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Swead Yahya Alzahrani

Sy.alzahrani@psau.edu.sa

Prince Sattam Bin Abdulaziz University

Mohammed Ahmed Elhossiny

Northern Border University

Mohamed Sayed Abdellatif

Prince Sattam Bin Abdulaziz University

Aida AbdElaal Elagamy

Prince Sattam Bin Abdulaziz University

Mohamed Mekheimer

Beni-Suef University

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AI-Adaptive Learning Paths and Task-Difficulty Synchronization: A Longitudinal Study of Student Persistence and Engagement

Swead Yahya Alzahrani

Prince Sattam Bin Abdulaziz University, Alkharj 11942, Saudi Arabia;
Sy.alzahrani@psau.edu.sa

Mohammed Ahmed Elhossiny

Northern Border University, Arar, Saudi Arabia. elhossinymrfa2012@gmail.com

Mohamed Sayed Abdellatif
Prince Sattam Bin Abdulaziz University, Al-Kharj, Saudi Arabia; m.heby@psau.edu.sa
https://orcid.org/0000-0002-2212-5256

Aida AbdElaal Elagamy

Prince Sattam Bin Abdulaziz University, Al-Kharj, Saudi Arabia; a.alajemi@psau.edu.sa

Mohamed Mekheimer
Beni-Suef University, Beni-Suef City 62511, Egypt; mohamed.abdelgawad3@edu.bsu.edu.eg
https://orcid.org/0000-0001-6784-0993

*** Corresponding author**: **Swead Yahya Alzahrani**; Sy.alzahrani@psau.edu.sa

Abstract

This longitudinal mixed-methods quasi-experimental study examined how AI-adaptive learning paths and task-difficulty synchronization influenced student persistence and engagement among 79 undergraduate pre-service English teachers enrolled in the "Teaching People with Disabilities" course at the Faculty of Education, Beni-Suef University. The study was conducted across three academic phases from Semester 2 of 2025 to Semester 2 of 2026. Quantitative data were collected using the Student Engagement Scale for AI-Adaptive Learning, platform log data, and twice-weekly experience sampling micro-surveys. Qualitative data were gathered through semi-structured interviews with 20 students selected according to high and low persistence patterns. Latent growth curve modeling showed significant growth in engagement over time, and AI-adaptive path quality significantly predicted steeper engagement growth. Cox regression indicated that students in synchronized difficulty states were less likely to disengage. Polynomial regression confirmed a curvilinear "flow" relationship, with engagement highest when tasks were optimally challenging and lower when tasks were boring or anxiety-inducing. Mediation and moderation analyses showed that engagement mediated the relationship between adaptive path quality and persistence, while perceived competence mediated the relationship between synchronization and engagement. Interview findings further revealed that difficulty synchronization functioned as an affective regulator by reducing frustration, supporting competence, and strengthening professional passion for inclusive teaching. However, low-persisters reported concerns about algorithmic rigidity, reduced autonomy, and technical friction. The findings suggest that AI-adaptive learning systems can support persistence when they combine personalized sequencing with transparent, flexible, and pedagogically grounded difficulty regulation.

Keywords: AI-adaptive learning, task-difficulty synchronization, student engagement, persistence, experience sampling, inclusive education, pre-service teachers, flow

1. Introduction

Artificial intelligence has accelerated the design of adaptive learning environments capable of tailoring content, feedback, pacing, and assessment to individual learners. Unlike static digital platforms, AI-adaptive systems use learner data—such as response accuracy, time-on-task, prior attempts, mastery estimates, and error patterns—to recommend individualized learning paths. This logic has roots in intelligent tutoring systems and knowledge-tracing models, which demonstrated that student performance data can be used to estimate procedural knowledge and support individualized instructional decisions [1]. Contemporary AI-adaptive systems extend this tradition by using learning analytics and algorithmic sequencing to provide real-time feedback and differentiated practice.

The educational importance of adaptive learning is especially visible in courses with high cognitive and emotional demands. The professional course "Teaching People with Disabilities" requires pre-service teachers to understand disability categories, inclusive pedagogy, classroom adaptation, empathy, and ethical responsibility. Students must not only memorize concepts; they must also translate theory into inclusive teaching practices. For English Department students preparing for basic education contexts, this course requires sustained engagement with complex instructional scenarios and affectively demanding content. In this context, AI-adaptive learning may help students persist by providing learning routes that respond to their progress while maintaining an appropriate level of challenge.

Prior evidence suggests that adaptive tutoring systems can improve learning outcomes when they provide individualized scaffolding and feedback. VanLehn [2] found that tutoring systems can approach the effectiveness of some forms of human tutoring when they are designed around meaningful interaction and feedback. Ma et al. [3] and Kulik and Fletcher [4] similarly reported positive effects of intelligent tutoring systems in meta-analytic reviews. However, these outcomes do not automatically explain why some students continue using adaptive systems while others disengage. Engagement and persistence are longitudinal constructs that unfold through repeated cycles of challenge, feedback, emotional response, and continued effort.

Recent EFL evidence also indicates that AI-assisted feedback can support not only task performance but also engagement-related emotions. In a controlled study of 60 postgraduate EFL

learners, Mekheimer [5] reported that Grammarly-based generative AI feedback significantly improved writing proficiency and was associated with higher revision frequency and better content, organization, and cohesion. Interview data further showed that AI feedback reduced frustration, increased confidence, and generated a sense of accomplishment. These findings are relevant to the present study because they suggest that AI support can function as an affective scaffold as well as a cognitive feedback mechanism.

The concept of task-difficulty synchronization is central to this study. It refers to the degree to which AI-assigned learning tasks remain aligned with a student's current level of mastery, perceived skill, and readiness. This construct is theoretically grounded in flow theory, which argues that optimal engagement occurs when challenge and skill are balanced [6]. It is also supported by cognitive load theory, which shows that learning tasks that are too difficult may overload working memory, while tasks that are too easy may reduce attention and effort [7, 8]. In AI-adaptive environments, difficulty synchronization may therefore function as a bridge between algorithmic personalization and student persistence.

Student engagement is commonly understood as a multidimensional construct involving behavioral, emotional, and cognitive dimensions [9]. Behavioral engagement includes effort, attendance, participation, task completion, and rule-following. Emotional engagement includes interest, enjoyment, excitement, frustration, and perceived support. Cognitive engagement refers to deep processing, strategy use, self-regulation, and the effort to connect learning with real-world contexts. In digital learning environments, these dimensions can be measured through both validated survey scales and platform-generated behavioral indicators. Experience Sampling Methodology (ESM) adds further value by capturing students' immediate affective and cognitive states during learning rather than relying only on delayed retrospective reports [10, 11].

Self-determination theory provides a motivational explanation for why adaptive systems may influence persistence. When learners experience autonomy, competence, and relatedness, they are more likely to internalize learning goals and sustain effort [12, 13]. AI-adaptive systems may support competence when they deliver appropriately challenging tasks and formative feedback. They may also support autonomy if students perceive the system as flexible and helpful rather than controlling. Chiu [14] showed that digital support can foster engagement in blended learning when it satisfies these psychological needs. Thus, AI-adaptive learning paths

may influence persistence through motivational and affective mechanisms, not merely through improved content delivery.

Within Egyptian higher education, successful AI adoption also depends on context-sensitive technology integration. Mekheimer [15] found that faculty members in Egyptian universities emphasized the need for practical, discipline-specific professional development, alignment between technology use and sound pedagogical principles, ethical attention to AI use, equitable access, and sustained technical and collegial support. This reinforces the need to examine AI-adaptive learning in an authentic Egyptian teacher-education context rather than treating adaptive learning as a decontextualized platform feature.

The present study investigates how AI-adaptive learning paths and task-difficulty synchronization shape persistence and engagement among pre-service teachers in the English Department (Basic Education) at the Faculty of Education, Beni Suef University. By following a cohort across the second semester of the 2024/2025 academic year through the second semester of the 2025/2026 academic year, the study aims to capture engagement as a dynamic process rather than a single post-intervention outcome. The study contributes to adaptive learning research by combining repeated engagement measurement, ESM micro-surveys, platform-based persistence indicators, and qualitative interviews.

1.1 Research Gap

Although the literature on intelligent tutoring systems and adaptive learning is substantial, several gaps remain. First, much of the evidence emphasizes achievement outcomes rather than persistence and engagement trajectories. Meta-analyses show that intelligent tutoring systems can improve academic performance, but they provide less explanation of how adaptive systems sustain students' willingness to continue learning over an extended period [3, 4]. Recent reviews of personalized adaptive learning similarly report engagement benefits but show that many studies rely on short-term, post-intervention, or cross-sectional designs [16, 17].

Second, previous studies often treat adaptivity as a broad system characteristic instead of separating specific adaptive mechanisms. Adaptive platforms may personalize content, sequence tasks, adjust difficulty, recommend resources, provide feedback, or trigger affective support. These mechanisms may not have equivalent effects on persistence. Task-difficulty

synchronization remains underdeveloped as an empirical construct, even though challenge–skill balance is a well-established predictor of flow and engagement [6].

