interviews was used to revise ambiguous items and enhance the instrument's overall usability.

C. Data analysis

The data analysis was structured to address each research question using both quantitative and qualitative data sources. The specific analytical methods employed for each research question are detailed below.

1. RQ1: Barriers to GenAI adoption

To investigate barriers preventing physics instructors from adopting GenAI, we conducted a two-stage analysis integrating demographic data and qualitative insights.

First, we examined demographic differences in GenAI adoption (Table I) to identify characteristics distinguishing users from nonusers. This analysis provided a foundation for understanding potential adoption patterns and user personas.

Next, we conducted a thematic analysis of responses to open-ended questions about reasons for not using GenAI, guided by resistance factors identified in the literature. This approach allowed us to categorize specific barriers such as technological unfamiliarity, concerns about accuracy, and ethical considerations.

2. RQ2: Factors influencing acceptance of GenAI

We examined the data from part 2 of the user-version survey for frequency across all variables to identify anomalies or values outside the defined range. To address RQ2, we analyzed responses to question 4.2, "How often do you typically use GenAI?," as an indicator of usage behavior (UB). This factor reflects how frequently users engage with the technology—in this case, GenAI. The response scale, ranging from "rarely" to "multiple times per day," quantified usage frequency, making it suitable for measuring UB. We performed the data analysis using spss version 26, dividing it into two parts:

Measurement model analysis. This analysis tested the validity and reliability of the latent variables or the ten factors.

- *Convergent validity* displays how well different items are related to the same concept and connected or consistent with each other. This was assessed using factor loadings, with a minimum threshold of 0.70 [52]. Items exceeding this value were retained, explaining at least 50% of the variance, while lower-loading items were removed to improve model fit [24].

- *Internal consistency reliability* was assessed to ensure that the items (indicators) for each factor consistently measured the corresponding latent variable. This was evaluated using Cronbach's alpha, where values above 0.70 [52] indicate acceptable internal consistency for each factor. Values above 0.70 indicate acceptable internal consistency.
- *Discriminant validity* checks whether the items for one factor are not accidentally measuring a different factor. This was assessed using the heterotrait-monotrait ratio (HTMT), ensuring that constructs were sufficiently distinct from one another. All HTMT values have to be below the threshold of 0.85, confirming satisfactory discriminant validity [18].

Structural model analysis. This phase focuses on testing the relationships between latent variables (constructs) in the model. It includes

- *Path coefficients* test the strength and direction of relationships between independent variables (nine factors) and dependent variables, behavioral intention (BI) and usage behavior (UB).
- *Hypothesis testing* determines whether the relationships (paths) in the model are statistically significant.
- *Explanatory power* uses the R^2 values to assess the model's ability to explain the variance in the dependent variables.
- *Moderating effects analysis* is an extension of the structural model analysis. This examined the moderating role of demographic variables (gender, role, teaching experience) on the relationships between constructs (e.g., HT $\rightarrow$ BI). Interaction terms are used to identify significant moderating effects.

The results from this analysis will be used to develop and plot the GenAI acceptance and usage model.

3. RQ3: Implementation of GenAI

The implementation stage in Rogers' innovation-decision process involves instructors integrating GenAI into their work-related tasks. To address this research question, we applied both quantitative and qualitative analyses using responses from part 3 and relevant questions in part 4 of the survey.

Adoption and usage frequency. Responses to questions 3.1 to 3.3 in part 3 were analyzed quantitatively to identify the adoption stage, access to GenAI, and usage frequency. These results, particularly regarding usage frequency and subscription type, were also used to determine the confirmation stage in Roger's theory.

Instructors' practices and policies on students using GenAI. Responses to questions 4.1 and 4.2, which address instructors' practices and policies regarding student use of GenAI in learning, were analyzed quantitatively.

Usage pattern of GenAI. Responses to questions 3.4 to 3.7 were analyzed quantitatively to identify patterns of GenAI usage among instructors.

Implementation of GenAI in teaching physics. For question 4.3, which asked for examples of GenAI use, we conducted content analysis on open-ended responses. This analysis helped identify specific examples of effective GenAI implementation, explore how instructors creatively adapt the technology to meet their teaching needs, and uncover common themes in using GenAI for teaching.

This mixed-method approach provided a comprehensive understanding of how physics instructors currently implement GenAI in their professional tasks, combining statistical trends with in-depth qualitative insights.

4. RQ4: Challenges and support needs

Challenges. Responses to question 4.4, which addressed the limitations and obstacles physics instructors face when using GenAI, were analyzed using descriptive statistics to identify common challenges.

Support needs. Open-ended responses from question 4.5 were analyzed using content analysis to gather detailed insights into the support instructors' need to use GenAI effectively. This approach captured specific suggestions and contextual concerns, providing a deeper understanding of instructors' needs.

By combining these methods, we gained a comprehensive understanding of both general trends and personalized perspectives on the challenges and support required for successful GenAI integration.

V. RESULTS

A. RQ1: Barriers to GenAI adoption

The demographic analysis in Table I revealed clear differences in GenAI adoption among physics instructors. Males showed higher adoption rates (72.0% users, 28.0% nonusers) compared to females. Younger instructors (<30 years) had the highest adoption rate (76.7% users), while those aged >50 years were mostly nonusers (67.6%).

Institutional and educational background also influenced GenAI adoption. University instructors (78.9% users) were more likely to adopt GenAI than teachers (60.0% users). Ph.D. holders exhibited the highest adoption rate (81.7%), while instructors with a bachelor's degree had the lowest (58.1%). Similarly, instructors with less than 2 years of experience were more likely to adopt GenAI (74.2% users), whereas those with over 20 years of experience were the least likely (47.4% users, 52.6% nonusers).

Table II summarizes the categorized responses of physics instructors (nonusers) regarding their reasons for not adopting GenAI. Notably, a lack of how-to knowledge emerged as the most significant barrier, with 51.75% of respondents indicating they felt not sufficiently skilled to use GenAI tools effectively. This was closely followed by a lack of awareness (13.16%), suggesting that many instructors are not even aware of GenAI's existence.

TABLE II. Responses of physics instructors (nonuser) for not using GenAI ($N = 114$).

Categorized responses	N	%
Lack of how-to knowledge	59	51.75
Lack of awareness knowledge	15	13.16
Perceived lack of necessity	10	8.77
Time constraints	5	4.39
Technical barriers	3	2.63
Ethical or practical concerns	3	2.63
Lack of budget	1	0.88
Energy consumption concern	1	0.88
No response	17	14.91

Other barriers included a perceived lack of necessity (8.77%) and time constraints (4.39%), suggesting that some instructors do not view GenAI as essential or struggle to find time to explore it. Additionally, technical barriers and ethical or practical concerns were each cited by 2.63% of respondents, highlighting smaller, yet notable, challenges. Less frequently mentioned barriers included a lack of budget and concerns about the energy consumption of GenAI.

TABLE III. Factor loading, means, and standard deviation (S.D.) of each item.

