

Modeling high school students' acceptance of GenAI for physics learning via an extended technology acceptance model: Disciplinary beliefs as a distal antecedent

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Generative artificial intelligence (GenAI) tools are increasingly used in physics classrooms, yet little is known about why high school students accept them for subject-specific learning. Prior technology-acceptance research, especially the technology acceptance model (TAM), shows that perceived usefulness and perceived ease of use shape attitudes and behavioral intention toward a tool. However, this work has rarely examined whether students' beliefs about the subject they are learning also shape those technology perceptions. Drawing on TAM and expectancy-value theory (EVT), we surveyed 340 Grade 10 students who had used DeepSeek in physics lessons and tested an extended structural equation model. Results showed that students were more willing to use DeepSeek when they perceived it as easy to use and useful and when they held positive attitudes toward using it for physics learning. Physics-specific beliefs helped explain these technology perceptions: students with stronger expectancy for success in physics perceived DeepSeek as easier to use; students who saw physics as useful for their future perceived DeepSeek as more useful; students who enjoyed physics held more positive attitudes; and perceived cost weakened both ease-of-use and attitude judgments. Students who regarded doing well in physics as personally important also tended to evaluate DeepSeek more favorably, partly because they saw it as useful for achieving physics-learning goals. Nested model comparisons clarified what the EVT extension added beyond the basic TAM framework. Adding physics-task values produced the largest incremental gain, especially for perceived usefulness ($\Delta R^2 = 0.151$). Supplementary follow-up evidence indicated that the same level of intention could reflect learning-oriented or shortcut-oriented use and that some students linked shortcut-oriented use to low confidence and topic difficulty rather than to disinterest alone. Overall, the findings suggest that GenAI acceptance in physics is shaped by both technology perceptions and students' motivational relationship with physics, supporting a domain-sensitive extension of TAM for subject-specific GenAI learning.

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I. INTRODUCTION

GenAI, as a transformative technology, has garnered significant attention for its demonstrated capabilities in physics contexts, including solving and explaining physics tasks and supporting human-machine collaboration in scientific problem solving [1–5]. However, current research predominantly focuses on the impact of AI and GenAI on instructional results [6,7], with less attention paid to the learners' own willingness to adopt the technology and their decision-making processes. Although

existing studies have begun to investigate the perspectives of university students and students in professional degree programs [8–10], student-centered research targeting high school students remains scarce [11], particularly within the context of high school physics education, students' acceptance of GenAI remains an underexplored area. Preliminary evidence suggests that students hold paradoxical attitudes toward such technology: while they acknowledge its advantages in personalized tutoring and efficiency enhancement [8,9,12], they simultaneously harbor concerns regarding its accuracy [3,9,13]. This ambivalence highlights the need for more systematic empirical inquiry. Therefore, it is not only essential to develop reliable instruments for measuring student acceptance [14] but also critical to understand the underlying motivations and perceptual drivers behind their adoption intentions, which is vital for the effective integration of GenAI in physics education.

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TABLE I. Latent constructs, abbreviations, and brief definitions.

Abbreviation	Full construct name	Brief definition in this study's context
PU	Perceived usefulness	Students' perception that using GenAI tools (DeepSeek) will enhance their physics-learning performance.
PEOU	Perceived ease of use	Students' perception that using GenAI tools (DeepSeek) for physics learning is easy to use and does not require much effort to master.
ATT	Attitude toward using GenAI for physics learning	Students' overall evaluative attitude toward using GenAI (DeepSeek) to learn physics.
BI	Behavioral intention to use GenAI for physics learning	Students' intention to use GenAI (DeepSeek) for physics learning in the near future.
EXP	Expectancy for success in physics	Students' expectancy beliefs and self-concept regarding how good they are at physics and their likelihood of succeeding in physics-related tasks.
IV	Intrinsic value of physics	The enjoyment and interest students experience when engaging in physics learning.
AV	Attainment value of physics	The perceived importance of doing well in physics for students' self-concept and identity.
UV	Utility value of physics	The perceived usefulness of learning physics for students' future education, careers, or everyday life.
COST	Perceived cost of learning physics	The perceived time, effort, stress, and opportunity costs associated with learning physics.

A widely used theoretical perspective for examining technology adoption is the technology acceptance model (TAM). Originally proposed by Davis [15], TAM is an adaptation of the theory of reasoned action within the context of computer usage. It posits that two dimensions—perceived ease of use, the extent to which a technology is judged to require little effort to operate, and perceived usefulness, the extent to which it is judged to improve task performance—shape users' attitude toward the technology, that is, their overall favorable or unfavorable evaluation of using it, which in turn influences their behavioral intention, the strength of their stated plan to use the technology in the near future (Table I summarizes the definitions of all nine constructs examined in this study). TAM and its extended models have been widely validated in educational settings [16–20]. Numerous studies and meta-analyses have confirmed that perceived ease of use and perceived usefulness are critical indicators for predicting users' attitudes and usage intentions regarding e-learning tools and educational software [16–19]. Its application encompasses university online learning platforms, teachers' classroom technology adoption, and AI assistants [17,18,20–23]. More recently, a growing body of work has applied the TAM and related frameworks such as UTAUT and UTAUT2 to investigate students' adoption of GenAI tools. These studies have identified trust, self-efficacy, and social influence as salient additional predictors of GenAI acceptance and use [24–32]. Despite these advances, existing research displays three consistent limitations: samples are predominantly drawn from university students or preservice teachers, with only isolated

exceptions at the school level [24]; investigations remain largely domain-general with limited attention to disciplinary differences; and the external variables included are technology-oriented rather than grounded in discipline-specific motivational beliefs. Although recent work has begun to apply expectancy-value constructs to students' perceptions of GenAI as a technology (see Sec. II B), to our knowledge, no study has modeled subject-specific expectancy-value beliefs as antecedents of GenAI acceptance among high school students.

While TAM effectively captures technology-related perceptions, it provides limited insight into domain-specific motivational drivers of adoption. Critics have argued that traditional TAM overlooks the motivational and volitional processes underlying users' adoption decisions [33], a limitation that is especially consequential in subject-specific learning contexts. Even extended TAM and UTAUT variants that incorporate self-efficacy, social influence, and hedonic motivation rely on generic individual differences rather than context-specific motivational constructs [34–37]. In educational settings, subject-specific beliefs matter greatly: low confidence in a given subject can suppress tool use despite favorable perceptions of ease of use, and low interest can prevent even useful tools from translating into sustained behavioral intention (see Sec. II B for the supporting evidence).

This limitation is particularly acute in physics. Physics education research has long established that physics poses distinctive cognitive and motivational demands: it requires flexible translation across verbal, mathematical, graphical, and diagrammatic representations [38,39]; it involves

robust misconceptions that resist conventional instruction [39]; problem solving relies on multistep reasoning that connects physical intuition to mathematical formalism [40]; and relative to other science, technology, engineering, and mathematics (STEM) subjects, physics exhibits a distinctive motivational profile characterized by comparatively low-intrinsic value and salient perceived cost [41,42]. These distinctive features imply that students' evaluations of GenAI for physics learning are shaped by discipline-specific cognitive and motivational factors that generic extensions of TAM cannot fully capture. Although recent work has examined physics instructors' acceptance of GenAI [43], the student perspective—especially when paired with domain-specific motivational variables—remains unaddressed.

These disciplinary characteristics carry direct implications for how students engage with GenAI. Students' physics motivation may shape not only whether they use GenAI tools but also how they use them. Students lacking interest in physics may still engage with GenAI, but for different purposes—such as seeking direct answers rather than deepening conceptual understanding. Conversely, highly engaged students tend to use GenAI as a cognitive scaffold. This distinction between learning-oriented and shortcut-oriented use highlights the need to understand motivational antecedents of adoption intentions directed specifically toward physics learning. Accordingly, researchers have called for integrating TAM with motivational frameworks to better account for interest, task values, and perceived cost [33,44]. Such an integration aligns with long-standing perspectives in technology acceptance research, which emphasize that factors beyond technical system properties can strongly shape behavioral intentions [15,16].

The EVT offers a complementary perspective on this issue. EVT is a general theory of achievement motivation positing that individuals' achievement-related choices—including course enrollment, effort investment, persistence, and career decisions—are jointly determined by their expectancy of success, that is, their belief that they can succeed at the task, and their subjective task values, comprising the interest, personal importance, and practical usefulness they attach to the task, offset by its perceived cost in time, effort, and emotional strain [45–48]. In the present study, we apply this framework to a specific achievement-related choice: whether and to what extent students choose to adopt GenAI as a resource for physics learning. Students' expectancy beliefs, including self-efficacy, directly influence their behavioral choices: those confident in their learning abilities are more inclined to actively participate in learning activities and use supportive tools [49,50]. Simultaneously, the subjective value assessment of the task is equally critical. When students perceive physics as interesting or important for their future development, they are more likely to invest effort in the

subject and to seek out supporting learning resources [51,52]. Empirical studies have shown that high value perception significantly enhances students' persistence and engagement in learning, as well as their continued use of technology-supported learning environments [19]. In contrast, perceived cost constitutes a potential barrier to adoption behavior; excessive costs can suppress students' motivation and persistence [53] and may plausibly spill over into their evaluations of new learning tools. In the STEM education domain, expectancy and value beliefs have been confirmed as independent and powerful predictors of students' academic choices [45,54]. Therefore, explaining behaviors such as GenAI tool adoption requires a comprehensive consideration that combines learners' own motivational mindsets with their perceptions of the technology.

Building on this argument, there is a need for an integrated framework that simultaneously captures students' technology-related perceptions and their physics-specific motivational beliefs. Although prior studies have expanded TAM by incorporating motivational constructs in broader educational technology settings [26,44], to our knowledge, no research has yet applied such a TAM-EVT-based perspective to explain students' adoption of GenAI for subject-specific learning, such as physics. To address this gap, the present study proposes a domain-sensitive extension of TAM that systematically incorporates physics expectancy-value-cost constructs as distal antecedents of technology acceptance. Rather than claiming a fundamentally new paradigm, this work makes a targeted, incremental contribution: it examines whether and to what extent each category of disciplinary beliefs improves the explanatory power of the TAM framework for GenAI acceptance. This is operationalized through a nested model comparison that quantifies the incremental gain (ΔR^2) at each extension step. Specifically, it addresses the following research questions:

RQ1: To what extent does the traditional TAM explain high school students' intention to use GenAI for physics learning?