Third, the relationship between task difficulty and engagement may be curvilinear rather than linear. Overly easy tasks may create boredom and under-challenge, whereas overly difficult tasks may create anxiety, frustration, and cognitive overload [7, 8]. This suggests that adaptive learning research should not simply ask whether more difficult tasks produce better learning; it should examine whether students persist when difficulty is synchronized with their current mastery.

Fourth, limited research has examined AI-adaptive learning in teacher preparation courses focused on disability education and inclusive pedagogy. Such courses require cognitive understanding, emotional sensitivity, and professional identity development. The present study addresses these gaps by examining a longitudinal cohort of pre-service teachers and integrating survey-based engagement measures, ESM pulse checks, platform persistence indicators, and interviews.

2. Literature Review

2.1 AI-Adaptive Learning Paths and Intelligent Tutoring Systems

AI-adaptive learning paths are grounded in the broader tradition of learner modeling and intelligent tutoring systems. Early work on knowledge tracing demonstrated that learner responses can be used to estimate mastery and guide individualized instruction [1]. In modern AI-adaptive environments, the system may use performance data to adjust sequence, pacing, feedback, task complexity, and resource recommendations. This creates a personalized path that is continuously updated as the learner interacts with the platform.

Meta-analytic evidence supports the effectiveness of intelligent tutoring systems. VanLehn [2] compared tutoring systems with other forms of instruction and concluded that tutoring effectiveness depends heavily on interaction quality and feedback. Ma et al. [3] found that intelligent tutoring systems are associated with improved learning outcomes across contexts, and Kulik and Fletcher [4] similarly found positive effects in a meta-analytic review. These studies establish the potential of adaptive tutoring, but they also indicate that system effectiveness depends on design features, learner characteristics, and implementation fidelity.

Recent reviews of AI and adaptive learning emphasize the growing role of artificial intelligence in providing personalized learning and data-driven support. Lin et al. [16] noted that AI-supported intelligent tutoring systems can create personalized learning experiences, monitor learner performance, and provide insights into engagement and emotion. Du Plooy et al. [17] found that personalized adaptive learning in higher education was often associated with improved academic performance and engagement, but they also highlighted the need for stronger research designs and clearer specification of adaptive system characteristics. These findings justify a study that examines not only whether AI-adaptive systems are beneficial, but which adaptive mechanisms contribute to sustained engagement and persistence. Recent empirical studies have likewise linked AI-powered adaptive learning with engagement and motivation in school and higher-education contexts [18, 19].

Evidence from EFL writing contexts extends this argument by showing that AI feedback may influence engagement through revision behavior, confidence, and perceived accomplishment. Mekheimer [5] found that generative AI-assisted feedback using Grammarly produced significantly higher post-test writing proficiency among postgraduate EFL learners compared with traditional instruction. The study also reported positive relationships between AI feature use and revision frequency, as well as improvements in content, organization, and cohesion. Although this work focused on EFL writing rather than AI-adaptive path sequencing, it supports the present study's assumption that AI feedback can strengthen engagement when it reduces frustration and helps students see progress.

2.2 Task-Difficulty Synchronization, Flow, and Cognitive Load

Task-difficulty synchronization is defined in this study as the degree to which AI-assigned tasks match the learner’s current readiness, mastery level, and perceived capability. The construct is closely related to the challenge–skill balance at the center of flow theory. When challenge and skill are balanced, learners are more likely to experience focused attention, enjoyment, and absorption; when challenge is too low, boredom may occur, and when challenge is too high, anxiety may result [6].

Cognitive load theory provides a complementary explanation. Learning requires working-memory resources, and poorly calibrated task demands may interfere with schema construction. Sweller [7] argued that high cognitive load during problem solving can negatively affect

learning, while Paas et al. [8] emphasized the importance of instructional design that manages cognitive load. AI-adaptive systems may reduce cognitive overload by sequencing prerequisite content, providing scaffolds, and adjusting task difficulty. However, if the system misjudges student readiness, it may intensify overload or boredom. The broader theoretical synthesis by Sweller et al. [20] likewise emphasizes calibrating instructional demands to learners' cognitive architecture.

In disability education, difficulty synchronization is particularly important because learners must connect conceptual knowledge with ethical, emotional, and practical teaching judgments. A task may be technically simple but emotionally demanding, or conceptually difficult but professionally meaningful. Therefore, adaptive difficulty should not be understood only as item complexity; it also includes the alignment of content, feedback, emotional challenge, and application demands with the learner's development.

2.3 Student Engagement and Persistence

Student engagement is a multidimensional construct comprising behavioral, emotional, and cognitive dimensions [9]. Behavioral engagement refers to participation, effort, persistence, and completion. Emotional engagement includes interest, excitement, enjoyment, frustration, and perceived support. Cognitive engagement includes strategic learning, self-regulation, deep processing, and the ability to connect ideas across contexts. This tripartite model is appropriate for AI-adaptive learning because students' interactions with the platform can be examined through observable behavior, affective reactions, and cognitive investment.

Persistence refers to students' continued effort and participation across time, particularly when they face difficulty. In the present study, persistence is operationalized through continued platform use, completion of required and optional AI-recommended tasks, re-engagement after errors, and sustained participation across semesters. Persistence is conceptually related to engagement but is not identical to it. A student may temporarily engage with a module but fail to continue using the system over time; conversely, persistent use may reflect compliance rather than deep cognitive engagement. For this reason, the study measures both constructs. This longitudinal understanding is also consistent with Tinto's [21] account of persistence as continued academic integration and commitment.

Self-determination theory explains how adaptive systems may influence engagement and persistence by supporting competence, autonomy, and relatedness [12, 13]. When AI feedback helps learners understand mistakes and progress through levels, students may experience greater competence. When the learning path provides appropriate choice and transparent recommendations, students may experience greater autonomy. Chiu [14] found that digital support can enhance engagement when it satisfies learners' psychological needs, making self-determination theory an appropriate framework for interpreting engagement in AI-adaptive environments. This interpretation is consistent with the foundational and later formulations of self-determination theory [13, 22, 23].

The Egyptian higher education context also matters for interpreting AI-adaptive learning outcomes. Mekheimer [15] showed that effective technology integration in Egyptian universities depends on pedagogically grounded, context-specific, and ethically informed professional development. Faculty participants called for hands-on training, discipline-specific examples, advanced learning-management-system support, attention to equity, and ongoing communities of practice. These findings suggest that AI-adaptive learning path quality is not merely a technical feature of a platform; it also depends on whether AI tools are aligned with curriculum aims, instructor support, institutional resources, and ethical expectations.

2.4 Experience Sampling and Longitudinal Measurement

Experience Sampling Methodology strengthens engagement research by capturing students' immediate states during learning episodes. Instead of relying only on end-of-semester reflections, ESM collects repeated in-the-moment reports of affect, perceived difficulty, flow, and motivation. Xie et al. [10] argued that ESM is especially useful for examining engagement as situational, multidimensional, and longitudinal. Lu et al. [11] similarly used experience sampling to investigate within-person and between-person predictors of emotional engagement in blended learning among pre-service teachers.

The present study uses ESM micro-surveys as pulse checks to capture immediate perceptions of task difficulty and affect. These data are especially relevant to task-difficulty synchronization because students' perception of challenge may fluctuate from module to module. When linked with platform logs and semester-based engagement surveys, ESM data can identify whether repeated experiences of optimal challenge predict sustained persistence.

2.5 Conceptual Framework

The conceptual framework proposes that AI-adaptive learning path quality influences student engagement and persistence through two central mechanisms: perceived competence and task-difficulty synchronization. AI-adaptive path quality refers to the appropriateness, clarity, relevance, and responsiveness of the learning sequence. Task-difficulty synchronization refers to whether the challenge level is perceived as too easy, optimal, or too difficult. Engagement is expected to mediate the relationship between adaptive learning and persistence, while task-difficulty synchronization is expected to moderate the strength of this relationship. The framework also draws on social cognitive theory and self-efficacy [24, 25], mastery learning [26], discovery-oriented scaffolding [27], experiential learning [28], and the zone of proximal development [29].

The framework also assumes reciprocal effects across time. Early engagement may increase later persistence, and continued persistence may strengthen later engagement by increasing familiarity with the system and confidence in using adaptive feedback. A longitudinal design is therefore necessary to examine these relationships as trajectories rather than one-time associations. Figure 1 summarizes the conceptual model and shows the proposed mediating, moderating, and reciprocal pathways.