Items	Loading	Means	S.D.
PE1	0.854	4.47	0.618
PE2	0.840	4.26	0.703
PE3	0.744	4.28	0.681
EE1	0.795	4.17	0.766
EE2	0.806	4.05	0.790
EE3	0.834	4.13	0.800
EE4	0.516	4.01	0.907
SI1	0.815	3.47	0.936
SI2	0.742	4.28	0.810
SI3	0.821	3.81	0.980
SI4	0.779	3.79	0.950
FC1	0.776	4.39	0.757
FC2	0.893	4.19	0.831
FC3	0.659	3.49	1.063
HM1	0.854	4.43	0.692
HM2	0.849	4.36	0.696
HM3	0.809	4.29	0.741
HT1	0.838	3.73	1.017
HT2	0.836	3.68	1.018
PI1	0.806	4.30	0.738
PI2	0.872	4.16	0.735
PV1	0.713	4.39	0.708
PV2	0.937	3.93	0.801
SE1	0.870	4.07	0.801
SE2	0.816	4.12	0.795
BI1	0.881	4.24	0.772
BI2	0.893	4.34	0.787

TABLE IV. Internal consistency reliability using Cronbach's alpha of each factor.

Factors	Cronbach's alpha	No. of items
Performance expectancy (PE)	0.808	3
Effort expectancy (EE)	0.757	4
Social influence (SI)	0.822	4
Facilitating conditions (FC)	0.706	3
Hedonic motivation (HM)	0.896	3
Habit (HT)	0.884	2
Personal innovativeness (PI)	0.724	2
Price value (PV)	0.715	2
Self-efficacy (SE)	0.840	2
Behavior intention (BI)	0.885	3

B. RQ2: Factors influencing acceptance of GenAI

Measurement model validation. Table III presents the factor loadings, with most items greater than 0.70, except items EE4 and FC3. Both items were removed to improve model fit in the next step.

Internal consistency reliability was evaluated using Cronbach's alpha, as shown in Table IV. All factors have values above 0.70, indicating acceptable internal consistency across factors [24].

The acceptable threshold for HTMT values is 0.85. The HTMT values in Table V were below this threshold, ranging from 0.359 to 0.747, indicating satisfactory discriminant validity.

Therefore, the factors in the UTAUT2 model in this study are reliable and valid to determine the GenAI acceptance and use model.

Structural equation modeling (SEM). Figure 1 displays the result of the SEM analysis, the standardized regression coefficients, which represent the relationships between variables, as well as the R^2 values shown inside the circles of each dependent variable—behavioral intention (BI) and usage behavior (UB).

The analysis revealed that the variable with the strongest positive effect on behavioral intention (BI) is hedonic motivation (HM) with a coefficient of 0.498. This is

followed by habit (HT) with a coefficient of 0.314 and self-efficacy (SE) with a coefficient of 0.304. Together, these variables explain 67.1% of the variance in BI ($R^2 = 0.671$). Additionally, the variables with positive effects on BI include personal innovativeness (PI) with a coefficient of 0.232, performance expectancy (PE) at 0.121, social influence (SI) at 0.100, and effort expectancy (EE) at 0.089, in descending order of their impact. For usage behavior (UB), the variable with the strongest effect is habit (HT) with a coefficient of 0.392, followed by BI at 0.323 and SE at 0.129. These three variables together explain 49.5% of the variance in UB ($R^2 = 0.495$).

Hypothesis testing. The analysis in Table VI revealed that two hypotheses H4 and H11 were not supported at a significant level. Hypothesis H4, which posited that facilitating conditions (FC) would affect BI, was not significant, indicating that FC does not have a meaningful effect on BI. Similarly, hypothesis H11, which posited that price value (PV) would affect BI, was also not significant.

Moderating effects analysis. A moderating variable facilitates the influence of an independent variable on a dependent variable. Among these, only the variable "Role" significantly moderated the relationship between habit (HT) and BI, with a correlation coefficient of 0.292. The other moderating variables showed no significant influence on either dependent variable (BI or UB). These results are detailed in the moderating effects Table VII.

C. RQ3: Implementation of GenAI

1. Adoption and usage pattern

The results highlight that physics instructors are in the early stages of GenAI adoption, with the majority having used GenAI for 1 month to 1 year (53.4%). As shown in Fig. 2, regular use is common, with most instructors reporting using GenAI weekly (32.52%) or several times per week (25.30%). However, usage patterns vary, with some instructors accessing it rarely or monthly. Regarding access, most instructors (82.52%) rely on free versions of GenAI, while only a small portion (17.48%) pay for subscriptions or access it through institutional support.

TABLE V. Discriminant validity using HTMT.

	BI	EE	FC	HT	HM	PE	PI	PV	SE	SI
EE	0.582									
FC	0.542	0.614								
HT	0.683	0.602	0.491							
HM	0.747	0.592	0.583	0.651						
PE	0.478	0.516	0.398	0.486	0.451					
PI	0.718	0.612	0.572	0.693	0.725	0.392				
PV	0.622	0.563	0.508	0.659	0.646	0.517	0.646			
SE	0.637	0.624	0.514	0.641	0.574	0.492	0.676	0.557		
SI	0.443	0.404	0.495	0.560	0.432	0.451	0.365	0.472	0.398	
UB	0.518	0.428	0.387	0.605	0.412	0.383	0.467	0.381	0.433	0.359

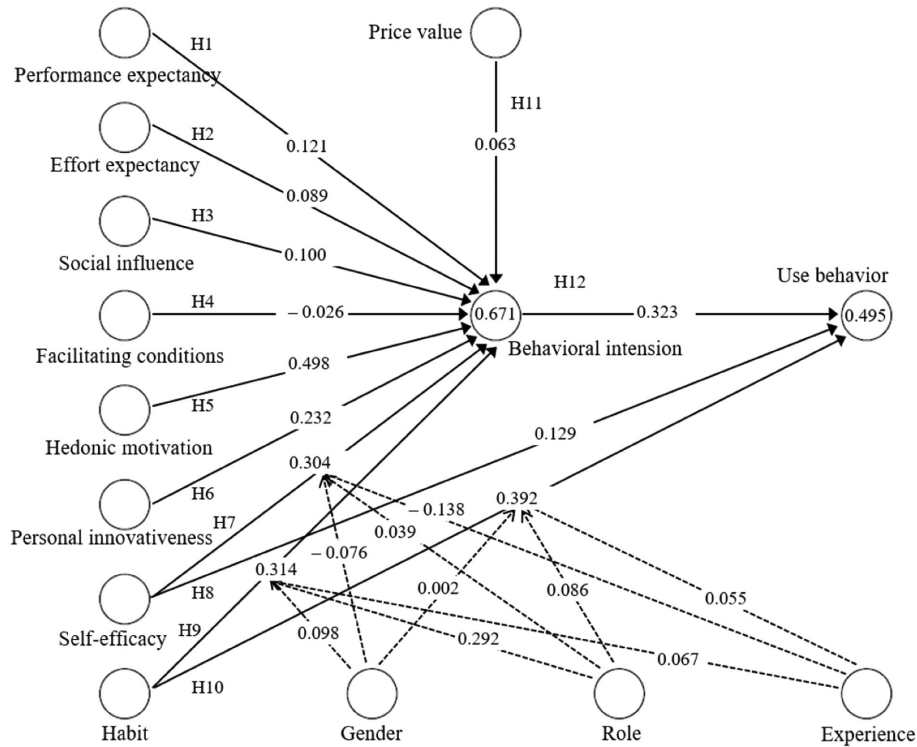


FIG. 1. The GenAI acceptance and use model.