RQ2: How do physics-related expectancy-value-cost beliefs predict TAM constructs and behavioral intention?

RQ3: To what extent does each group of EVT variables (expectancy, subjective task values, and cost) incrementally improve the explanatory power of TAM for GenAI acceptance?

In addition to these structural equation modeling (SEM)-focused research questions, we included supplementary follow-up components to clarify how students' reported behavioral intention should be interpreted in the dual-use context of GenAI. Unlike many earlier educational technologies, GenAI can support conceptual learning, but it can also be used to obtain direct answers with limited engagement. Thus, a high behavioral-intention

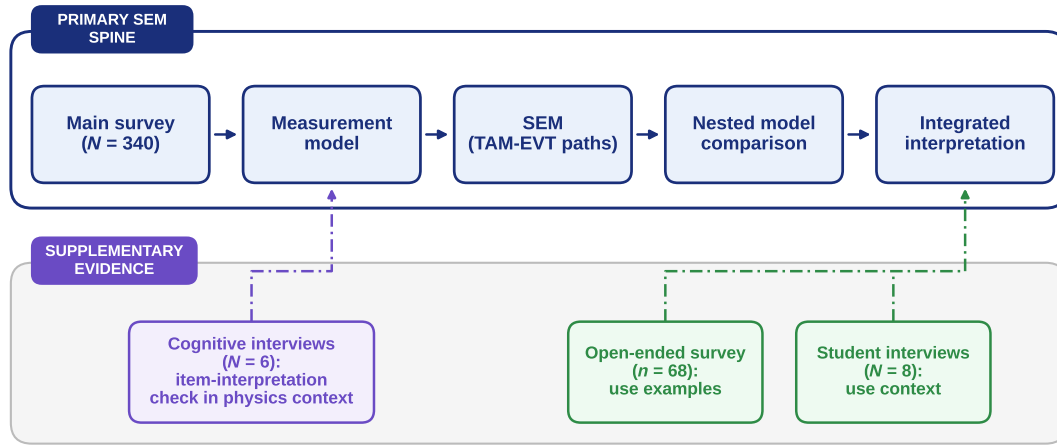


FIG. 1. Research design and methodological relationships.

score does not necessarily indicate the same use orientation for all students. The follow-up survey and semi-structured interviews were used to examine whether students described learning-oriented, shortcut-oriented, or mixed uses of DeepSeek, while the cognitive interviews were used to check how students interpreted the physics-learning anchor in the TAM items. These components were not designed as separate research questions; rather, they support interpretation of the SEM findings and measurement refinement. The overall research design and the methodological relationships among the primary SEM analysis and the supplementary evidence components are summarized in Fig. 1.

Through this integrated paradigm, the study aims to theoretically extend the boundaries of TAM in the context of subject-specific GenAI learning and, in practice, provide actionable diagnostic tools and intervention cues for promoting the deep integration of GenAI with secondary school physics teaching.

II. THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

For ease of presentation, we use abbreviations for the nine latent constructs examined in this study; their full names and brief conceptual definitions are summarized in Table I.

A. Technological-acceptance paths: Based on the technology acceptance model framework

The technology acceptance model is a widely used framework for explaining individuals' adoption of information technologies [35,55–57]. It centers on two key beliefs: PU, the extent to which a person believes that using a technology will enhance task performance, and PEOU, the perceived effort required to use that technology. In this study, PU and PEOU refer specifically to high school students' judgments about using GenAI tools (with

DeepSeek as the exemplar) for physics learning. Meta-analytic and empirical evidence shows that PEOU is a robust positive predictor of PU and that both beliefs jointly shape users' ATT, which in turn influences their BI [56–59]. One plausible interpretation of the PEOU → PU link is a cognitive resource argument: when a technology is easy to operate, users expend less effort on the interface itself, freeing cognitive resources to explore and appreciate the tool's functional capabilities [15,60]. In the context of GenAI-assisted physics learning, a student who can effortlessly formulate queries and parse DeepSeek's responses is better positioned to recognize how the tool supports problem solving and conceptual understanding, thereby developing a stronger perception of its usefulness. Recent work on educational applications of GenAI similarly identifies PU and PEOU as core antecedents of students' willingness to adopt such tools [24–28].

Building on these classic TAM relationships, we formulate the following hypotheses of technological acceptance paths in our model:

- H1: PEOU positively predicts PU [15,56,61].
- H2: PEOU positively predicts ATT [56,58].
- H3: PU positively predicts ATT [56,59].
- H4: ATT positively predicts BI [35,56,59].
- H5: PU positively predicts BI directly, in addition to its indirect effect via ATT [16,44,60].

B. The disciplinary-beliefs paths: Based on the expectancy-value theory

Although TAM has strong explanatory power for technology-related beliefs and intentions, it offers limited insight into why students choose to adopt a tool for learning a particular subject, such as physics. To capture these disciplinary beliefs, we draw on expectancy-value theory [46,62,63]. EVT proposes that achievement-related choices depend on two broad types of beliefs: expectancy, referring to learners' confidence that they can succeed in a given task, and subjective task values, typically decomposed into three

positive value components and one negative component. IV captures the interest and enjoyment experienced when engaging in a task; AV reflects the importance of doing well in the domain for one's self-concept and identity; UV concerns the perceived usefulness of the task for future education, career, or everyday life; and cost represents the time, effort, emotional strain, and opportunity costs associated with completing the task.

Prior research shows that expectancy and value-cost beliefs are strongly domain-specific in STEM fields such as physics and are powerful predictors of students' course enrollment, persistence, and achievement [41,42,62,64–68]. In the present study, EVT is used to represent students' relatively stable beliefs toward “the subject of physics” and to investigate how these disciplinary beliefs interact with TAM constructs to shape GenAI adoption for physics learning.

1. Expectancy

In EVT, expectancy closely parallels the construct of self-efficacy and refers to students' beliefs in their ability to successfully accomplish physics-learning tasks [45,62,69]. In physics education, self-efficacy, interest, and related motivational beliefs are associated with students' engagement and persistence [67,68,70–72]. In technology adoption research, self-efficacy has been identified as an important antecedent of both PEOU and PU [57], because students who feel competent in a domain are more inclined to view related digital tools as manageable and beneficial. Recent GenAI research further shows that students' perceived value and cost of GenAI itself are associated with their intention to use it [73], suggesting that expectancy-value constructs are relevant to GenAI adoption. Building on this literature, we formulate the following hypotheses:

- H6: EXP positively predicts PEOU.
- H7: EXP positively predicts PU.
- H8: EXP positively predicts BI.

2. Subjective task values

Subjective task values are a central source of motivation in EVT and predict students' engagement and persistence in STEM subjects, including physics [41,42,67,68,70,71]. Although both IV and AV are positively valenced, IV is primarily affective, while AV is more identity-relevant. In technology-supported learning, higher intrinsic value for the learning task has been linked to greater satisfaction, more positive attitudes, and stronger continuance intentions toward web-based learning systems and learning management systems [74–77]. Direct evidence on AV and student technology use is more limited, but teacher expectancy-value research shows that value beliefs are related to technology integration and use [78,79], providing indirect support for the idea that students with higher attainment value for physics may also evaluate GenAI

more favorably as a physics-learning aid. In addition, UV beliefs about technology and its relevance for academic or career goals are positively related to PU and intentions to learn and use AI or other digital technologies [80]. Taken together, these findings suggest that IV, AV, and UV, although conceptually distinct, can systematically shape learners' evaluations and adoption of educational technologies.

On the basis of the empirical findings and theoretical arguments reviewed above, we formulate the following hypotheses.

- H9: IV positively predicts ATT.
- H10: IV positively predicts BI.
- H11: AV positively predicts ATT.
- H12: UV positively predicts PU.
- H13: UV positively predicts BI.

3. Perceived cost

In EVT, cost captures the negative side of motivation, including the effort, time investment, and emotional strain associated with learning physics [63]. Elevated perceived cost has been shown to undermine students' motivation and persistence across STEM subjects [41,63,64,81]. In the context of GenAI-supported physics learning, we expect these costs to “spillover” into technology-related judgments: when students already experience physics as demanding and stressful, learning to use a new tool may be perceived as an extra burden, leading to lower PEOU, more negative ATT, and reduced BI toward GenAI [56,57,73]. On this basis, we propose the following hypotheses:

- H14: COST negatively predicts ATT.
- H15: COST negatively predicts BI.
- H16: COST negatively predicts PEOU.

Taken together, these hypotheses, summarized in Fig. 2, are grounded in prior theoretical and empirical work and specify the core structural relations examined in our SEM.

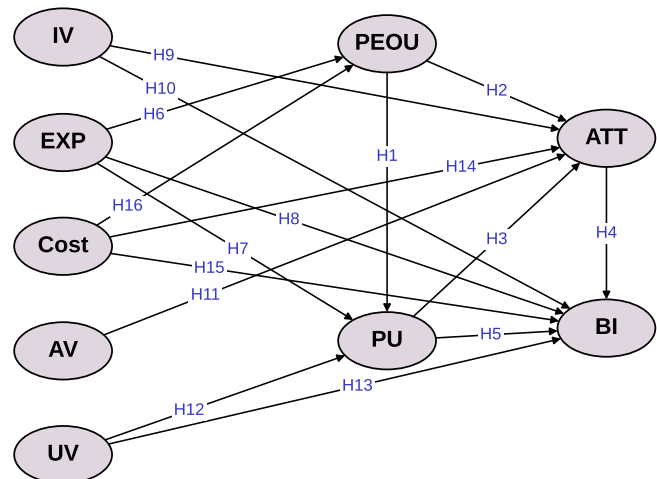


FIG. 2. The technology-subject dual-channel model for GenAI adoption in physics learning.

For potential links between disciplinary beliefs and technology perceptions that lack clear theoretical or empirical justification, we deliberately refrain from formulating *a priori* hypotheses. Instead, these additional paths are probed in the Results section via an extended structural model (see S2 of Supplemental Material [82].) in order to identify any theoretically meaningful relations that may have been overlooked initially.