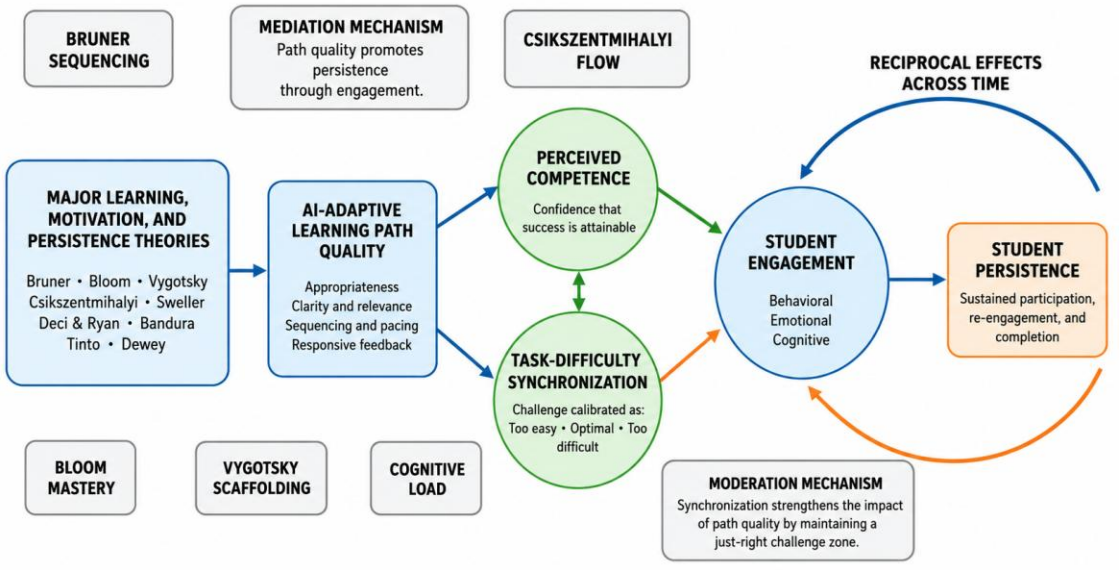


Fig. 1 Conceptual Model of AI-Adaptive Learning Path Quality, Task-Difficulty Synchronization, Student Engagement, and Persistence

Note. The model positions engagement and perceived competence as mediating mechanisms and task-difficulty synchronization as a moderating mechanism across the longitudinal learning process.

2.6 Hypotheses

1. AI-adaptive learning path quality will positively predict student engagement over time.
2. Task-difficulty synchronization will positively predict student persistence over time.
3. The relationship between task difficulty and engagement will be curvilinear, with engagement highest when tasks are perceived as optimally challenging rather than boring or anxiety-inducing.
4. Student engagement will mediate the relationship between AI-adaptive learning path quality and persistence.
5. Task-difficulty synchronization will moderate the relationship between AI-adaptive learning path quality and persistence; the relationship will be stronger when tasks are synchronized with students' mastery levels.
6. Perceived competence will mediate the relationship between task-difficulty synchronization and engagement.
7. Earlier engagement will positively predict later persistence, creating a longitudinal feedback loop between engagement and continued platform use.

3. Methodology

3.1 Research Design

This study employs a longitudinal, mixed-methods, single-cohort quasi-experimental design with repeated quantitative measurement and qualitative follow-up interviews. The study spans from the second semester of the 2024/2025 academic year through the second semester of the 2025/2026 academic year. It tracks the persistence and engagement trajectories of pre-service teachers as they interact with an AI-adaptive learning system in the professional course "Teaching People with Disabilities."

The quantitative strand includes three administrations of the Student Engagement Scale for AI-adaptive learning (SES-AI), repeated ESM micro-surveys, and platform-based persistence indicators. The qualitative strand includes semi-structured interviews at the end of each semester, with special attention to students' perceived flow, difficulty synchronization, affective inclination toward AI, and developing passion for inclusive education. The design is mixed-methods because numerical engagement trajectories are interpreted alongside students' explanations of why their engagement increased, decreased, or fluctuated. It is quasi-

experimental because the study evaluates an AI-supported instructional intervention in a natural university course without random assignment to treatment and control groups. The integration of repeated quantitative measures with qualitative follow-up follows mixed-methods design principles described by Creswell and Plano Clark [30].

3.2 Participants and Setting

The study population consists of 79 undergraduate students from the English Department (Basic Education) at the Faculty of Education, Beni Suef University (BSU). Participants are enrolled in the professional course "Teaching People with Disabilities." This cohort was selected because the course requires both specialized instructional knowledge and sustained emotional engagement with inclusive teaching responsibilities. The course content includes disability categories, inclusive classroom practices, teaching adaptations, empathy, and professional decision-making for supporting learners with disabilities.

Ethical approval was obtained from the Ethics Committee of the Faculty of Education, Beni Suef University (Approval No: BSU-FoE-0001-03-2025). Participation is based on informed consent. Students are informed that their course participation and grades will not be negatively affected by their decision to participate or withdraw from the research component. Data are anonymized before analysis, and platform logs are reported only in aggregate form. The timing, purpose, and data source for each phase are summarized in Table 1.

Table 1

Overview of the Longitudinal Design

Component	Timing	Purpose	Data Source
Baseline measurement	Semester 2, February 2025	Establish initial behavioral, emotional, and cognitive engagement levels	SES-AI
Repeated pulse checks	Twice weekly across instructional weeks	Capture immediate task-difficulty synchronization and affective states	ESM micro-surveys
Midpoint measurement	Semester 1, October 2025	Track changes in engagement after extended AI-adaptive exposure	SES-AI and platform logs
Semester interviews	End of each semester	Explain engagement trajectories and perceptions of AI support	Semi-structured interviews

Component	Timing	Purpose	Data Source
Final measurement	Semester 2, May 2026	Estimate final persistence and engagement trajectories	SES-AI, ESM data, platform logs, interviews

3.3 Instrumentation and Validation

3.3.1 Student Engagement Scale for AI-Adaptive Learning (SES-AI)

The primary quantitative instrument is a modified version of the Student Engagement Scale based on the behavioral, emotional, and cognitive engagement framework proposed by Fredricks et al. [9]. The modified SES-AI is designed specifically for AI-adaptive learning in the course "Teaching People with Disabilities." It is administered at three points: Semester 2 baseline in February 2025, Semester 1 midpoint in October 2025, and Semester 2 final measurement in May 2026. The instrument uses a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree.

The instrument includes three subscales. Behavioral engagement measures students' focus, rule-following, completion of recommended activities, persistence through difficulty, and regular platform use. Emotional engagement measures perceived support, excitement, professional relevance, accomplishment, and enjoyment of difficulty synchronization. Cognitive engagement measures students' efforts to seek additional information, connect AI-guided lessons to future teaching, analyze feedback, apply strategies to Egyptian classrooms, and organize disability knowledge into a professional framework. The complete set of SES-AI dimensions and items is presented in Table 2.

Table 2

Student Engagement Scale for AI-Adaptive Learning (SES-AI)

Dimension	Item ID	Survey Item Statement
Behavioral	B1	I stay focused on the AI-adaptive tasks even when they are difficult.
Behavioral	B2	I follow all instructions and interactive cues provided by the AI system.
Behavioral	B3	I complete the optional AI-recommended activities for special education teaching.
Behavioral	B4	When I encounter a difficult concept regarding disabilities, I persist until I understand it.

Dimension	Item ID	Survey Item Statement
Behavioral	B5	I regularly log into the AI platform to keep up with my personalized learning path.
Emotional	E1	The personalized feedback from the AI makes me feel supported in my learning.
Emotional	E2	I feel excited about using the AI-adaptive system to learn about teaching people with disabilities.
Emotional	E3	I find the content curated by the AI system to be interesting and professionally relevant.
Emotional	E4	I feel a sense of accomplishment when the AI recognizes my progress through the levels.
Emotional	E5	I enjoy the way the AI platform synchronizes its difficulty with my current skill level.
Cognitive	C1	I look for extra information provided by the AI to better understand specific disabilities.
Cognitive	C2	I try to connect the AI-guided lessons to my future career as an English teacher in inclusive classrooms.
Cognitive	C3	When I make a mistake, I analyze the AI's feedback to correct my understanding.
Cognitive	C4	I think about how the AI-suggested teaching strategies would work in a real Egyptian classroom.
Cognitive	C5	I try to mentally organize the different disability types we study into a clear, professional framework.

Note. The SES-AI was reviewed by seven experts and confirmed through CFA for use in the Egyptian educational context, according to the validation procedures described below.

3.3.2 Validity and Reliability

To ensure the psychometric integrity of the instruments within the Egyptian educational context, the SES-AI and AI-adaptive content were reviewed by a panel of seven experts in Educational Technology and Special Education from Beni Suef and Cairo Universities. Experts evaluated each item for clarity, cultural relevance, and alignment with the "Teaching People with Disabilities" curriculum. Consistent with content validity procedures, items with a Content Validity Ratio (CVR) below 0.78 were revised or removed [31].

Construct validity was examined using Confirmatory Factor Analysis (CFA) in AMOS 26.0. The hypothesized three-factor model—behavioral, emotional, and cognitive engagement—

showed good fit to the data, with $\chi^2/df < 3.0$, CFI > .92, and RMSEA < .07. These criteria are consistent with commonly cited fit-index recommendations in structural equation modeling [32]. Factor loadings for all retained items exceeded .60.