These findings suggest that while GenAI is gaining traction among physics instructors, its current usage is characterized by cost-free tools and varying levels of engagement.

2. Instructors' practices and policies on students using GenAI

Figure 3 presents responses to question 4.1 and question 4.2 regarding instructors' practices and policies on student use of GenAI in learning. A majority of instructors (60.19%) reported teaching students to use GenAI (Q4.1), while 39.81% have not yet introduced it. For

Q4.2, most instructors (52.91%) allow students to use GenAI in some cases, with some (45.15%) fully permitting it and a smaller group (1.94%) prohibiting its use entirely. These findings reveal varying levels of acceptance and highlight the need for clearer guidelines or support for integrating GenAI into student learning.

3. Usage patterns of GenAI

Figure 4 shows that GenAI is most frequently used for content preparation (T2), teaching slides (T3), and designing learning activities (T4), with a higher proportion of regular (green) and occasional use (blue). Moderate use was reported for tasks like lesson planning/syllabus creation (T1), developing teaching materials (T5), and

TABLE VI. Path coefficients for each hypothesis (H) and the results of the significance tests.

H	Path	Coefficient (β)	p values	Confirmed
H1	PE $\rightarrow$ BI	0.121	0.026	Yes
H2	EE $\rightarrow$ BI	0.089	0.041	Yes
H3	SI $\rightarrow$ BI	0.100	0.037	Yes
H4	FC $\rightarrow$ BI	-0.026	0.649	No
H5	HM $\rightarrow$ BI	0.498	0.000	Yes
H6	PI $\rightarrow$ BI	0.232	0.002	Yes
H7	SE $\rightarrow$ BI	0.304	0.000	Yes
H8	SE $\rightarrow$ UB	0.129	0.045	Yes
H9	HT $\rightarrow$ BI	0.314	0.000	Yes
H10	HT $\rightarrow$ UB	0.392	0.000	Yes
H11	PV $\rightarrow$ BI	0.063	0.212	No
H12	BI $\rightarrow$ UB	0.323	0.000	Yes

TABLE VII. Moderating effects from moderating variables including gender, role, and experience (Exp).

Path	Coefficient	p values	Confirmed
Gender $\times$ HT $\rightarrow$ BI	0.098	0.270	No
Gender $\times$ HT $\rightarrow$ UB	0.002	0.978	No
Gender $\times$ SE $\rightarrow$ BI	-0.076	0.451	No
Role $\times$ HT $\rightarrow$ BI	0.292	0.000	Yes
Role $\times$ HT $\rightarrow$ UB	0.086	0.284	No
Role $\times$ SE $\rightarrow$ BI	0.039	0.641	No
Exp $\times$ HT $\rightarrow$ BI	0.067	0.741	No
Exp $\times$ HT $\rightarrow$ UB	0.055	0.770	No
Exp $\times$ SE $\rightarrow$ BI	-0.138	0.564	No

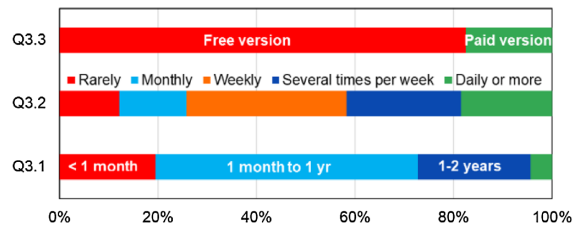


FIG. 2. Physics instructors' GenAI adoption patterns. The figure summarizes responses to three survey items: experience duration (Q3.1), with most instructors having used GenAI for 1 month to 1 year; usage frequency (Q3.2), showing weekly and several-times-per-week use as most common; and access methods (Q3.3), with a majority relying on free versions rather than paid subscriptions.

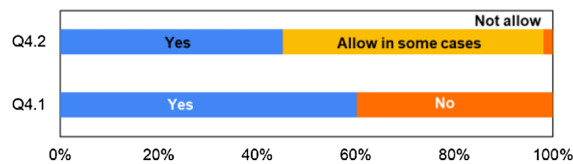


FIG. 3. Physics instructors' approaches to student use of GenAI. The figure displays responses to two questions: whether instructors teach students to use GenAI (Q4.1, bottom bar) and their policies regarding student use of GenAI (Q4.2, top bar). Response options for Q4.1 were "Yes" or "No"; for Q4.2, options were "Allow," "Allow in some cases," and "Not allow." See Appendix, Sections 4.1–4.2 for question details.

illustrations/videos (T6). In contrast, tasks such as managing lab equipment (T7), creating physics-related songs (T8), and suggesting project topics (T9) had the highest levels of "not interested" and "interested to use" responses. These results suggest that instructors primarily use GenAI for teaching preparation and delivery, while creative or administrative tasks see lower adoption.

Figure 5 shows that creating physics questions or problems with solutions (A1) is the most frequently used

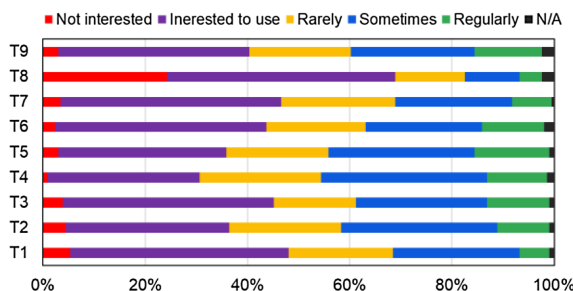


FIG. 4. Frequency of GenAI usage for physics teaching tasks (question 3.4). The figure displays responses across nine teaching tasks (T1–T9), including content preparation, slide creation, and activity design. Color coding represents frequency of use, ranging from "Not interested" (red) to "Regularly" (green). Full task descriptions are provided in Appendix 3.4.

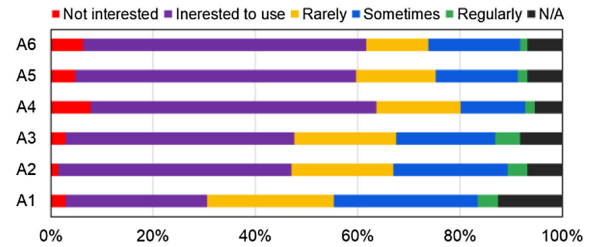


FIG. 5. Frequency of GenAI usage for assessment and evaluation tasks (question 3.5). The figure displays usage patterns for six assessment-related tasks (A1–A6), ranging from creating physics problems to predicting learning trends. Response categories range from "Not interested" (red) to "Regularly" (green). Full task descriptions are provided in Appendix 3.5.

task, with a high percentage of respondents using GenAI regularly or sometimes. Moderate use is observed for automatic work checking and feedback (A4) and creating scoring rubrics for problem solving (A2), as well as for presentations or experiments (A3), with many reporting occasional or rare usage. In contrast, tasks like analyzing learning outcomes (A5) and predicting learning trends (A6) show the highest levels of "not interested" and "interested to use" responses, indicating limited current adoption but potential for future interest. These results suggest that instructors primarily use GenAI for practical tasks like question creation and feedback automation, while advanced analytical tasks remain underexplored.