III. METHODOLOGY

A. Participants

The participants were students from a public regular (nonelite, nonspecialized) senior high school in Hangzhou, Zhejiang Province, China. The findings may therefore be most relevant to students in similar nonselective public schools. The grade 10 cohort comprised 16 intact classes with a total enrollment of approximately 706 students. We employed purposive cluster sampling based on three criteria: (a) DeepSeek usage prerequisite—classes were eligible only if their physics teacher had integrated DeepSeek into at least one instructional unit, ensuring that students' survey responses reflected actual rather than hypothetical experience; (b) teacher cooperation—survey administration required class-period allocation and teacher coordination; and (c) academic-level coverage—the selected classes spanned the school's internal tracking tiers (three advanced track, five regular track), proportionally reflecting the grade's overall composition. Of the 16 classes, 10 met criterion (a), and 8 of these 10 met criteria (b) and (c), yielding a final sample of 8 classes (50% of the grade-level population). This grade level was selected because grade 10 students face less pressure from high-stakes entrance exams, allowing greater flexibility in exploring new technologies during their formative learning phase.

A total of 351 questionnaires were distributed. After excluding questionnaires with extensive missing data or obvious response anomalies, a final total of 340 valid questionnaires was obtained, resulting in an effective response rate of approximately 96.9%. This sample size falls within ranges commonly used in SEM research, although adequacy depends on model complexity, indicator quality, distributional characteristics, and estimation method [83,84]. The final sample comprised 180 males (52.9%) and 160 females (47.1%), with an average age of approximately 16.0 years. All participants were enrolled in a unified physics curriculum and had used DeepSeek in at least one physics instructional unit prior to the survey.

Prior to formal administration, researchers orally explained the study's purpose (exploring students' views and willingness to use GenAI tools in physics learning) to the students. The survey was completely anonymous, intended solely for academic research, and had no bearing on course grades or teacher evaluations. Participation was

voluntary, with students free to withdraw at any time. The distribution and collection process was assisted by course instructors to ensure classroom order and adherence to the principles of informed consent and voluntary participation, complying with ethical requirements in general educational settings. The study was conducted with the permission of the participating school. Because the participants were minors, their parents or guardians were informed of the study before data collection. In the follow-up interviews, students were again reminded that participation was voluntary and unrelated to grades and that they could skip any question, and the interview material shared with the teacher raters was deidentified.

In addition to the main survey, we conducted three supplementary follow-up components to clarify the interpretation and measurement of GenAI acceptance in the physics-learning context. These components were motivated by the dual-use nature of GenAI: students may use DeepSeek to support conceptual understanding and problem solving, but they may also use it to obtain direct answers with limited engagement. Because the main survey was anonymous, individual-level SEM construct scores could not be linked to follow-up responses. We therefore readministered the four intrinsic-value items and the three BI items to four of the original eight classes, selected based on scheduling feasibility, yielding a follow-up cohort of $n = 68$ students from the original sample.

From this follow-up cohort, we conducted three activities. First, an open-ended follow-up survey asked students to describe the physics-related tasks for which they typically used DeepSeek. Second, semistructured interviews were conducted with eight students purposively sampled across intrinsic-value levels to examine whether their GenAI use was primarily learning-oriented, shortcut-oriented, or mixed. Third, cognitive interviews were conducted with six students, also sampled across intrinsic-value levels, to examine how students interpreted the TAM items and what physics-learning scenarios they associated with them. These supplementary components were not used to test additional SEM hypotheses. Instead, the follow-up survey and semistructured interviews clarify the meaning of behavioral intention in a dual-use GenAI context, while the cognitive interviews provide an exploratory check of item interpretation.

Because these follow-up components had to be conducted with students from the original cohort under normal school schedules and voluntary student availability, the interview samples were necessarily modest and purposive. They should therefore be interpreted as information-rich exploratory evidence rather than statistically representative evidence for the full main-sample population. Detailed prompts, interview protocols, coding procedures, and extended examples are reported in S5 of Supplemental Material [82].

B. Survey instruments

Because each construct in the integrated model was developed and validated at a different stage within its respective theoretical tradition, items for each construct were drawn from the authoritative source instrument for that specific construct. The questionnaire items were initially developed in English.

All items were anchored on DeepSeek rather than “generative AI” as a generic category. This design choice served two purposes: it ensured ecological validity, because students evaluated a tool they had actually used in their physics classes, and it ensured measurement consistency, because all respondents assessed the same technological referent. This anchoring strategy is also consistent with recent TAM-based GenAI acceptance studies, which predominantly anchor on specific platforms such as ChatGPT [26,31].

To ensure cross-linguistic equivalence, we followed Brislin’s translation-back-translation protocol [85]: two bilingual researchers independently translated all items from English into Chinese; a third bilingual expert, not involved in the forward translation, back-translated the Chinese version into English; the research team then compared the two English versions, resolved discrepancies, and pilot-tested the final Chinese instrument with one nonsample class before formal administration.

To examine how students interpreted the physics-learning anchor in the TAM items, we conducted a small supplementary cognitive-interview component with six students from the follow-up cohort described in Sec. III A. Each student was shown the eight PU and PEOU items and asked what physics-learning situations came to mind when reading each item. This component was used as an exploratory check of item interpretation rather than as confirmatory validation. Three physics

teachers were additionally asked to judge whether the physics-learning situations students reported for each item represented genuine physics-learning activities. Detailed prompts, descriptive scenario summaries, and item-level response examples are reported in S5 of Supplemental Material [82].

For the TAM items, adaptation was conservative: the generic technological referent in the source instruments was replaced with “DeepSeek,” and the domain anchor “for physics learning” or “for physics-learning tasks” was added. The substantive meaning of the original PU, PEOU, ATT, and BI indicators was otherwise retained.

The detailed constructs, sample items, sources, and Cronbach’s α coefficients are presented in Table II. The complete 35-item instrument, including all items in both English and Chinese, is available from the corresponding author upon reasonable request.

Items for PU and PEOU were directly adapted from the TAM scale developed and validated by Davis, which reported high internal consistency and a clear two-factor structure in original studies [15]. Subsequent TAM2 longitudinal studies and a meta-analysis based on 88 empirical studies have repeatedly used these constructs and confirmed their predictive relevance across different contexts [16,60], and they have been widely adopted in research on technology use among preservice teachers [89]. ATT was measured using the semantic differential scale by Taylor and Todd [86]. BI items were adapted from Bhattacharjee and Sanford’s IT acceptance research [87], which was itself built upon Taylor and Todd’s intention measurement [86] and has been proven to have good reliability in numerous TAM studies and meta-analyses [16].

Expectancy items were adapted from the Self-Concept of Ability and Expectancy for Success Scale developed by Eccles and Wigfield in their classic expectancy-value

TABLE II. Measurement instruments and reliability statistics.

Variable	Number of items	Type of items	Sample item	Cronbach’s α	References
PU	4	Seven-point Likert scale	I would find DeepSeek useful for learning physics.	0.82	Davis [15]
PEOU	4	Seven-point Likert scale	I would find DeepSeek easy to use for learning physics.	0.83	Davis [15]
ATT	4	Seven-point semantic differential scale	Using DeepSeek to learn physics is a (bad ... good) idea.	0.82	Taylor and Todd [86]
BI	3	Seven-point Likert scale	I intend to use DeepSeek to learn physics in the near future.	0.78	Bhattacharjee and Sanford [87]
EXP	4	Seven-point rating scale	How good at physics are you?	0.77	Eccles and Wigfield [88]
IV	4	Seven-point Likert scale	Physics is fun to me.	0.81	Gaspard <i>et al.</i> [42]
AV	4	Seven-point Likert scale	It is important to me to be good at physics.	0.82	Gaspard <i>et al.</i> [42]
UV	4	Seven-point Likert scale	A good knowledge of physics will help me in my future job.	0.79	Gaspard <i>et al.</i> [42]
COST	4	Seven-point Likert scale	Studying physics is too stressful.	0.77	Flake <i>et al.</i> [53]

model research [88]. Subsequent research, such as the longitudinal tracking of students in grades 1–12 by Jacobs *et al.*, used comparable expectancy and value measures longitudinally across grades and domains, documenting developmental and domain-specific patterns [90]; Muenks *et al.* further examined the structural relations among expectancy, value, and cost [91]. Intrinsic value, attainment value, and utility value items were adapted from the multidimensional task value scale developed by Gaspard *et al.* across five subjects [42]; this scale is based on the more refined value subscales proposed in mathematics contexts [92] and has received support in cross-subject and longitudinal validation research, including a Chinese-language school sample [93].

Cost items were derived from the multidimensional cost scale proposed by Flake *et al.* [53], which conceptualizes academic cost in several interrelated facets and has been validated through expert review and confirmatory factor analysis. Subsequently, studies such as the work of Jiang *et al.* on the prediction of adolescent academic motivation and achievement under the “expectancy-value-cost” framework [81], the work of Muenks *et al.* on the further examination of cost structure [91], and Jiang and Zhang’s latent profile analysis of Chinese high school students’ motivation profiles in mathematics and English [64], all utilized similar cost and task value scales and obtained good reliability and validity indicators. In summary, the contextual adaptation of the latent variable scales in this study is grounded in a solid body of prior research.

The complete 35-item integrated instrument, including all items in both English and Chinese, is available from the corresponding author for research purposes upon request. Researchers seeking to use or adapt the instrument are encouraged to contact the corresponding author to ensure appropriate contextual adaptation and citation.

C. Data analysis

Data analysis was performed using the lavaan package in the R computing environment [94], utilizing maximum likelihood (ML) estimation. The psychometric validation followed a systematic trajectory starting with descriptive statistics and normality checks to confirm data suitability. Subsequently, the instrument’s latent structure was first verified through an exploratory factor analysis, providing the basis for a confirmatory factor analysis to ratify the nine-construct measurement model. Reliability and validity were rigorously established through composite reliability, average variance extracted, and the Fornell-Larcker criterion, ensuring that the measurement properties met standard psychometric requirements before structural evaluation.