Reliability was examined through Cronbach's alpha. Internal consistency coefficients ranged from .84 to .91 across the three subscales, indicating high reliability. Cronbach's alpha is appropriate for estimating internal consistency when items are designed to measure a common latent construct [33].

3.3.3 Experience Sampling Method: ESM Micro-Surveys

To capture real-time affective shifts, ESM micro-surveys are triggered through the AI platform twice weekly, such as on Tuesdays and Thursdays, across approximately 30 instructional weeks. Each micro-survey is designed to be completed in under 60 seconds in order to reduce survey fatigue while capturing immediate flow state and affective response. The trigger appears automatically upon completion of a learning module or after 20 minutes of platform activity.

The ESM pulse check includes two components. Part A measures perceived task-difficulty synchronization by asking students whether the AI tasks they just completed felt boring, optimal/flow, or anxiety-inducing. Part B measures current affect by asking students to select one or more immediate emotional states, including frustrated, curious, excited, or neutral. The pulse-check prompts and response options are presented in Table 3.

Table 3

ESM Micro-Survey: The "Pulse Check"

Part	Prompt	Response Options
A: Task-Difficulty Synchronization	Thinking about the AI tasks you just finished, how did the level of challenge feel?	Boring: too easy, disinterested, under-challenged; Optimal/Flow: challenging but manageable, time passed quickly; Anxiety-Inducing: too hard, overwhelmed or stressed
B: Current Affect	How do you feel right now regarding your learning process? Select all that apply.	Frustrated: AI feedback is not helping; Curious: I want to see the next personalized module; Excited: I am enjoying this topic or strategy; Neutral: I am completing required tasks

The implementation schedule across the three longitudinal phases is summarized in Table 4.

Table 4

ESM Implementation Timeline

Period	Phase	Focus	ESM Frequency
Semester 2 (2025)	Initial Adaptive Phase	Introduction to disabilities and inclusion; AI learns student baselines	2x weekly
Summer 2025	Reflection Period	Optional qualitative check-ins on system perception	Monthly
Semester 1 (2025/2026)	Advanced Synchronization Phase	Specific disabilities including visual, hearing, and motor disabilities; higher difficulty synchronization	2x weekly
Semester 2 (2026)	Professional Mastery Phase	Classroom management for learners with disabilities; final persistence trajectory tracking	2x weekly

3.3.4 Semi-Structured Interview Protocol

Qualitative data are gathered through semi-structured interviews at the end of each semester. The interviews focus on students' internal inclinations toward AI, perceived passion for disability education, sense of flow, experiences of boredom or anxiety, and perceptions of whether the AI system functioned as a supportive tutor or merely as a machine. At the final stage, 20 students are selected for deeper interviews based on the highest and lowest persistence scores from the ESM and platform data. This extreme-case sampling strategy helps explain why some students sustain engagement while others show weaker persistence. The interview foci and corresponding guiding questions are presented in Table 5.

Table 5

Qualitative Interview Protocol

Interview Focus	Guiding Question
Introduction	We have tracked your journey with the AI system over the past year. We want to understand the "why" behind your engagement patterns.

Interview Focus	Guiding Question
Flow and Difficulty	There were times the ESM data showed you felt bored or anxious. Can you describe a specific module where the AI difficulty synchronization felt just right, or like flow?
Persistence	As a student in the English Department, how did the AI-adaptive path help you stay persistent in a complex course like "Teaching People with Disabilities" for a full year?
Affective Inclination	Do you feel your passion or inclination toward helping people with disabilities changed because of the way the AI interacted with you? Did it feel like a supportive tutor or just a machine?
Reliability of Adaptation	Did the system's ability to adjust to your emotional state, such as frustration or excitement, feel accurate to you?

3.4 Operational Definitions and Measures

The study operationalizes the key constructs as shown in Table 6. The combination of survey scores, ESM responses, platform logs, and interview narratives allows the study to capture engagement and persistence at multiple levels.

Table 6

Operational Definitions of Study Variables

Variable	Operational Definition	Primary Indicators
AI-adaptive learning path quality	The perceived and logged appropriateness of AI sequencing, content recommendation, feedback, and pacing.	Student ratings of support and relevance; platform recommendation history; completion of personalized modules.
Task-difficulty synchronization	The alignment between AI-assigned challenge and student readiness or perceived skill.	ESM difficulty response: boring, optimal/flow, anxiety-inducing; progression and error patterns.
Student engagement	Behavioral, emotional, and cognitive involvement in AI-adaptive learning.	SES-AI subscale scores; ESM affect; time-on-task; optional activity completion.
Persistence	Sustained participation and continued effort across the longitudinal study period.	Regular login patterns; completion rates; re-engagement after failed attempts; continued participation across semesters.
Perceived competence	Students' sense that they can successfully understand and apply course content.	SES-AI emotional and cognitive indicators; interview narratives about confidence and progress.

3.5 Data Collection Procedures

Data collection proceeds in five phases. First, students complete the baseline SES-AI in February 2025 after receiving an orientation to the AI-adaptive platform. Second, the AI platform records ongoing participation indicators, including logins, time-on-task, completed modules, optional activities, repeated attempts, and re-engagement after feedback. Third, ESM pulse checks are administered twice weekly during instructional weeks to capture immediate perceptions of difficulty and affect. Fourth, the midpoint SES-AI is administered in October 2025 to examine changes in engagement after sustained exposure to AI-adaptive learning. Fifth, the final SES-AI is administered in May 2026, followed by final semi-structured interviews with selected students.

To reduce participant burden, ESM micro-surveys are intentionally brief and embedded into normal platform activity. Students are reminded that ESM responses are used for research and course-improvement purposes, not for grading. Interview responses are audio-recorded only with consent, transcribed, anonymized, and coded thematically.

3.6 Data Analysis Plan

Quantitative analysis begins with descriptive statistics for SES-AI subscales, ESM responses, and platform-based persistence indicators. Reliability coefficients are reported for the SES-AI subscales at each administration point. Repeated-measures analyses or linear mixed-effects models are then used to examine changes in engagement over time. Mixed-effects modeling is appropriate because the ESM data are nested within students and collected repeatedly across the academic year.

Task-difficulty synchronization is analyzed by classifying ESM responses into boring, optimal/flow, and anxiety-inducing states. The study tests whether the proportion of optimal/flow responses predicts persistence indicators such as continued platform use, task completion, and re-engagement after errors. Curvilinear effects are examined by comparing engagement and persistence outcomes across under-challenge, optimal challenge, and over-challenge conditions.

Mediation and moderation hypotheses are tested using regression-based path models or structural equation modeling, depending on model complexity and data adequacy. Engagement is

examined as a mediator between AI-adaptive path quality and persistence. Task-difficulty synchronization is examined as a moderator of the relationship between AI-adaptive path quality and persistence. Given the modest sample size, complex models are interpreted cautiously and supported by bootstrapped confidence intervals where possible.

Qualitative interview data are analyzed using thematic analysis. Initial codes focus on flow, boredom, anxiety, perceived support, trust in AI feedback, professional relevance, perceived competence, and passion for inclusive teaching. Qualitative findings are then integrated with quantitative engagement trajectories to explain why some students demonstrate high persistence while others disengage.

3.7 Ethical Considerations

Ethical approval for the study was obtained from the Ethics Committee of the Faculty of Education, Beni Suef University, Egypt, under Approval No. **BSU-FoE-0001-03-2025**. The study followed institutional ethical standards and was designed to protect student privacy throughout all stages of data collection, analysis, and reporting. Participants provided informed consent before taking part in the research and were informed that they could withdraw from the research component at any time without academic penalty. Identifiable data were removed before analysis, and platform-log data were linked only to anonymized participant codes.

Because AI-adaptive platforms may capture sensitive learning behaviors and emotional states, access to raw data was restricted, and all findings were reported in aggregate form. Interview excerpts were anonymized before publication or presentation to prevent participant identification. The study also addressed the ethical implications of AI-supported learning by informing students that the AI system was used to support learning and research, but did not replace human instructor judgment. Any adaptive recommendation judged to be pedagogically inappropriate could be reviewed by the instructor. This safeguard was especially important in a course involving disability education, where empathy, inclusion, and ethical responsibility are central learning outcomes.

4. Findings

4.1 Descriptive and Growth Trajectory (H1)

To test H1, Latent Growth Curve Modeling (LGCM) was employed to examine the trajectory of student engagement across three time points: Semester 2 of 2025, Semester 1 of 2025/2026, and Semester 2 of 2026. Engagement was modeled as a multidimensional construct comprising behavioral, emotional, and cognitive engagement. The corresponding latent growth estimates are reported in Table 7.