Figure 6 shows that GenAI is frequently used for tasks such as studying unfamiliar physics topics (R1), translating academic articles (R4), and drafting/editing research proposals or papers (R5), with a high proportion of "sometimes" and "regularly" responses. Moderate usage is seen for tasks like summarizing literature (R7), writing research code (R6), and improving academic writing (R11). In contrast, tasks requiring more specialized skills, such as suggesting quantitative methods (R9) and analyzing

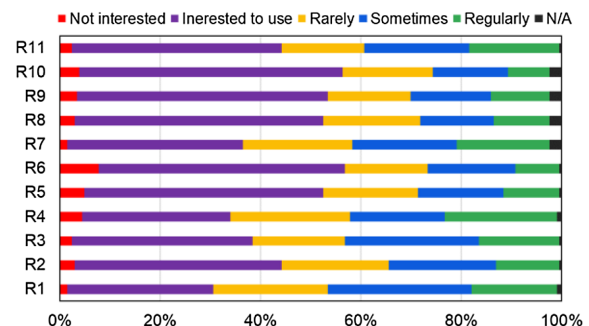


FIG. 6. Frequency of GenAI usage for research and professional development tasks (question 3.6). The figure displays adoption patterns across eleven research-related tasks (R1–R11), including studying physics topics, drafting papers, and analyzing research data. Color coding represents usage frequency from "Not interested" (red) to "Regularly" (green). Full task descriptions are provided in Appendix 3.6.

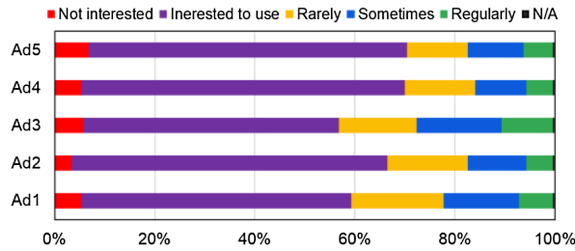


FIG. 7. Frequency of GenAI usage for advanced teaching technologies (question 3.7), including feedback systems (Ad1), adaptive learning systems (Ad2), virtual teaching assistants (Ad3), diagnostic tools (Ad4), and customized chatbots (Ad5). Response categories range from “Not interested” (red) to “Regularly” (green). Full descriptions of each application are provided in Appendix 3.7.

qualitative research (R10), show higher levels of “Not interested” and “Interested to use,” indicating limited adoption but potential interest. Overall, these results suggest that GenAI is primarily utilized for research support and writing tasks, while more technical applications remain underexplored.

Figure 7 shows that GenAI is moderately used for evaluating problem-solving with immediate feedback (Ad1) and developing adaptive learning systems (Ad2). Tasks like using GenAI as a virtual teaching assistant (Ad3) and diagnosing problems to assign work (Ad4) show lower current use but significant interest, as indicated by “Interested to use” responses. The least adopted task is developing customized chatbots (Ad5), with the highest proportion of “Not interested” and “Interested to use” responses. Overall, the findings suggest that while GenAI is used for feedback and adaptive tasks, advanced applications like chatbots remain underutilized, highlighting the need for more support and training.

4. Implementation of GenAI in teaching physics

Table VIII displays how instructors effectively integrate GenAI into various instructional tasks. Assessment and Evaluation (38.83%) emerged as the most common use, with instructors leveraging GenAI to create diverse practice problems and exercises. For instance, one instructor described generating electromagnetic problems with varying difficulty levels, verifying their accuracy, and using them in class.

Instructional planning and design (10.19%) also played a significant role, where instructors used GenAI to prepare specialized lessons, such as connecting fluid mechanics principles to medical applications. Content creation (4.85%) included developing lesson introduction scripts for complex topics like nuclear physics, resulting in smoother and more engaging lessons. Additionally, personalized learning tools (8.74%) involved using GenAI to guide students in coding physics solutions and generating collaborative practice problems.

Instructors also reported using GenAI for professional development (5.83%), such as conducting in-depth research on physics-related topics. No response (31.55%) suggested that some instructors may still be exploring how to integrate GenAI into their teaching practices effectively. These examples illustrate how GenAI can support physics instruction across multiple dimensions, from content creation to personalized learning.

D. RQ4: Challenges and support needs

1. Challenges

The results in Fig. 8 show that the most common challenge instructors face when using GenAI is incorrect or incomplete information (C1), reported by 68.4% of respondents. This is followed by concerns about students’ analytical thinking (C2) at 58.7% and limitations in processing the Thai language (C3) at 50.5%. Challenges with accessing and using GenAI effectively (C6), including prompt-writing and language skills, were noted by 46.1% of respondents. Moderate challenges include academic ethics (C4), reported by 33.5% of respondents, and difficulty evaluating student work (C7), reported by 33.9%. Less frequently reported issues were privacy and data security concerns (C5) at 27.2% and reduced teacher-student interaction (C8) at 30.6%.

2. Support needs

Table IX reveals distinct support needs between paid and free GenAI users. While both groups similarly prioritize workshops on using GenAI (41.67% paid vs 45.88% free), other requirements differ substantially. Half of paid users (50.00%) request budget support for GenAI services compared to only 17.65% of free users, suggesting financial sustainability is a major concern for those who have already experienced premium features.

Interestingly, prompt-writing guidelines are significantly more important to paid users (30.56% compared to only 6.47% of free users), contradicting the assumption that advanced models require less prompt engineering skill. This may indicate that paid users are more aware of how strategic prompting can maximize the capabilities of advanced models. Infrastructure needs like improved Internet systems were also more frequently mentioned by paid users (8.33% vs 2.35%), possibly reflecting their experience with more resource-intensive applications.

The higher nonresponse rate among free users (25.88% vs 13.89% for paid users) may indicate less clarity about what support would be beneficial, consistent with having less experience with GenAI’s full capabilities. These findings suggest that support strategies should be tailored differently depending on whether instructors are using free or paid versions.

TABLE VIII. Analysis of responses on implementation of GenAI in physics teaching with example for each type of responses.