The structural analysis phase proceeded in two distinct stages. The primary focus was to estimate the hypothesized technology-subject dual-channel model, examining the significance of path coefficients and the variance

explanation (R^2) for key endogenous variables to test the core theoretical propositions. Extending beyond these *a priori* hypotheses, we then probed the model’s theoretical boundaries by contrasting it against a saturated alternative where all cross-disciplinary paths were freely estimated. This comparative scrutiny revealed nuanced structural dynamics—particularly regarding the transmission of attainment value—which prompted a *post hoc* mediation analysis to disentangle the specific indirect mechanisms at play. To quantify the incremental contribution of each variable group, four nested models were estimated: Model 1 (Pure TAM, H1–H5 only), model 2 (+EXP, H6–H8), model 3 (+Values: IV, AV, UV, H9–H13), and model 4 (+COST, H14–H16). At each step, R^2 changes for the key endogenous variables and model fit indices were compared. Because the four models contain different sets of indicators, they are nested in their predictor sets rather than in the strict statistical sense; fit indices were therefore compared descriptively, and no χ^2 difference tests were performed.

The supplementary follow-up data were analyzed to clarify use orientation and item interpretation rather than to test additional SEM hypotheses. Open-ended survey responses and semistructured interviews were coded to identify learning-oriented, shortcut-oriented, and mixed-use patterns. Cognitive interview responses were coded to identify the physics-learning situations students associated with each TAM item. Detailed survey prompts, interview protocols, coding procedures, interrater agreement information, supplementary descriptive figures, and representative examples are provided in S5 of Supplemental Material [82].

IV. RESULTS

A. Descriptive statistics and reliability

All items were rated on seven-point scales (1 = strongly disagree, 7 = strongly agree for Likert-type items; see Table II for the response format of each scale). The descriptive statistics and internal consistency coefficients for each latent variable are presented in Table III. Overall, students’ technological perceptions and willingness to use

TABLE III. Descriptive statistics and normality indices for study variables.

Variable	Mean	Standard deviation	Skewness	Kurtosis
PEOU	5.33	1.21	−0.63	−0.41
PU	5.20	1.29	−0.61	−0.33
ATT	4.90	1.30	−0.50	−0.24
BI	4.89	1.39	−0.50	−0.50
EXP	4.57	1.27	−0.13	−0.74
IV	4.11	1.34	−0.05	−0.61
AV	5.62	1.13	−0.82	0.32
UV	4.95	1.25	−0.41	−0.50
COST	4.84	1.24	−0.25	−0.68

DeepSeek in physics learning were generally positive. Specifically, PEOU ($M = 5.33$, $SD = 1.21$) and PU ($M = 5.20$, $SD = 1.29$) were higher than the scale midpoint of 4, indicating that most students considered DeepSeek relatively easy to master and beneficial for their physics learning performance. ATT ($M = 4.90$, $SD = 1.30$), and BI ($M = 4.89$, $SD = 1.39$) were also at a moderately high level, reflecting that students are generally willing to continue or increase their use of DeepSeek for physics learning in the future.

Regarding motivation at the disciplinary level of physics, students' EXP ($M = 4.57$, $SD = 1.27$), AV ($M = 5.62$, $SD = 1.13$), UV ($M = 4.95$, $SD = 1.25$), and COST ($M = 4.84$, $SD = 1.24$) were all above the midpoint, indicating a moderately high level overall. Among these, AV scored the highest, suggesting that students generally consider "learning physics well" to be important to them. UV and Cost were also relatively high, indicating that while students acknowledge the utility of physics for future education and careers, they also perceive a certain degree of pressure regarding the time and psychological burden associated with learning physics. In contrast, IV ($M = 4.11$, $SD = 1.34$) was only slightly above the scale midpoint and noticeably lower than the other value components, indicating a more moderate level of intrinsic interest in physics. This suggests that students' feelings that physics is "fun and interesting" are relatively average.

In terms of distribution, the skewness of the latent variables ranged from -0.82 to -0.05 and kurtosis ranged from -0.74 to 0.32 . No severe skewness or kurtosis was observed; the data generally exhibited a slight negative skew and were somewhat concentrated on the upper end of the scale, satisfying the assumption of approximate normality required for subsequent structural equation modeling.

B. Measurement model summary

The measurement model showed acceptable psychometric quality. The EFA supported the expected nine-factor structure, with all items loading most strongly on their intended factors and no problematic cross-loadings. The CFA results also supported convergent validity: standardized factor loadings ranged from 0.55 to 0.81 , Cronbach's α and composite reliability values exceeded 0.70 for all constructs, and AVE values were acceptable considering the reliability and loading patterns. Discriminant validity was supported by the Fornell-Larcker criterion. Full EFA eigenvalues, CFA loadings, reliability indices, AVE values, and latent correlation matrices are reported in S1 of Supplemental Material [82].

In practical terms, these results indicate that the survey instrument captured nine empirically distinguishable dimensions of students' technology perceptions and physics-specific disciplinary beliefs, providing an adequate measurement foundation for the structural model.

C. Structural model

1. Overall model fit and explanatory power

Based on the supported measurement model, this study further estimated the structural model integrating TAM and EVT. The overall fit indices were $\chi^2(534) = 854.36$, $\chi^2/\text{d.o.f.} = 1.60$, comparative fit index (CFI) = 0.934 , Tucker-Lewis index (TLI) = 0.927 , root mean square error of approximation (RMSEA) = 0.042 , standardized root mean square residual (SRMR) = 0.049 , and goodness-of-fit index (GFI) = 0.862 (see Table IV). Overall, χ^2/df was close to 1, and RMSEA = 0.042 and SRMR = 0.049 satisfied commonly cited close-fit criteria, whereas CFI = 0.934 and TLI = 0.927 exceeded 0.90 but fell below the more stringent ~ 0.95 benchmarks proposed by Hu and Bentler [95]. Although GFI was slightly below 0.90 , this index is often conservative in models with relatively complex structures; considering the indices jointly, model fit was judged acceptable rather than excellent [83,95,96].

Regarding explanatory power, the coefficients of determination (R^2) for the main endogenous latent variables (i.e., those predicted by other constructs in the model) were $R^2(\text{PEOU}) = 0.29$, $R^2(\text{PU}) = 0.63$, $R^2(\text{ATT}) = 0.67$, and $R^2(\text{BI}) = 0.58$. These values are reported descriptively rather than classified using cutoff rules developed for other estimation traditions. The model accounted for a relatively modest proportion of variance in PEOU, whereas more than half of the variance in PU, ATT, and BI was explained. This indicates that when both technological perceptions and physics disciplinary-beliefs factors are considered, the model can well explain students' PU, ATT, and BI regarding DeepSeek.

2. Path coefficients and hypothesis testing

Table V and Fig. 3(a) presents the standardized path coefficients and hypothesis testing results for the integrated TAM-EVT structural model (significance level $\alpha = 0.05$). Regarding the technological acceptance paths, all five hypothesized paths were significant: PEOU $\rightarrow$ PU (H1, $\beta = 0.52$, $p < .001$), PEOU $\rightarrow$ ATT (H2, $\beta = 0.34$, $p < 0.001$), PU $\rightarrow$ ATT (H3, $\beta = 0.28$, $p < 0.001$), ATT $\rightarrow$ BI (H4, $\beta = 0.34$, $p = 0.001$), and PU $\rightarrow$ BI (H5, $\beta = 0.29$, $p = 0.003$).

In the physics disciplinary-beliefs paths, the path from EXP to PEOU was significantly positive (H6, $\beta = 0.39$, $p < 0.001$), but the paths to PU and BI were not significant (H7: $\beta = 0.07$, $p = .269$; H8: $\beta = 0.13$, $p = 0.071$). The

TABLE IV. Model fit indices for the integrated structural model.

χ^2/df	CFI	RMSEA	SRMR	TLI	GFI
1.600	0.934	0.042	0.049	0.927	0.862
≤ 3.000	≥ 0.900	≤ 0.050	≤ 0.050	≥ 0.900	≥ 0.900

TABLE V. Standardized path coefficients and hypothesis testing results. Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. SE and C.R. refer to the unstandardized estimates; the same applies to Tables B1 and C2 in Supplemental Material [82].

Hypothesis	Path	Standardized estimate β	Standard error SE	Critical ratio C.R.	p value	Result
H1	PEOU $\rightarrow$ PU	0.524	0.104	6.928	<.001	Supported
H2	PEOU $\rightarrow$ ATT	0.345	0.113	4.449	<.001	Supported
H3	PU $\rightarrow$ ATT	0.283	0.082	3.669	<.001	Supported
H4	ATT $\rightarrow$ BI	0.337	0.092	3.275	0.001	Supported
H5	PU $\rightarrow$ BI	0.290	0.093	2.946	0.003	Supported
H6	EXP $\rightarrow$ PEOU	0.391	0.085	5.451	<.001	Supported
H7	EXP $\rightarrow$ PU	0.074	0.109	1.106	0.269	Not supported
H8	EXP $\rightarrow$ BI	0.128	0.109	1.803	0.071	Not supported
H9	IV $\rightarrow$ ATT	0.198	0.121	2.842	0.004	Supported
H10	IV $\rightarrow$ BI	0.082	0.118	1.078	0.281	Not supported
H11	AV $\rightarrow$ ATT	0.129	0.107	2.074	0.038	Supported
H12	UV $\rightarrow$ PU	0.429	0.112	6.286	<.001	Supported
H13	UV $\rightarrow$ BI	0.112	0.121	1.427	0.154	Not supported
H14	COST $\rightarrow$ ATT	-0.157	0.103	-2.641	0.008	Supported
H15	COST $\rightarrow$ BI	0.020	0.102	0.305	0.760	Not supported
H16	COST $\rightarrow$ PEOU	-0.265	0.080	-3.925	<.001	Supported

path from IV to ATT was significant (H9, $\beta = 0.20$, $p = 0.004$), while the path to BI was not significant (H10: $\beta = 0.08$, $p = 0.281$). The path from AV to ATT was significantly positive (H11, $\beta = 0.13$, $p = 0.038$). The path from UV to PU was significantly positive (H12, $\beta = 0.43$, $p < 0.001$), while the path to BI was not significant (H13: $\beta = 0.11$, $p = 0.154$). The paths from Cost (COST) to ATT and PEOU were significantly negative (H14: $\beta = -0.16$, $p = 0.008$; H16: $\beta = -0.27$, $p < 0.001$), but the direct path to BI was not significant (H15: $\beta = 0.02$, $p = 0.760$).