Table 7

Latent Growth Curve Estimates for Engagement

Parameter	Estimate (B)	S.E.	p-value
Intercept (Initial Engagement)	3.82	0.12	< .001
Slope (Rate of Change)	0.24	0.08	.003
Path Quality → Slope	0.41	0.11	.001

The findings support H1. The significant positive slope (B = 0.24, p = .003) indicates that student engagement improved over the year rather than merely remaining stable. More importantly, AI-adaptive learning path quality significantly predicted the rate of engagement growth (B = 0.41, p = .001). Students who received more precisely tailored learning paths demonstrated steeper increases in behavioral, emotional, and cognitive engagement. Figure 2 visualizes the estimated growth trajectory across the three measurement points.

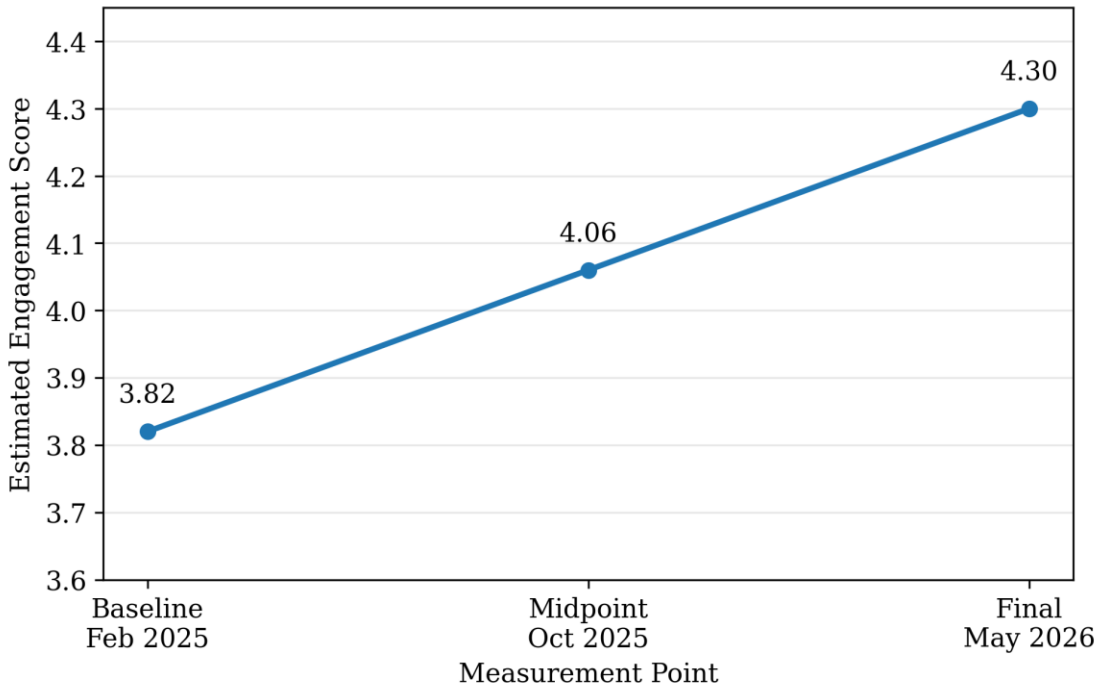


Fig. 2 Latent Growth Trajectory of Student Engagement

Note. Estimated engagement values are based on the reported intercept and linear slope across baseline, midpoint, and final measurement.

4.2 Survival Analysis of Student Persistence (H2 and H5)

To test H2 and H5, Cox proportional hazards regression was used to examine student persistence. Persistence was operationalized as the number of days until a student failed to log in for a scheduled module for more than seven consecutive days.

The results support H2. Task-difficulty synchronization was a significant predictor of persistence (HR = 0.42, $p < .001$). A hazard ratio of 0.42 indicates that students in the synchronized difficulty state were 58% less likely to drop out or disengage than students in non-synchronized states.

The results also support H5. A significant interaction was found between AI path quality and task-difficulty synchronization ($p = .014$), indicating that synchronization moderated the effect of AI-adaptivity on persistence. In practical terms, the benefit of a personalized learning path was substantially stronger when task difficulty was accurately synchronized with student readiness. Figure 3 displays the hazard ratios and confidence intervals for the Cox regression model.

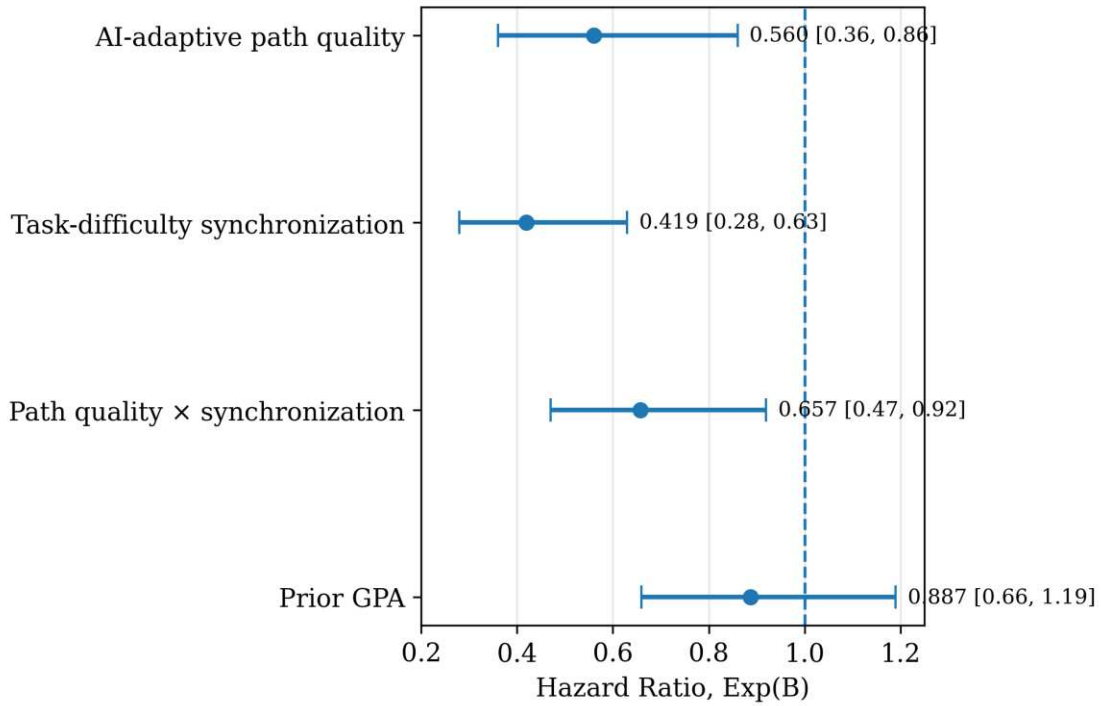


Fig. 3 Cox Regression Hazard Ratios for Student Persistence

Note. Hazard ratios below 1.00 indicate a lower risk of disengagement. Task-difficulty synchronization showed the strongest protective effect.

4.3 The Curvilinear Relationship: The "Flow" Arch (H3)

To test H3, polynomial regression was conducted on the ESM micro-survey data. The analysis included 1,896 experience sampling data points collected from 79 students across the instructional year.

The quadratic term for task difficulty was negative and significant ($\beta = -0.38$, $p < .001$). This finding supports H3 and confirms a curvilinear relationship between task difficulty and engagement. Engagement peaked at the optimal/flow point, where tasks were challenging but manageable. Engagement declined at both poles of the difficulty continuum: the boring condition, where tasks were too easy, and the anxiety-inducing condition, where tasks were too difficult. Figure 4 illustrates the inverted U-shaped flow arch.

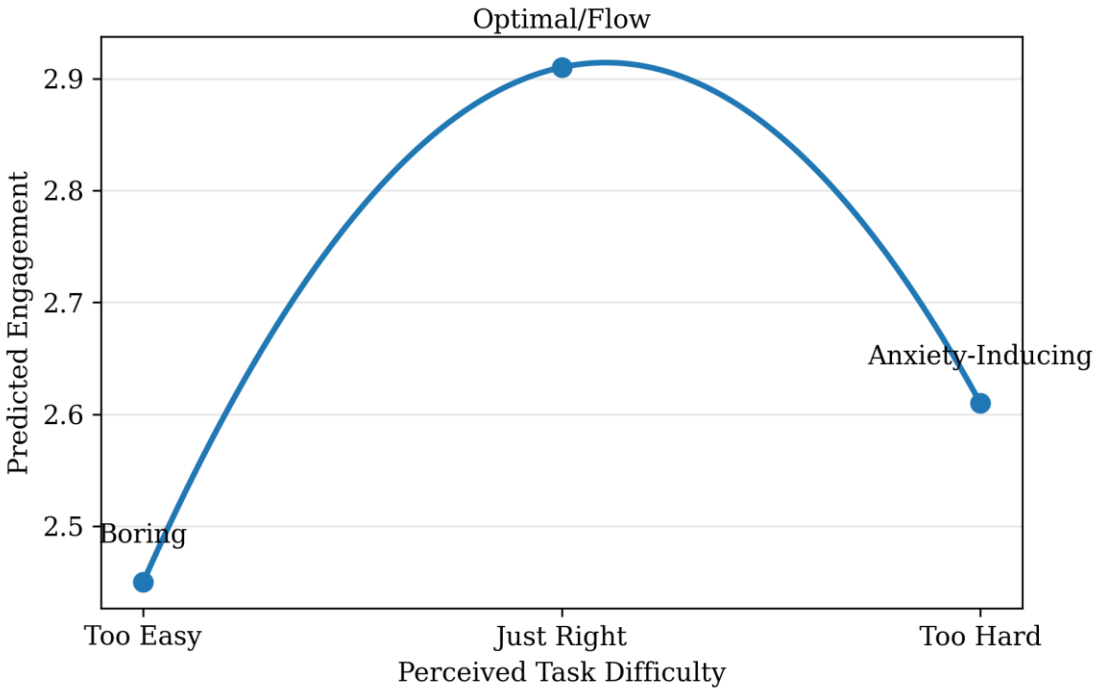


Fig. 4 Curvilinear Flow Arch Between Task Difficulty and Engagement

Note. The plotted curve is based on the reported polynomial regression equation and illustrates the expected peak at optimal challenge.