Types	<i>N</i>	%	Examples
Content creation	10	4.85	"I used ChatGPT to create an introduction script for a nuclear physics lesson for 12th grade students. I started by having ChatGPT read various articles related to nuclear physics, from the history of studies in this field to applications and the future of nuclear physics. Then I had ChatGPT generate multiple versions of lesson introduction scripts. I selected the best version and adapted it to my own language style. As a result, the lesson introduction became smoother and more engaging than before."
Instructional planning and design	21	10.19	"I used ChatGPT to prepare a fluid mechanics lesson focusing on medical applications for first-year physical therapy students. The process involved: - Having ChatGPT search for information about medical applications of fluid mechanics at the undergraduate level, including explanations of principles - Verifying the accuracy and consistency of the content - Adjusting the language to be appropriate, easy to understand, and clear in meaning The result was obtaining teaching content and case studies showing diverse applications of fluid mechanics in medicine, helping students understand the principles and connect theoretical physics knowledge to professional practice."
Assessment and evaluation	80	38.83	"I used ChatGPT to create electromagnetic practice problems for 12th grade students. The process involved: - Having ChatGPT generate problems with varying levels of difficulty - Personally, verifying the accuracy of both questions and answers - Using the resulting exercises with students" "I used ChatGPT to create practice problems for the Physics for Science Teachers course targeted at undergraduate science education students. Focusing on topics in force and motion and modern physics, I crafted specific prompts that defined problem scenarios and emphasized scientific explanations. I also had ChatGPT design assessment rubrics for these problems. After generating the initial content, I refined the language and assessment criteria to create parallel practice exercises and exam questions. The result was a collection of engaging, consistent problem sets that I've compiled into my own personal question bank for future use."
Personalized learning tool	18	8.74	"1. Had students write Python programs to solve physics problems, using ChatGPT as a guide or when encountering bugs 2. Used ChatGPT to generate practice problems and had students collaboratively analyze them"
Professional development	12	5.83	"I used ChatGPT for in-depth research of physics research papers and various physics-related work"
No response	65	31.55	

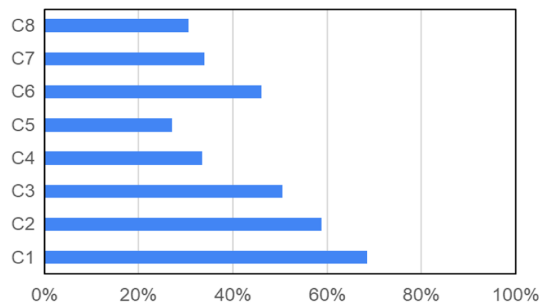


FIG. 8. Reported challenges in using GenAI for physics teaching based on responses to question 4.4. The figure displays the percentage of instructors ($N = 206$) identifying each of the eight predefined challenges (C1–C8), including issues such as inaccurate information, effects on student analytical thinking, and language limitations. Bar length represents the proportion of respondents citing each challenge. Full challenge descriptions are available in Appendix, Section 4.4.

TABLE IX. Categorized responses of question 4.5, comparing support needs between paid GenAI users ($N = 36$) and free users ($N = 170$), presented as percentages.

Categorized responses	Paid (%)	Free (%)
(1) Workshops about using GenAI in physics teaching	41.67	45.88
(2) Guidelines for writing prompts to use GenAI effectively for physics teaching	30.56	6.47
(3) Improving classroom Internet systems for higher speed and stability to support GenAI use	8.33	2.35
(4) Budget for purchasing or subscribing to GenAI services	50.00	17.65
No response	13.89	25.88

VI. DISCUSSION

In this section, we address the four research questions from Sec. III.

A. Barriers to GenAI adoption

The analysis revealed distinct patterns in GenAI adoption across different instructor demographics, alongside key barriers preventing adoption. Demographic data showed clear adoption disparities: younger instructors (<30 years) had the highest adoption rate (76.7%) while those over 50 showed the lowest (32.4%). Similarly, Ph.D. holders demonstrated significantly higher adoption rates (81.7%) compared to those with bachelor's degrees (58.1%), and university instructors (78.9%) showed higher adoption than high school teachers (60.0%).

The most significant barrier was a lack of knowledge, with 65% of nonusers citing either insufficient understanding of GenAI or uncertainty about its implementation. This included both awareness knowledge (13.16%)—basic awareness of GenAI's existence and capabilities—and how-to knowledge (51.75%)—understanding how to use GenAI in practice [12]. Practical obstacles such as time constraints (4.39%), technical barriers (2.63%), and ethical concerns (2.63%) were reported less frequently. These findings suggest that knowledge gaps, rather than resource limitations, are the primary barrier to adoption.

B. Factors influencing acceptance of GenAI

The findings reveal that behavioral intention (BI) to adopt GenAI among Thai physics instructors is influenced by several key factors, including hedonic motivation (HM) ($\beta = 0.498$), habit (HT) ($\beta = 0.314$), and self-efficacy (SE) ($\beta = 0.304$), which emerged as the most significant predictors. This highlights the importance of intrinsic enjoyment, habitual usage, and confidence in using GenAI tools. Additionally, variables such as personal innovativeness (PI) ($\beta = 0.232$), performance expectancy (PE) ($\beta = 0.121$), social influence (SI) ($\beta = 0.100$), and effort expectancy (EE) ($\beta = 0.089$) contributed positively but with lower impact.

Consequently, facilitating conditions (FC) and price value (PV) were not significant predictors of behavioral intention (BI) due to low factor loadings (<0.70). Price value (PV) had no significant impact on BI [23], likely because most instructors used the free version of GenAI [24], as indicated by responses in Q3.3. Effort expectancy (EE4) also showed limited impact, possibly due to language barriers. As shown in Fig. 8, 50.5% of instructors identified “limitations in processing Thai language” as a key obstacle to using GenAI, with some instructors lacking confidence in their language skills for effective implementation.

The limited effect of facilitating conditions (FC) may be attributed to instructors still needing institutional support,

including reliable Internet access, appropriate learning resources, and clear policies promoting GenAI integration. These findings align with previous research highlighting external barriers such as resource availability and institutional backing as critical factors in technology adoption [18,23].

For usage behavior (UB), the strongest predictor was habit (HT) ($\beta = 0.392$), followed by behavioral intention (BI) ($\beta = 0.323$) and self-efficacy (SE) ($\beta = 0.129$). However, the variance explained in UB was modest ($R^2 = 0.495$). This relatively low explanatory power can be attributed to the early stage of GenAI adoption in Thailand. Most instructors reported using GenAI for less than a year, with only a small percentage (less than 20%) using the technology daily or multiple times per day. As a result, while many respondents showed positive behavioral intentions (scores of 4 or 5), their actual usage behaviors remain limited. This disconnect suggests that the relationship between BI and UB, as well as the effects of HT and SE, are still in their formative stages and would strengthen as adoption matures and usage frequency increases.

Moderation analysis revealed that among the demographic variables—gender, role, and experience—only role significantly moderated the relationship between habit (HT) and behavioral intention (BI) ($\beta = 0.292$). This finding suggests that university instructors may be more influenced by habit due to having greater autonomy and flexibility to incorporate GenAI in their teaching. Other contributing factors may include better institutional support, more access to facilities, or stronger English proficiency, which could make it easier for them to integrate GenAI. In contrast, high school instructors may face stricter administrative guidelines or limited resources, reducing opportunities for habitual use. Further investigation is warranted to explore these contextual differences.

C. Implementation of GenAI

Analysis of implementation patterns reveals that Thai physics instructors primarily use GenAI as a tool for teaching preparation rather than for directly supporting student learning. This trend may be influenced by their reliance on free versions of GenAI (82.52% of users). The majority of instructors (38.83%) reported using GenAI to help with assessment tasks, primarily by generating physics problems and exercises. A smaller portion (10.19%) use GenAI for lesson planning. All of these tasks can be done effectively using the free versions of GenAI.