Overall, 11 of the 16 *a priori* hypothesized paths were statistically significant, whereas the remaining 5 were not. To examine whether the hypothesized structural model might omit theoretically meaningful relations, we additionally estimated a more saturated model in which all five disciplinary EVT dimensions were allowed to predict all four TAM constructs (see Fig. 3(b) and S2 of

Supplemental Material [82]). This exploratory analysis yielded a largely convergent pattern, with almost all nonhypothesized paths remaining nonsignificant. One noteworthy exception was attainment value, which exerted a positive and statistically significant effect on perceived usefulness ($p = 0.018$), while its direct effect on attitude was reduced to a marginal level ($p = 0.059$). This pattern suggests that, although H11 was supported in the hypothesized model, the influence of AV on students' attitudes may be conveyed partly via PU rather than solely through a direct path—a possibility examined more formally in the mediation analysis reported below.

Students who find physics useful for their future tend to see DeepSeek as a powerful learning aid (UV $\rightarrow$ PU, $\beta = 0.43$); students confident in physics find GenAI tools easier to operate (EXP $\rightarrow$ PEOU, $\beta = 0.39$); students who enjoy physics have more favorable attitudes toward GenAI (IV $\rightarrow$ ATT, $\beta = 0.20$); and students burdened by physics

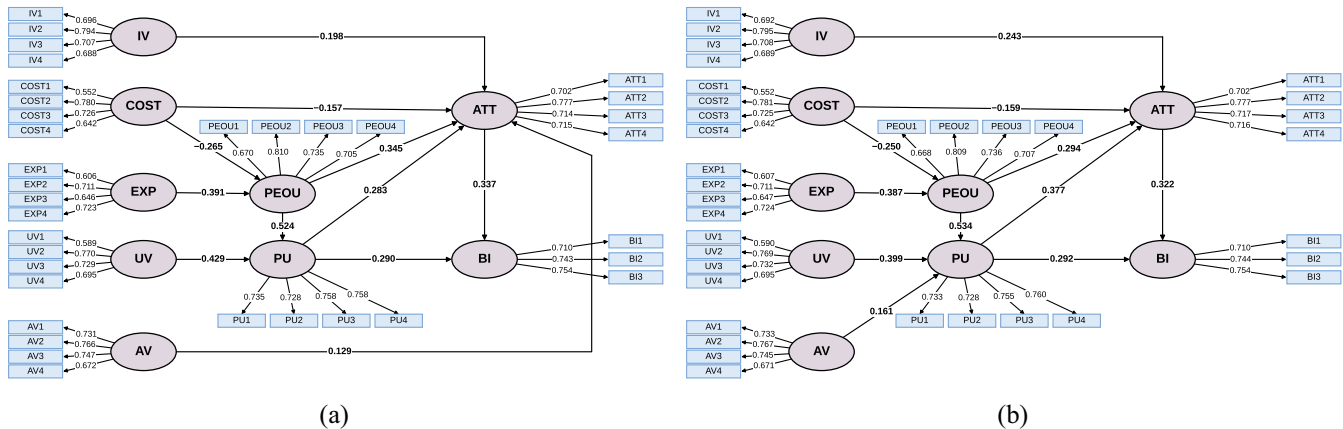


FIG. 3. Integrated TAM-EVT structural model: (a) hypothesized model; (b) exploratory model with all paths estimated.

TABLE VI. Mediation analysis: attainment value, perceived usefulness, and attitude.

Effect type	Path	B	SE	z	p	95% CI lower	95% CI upper	Beta
a path	AV $\rightarrow$ PU	0.451	0.082	5.507	<0.001	0.296	0.623	0.411
b path	PU $\rightarrow$ ATT	0.808	0.138	5.835	<0.001	0.584	1.131	0.617
Direct effect c'	AV $\rightarrow$ ATT	0.276	0.093	2.956	0.003	0.104	0.470	0.192
Indirect effect	AV $\rightarrow$ PU $\rightarrow$ ATT	0.365	0.080	4.541	<0.001	0.231	0.549	0.254
Total effect	AV $\rightarrow$ ATT	0.641	0.120	5.341	<0.001	0.432	0.907	0.446

workload tend to view GenAI as an additional obstacle rather than a support (COST $\rightarrow$ PEOU, $\beta = -0.27$; COST $\rightarrow$ ATT, $\beta = -0.16$). The overarching pattern is that students' physics motivation is closely associated with how they perceive and evaluate GenAI tools.

3. Mediation analysis of AV, PU, and ATT

A mediation analysis focusing on AV, PU, and ATT was conducted to examine whether PU mediates the effect of AV on ATT. AV had a significant positive effect on PU (a path: $B = 0.451$, $SE = 0.082$, $z = 5.51$, $p < 0.001$, $\beta = 0.41$), and PU positively predicted ATT (b path: $B = 0.808$, $SE = 0.138$, $z = 5.84$, $p < 0.001$, $\beta = 0.62$). After controlling for PU, AV still showed a significant direct effect on ATT (c' path: $B = 0.276$, $SE = 0.093$, $z = 2.96$, $p = 0.003$, $\beta = 0.19$). The indirect effect of AV on ATT via PU was significant ($B = 0.365$, $SE = 0.080$, $z = 4.54$, $p < 0.001$, $\beta = 0.25$, 95% confidence interval (CI) [0.23, 0.55]), and the total effect of AV on ATT was also significant ($B = 0.641$, $SE = 0.120$, $z = 5.34$, $p < 0.001$, $\beta = 0.45$, 95% CI [0.43, 0.91]). Taken together, these results indicate that PU plays a significant, but only partial, mediating role in the relationship between AV and ATT. The detailed results of the mediation analysis are shown in Table VI; 95% confidence intervals were obtained using percentile bootstrapping with 5000 resamples.

It is worth noting that the significance of AV's direct effect on ATT varies across the three-model configurations: significant in the hypothesized model ($p = 0.038$), marginal in the exploratory model ($p = 0.059$), and significant in the mediation model ($p = 0.003$). This variation reflects model-dependent variance redistribution. When the AV $\rightarrow$ PU path is introduced in the exploratory model, AV's influence is split across two channels, attenuating the direct path. In the mediation model, with no competing predictors, the direct effect retains significance. Crucially, wherever the AV $\rightarrow$ PU path was estimated, it was positive and significant, confirming that the three analyses are complementary rather than contradictory.

Students who consider doing well in physics important for their identity (high attainment value) do not embrace GenAI based on abstract affinity alone. Instead, their favorable attitudes develop partly because they recognize the tool as genuinely useful for achieving their physics goals. In other words, attainment value operates partly

through a cognitive appraisal of usefulness rather than solely through a direct emotional response.

4. Nested model comparison

Table VII and Fig. 4 summarizes fit indices, R^2 , and ΔR^2 across the four nested models.

The most substantial gain occurred at step 3 (introduction of subjective task values). $R^2(\text{PU})$ jumped from 0.475 to 0.626 ($\Delta R^2 = +0.151$), driven primarily by the UV $\rightarrow$ PU path ($\beta = 0.429$, $p < 0.001$). $R^2(\text{ATT})$ increased from 0.575 to 0.644 ($\Delta R^2 = +0.069$), reflecting the combined contributions of IV $\rightarrow$ ATT and AV $\rightarrow$ ATT. By contrast, adding expectancy alone (step 2) yielded only $\Delta R^2 = +0.044$ for PU. Adding cost (step 4) further raised $R^2(\text{PEOU})$ from 0.241 to 0.294 ($\Delta R^2 = +0.053$), consistent with the spillover hypothesis that perceived learning burden lowers ease-of-use appraisals.

Notably, PEOU transitions from a purely exogenous variable in model 1 to an endogenous construct with $R^2 = 0.294$ in model 4, indicating that ease-of-use judgments are partly associated with disciplinary beliefs rather than being purely technological assessments. In sum,

TABLE VII. Nested model comparison: fit indices and explained variance (ΔR^2). *Note.* PEOU is exogenous in model 1 (pure TAM) and thus has no R^2 or ΔR^2 value. ΔR^2 represents the change in explained variance relative to the preceding model. $N = 340$. All models estimated with maximum likelihood.

	Model 1	Model 2	Model 3	Model 4
	Pure TAM	TAM + EXP	TAM + EXP + values	Full model
χ^2/df	1.961	1.744	1.674	1.600
CFI	0.963	0.960	0.937	0.934
TLI	0.954	0.952	0.929	0.927
RMSEA	0.053	0.047	0.045	0.042
$R^2(\text{PEOU})$		0.239	0.241	0.294
$R^2(\text{PU})$	0.431	0.475	0.626	0.627
$R^2(\text{ATT})$	0.568	0.575	0.644	0.666
$R^2(\text{BI})$	0.541	0.556	0.576	0.581
$\Delta R^2(\text{PEOU})$		+0.239	+0.002	+0.053
$\Delta R^2(\text{PU})$		+0.044	+0.151	+0.001
$\Delta R^2(\text{ATT})$		+0.007	+0.069	+0.022
$\Delta R^2(\text{BI})$		+0.015	+0.020	+0.005

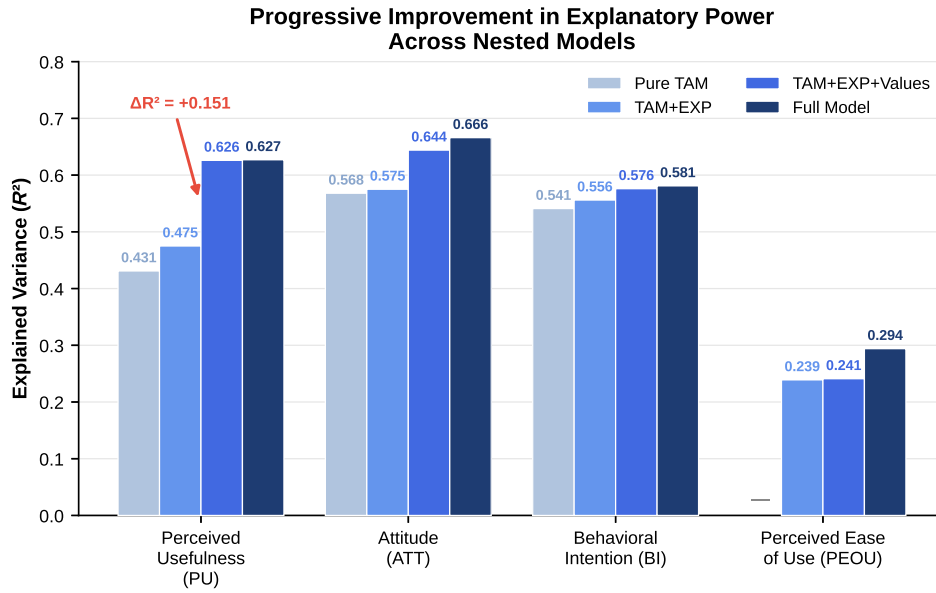


FIG. 4. Progressive improvement in explanatory power (R^2) across nested models for key endogenous constructs. Data labels show R^2 values on the 0-1 scale.

subjective task values represent the largest single source of incremental improvement, with expectancy contributing primarily to PEOU and cost providing additional gains for PEOU and ATT. A stepwise decomposition of these incremental gains and the structural role shift of PEOU are visualized in S3 of Supplemental Material [82].