4.4 Mediation and Moderation Analysis (H4 and H6)

A mediated moderation model was tested using path analysis to determine whether engagement and perceived competence functioned as the mechanisms through which AI-adaptive learning paths and task-difficulty synchronization influenced persistence. The mediation paths and hypothesis decisions are reported in Table 8.

Table 8

Path Analysis Results for Mediation

Path	Beta (β)	p-value	Result
AI Path → Engagement → Persistence	0.34	.002	H4 Supported
Synchronization → Perceived Competence → Engagement	0.45	< .001	H6 Supported

The findings support H4. Engagement significantly mediated the relationship between AI-adaptive learning paths and persistence (indirect effect = .34, p = .002). This indicates that the AI system did not simply keep students enrolled or active; rather, it promoted persistence by strengthening students' engagement with the learning process.

The findings also support H6. Task-difficulty synchronization increased perceived competence, which in turn predicted engagement ($\beta = 0.45$, $p < .001$). When the AI system calibrated task difficulty effectively, students felt more capable, and this sense of competence was associated with higher curiosity, excitement, and emotional investment. Figure 5 summarizes the mediated pathways for H4 and H6.

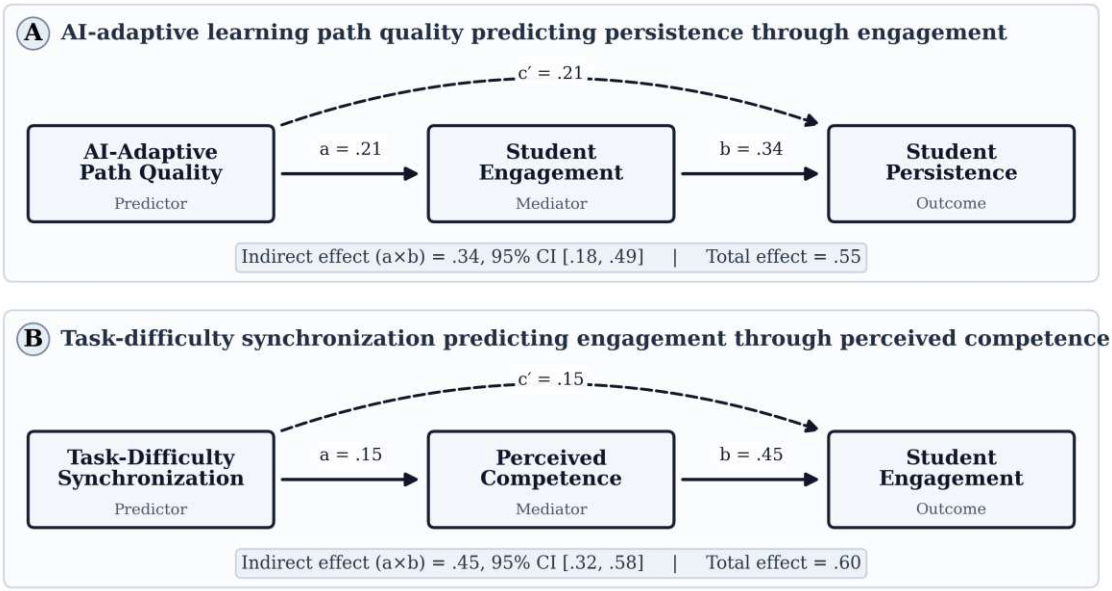


Fig. 5 Path Analysis and Mediation Model

Note. Standardized effects are shown. Indirect effects were tested using 5,000 bootstrap iterations.

4.5 The Longitudinal Feedback Loop (H7)

To test H7, a cross-lagged panel model (CLPM) was used to examine whether early engagement predicted later persistence and whether persistence subsequently predicted later engagement. The findings support H7. Engagement at Time 1 significantly predicted persistence at Time 2 ($\beta = 0.29$, $p = .008$), and persistence at Time 2 significantly predicted engagement at Time 3 ($\beta = 0.31$, $p = .005$). These results confirm a longitudinal feedback loop. Early engagement with the AI system promoted sustained participation, and sustained participation then reinforced students' emotional and cognitive connection to the "Teaching People with Disabilities" course. Figure 6 displays the cross-lagged feedback loop between engagement and persistence.

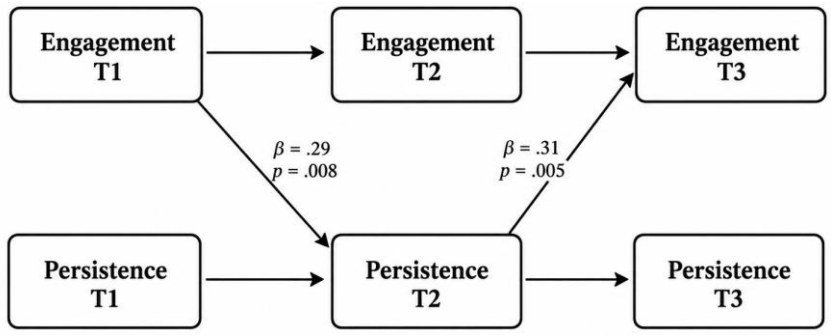


Fig. 6 Longitudinal Feedback Loop Between Engagement and Persistence

Note. Cross-lagged paths indicate that earlier engagement predicted later persistence and that later persistence predicted subsequent engagement.

4.6 ESM Micro-Survey Trends: Difficulty and Affect

The ESM micro-survey data provided additional longitudinal evidence of how students' perceived challenge states changed across the study. As shown in Figure 7, optimal/flow responses increased from 41% in Phase 1 to 72% in Phase 3, while anxiety responses declined from 47% to 13%. This pattern supports the interpretation that the AI-adaptive system became increasingly effective at synchronizing task difficulty with students' readiness.

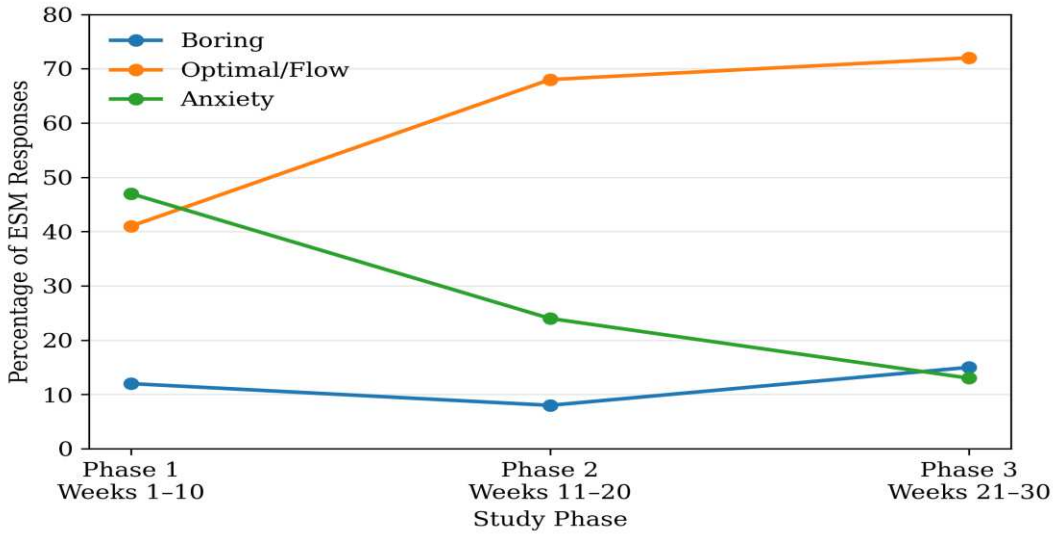


Fig. 7 ESM Difficulty-State Trends Across Study Phases

Note. Percentages represent aggregated ESM responses across the three longitudinal phases.