In contrast, only 8.74% of instructors reported using GenAI as a personalized learning tool to directly assist students. The limited adoption of advanced applications like virtual teaching assistants (Ad3) or customized chatbots (Ad5) may be partly due to these features often requiring paid subscriptions or additional technical resources.

Most instructors (52.91%) reported a cautious approach to student use, allowing GenAI only in specific cases. While instructors clearly recognize GenAI's value for enhancing teaching preparation, the predominant use of free versions may constrain their ability to implement more advanced applications that directly support student learning. The significant proportion of nonresponses (31.55%) in implementation examples further suggests that many instructors are still exploring cost-effective ways to integrate GenAI into their teaching practices.

D. Challenges and support needs

The challenges faced by physics instructors when integrating GenAI into their teaching align with barriers previously discussed in the context of Rogers' diffusion of innovation (DOI) theory, particularly during the implementation stage. The most commonly reported challenge—incorrect or incomplete information (68.4%)—highlights concerns about GenAI's reliability in content accuracy, which is especially critical in physics education [5,44]. Additional concerns include GenAI's potential to undermine students' analytical thinking skills (58.7%) and its limitations in processing the Thai language (50.5%), which may disadvantage non-English speakers and reduce equitable access [1,5,43,44].

Technical and pedagogical challenges, such as difficulty using GenAI effectively (46.1%), ethical concerns related to academic integrity and assessment (33%–34%), and reduced teacher-student interaction (30.6%), were also reported. Privacy and data security (27.2%) reflect institutional hesitations about adopting cloud-based AI tools [1]. These issues suggest that although awareness of GenAI is growing, many instructors are still experimenting with its use and encountering friction during implementation. According to the DOI theory, unresolved challenges at this stage can lead to rejection or discontinuation of the innovation [12].

Instructors using free versus paid versions of GenAI demonstrate markedly different support requirements, highlighting a clear divide in their needs beyond the common challenges. As shown in Table IX, both groups similarly prioritize workshops on using GenAI in physics teaching (41.67% of paid users vs 45.88% of free users), reinforcing the need for structured training regardless of tool access level.

However, other support needs diverge. Budget support for GenAI services was requested by half of the paid users (50.00%), but only 17.65% of free users, suggesting that financial sustainability is a pressing concern for instructors who have experienced premium features. Remarkably, guidelines for prompt writing were valued far more by paid users (30.56%) than free users (6.47%). This may reflect greater awareness among paid users of how strategic prompting can improve outcomes with powerful models. Paid users also reported a higher need for improved Internet

infrastructure (8.33% vs 2.35%), possibly due to their engagement with more resource-intensive applications.

Notably, free users had a higher nonresponse rate (25.88% vs 13.89%), which may indicate uncertainty or inexperience with GenAI, making it difficult to articulate specific support needs. These contrasts suggest that support strategies should be differentiated based on user experience and access level. Paid users may benefit from deeper technical training and resource subsidies, while free users may need more foundational orientation and exposure to GenAI's full capabilities.

E. Implications of free vs. paid version differences

The differences in support needs between paid and free GenAI users reveal an important dimension of analysis that extends beyond subscription preferences. Current GenAI tools show notable capability gaps between models such as GPT-3.5 (commonly available for free) and more advanced models like GPT-4o or o1 (accessible through paid subscriptions) [47,53].

These differences have important implications for physics education. While free models are generally sufficient for basic content creation and simple problem generation, they often struggle with complex physics concepts, mathematical notation, and nuanced explanations [47]. In contrast, paid versions tend to demonstrate superior capabilities—particularly when paired with refined prompting—such as generating accurate physics content, solving multistep problems, and producing pedagogically useful explanations. This performance gap becomes especially salient in advanced topics that require higher-order reasoning and multimodal understanding [47,53]. Given that a large majority of instructors (82.52%) rely solely on free versions, many may be forming impressions of GenAI's educational value based on limited exposure to less capable tools. This may lead to underestimations of GenAI's true potential in physics teaching and learning.

Contrary to expectations, our findings challenge the common belief that advanced AI models are easier to use. The higher demand for prompt-writing guidelines among paid users (30.56% vs 6.47%) suggests that those using more powerful models become more aware of the importance of crafting effective prompts. This observation is supported by Yeadon and Hardy [53], who found that refining prompts significantly improved GPT-4's performance on physics coding tasks—from 71.9% to 81.1% ($p = 1.661 \times 10^{-4}$). Their results highlight that, even with state-of-the-art models, thoughtful prompt engineering remains critical for producing accurate and educationally valuable outputs, especially in the complex field of physics.

VII. PRACTICAL CONSIDERATIONS

Our findings reveal several contextual considerations specific to physics education that can inform effective

GenAI implementation strategies. To support instructors across various stages of the adoption process, institutions should prioritize the following targeted initiatives. These recommendations address the specific support needs and barriers identified in our data.

Drawing on Rogers' diffusion of innovation theory, resistance to GenAI adoption tends to be strongest among late adopters and laggards. These instructors are typically more cautious, less confident with new technologies, and heavily influenced by institutional norms [12,13]. This resistance can be reduced through hands-on professional development that highlights successful use cases, demonstrates pedagogical benefits, and addresses common misconceptions. Such support can help lower perceived risks and foster more positive attitudes toward adoption.

A. Physics-specific GenAI workshops

Workshops aimed at supporting GenAI integration in physics instruction should move beyond general AI literacy and focus on discipline-specific applications. Effective workshops would illustrate how GenAI can enhance physics teaching through tasks such as generating conceptual bridging analogies that connect abstract principles to everyday experiences, creating scaffolded problem sets that progress from basic to advanced levels, and producing contextualized examples that link theoretical content to real-world phenomena.

Instructors should also be supported in using GenAI to design personalized remediation materials for students with learning gaps, develop inquiry-based laboratory activities that promote scientific reasoning, and generate visualizations to support the understanding of spatially complex topics such as electromagnetic fields or wave propagation. When appropriately prompted, GenAI can also assist in the construction of formative assessments targeting specific misconceptions, as well as the development of differentiated instructional materials tailored to students with diverse mathematical backgrounds.

To build these competencies, workshops should include hands-on activities in which instructors critically evaluate GenAI outputs for physical plausibility, identify mathematical inaccuracies, revise flawed explanations, and construct physics-specific prompts across varying levels of complexity. These activities are essential for fostering the pedagogical judgment required to implement GenAI tools responsibly and effectively within the physics classroom.

B. Collaborative prompt template libraries

Institutions should invest in the cocreation and testing of physics-optimized prompt templates, tailored for different domains like electromagnetism, kinematics, and thermodynamics. As Yeadon *et al.* [53] demonstrated, prompt engineering significantly improves performance on physics-based code and problem-solving tasks. Our finding that

paid users request prompt guidance more frequently (30.56%) than free users (6.47%) further underscores the ongoing need for structured prompt design support.

To maximize accessibility and effectiveness, prompt libraries should include examples at three levels of sophistication.

1. Level 1: Simple prompts (Beginners)

These prompts offer simple, accessible starting points for instructors new to GenAI.