This indicates that subject-specific motivation, especially subjective task values, provides meaningful explanatory value beyond the basic TAM framework.

D. Supplementary follow-up evidence: Clarifying use orientation behind behavioral intention

1. Why focus on intrinsic value when interpreting BI?

We focused on intrinsic value because this supplementary analysis concerns the orientation of GenAI use rather than acceptance level alone. Intrinsic value captures students' enjoyment and interest in physics and is therefore most directly related to whether students use DeepSeek for conceptual engagement, reasoning, and exploration. In contrast, attainment value and utility value may motivate GenAI use for achievement, exam preparation, homework completion, or future-oriented reasons, but they do not by

themselves distinguish learning-oriented use from shortcut-oriented use. AV and UV are therefore examined in the main SEM and nested model comparison, whereas IV is used here as the grouping variable for interpreting use orientation.

In this study, learning-oriented use refers to using DeepSeek to understand physics concepts, examine reasoning steps, compare solution methods, check derivations after attempting a problem, or explore physics questions beyond class. Shortcut-oriented use refers to using DeepSeek primarily to obtain final answers, copy solutions, or complete homework quickly with limited conceptual engagement. Mixed use refers to responses containing both patterns.

Students were divided into low ($n = 128$, $M_{IV} = 2.73$), medium ($n = 112$, $M_{IV} = 4.27$), and high IV groups ($n = 100$, $M_{IV} = 5.70$) by tercile split. Analysis of variance (ANOVA) revealed a significant main effect on BI, $F(2, 337) = 20.36$, $p < 0.001$, $\eta^2 = 0.108$, with all pairwise differences significant [Table VIII; Fig. 5(a)]. A quadratic regression adding IV^2 confirmed that the relationship is linear rather than curvilinear [$\Delta R^2 = 0.001$, $p = 0.584$; Fig. 5(b)].

TABLE VIII. *Post hoc* group comparison: behavioral intention by intrinsic-value tercile. Note. ANOVA: $F(2, 337) = 20.36$, $p < 0.001$, $\eta^2 = 0.108$. Quadratic term (IV^2): $\Delta R^2 = 0.001$, $p = 0.584$. ** $p < 0.01$, *** $p < 0.001$.

Comparison	n_1	M_1 (SD)	n_2	M_2 (SD)	t	p	Cohen's d
Low vs medium	128	4.41 (1.37)	112	4.88 (1.29)	-2.75	0.006**	0.36
Low vs high	128	4.41 (1.37)	100	5.53 (1.26)	-6.34	<0.001***	0.85
Medium vs high	112	4.88 (1.29)	100	5.53 (1.26)	-3.66	<0.001***	0.51

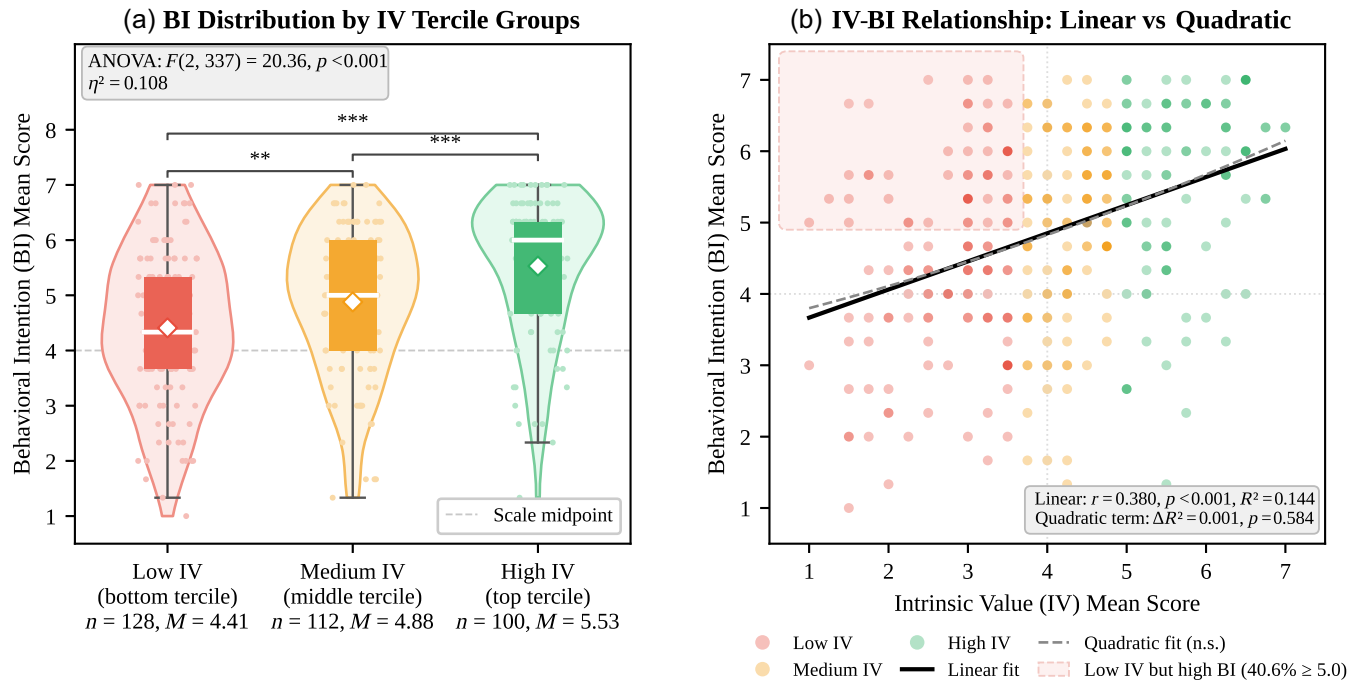


FIG. 5. Behavioral intention by intrinsic-value tercile groups: (a) distributions and (b) linear versus quadratic fits.

The IV-BI pattern is consistent with the SEM result that intrinsic value is related to students' attitudes and the broader adoption process. More importantly, it shows why BI requires careful interpretation in the GenAI context. Although BI increased across IV groups, 40.6% of low-IV students still reported $BI \geq 5.0$, indicating that some students with low interest in physics nevertheless intended to use DeepSeek. Their intended use may not necessarily be conceptual or learning-oriented, which motivated the follow-up use-orientation analysis below.

2. Follow-up survey and student interviews

Using the follow-up cohort described in Sec. III A, the open-ended survey ($n = 68$) and semistructured interviews ($N = 8$) helped clarify what high BI meant for students with different levels of intrinsic value. The survey responses were coded into physics-related use categories, including concept understanding, problem solving, formula or derivation checking, exam preparation, extracurricular exploration, and direct answer copying. High-IV students more often described learning-oriented uses, such as understanding physics concepts, checking derivations, comparing solution methods, and exploring physics questions beyond class. In contrast, low-IV students more often described homework-completion or answer-seeking uses, including directly obtaining solutions.

The semistructured interviews further illustrated how these orientations unfolded in students' reasoning. Some low-IV students reported turning to DeepSeek before fully working through a task, mainly to save time, obtain a final answer, or reduce the burden of homework completion.

Their after-use actions often involved copying or lightly adapting the response with limited checking. By contrast, high-IV students more often described trying the problem first and then using DeepSeek to diagnose errors, check derivation steps, compare alternative solution methods, or ask follow-up "why" questions. Mixed patterns, reported by one low-IV and one medium-IV student, depended on topic difficulty and time pressure.

Three further patterns qualify this picture. First, some students explained shortcut-oriented use in terms of confidence rather than interest: low-IV students attributed answer seeking to being unable to make progress on physics tasks independently rather than to indifference toward the subject (e.g., S1). Second, use orientation was often situational rather than stable, with students reporting more answer seeking for topics they found confusing (S2, S5). Third, the accounts pointed to an observable marker distinguishing the two orientations: whether the student attempted the task before querying DeepSeek, and what was done with the output afterward. The first two patterns parallel the EXP and COST paths in the SEM and indicate that use orientation is not fixed by interest alone; the third yields a marker that teachers can observe without access to construct scores and is taken up in Sec. V D.

These findings do not constitute an additional test of the SEM model. Rather, they clarify the meaning of BI in the GenAI context: the SEM can explain the level of students' intention to use DeepSeek for physics learning, but supplementary evidence is needed to distinguish whether that intention reflects learning-oriented, shortcut-oriented, or mixed use. Detailed interview profiles, representative

responses, and interpretive notes are reported in S5 of Supplemental Material [82].

3. Synthesis

The IV-BI analysis and follow-up evidence together clarify the interpretive scope of behavioral intention. Higher intrinsic value was associated with stronger BI, which is consistent with the SEM pattern. However, the presence of low-IV students with high BI indicates that the same BI score may reflect different use orientations. Some students' own explanations further linked shortcut-oriented use to low confidence and topic difficulty rather than to disinterest alone, indicating that use orientation is situational and therefore open to instructional influence. In the dual-use context of GenAI, behavioral intention should therefore not be interpreted automatically as productive learning-oriented use. This issue is discussed further in Sec. V D.