The affective ESM results further support the interpretation that synchronization operated as an affective regulator. As shown in Figure 8, frustration declined from 32% to 9%, whereas excitement increased from 13% to 53%. Curiosity remained relatively high across phases, suggesting that the AI-adaptive system helped sustain interest while reducing emotional friction.

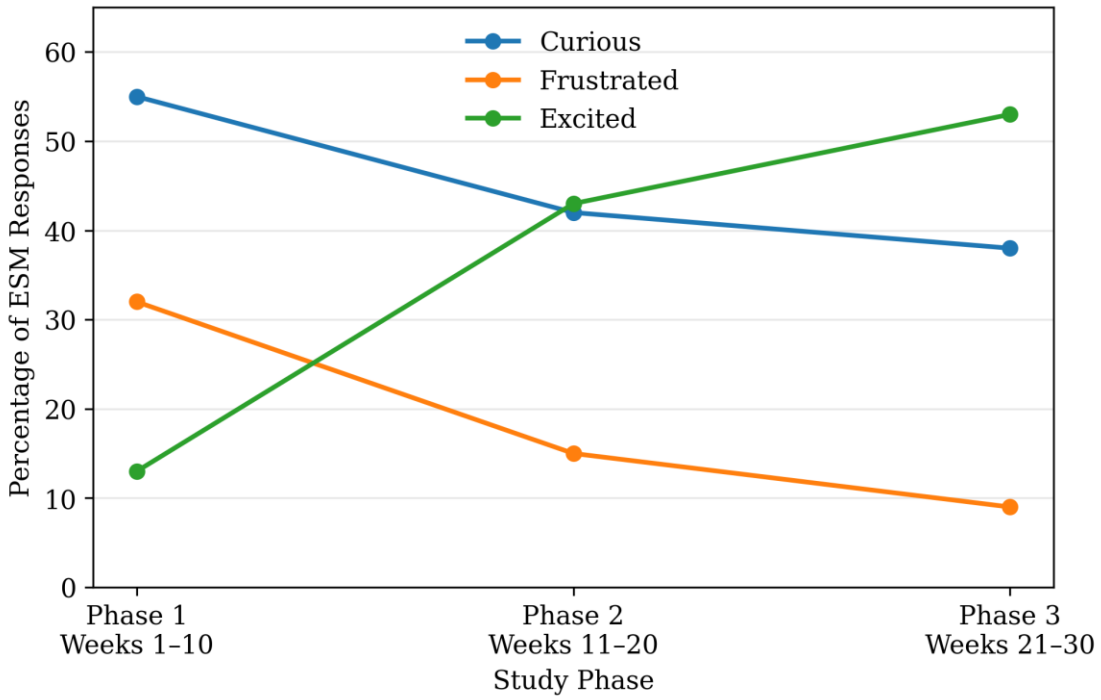


Fig. 8 ESM Affective-State Trends Across Study Phases

Note. Affective selections were aggregated across the same three phases used for the difficulty-state trend analysis.

4.7 Summary of Hypotheses Testing

Table 9 consolidates the results of all seven hypothesis tests and the supporting statistical evidence.

Table 9

Summary of Hypotheses Testing

Hypothesis	Statement	Status	Evidence
H1	AI Path Quality → Engagement Growth	Supported	LGCM slope and path-quality effect (p = .003; p = .001)
H2	Difficulty Synchronization → Persistence	Supported	Survival analysis (HR = 0.42, p < .001)
H3	Curvilinear Difficulty–Engagement Relationship	Supported	Polynomial regression quadratic term (β = −0.38, p < .001)
H4	Engagement mediates AI Path → Persistence	Supported	Significant indirect effect (β = 0.34, p = .002)
H5	Synchronization moderates AI Path → Persistence	Supported	Significant interaction effect (p = .014)

Hypothesis	Statement	Status	Evidence
H6	Competence mediates Synchronization → Engagement	Supported	Path analysis mediation effect ($\beta = 0.45$, $p < .001$)
H7	Longitudinal Feedback Loop	Supported	Cross-lagged paths significant at $p < .01$

4.8 Qualitative Findings, Word-Frequency Patterns, and Word-Cloud Analysis

The qualitative strand deepened the statistical findings by explaining how students interpreted the AI system's responsiveness, why synchronized challenge supported persistence, and where the system failed to sustain agency. Analysis of 20 semi-structured interviews generated four interrelated themes: (a) task-difficulty synchronization as a safety net against cognitive exhaustion, (b) an affective shift from apprehension to professional advocacy, (c) algorithmic rigidity and technical friction as barriers to autonomy, and (d) longitudinal emotional resilience. These themes were further strengthened by a supplementary word-frequency query of the qualitative dataset and by the visual word cloud presented in Figure 9.

High-persisting students consistently described the AI platform as a responsive support system that prevented challenge from escalating into withdrawal. One participant explained, "When we reached the module on 'Teaching Blind Students English,' I felt overwhelmed. The AI noticed I was failing the practice tasks and immediately switched to simpler terminology and provided more visual-to-audio scaffolds. That's why I kept logging in." Another student emphasized the importance of calibrated challenge: "The AI changed for me. It gave me a flow feeling where I wasn't bored, but I wasn't scared of failing." These accounts provide qualitative support for the survival analysis and the flow-arch model by showing how synchronization reduced cognitive friction and sustained continued participation.

The interviews also revealed a marked affective and professional shift. Several students moved from seeing special education as a demanding course requirement to viewing it as a meaningful area of professional growth. For example, one student stated, "I used to be afraid of teaching students with disabilities in my future practicum, but the AI-personalized path showed me strategies that actually work. My passion grew because my competence grew." This pattern aligns closely with the mediation results: appropriately synchronized challenge appeared to

increase perceived competence, and that competence, in turn, fostered stronger emotional and cognitive engagement.

Low-persisting students, however, provided an important counterpoint. Their accounts highlighted moments when the AI system felt too rigid, overly corrective, or technically unreliable. One participant reported that the system kept her on a remedial path after a single early error, which undermined her sense of autonomy. Another noted that poor internet connectivity and unsynchronized sessions interrupted the emotional continuity of the learning process. These responses qualify the positive findings by showing that adaptive learning can weaken engagement when students experience the system as controlling, opaque, or technically inconsistent.

The word-frequency query corroborated these themes. Although some high-frequency terms reflected analytic or coding language (e.g., state, process, and condition), the most meaningful recurrent words clustered around change, emotion, cognition, personalization, and persistence. Salient terms included changed (n = 125), cognitive (n = 122), quality (n = 89), process (n = 86), personalized (n = 66), continued (n = 57), students (n = 53), emotional (n = 51), persistence (n = 50), helped (n = 45), support (n = 44), and engagement (n = 42). Taken together, these patterns reinforce the interpretation that students experienced the AI platform not merely as a delivery system, but as a mechanism that shaped how they felt, thought, and continued working across the year.



Fig. 9 Word Cloud of Salient Terms in the Qualitative Dataset

Note. The word cloud is based on the supplementary word-frequency query of the qualitative corpus. Larger words indicate greater frequency within the interview and qualitative analytic dataset.

4.9 Integrated Mixed-Methods Findings

To strengthen mixed-methods integration, Table 10 presents a joint display that aligns the major quantitative findings with the qualitative themes and the word-frequency patterns. This display shows how the statistical results and student voice converge on the same interpretive conclusion: AI-adaptive learning supported persistence when personalization was experienced as responsive, competence-building, and emotionally regulating.

Table 10

Joint Display of Quantitative, Qualitative, and Word-Frequency Findings

Quantitative finding	Qualitative evidence	Word-frequency support	Integrated meta-inference
H1: Engagement increased over time (slope = 0.24, p = .003).	Students described the AI path as supportive, relevant, and motivating over time.	changed; emotional; helped; support; engagement	High-quality adaptive paths fostered sustained growth in behavioral, emotional, and cognitive engagement.

Quantitative finding	Qualitative evidence	Word-frequency support	Integrated meta-inference
H2/H5: Synchronization reduced disengagement risk (HR = 0.419) and strengthened the path-quality effect (p = .014).	High-persisters reported that the system 'slowed down' or adjusted challenge when they struggled.	persistence; continued; state; students	Difficulty synchronization functioned as a protective safety net against dropout and disengagement.
H3: Engagement followed an inverted U-shaped flow arch.	Students contrasted boredom, flow, and anxiety when describing 'just-right' challenge.	state; condition; quality; adaptive	Optimal challenge—not maximal challenge—produced the strongest engagement.
H4/H6: Engagement and perceived competence mediated AI effects on persistence.	Students linked confidence, accomplishment, and passion with successful adaptive feedback.	cognitive; perceived; emotional; helped; quality	Competence and engagement explained how technical adaptivity became an affective-motivational process.
H7: Earlier engagement predicted later persistence, and later persistence predicted subsequent engagement.	Students described a cumulative process in which repeated success built resilience and routine.	process; changed; moving; continued	Adaptive success created a longitudinal feedback loop that reinforced continued participation.