- *Prompt A1*: Explain Newton's second law.
- *Prompt B1*: Describe how a transistor works.

2. Level 2: Detailed prompts (Intermediate Users)

Detailed prompts specify audience, content, and format, improving output quality while remaining easy to adapt.

At this level, users learn to structure their prompts using the role-task-requirements framework, which significantly improves AI responses. Effective prompts typically include three key components:

Role—assigning the AI a specific persona or professional identity to frame its perspective

Task—clearly stating the objective or action you want the AI to accomplish

Requirements and instructions—providing detailed context, constraints, and specifications that guide the AI's output, such as format preferences, content elements, and specific parameters

- *Prompt A2*: Act as a physics educator [role]. Explain Newton's second law to 10th grade students [task]. Include the mathematical formula, three everyday examples, and common student misconceptions [requirements].
- *Prompt B2*: Take on the role of an electronics instructor [role]. Describe how a transistor works in a basic amplifier circuit [task]. Explain the function of each component and describe the current flow through different parts of the circuit using clear, step-by-step explanations suitable for engineering freshmen [requirements].

3. Level 3: Enhanced detailed prompts (advanced users)

Enhanced prompts use pedagogical frameworks, target varied cognitive levels, and include metacognitive elements to produce classroom-ready materials. These prompts fully leverage the role-task-requirements structure with advanced parameters.

- *Prompt A3*: Act as an experienced high school physics teacher specializing in mechanics [role]. Create an explanation of Newton's second law for 10th grade physics students using the 5E instructional model [task]. Begin with an engaging scenario involving sports, derive $F = ma$ with attention to the vector

nature of forces, address the common misconception that mass and weight are identical, provide scaffolded application examples moving from 1D to 2D scenarios, and include formative assessment questions targeting different levels of Bloom's taxonomy [requirements].

- *Prompt B3*: Assume the role of a university electronics professor with expertise in semiconductor devices [role]. Develop a comprehensive explanation of transistor operation in amplifier circuits for an undergraduate electronics course [task]. Contrast the conceptual understanding needed for introductory students (focusing on current control) with the mathematical modeling (including gain calculations and load line analysis) appropriate for advanced students. Include both simplified and rigorous explanations of how changing the base current affects collector-emitter current, with attention to the limitations of each model [requirements].

These examples demonstrate how increasing prompt complexity leads to progressively more pedagogically sound and physics-focused outputs. By providing this range of templates, institutions can support instructors at all stages of GenAI adoption.

C. Infrastructure support

The successful integration of GenAI into physics education depends on robust infrastructure. This includes ensuring stable, high-speed Internet access in laboratories and classrooms, particularly during GenAI-supported activities such as simulations, conceptual visualizations, and code-based modeling tasks. Institutions should also provide adequate computing resources to support simultaneous GenAI usage, integrate GenAI tools with existing physics education platforms, and implement secure protocols for sharing student-generated content with AI systems.

D. Subscription evaluation frameworks

Institutions should compare the pedagogical gains of advanced GenAI models against licensing costs. Given the disparity in budget-related needs between paid (50%) and free users (17.65%), these decisions should be data driven and linked to intended learning outcomes. Evaluation frameworks should consider the following factors:

- Improvements in physics-specific content accuracy from advanced models.
- Instructor time savings relative to subscription costs.
- Student learning outcomes when using basic versus advanced tools.
- Access needs based on course level and teaching context.

These contextual considerations address the unique challenges of physics education while providing actionable guidance for instructors at different stages of GenAI adoption. By implementing these recommendations in a

staged approach that begins with training workshops and prompt templates before progressing to infrastructure and subscription evaluations, institutions can systematically support physics instructors through each phase of the Rogers' innovation-decision process.

VIII. CONCLUSIONS

The findings demonstrate that Thai physics instructors are at different stages of Rogers' innovation-decision process in their adoption of GenAI. At the knowledge stage, a significant barrier is the lack of both awareness knowledge (13.16%) and how-to knowledge (51.75%), particularly among older instructors and those with bachelor's degrees. This suggests a need for targeted knowledge-building initiatives.

In the persuasion stage, instructors' attitudes are primarily influenced by hedonic motivation (enjoyment), habit, and self-efficacy, rather than external factors like facilitating conditions or price value. The influence of teaching role on habit formation indicates that institutional context significantly shapes adoption attitudes.

The decision stage is reflected in the current adoption rate, with 64.4% of instructors choosing to use GenAI. However, their decisions appear constrained by factors such as English language proficiency and access to institutional support. At the implementation stage, most adopters are using free versions (82.52%) and focusing primarily on teaching preparation tasks rather than advanced applications. This pattern suggests a pragmatic adaptation to resource limitations.

The confirmation stage remains tentative, with many instructors still exploring effective integration methods, as evidenced by the 31.55% nonresponse rate for implementation examples. To support continued adoption, institutions should address key needs identified by instructors: structured training (45.15%), guidance on prompt writing (37.38%), improved infrastructure (20.39%), and financial support (11.17%).

Overall, these findings suggest that successful GenAI integration into physics education requires a comprehensive, stage-specific approach. This includes enhancing knowledge through professional development, fostering positive attitudes through demonstrated pedagogical benefits, enabling informed decisions through supportive policies, facilitating implementation via access to appropriate tools and infrastructure, and reinforcing long-term use through sustained institutional support.

While prior research has explored general trends in GenAI adoption, this study offers several distinct contributions. First, it situates adoption patterns within Thailand's unique educational context, where English is not the primary language—surfacing language-processing barriers often overlooked in Western-centric literature. Second, by focusing on physics instructors across both secondary and higher education, it provides discipline-specific

insights into how GenAI supports core practices such as conceptual explanation, problem solving, and assessment design. Third, through the combined application of Rogers’ diffusion of innovation (DOI) theory and the unified theory of acceptance and use of technology 2 (UTAUT2), the study highlights how cultural, institutional, and resource-related factors interact to shape GenAI adoption.

These findings offer actionable, context-sensitive guidance for institutions aiming to support responsible and effective GenAI integration in physics education, particularly in non-English-speaking and resource-constrained settings.

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DATA AVAILABILITY

The data that support the findings of this article are not publicly available because they contain sensitive personal information. The data are available from the authors upon reasonable request.