V. DISCUSSION

A. The gateway to adoption: Validating the technological pathway and the primacy of ease of use

The empirical evidence from this study indicates that high school students are generally willing to adopt DeepSeek for physics learning and that this willingness is closely linked to their perceptions of the tool's ease of use and usefulness. This adoption pattern is broadly consistent with the core propositions of the TAM, in which perceived ease of use feeds into perceived usefulness and, together, shapes attitudes and behavioral intentions [15,17,60,97].

Crucially, a granular analysis of the structural dynamics reveals that perceived ease of use (PEOU) functions not merely as a variable but as a gateway determinant for novices. The substantial magnitude of path coefficients from PEOU to both perceived usefulness (PU) and attitude, juxtaposed with the more moderate effects of usefulness on intention, suggests that for students navigating this novel technology, operational simplicity may be a prerequisite for utility judgment. Students must surmount the initial barrier of interaction complexity before they can fully appreciate DeepSeek's capacity to scaffold problem solving and conceptual understanding. This observation nuances Davis's original emphasis on usefulness as the dominant determinant [15,60] by showing that, for novice users, ease of use operates as an entry condition for usefulness judgments and is consistent with meta-analytic evidence that ease of use remains consequential in educational technology acceptance [97].

This hierarchical adoption process—characterized by ease of use as the entry point and usefulness as the anchor—corroborates contemporary discourse on emerging educational technologies. Whether in digital reading tools [21], AI-assisted learning systems [98],

AR applications [99], or GenAI agents like ChatGPT [26,29,100], ease-of-use perceptions have repeatedly been linked to adoption-related outcomes, although the role of perceived usefulness varies by technology and model specification. From a pedagogical standpoint, this implies that the successful integration of GenAI tools [17,26,97] is contingent less on the theoretical promise of efficiency and more on the tangible reduction of cognitive load. Instructional strategies that prioritize scaffolded familiarization—utilizing demonstrations and structured prompts to render the interface transparent—are thus critical, as they allow the substantive benefits of the tool to emerge naturally, transforming initial curiosity into sustained academic reliance.

B. Beyond parallelism: Disciplinary beliefs as a distal antecedent to technology acceptance

The integrated model suggests that physics expectancy-value beliefs are not simply parallel to TAM constructs but instead influence technology acceptance indirectly through PEOU, PU, and ATT. By situating students' disciplinary epistemology as the foundational lens through which they evaluate technological tools, the analysis reveals that the influence of subject-specific motivation is transmitted primarily through the proximal mediators of PEOU, PU, and ATT, rather than driving usage intention directly.

In the domain of expectancy beliefs, the data indicate that physics self-efficacy serves as a significant antecedent to PEOU, a finding that is conceptually analogous to evidence that computer self-efficacy can act as an antecedent of perceived ease of use [34,36]; students possessing greater confidence in their physics capabilities appear predisposed to view large language model-based tools as manageable and within their control. However, the absence of a direct link to PU or BI suggests that high subject-matter self-efficacy is related to GenAI's perceived academic utility only indirectly via ease of use. One possible explanation, which the present cross-sectional design cannot test directly, is that capable students may not perceive a need for external assistance, preferring instead to rely on their own reasoning capacities. This distinct dynamic—where expectancy predicts ease of use but not usefulness—mirrors phenomena observed in online learning contexts, where learner confidence and task value operate as distinct predictors of learning outcomes [75,76].

Distinct motivational pathways emerge for the value components. Intrinsic value functions primarily through the attitude channel, implying that an inherent affinity for physics fosters a more favorable overall evaluation of the learning tool. Conversely, utility value serves as a strong predictor of PU, indicating that students perceiving physics as instrumental to their future education and career goals are more inclined to recognize the power of GenAI in realizing these long-term aspirations [80]. This hierarchical configuration—where disciplinary value shapes

TABLE IX. Pedagogical principles derived from structural model pathways. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Significant pathway	β	Plain-language interpretation	Pedagogical principle for GenAI integration
$EXP \rightarrow PEOU$	0.39***	Students confident in physics find GenAI tools easier to use	Build physics confidence first: use tiered tasks that ensure success experiences before introducing GenAI tools
$UV \rightarrow PU$	0.43***	Students who see physics as useful for their future value GenAI as a learning aid	Establish subject relevance first: show how physics connects to careers and real life, then demonstrate how GenAI supports these goals
$IV \rightarrow ATT$	0.20**	Students who enjoy physics have more positive attitudes toward GenAI tools	Use curiosity as the entry point: introduce GenAI through engaging “what-if” physics scenarios and exploratory questions, not routine drill
$AV \rightarrow PU$ (mediated)	0.16*	Students who value physics achievement accept GenAI partly by recognizing its usefulness	Highlight GenAI as a performance tool: show achievement-oriented students how GenAI supports exam preparation and deepens problem-solving skills
$COST \rightarrow PEOU$	-0.27***	Students burdened by physics workload also find GenAI difficult to use	Embed GenAI into existing workflow: replace rather than add tasks; integrate GenAI into regular assignments so it reduces cognitive load
$COST \rightarrow ATT$	-0.16**	High physics stress leads to rejection of new tools	Provide scaffolding to lower entry barriers: offer structured prompt templates and guided demonstrations so GenAI becomes a stress-relief tool
$PEOU \rightarrow PU$	0.52***	Ease of use unlocks perceived value	Prioritize first-use experience: arrange in-class demonstrations and hands-on guided sessions to ensure students can operate GenAI before exploring its value
$PU \rightarrow ATT \rightarrow BI$	0.28***, 0.34**	Perceived value drives positive attitude and intention to use	Let value emerge from experience: after students master basic operations, assign tasks where GenAI’s learning benefits become self-evident

technological attitude and usefulness—aligns with evidence from e-learning continuance research [19] and teacher technology-acceptance research [17,78]. Simultaneously, the pervasive negative influence of Cost on both PEOU and ATT highlights a barrier effect: when the cognitive or emotional load of physics is high, the introduction of a new tool is interpreted as an additional burden rather than an aid, consistent with the expectancy-value-cost framework’s posit that high cost erodes engagement [53,63].

A more granular examination of the saturated model further elucidates the mechanism of attainment value. The additional $AV \rightarrow PU$ path in the saturated model suggests that students deeply invested in physics achievement do not embrace GenAI based on abstract affinity alone. Instead, their favorable attitudes depend partly on whether the tool is appraised as instrumentally useful for attaining performance goals. In other words, attainment-related

concerns are translated into technology acceptance partly through cognitive evaluations of usefulness.

Collectively, these structural relationships map a technology-subject dual-channel landscape where disciplinary beliefs act as distal antecedents that shape the proximal, mediating hubs of PEOU, PU, and ATT. This offers a clearer structural hierarchy than research that simply splices TAM with motivational variables, clarifying how physics expectancy-value frames the student mindset toward GenAI [33,42,44]. Practically, these pathway-specific mechanisms suggest that effective GenAI integration requires targeted, rather than generic, pedagogical strategies. Table IX translates each significant pathway into a concrete pedagogical principle, making explicit the connection between statistical findings and classroom practice. The paragraph that follows the table links each of these principles to the student accounts reported in S5 of Supplemental Material [82] so that every recommendation

can be traced both to a statistical estimate and to how students described their actual use of DeepSeek.

Most of these principles can be traced to the student accounts reported in S5 of Supplemental Material [82], as well as to a path coefficient. The confidence pathway is visible in S1, who attributed answer copying to being unable to work physics problems out alone rather than to disinterest; and the curiosity pathway in S6, who used DeepSeek to explore physics beyond class. The value pathways appear in how students read the usefulness items, with high-intrinsic-value students describing connections between physics topics and low-intrinsic-value students describing improved grades (PU2), while ease of use meant typing in a homework question for the latter but formulating precise physics queries for the former (PEOU1 and PEOU3). The final pathway is illustrated by S7 and S8, for whom the value of the tool emerged only after an independent attempt, through method comparison and derivation checking. Read together with Table IX, these accounts indicate that the recommended strategies address use patterns students themselves described, rather than being inferred from the coefficients alone.

C. Quantifying incremental value: Evidence from nested model comparison

The nested model comparison (Sec. IV C 4) indicated that subjective task values—not self-efficacy, which has prior TAM precedent [34,57]—are the primary source of incremental explanatory power. A question that the Results section did not address is whether these disciplinary variables merely add explained variance alongside TAM or actively reshape the model’s internal structure. The path attenuation analysis in Fig. 6 speaks directly to this question.

As disciplinary beliefs enter the model, two core TAM path coefficients are substantially attenuated: PEOU $\rightarrow$ PU

decreases from 0.656 (pure TAM) to 0.524 (full model) and PU $\rightarrow$ ATT from 0.458 to 0.283. Crucially, all core TAM paths remain significant ($p < 0.01$), indicating that technological perceptions retain independent predictive validity. The attenuation therefore reflects a redistribution of explanatory weight—not a displacement—from technology-level perceptions to discipline-level beliefs. This pattern is consistent with the view that disciplinary beliefs function as distal antecedents that reshape the model’s internal dynamics, rather than merely additive covariates that inflate R^2 without altering the explanatory architecture. The stepwise decomposition in S3 of Supplemental Material [82] further illustrates this redistribution.

All four models showed acceptable fit (CFI and TLI ≥ 0.927); although fit indices are not strictly comparable across models with different indicator sets, the R^2 gains documented in Table VII indicate that the integrated framework adds explanatory power. More broadly, the contribution of this work is empirical rather than paradigmatic: the nested comparison and attenuation analysis together provide quantifiable, testable evidence that physics-specific motivational beliefs—particularly utility value—systematically improve the explanatory architecture of TAM for GenAI acceptance, moving beyond conceptual claims of integration.