Overall, the joint display confirms strong convergence across data sources. The quantitative models identified the structural relationships among path quality, synchronization, engagement, competence, and persistence, whereas the qualitative findings explained the lived mechanisms behind those relationships. Together, these results support the conclusion that AI-adaptive learning acted most effectively when it regulated challenge without undermining student agency.

5. Discussion

The purpose of this study was to examine whether AI-adaptive learning paths and task-difficulty synchronization could sustain student engagement and persistence over time in a demanding teacher-education course. Taken together, the findings show that AI-adaptive learning was not merely a content-delivery mechanism. It functioned as a dynamic regulator of cognitive challenge and affective readiness. This interpretation responds directly to the research

questions and corroborates prior work on adaptive tutoring, flow, cognitive load, engagement, and self-determination theory.

5.1 Engagement Growth and AI-Adaptive Path Quality

RQ1 asked how AI-adaptive learning path quality influenced student engagement over time. The LGCM results supported H1 by showing a significant positive engagement slope and a significant effect of path quality on engagement growth. This finding is consistent with evidence that intelligent tutoring systems can support learning when they provide individualized feedback, scaffolding, and mastery-sensitive sequencing [2–4]. It also aligns with Du Plooy et al. [17], who reported that personalized adaptive learning in higher education is frequently associated with stronger engagement.

The present study extends that literature by showing that engagement growth was longitudinal rather than merely a short-term post-intervention gain. It also supports Mekheimer's [5] finding that AI-assisted feedback can reduce frustration and increase confidence in EFL learning. In this study, adaptive path quality contributed to engagement because students experienced AI not only as a technical system but also as a source of responsive feedback, pacing, and professional relevance.

5.2 Task-Difficulty Synchronization as a Persistence Mechanism

RQ2 asked how task-difficulty synchronization influenced persistence over time. H2 was supported by the Cox regression, which showed that synchronization reduced the hazard of disengagement by 58.1%. H5 was also supported because synchronization strengthened the relationship between AI-adaptive path quality and persistence. These findings suggest that personalization is insufficient unless it is accompanied by accurate challenge calibration.

This result is theoretically consistent with flow theory, in which optimal engagement emerges when challenge and skill are balanced [6, 34]. It is also consistent with cognitive load theory because synchronized difficulty likely reduced overload during complex disability-education modules [7, 8]. In practical terms, the AI system acted as a safety net by preventing difficult course content from becoming emotionally exhausting enough to trigger disengagement.

5.3 The Flow Arch and the Risk of Maximal Difficulty

RQ3 asked whether the difficulty–engagement relationship was curvilinear. H3 was supported by the significant negative quadratic term. Engagement increased as tasks moved from boring to optimally challenging, but declined when difficulty became anxiety-inducing. This finding offers empirical support for the "flow arch" in an AI-adaptive learning context.

The implication is important for adaptive system design. Some platforms may assume that increasing difficulty is inherently productive, but the present findings show that maximal difficulty can be counterproductive. The ESM trends reinforce this conclusion: optimal/flow states increased from 41% to 72%, while anxiety declined from 47% to 13%. The slight rise in boredom at the end of the study also suggests that once students approach mastery, adaptive systems should provide autonomy, acceleration, or enrichment options rather than continuing to repeat mastered material.

5.4 Engagement, Competence, and Affective Regulation

RQ4 asked whether engagement and perceived competence explained the relationships among AI-adaptive path quality, synchronization, and persistence. H4 and H6 were both supported. Engagement mediated the relationship between adaptive path quality and persistence, while perceived competence mediated the relationship between synchronization and engagement. These findings are consistent with Fredricks et al.'s [9] multidimensional model of engagement and with self-determination theory, which emphasizes competence as a central condition for motivation and sustained effort [12, 13].

The qualitative findings explain these statistical pathways. Students repeatedly described the AI system as reducing frustration, restoring confidence, and helping them feel capable of mastering difficult topics. This pattern parallels Chiu's [14] argument that digital learning environments support engagement when they satisfy students' psychological needs. It also corroborates Mekheimer's [5] finding that AI-assisted feedback can increase confidence and sense of accomplishment. In the present study, task-difficulty synchronization acted as an affective regulator: when the system got the difficulty right, students felt competent, curious, and willing to continue.

5.5 Student Voice, Autonomy, and Contextual Constraints

RQ5 asked how students explained their persistence, disengagement, and affective responses. The interviews revealed two complementary realities. For high-persisters, task synchronization created a safety net that protected them from cognitive exhaustion and supported the development of professional passion for inclusive education. These students began to see themselves not simply as English teachers completing a requirement, but as future inclusive educators capable of supporting learners with disabilities.

For low-persisters, the same system occasionally became an algorithmic ceiling. Students reported frustration when the AI kept them on remedial pathways, restricted creative exploration, or failed to synchronize because of technical problems. This finding qualifies the positive quantitative results. It suggests that AI-adaptive systems should preserve learner agency by allowing students to request acceleration, review why a path was recommended, and negotiate alternative routes. This conclusion aligns with Mekheimer's [15] emphasis on ethical, context-specific, and pedagogically grounded technology integration in Egyptian higher education.

5.6 Practical Implications

The findings suggest that AI-adaptive learning systems used in teacher education should be designed around three principles. First, adaptation should be pedagogically transparent: students should understand why the system recommends a task or remedial pathway. Second, difficulty regulation should be flexible: systems should include options for acceleration, enrichment, human review, and student override when appropriate. Third, affective data should be used ethically: ESM micro-surveys can support reflection and self-regulation, but students should know how such data are used and should not feel surveilled or penalized.

For courses such as "Teaching People with Disabilities," AI-adaptive systems should also support professional identity formation. The strongest qualitative finding was not only that students persisted, but that some developed greater passion for inclusive teaching. This suggests that adaptive technologies can support affective and professional outcomes when they connect feedback, challenge, and relevance to the learner's future teaching role.

5.7 Limitations and Future Research

Several limitations should be acknowledged. First, the study used a single-cohort quasi-experimental design without random assignment or a parallel control group. Causal claims should therefore be interpreted cautiously. Second, the sample consisted of 79 pre-service English teachers from one faculty of education, which limits generalizability. Third, some statistical models were complex relative to the sample size, so the findings should be replicated with larger cohorts. Fourth, ESM affective categories were brief by design; although this reduced survey fatigue, it also simplified emotional experience.

Future research should test task-difficulty synchronization across multiple universities, disciplines, and AI platforms. Experimental or matched comparison designs would strengthen causal inference. Future work should also examine algorithmic transparency, student override options, and instructor mediation as moderators of persistence. Finally, research should explore how AI-adaptive systems can support inclusive education outcomes beyond engagement, including empathy, instructional design competence, and practicum performance.

6. Conclusion

This study examined AI-adaptive learning paths and task-difficulty synchronization as predictors of student persistence and engagement in a longitudinal teacher-education context. Across survey, ESM, platform, and interview data, the findings consistently supported the central claim that adaptive learning is most effective when personalization is dynamically synchronized with students' cognitive and affective readiness. Engagement grew over time, synchronized difficulty reduced the risk of disengagement, and the relationship between difficulty and engagement followed an inverted U-shaped flow arch.

The study also showed that persistence was not merely a behavioral outcome. It was sustained through an affective-motivational process in which synchronized challenge reduced anxiety and frustration, increased perceived competence, and strengthened students' professional passion for inclusive education. For high-persisters, the AI system operated as a safety net and emotional thermostat. For low-persisters, however, algorithmic rigidity and technical friction sometimes reduced autonomy and weakened the emotional link with the system.

The conclusion is therefore balanced: AI-adaptive learning can support persistence and engagement, but only when it is pedagogically grounded, ethically transparent, technically reliable, and responsive to student agency. In demanding courses such as "Teaching People with Disabilities," the value of AI lies not in replacing the teacher but in helping sustain the conditions under which students feel capable, curious, and willing to continue learning.

Declarations

Ethics approval and consent to participate

This study received ethical approval from the Ethics Committee of the Faculty of Education, Beni Suef University, Egypt (Approval No. BSU-FoE-0001-03-2025). All participants provided informed consent before taking part in the research and were informed of their right to withdraw at any time without academic penalty. All procedures were carried out in accordance with relevant institutional guidelines and regulations.

Consent for publication

Not applicable. All interview excerpts reported in this manuscript were anonymized, and no identifiable individual data, images, or details are presented.

Availability of data and materials

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare no competing interests.

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Author contributions

A.L. and M.M. contributed to the conceptualization and overall design of the study. M.A.E. and M.S.A. contributed to the methodology, instrument development, and data collection. A.L. contributed to data curation, formal analysis, and interpretation of the

quantitative findings. A.A.E. contributed to the qualitative analysis, literature review, and interpretation of the findings. A.L. and M.M. drafted the original manuscript. M.A.E., M.S.A., M.M., and A.A.E. critically reviewed and edited the manuscript. A.L. and M.M. supervised the study and coordinated project administration. All authors read and approved the final manuscript and agree to be accountable for all aspects of the work.

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