APPENDIX: SURVEY (USER VERSION)

This appendix displays the survey items used for data collection, with corresponding codes (e.g., T1, EE3, etc.) for analyzing results and facilitating discussion. The survey is divided into four parts, as shown below:

Part 1: Demographics

1.1 Gender

☐ Male

☐ Female

1.2 Teaching role

☐ Teacher

☐ Lecturer

1.3 Age

1.4 Education level

☐ Bachelor

☐ Master

☐ PhD

1.5 Teaching experience

☐ < 2 years

☐ 3–5 years

☐ 6–10 years

☐ 11–20 years

☐ > 20 years

Part 2: Acceptance of GenAI

Please indicate your level of agreement with the following statements about perspectives on using GenAI in physics teaching.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

Note “Neutral” indicates an opinion that does not lean towards either agreement or disagreement

Code	Statement
PE1	I believe GenAI is beneficial for developing my physics teaching.
PE2	Using GenAI increases opportunities to achieve my important physics teaching goals.
PE3	Using GenAI helps increase efficiency in teaching and assessing physics learning outcomes.
EE1	I can quickly learn basic ways to use GenAI in physics teaching.
EE2	I can interact with GenAI to create clear and understandable physics teaching content.
EE3	Developing advanced skills in using GenAI to improve my physics teaching is not difficult.
EE4	My English language skills are not a barrier to using GenAI in physics teaching.
SI1	My students expect me to use GenAI in physics teaching.
SI2	The trend of using GenAI in education makes me feel I should integrate GenAI into my physics teaching.
SI3	My colleagues support using GenAI in physics teaching.
SI4	My organization/institution promotes the use of GenAI in teaching and learning.
FC1	I have sufficient time and resources (e.g., computer, internet) to develop skills in using GenAI for physics teaching.
FC2	I can access necessary training or knowledge resources for using GenAI in physics teaching.
FC3	My institution has clear policies and guidelines supporting the use of GenAI for physics teaching.
HM1	I feel excited and enthusiastic about using GenAI to create new and interesting physics teaching methods or activities.
HM2	I feel happy and satisfied when seeing students more interested and engaged in physics learning using GenAI.
HM3	I enjoy and am satisfied when using GenAI in physics teaching.
HT1	Using GenAI in physics lesson preparation is becoming part of my daily routine.
HT2	I find myself frequently using GenAI in physics teaching tasks without much hesitation.
PI1	I don’t hesitate to experiment with GenAI in developing new physics teaching materials.
PI2	When I learn about new GenAI capabilities, I often think of ways to use them in physics teaching.
PV1	The benefits of GenAI in physics teaching (e.g., time savings, teaching quality improvement) are worth more than the costs and time invested.
PV2	The improved learning outcomes from using GenAI in physics teaching are worth the resources invested.
SE1	I feel confident in my ability to use GenAI effectively in physics teaching.
SE2	I can learn to use GenAI in physics teaching even without anyone’s help.
BI1	I intend to continue using GenAI in physics teaching in the future.

(Table continued)

(Continued)

- BI2 I plan to learn more about using GenAI effectively in physics teaching
- BI3 I intend to integrate GenAI with my traditional physics teaching methods to increase learning effectiveness

Part 3: GenAI usage

3.1 How long have you been using GenAI (e.g., ChatGPT, Gemini, or Claude) for physics-related work?

- ☐ < 1 month
- ☐ 1 month to 1 year
- ☐ 1–2 years
- ☐ > 2 years

3.2 How often do you typically use GenAI?

- ☐ Rarely (once every few months)
- ☐ Monthly
- ☐ Weekly
- ☐ Several times per week
- ☐ Daily or more

3.3 What is your current GenAI subscription status? (for platforms like ChatGPT, Gemini, Claude, midjourney, or SciSpace)

- ☐ Using free versions only
- ☐ Institution/grant provides access
- ☐ Personal subscription to one GenAI platform
- ☐ Personal subscriptions to multiple GenAI platforms

Please use these criteria to answer question 3.4–3.7.

- 1 | Never used and not interested to use
- 2 | Never used but interested
- 3 | Rarely (1–2 times per year)
- 4 | Sometimes (1–2 times per month)
- 5 | Regularly (almost daily or whenever possible)

3.4 How frequently do you use GenAI for physics teaching tasks?

Code	Tasks
T1	Writing lesson plans (teachers) or course syllabi (lecturers)
T2	Preparing and organizing teaching content
T3	Creating teaching slides
T4	Designing learning activities (e.g., physics experiments, problem solving)
T5	Creating teaching materials (e.g., worksheets, exercises)
T6	Creating illustrations or videos for teaching
T7	Managing and planning lab equipment use
T8	Creating songs related to physics content for teaching
T9	Suggesting physics project topics

3.5 How frequently do you use GenAI for assessment and evaluation tasks?

Code	Tasks
A1	Creating physics questions or problems with solutions
A2	Creating scoring rubrics for problem-solving
A3	Creating scoring rubrics for presentations or experiments
A4	Automatic work checking and feedback
A5	Analyzing learning outcomes
A6	Analyzing trends and predicting learning

3.6 How frequently do you use GenAI in research and professional development tasks?

Code	Tasks
R1	Studying unfamiliar physics topics or research
R2	Analyzing gaps in research of interest
R3	Brainstorming/suggesting new research ideas
R4	Translating and understanding foreign academic articles
R5	Drafting/editing research proposals or academic papers
R6	Writing computer code for research
R7	Finding and summarizing relevant research for literature reviews
R8	Designing research tools like questionnaires or interviews
R9	Suggesting methods for quantitative data analysis
R10	Analyzing qualitative research results
R11	Organizing, proofreading, and improving academic writing

3.7 How frequently do you use GenAI for Advanced Teaching Technologies?

Code	Tasks
Ad1	Evaluating complex physics problem-solving and providing immediate individual feedback
Ad2	Developing physics learning systems that adapt to individual student progress
Ad3	Using as a virtual teaching assistant in physics (e.g., answering questions, explaining concepts)
Ad4	Diagnosing problems and helping assign appropriate work for individual students
Ad5	Using or developing customized chatbots for teaching practice, knowledge assessment, or answering physics questions

Part 4: Application and impact of using GenAI in teaching

4.1 Have you ever taught students to use GenAI in learning?
☐ Yes ☐ No

4.2 Do you allow students to use GenAI in learning?
☐ Allow ☐ Allow in some cases
☐ Not allow

4.3 Please provide examples of using GenAI in physics teaching (e.g., lesson preparation, classroom teaching, assessment) that you find most effective in promoting student learning. (if none, please type ‘none’)

4.4 What limitations or obstacles have you encountered in using GenAI for physics teaching? (You can select more than 1 option)

Code	Options
C1	☐ GenAI sometimes provides incorrect or incomplete information (e.g., incorrect physics problem solving, inaccurate theory explanation).
C2	☐ Using GenAI may affect students’ analytical thinking and independent problem-solving skills.
C3	☐ GenAI has limitations in understanding and processing Thai language.
C4	☐ GenAI has limitations in awareness and adherence to academic ethics.

(Table continued)

(Continued)

C5	☐ Concerns about privacy and data security when using GenAI.
C6	☐ Accessing and using GenAI effectively is still challenging (e.g., prompt writing, English language skills).
C7	☐ Difficulty in evaluating student work created using GenAI.
C8	☐ GenAI may reduce opportunities for communication and interaction between teachers and students.

4.5 What support or assistance do you need from your affiliated organization or related agencies to be able to use GenAI effectively in physics teaching and learning? (if none, please type ‘none’)

Examples of support or assistance:

- Organizing workshops about using GenAI in physics teaching
- Guidelines for writing prompts to use GenAI effectively for physics teaching
- Improving classroom Internet systems for higher speed and stability to support GenAI use
- Budget for purchasing or subscribing to GenAI services

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Correction: The third author's name has been changed from Duanghatai Katwibun to Duanghathai Katwibun.