D. Interpreting behavioral intention in a dual-use GenAI context

The supplementary follow-up evidence clarifies an important interpretive issue for the SEM results. The SEM explains students’ reported intention to use DeepSeek for physics learning, but BI does not by itself distinguish how students intend to use the tool. This distinction matters because GenAI can function as a cognitive scaffold, such as when students use it to compare solution methods or

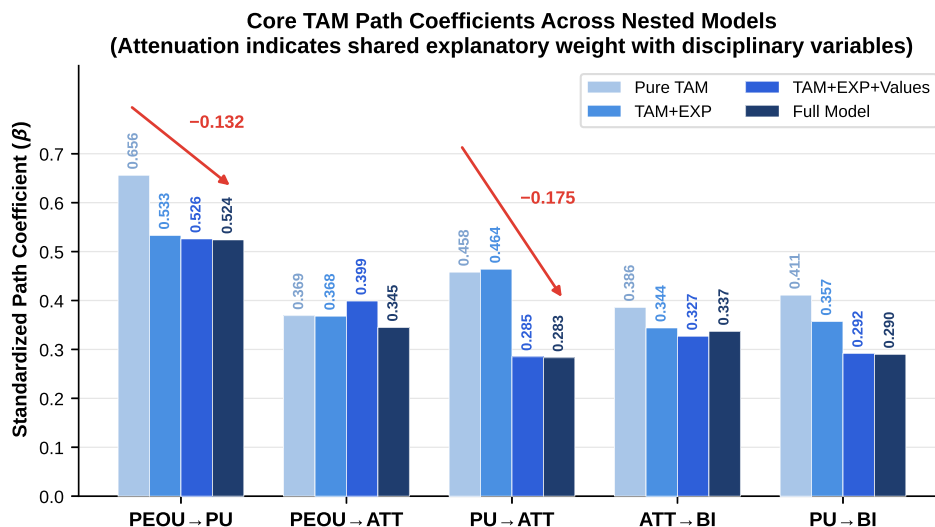


FIG. 6. Core TAM path coefficients across nested models.

check derivation steps, but it can also function as a shortcut for obtaining answers.

The follow-up survey and semistructured interviews suggest that high BI should not automatically be interpreted as productive learning-oriented use for all students. In particular, some low-intrinsic-value students with high BI described answer-seeking or homework-completion uses. Thus, the supplementary evidence does not change the SEM results; rather, it clarifies the interpretive scope of BI.

These accounts also yield a concrete implication for task design. The high-intrinsic-value students described a recurring workflow: attempt the problem first, then use DeepSeek to check the derivation, diagnose the error, or compare solution methods. This is a sequence of actions that the task itself can require rather than a trait that less interested students lack. Assignments can record the student's own attempt before any GenAI use and make the deliverable an error diagnosis or a comparison of two solution paths rather than a final answer so that the payoff of answer seeking is reduced and the marker identified in Sec. IV D becomes visible to the teacher. This is consistent with warnings that unguided GenAI use invites unreflective acceptance of generated solutions [13] and with evidence that GenAI supports learning when embedded in metacognitive and self-regulated learning scaffolds [26].

Future research should develop intention measures that distinguish learning-oriented, shortcut-oriented, and mixed GenAI use and should combine self-report data with behavioral logs when possible.

VI. CONCLUSION

A. Validating the technology-subject dual-channel model

This study provides empirical support for the technology-subject dual-channel model, demonstrating that high school students' adoption of GenAI is consistent with a hierarchical pattern. While the canonical TAM

constructs—perceived ease of use and perceived usefulness—remain the proximal drivers of behavioral intention, their activation is partly anchored in students' disciplinary beliefs. By positioning physics expectancy and value-cost beliefs as distal antecedents, this framework theoretically extends TAM, suggesting that technology acceptance is not merely a system-level assessment but a process deeply contextualized by the learner's subject-specific identity.

B. The distinct role of disciplinary beliefs

The structural analysis reveals precise mappings between physics motivation and technological perceptions. Specifically, students' physics self-efficacy functions as a critical “gateway,” primarily predicting perceived ease of use, whereas the utility value of physics serves as the dominant determinant of perceived usefulness. Conversely, perceived cost exerts a pervasive negative influence, inhibiting both attitude and ease of use. These findings clarify that students do not evaluate tools like DeepSeek in isolation; their technological appraisals are inextricably linked to their confidence in mastering physics and their recognition of the subject's instrumental value.

C. Implications for holistic GenAI integration

These findings suggest a specific pedagogical sequence for GenAI integration, informed by the model's significant pathways (Fig. 7). Phase 1 (build foundation) addresses the strongest distal predictors: teachers should first cultivate physics confidence and value recognition through tiered success-experience tasks and future-relevance activities ($\text{EXP} \rightarrow \text{PEOU}$, $\beta = 0.39$; $\text{UV} \rightarrow \text{PU}$, $\beta = 0.43$). Phase 2 (reduce barriers) targets the negative cost pathways by embedding GenAI into existing workflows rather than adding new tasks and by providing structured prompt templates ($\text{COST} \rightarrow \text{PEOU}$, $\beta = -0.27$; $\text{COST} \rightarrow \text{ATT}$, $\beta = -0.16$). Phase 3 (guided exploration) targets the positive utility pathways by embedding GenAI into existing workflows rather than adding new tasks and by providing structured prompt templates ($\text{IV} \rightarrow \text{ATT}$, $\beta = 0.20$; $\text{PEOU} \rightarrow \text{PU}$, $\beta = 0.52$). Phase 4 (deepen adoption) targets the final outcome by providing structured prompt templates ($\text{PU} \rightarrow \text{ATT} \rightarrow \text{BI}$, $\beta = 0.28, 0.34$). For example, rather than assigning a separate

Proposed GenAI Integration Sequence for Physics Classrooms

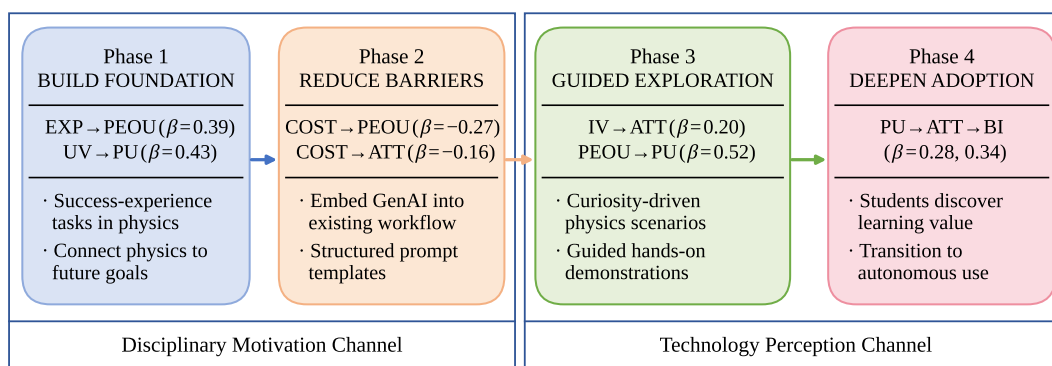


FIG. 7. Proposed four-phase GenAI integration sequence for physics classrooms.

“GenAI exploration” task on top of regular homework—which would increase the very workload burden that COST captures—a teacher might replace a traditional end-of-chapter review exercise with one that asks students to use DeepSeek to check their own solutions and identify where their reasoning diverged from the GenAI’s derivation. This embeds GenAI into a task students would complete regardless, transforming it from an additional cognitive demand into a built-in self-assessment scaffold. Phase 3 (guided exploration) leverages curiosity and ease of use: teachers extend GenAI use through engaging physics scenarios with guided demonstrations (IV $\rightarrow$ ATT, $\beta = 0.20$; PEOU $\rightarrow$ PU, $\beta = 0.52$). Phase 4 (deepen adoption) allows perceived value to emerge from authentic use, transitioning students toward autonomous engagement (PU $\rightarrow$ ATT $\rightarrow$ BI). At this stage, the workflow described by high-intrinsic-value students in Sec. IV D—attempt first, then check, diagnose, and compare—can be taught explicitly and built into assignment requirements so that it is not left to emerge only among students already interested in physics. This sequence transforms the structural model into a practitioner-ready framework: rather than generic advice to “bolster self-efficacy,” it specifies what to address first, what to address next, and why. The sequence is also diagnostic rather than only prescriptive. A class reporting high intention alongside low confidence and high perceived cost may be at elevated risk of shortcut-oriented use, and the indicated response is phase 2 rather than an accelerated introduction of the tool.

D. Limitations

Despite these contributions, several limitations necessitate cautious interpretation of the findings and point toward avenues for future inquiry.

First, the data were derived from a cross-sectional self-report survey within a single general high school in China. This design captures only a snapshot of adoption intentions, limiting the ability to infer causality or generalize findings to diverse educational cultures or varying socioeconomic contexts.

Second, the study focused exclusively on DeepSeek within the domain of physics. As different GenAI tools possess unique affordances and different academic disciplines invoke distinct motivational profiles, the

transferability of this Dual-Channel Model to other subjects or other GenAI platforms remains to be verified. Regarding platform specificity, while absolute construct means (particularly PEOU and PU) may differ across GenAI tools with different interfaces or physics reasoning capabilities, the structural relationships between disciplinary beliefs and technology perceptions—the theoretical contribution of this study—are expected to be more robust to platform variation. Future research should conduct cross-platform comparisons to empirically test this expectation.

Third, several measurement boundaries should be noted. The BI scale captures students’ intention to use DeepSeek for physics learning, but it does not distinguish learning-oriented, shortcut-oriented, and mixed use. As Sec. IV D suggests, some low-interest students may also report high BI while describing answer-seeking or homework-completion uses. Relatedly, the small cognitive-interview component suggested that students could associate the PU and PEOU items with physics-learning situations, but these exploratory responses should not be treated as confirmatory validation of the item anchoring. The same caution applies to the small teacher-judgment component used to check those responses. Future studies should develop multidimensional intention scales that differentiate use orientations and construct more fine-grained physics-task-specific TAM items, such as conceptual understanding, problem solving, derivation checking, homework completion, and answer seeking. Incorporating behavioral log data would further strengthen the validity of self-reported intentions.

Finally, the present study is primarily analytical in orientation, focusing on identifying and modeling the structural pathways through which disciplinary beliefs shape GenAI acceptance. Future research could advance this line of inquiry by subjecting the pedagogical framework proposed in Sec. VIC to controlled intervention studies, thereby moving from descriptive modeling toward prescriptive, evidence-tested practice.

DATA AVAILABILITY

There are no publicly available research data or software supporting this manuscript. Requests for further information or data should be sent to the authors.

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