

Artificial Intelligence as a Catalyst for Educational Reform in Economics: A Structural Equation Modeling Approach to Understanding Student Adoption Behavior, Engagement Mechanisms, and Perceived Learning Gains.

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ABSTRACT

The rapid integration of artificial intelligence (AI) into educational environments has generated significant interest in its potential to catalyze pedagogical reform, particularly in disciplines such as economics that require the synthesis of abstract theory, quantitative reasoning, and real-world interpretation. Despite the growing availability of AI-enabled learning tools such as conversational agents, adaptive tutoring systems, and intelligent feedback platforms empirical understanding of the mechanisms through which students adopt these technologies and translate usage into meaningful learning outcomes remains limited. This study addresses this gap by proposing and empirically validating a comprehensive structural equation model that explains AI adoption behavior among economics students and examines the engagement pathways through which AI use contributes to perceived learning gains. Drawing on established technology adoption theories and student engagement

literature, the proposed framework integrates key antecedents of AI adoption, including perceived usefulness, ease of use, social influence, facilitating conditions, trust in AI, perceived risk, and AI self-efficacy. The model further conceptualizes student engagement as a multidimensional construct encompassing cognitive, behavioral, and agentic engagement, positioning engagement as a mediating mechanism between AI adoption and learning outcomes. Data were collected through a structured survey administered to undergraduate and postgraduate economics students across multiple higher education institutions. The measurement and structural models were analyzed using structural equation modeling, with rigorous assessments of reliability, convergent validity, discriminant validity, and model fit. The empirical results demonstrate that perceived usefulness, trust in AI, and AI self-efficacy exert strong positive effects on students' intention to adopt AI tools for economics learning, while perceived risk negatively influences adoption behavior. Adoption intention is found to significantly enhance student engagement, particularly in terms of cognitive and agentic engagement, reflecting deeper conceptual processing and proactive learning behaviors facilitated by AI interactions. Engagement, in turn, exhibits a substantial positive effect on perceived learning gains, including improved conceptual understanding, problem-solving confidence, and perceived academic performance. Mediation analysis confirms that student engagement plays a critical intermediary role in translating AI adoption into learning benefits. By elucidating the structural relationships among AI adoption drivers, engagement mechanisms, and learning outcomes, this study contributes to the emerging literature on AI-enabled education and provides actionable insights for educators, curriculum designers, and policymakers. The findings underscore that effective AI-driven educational reform in economics depends not merely on technological access but on fostering trust, competence, and engagement-centered learning practices that enable students to meaningfully leverage AI for academic growth.

Keywords: Artificial Intelligence; Economics Education; Structural Equation Modeling; Technology Acceptance Model; Student Engagement; Learning Outcomes; AI Adoption.

Introduction:

Artificial intelligence (AI) has rapidly transitioned from an experimental technological concept to a foundational component of contemporary educational ecosystems. Advances in machine learning, natural language processing, and adaptive analytics have enabled AI-driven educational tools capable of providing personalized explanations, automated feedback, intelligent content generation, and real-time learning support. As higher education institutions increasingly adopt AI-enabled platforms, the discourse has expanded beyond technological feasibility toward understanding the pedagogical, behavioral, and cognitive implications of AI-mediated learning [1]. In this evolving landscape, AI is no longer viewed merely as an instructional aid but as a potential catalyst for systemic educational reform reshaping how students engage with knowledge, instructors design learning environments, and institutions evaluate learning effectiveness. Economics education represents a particularly demanding and consequential domain in which to examine the

educational impact of AI. Learning economics requires students to simultaneously comprehend abstract theoretical constructs, apply mathematical and statistical techniques, interpret empirical data, and contextualize findings within real-world policy and market dynamics [2]. These multifaceted cognitive demands often contribute to learning difficulties, reduced motivation, and surface-level engagement, especially in large and diverse classroom settings. AI-based learning tools offer promising solutions by enabling adaptive explanations of economic models, step-by-step problem-solving assistance, interactive simulations, and instant clarification of complex quantitative relationships. However, the educational value of such tools depends not only on their availability but on students' willingness to adopt them and the manner in which they are used during the learning process [3]. Existing research on educational technology adoption has predominantly relied on established theoretical frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). These models emphasize constructs such as perceived usefulness, ease of use, social influence, and facilitating conditions as primary determinants of technology adoption behavior. While these frameworks have demonstrated robust explanatory power across various educational technologies, their direct application to AI-enabled learning environments presents conceptual limitations. Unlike conventional digital tools, AI systems actively generate content, guide reasoning processes, and influence decision-making, thereby introducing new dimensions of uncertainty, ethical concern, and dependency [4]. Students may simultaneously perceive AI as an efficient learning companion and as a source of risk due to potential inaccuracies, hallucinated explanations, privacy concerns, or threats to academic integrity. Consequently, trust in AI and perceived risk emerge as critical constructs that must be explicitly incorporated into adoption models to reflect the distinctive characteristics of AI-mediated education. Beyond adoption, a growing body of educational research emphasizes that learning technologies exert meaningful academic impact primarily through student engagement. Engagement is increasingly conceptualized as a multidimensional construct encompassing behavioral engagement (effort, participation, persistence), cognitive engagement (deep processing, self-regulation, conceptual elaboration), and agentic engagement (students' proactive involvement in shaping their learning experience). AI tools possess unique affordances that can influence all three dimensions by encouraging iterative questioning, enabling personalized exploration paths, and allowing students to actively steer their learning through prompt engineering and feedback refinement [5]. However, much of the existing AI-in-education literature treats engagement either as an implicit assumption or as a secondary outcome, rather than modeling it as a central explanatory mechanism linking adoption to learning gains. Furthermore, empirical research examining AI use in economics education remains fragmented. Many studies focus on isolated outcomes such as student satisfaction, performance improvement, or system usability, often employing descriptive statistics or experimental designs with limited theoretical integration [6]. There is a notable lack of comprehensive, theory-driven empirical models that simultaneously examine (i) the antecedents of AI adoption, (ii) the engagement mechanisms activated by AI use, and (iii) the resulting learning outcomes. Structural equation modeling (SEM) offers a powerful analytical approach

to address this gap by enabling the simultaneous estimation of complex relationships among latent constructs, testing mediation effects, and assessing the overall explanatory strength of integrated theoretical frameworks. Despite its suitability, SEM has been underutilized in research exploring student interaction with AI-enabled learning tools, particularly within economics education. To clarify the positioning of the present study within the existing literature and highlight its theoretical and empirical contributions, Table 1 synthesizes dominant research streams, their primary focus, and the gaps addressed by this study.

Table 1: Synthesis of Prior Research and Positioning of the Present Study

Research Stream	Primary Focus	Key Limitations in Existing Literature	Contribution of This Study
Educational Technology Adoption (TAM/UTAUT)	Explains intention and usage of digital tools	Limited consideration of AI-specific issues such as trust, risk, and content generation	Integrates trust and perceived risk into AI adoption modeling
AI in Education (AIEd)	Tool development, performance, and usability	Often descriptive; limited theory-driven behavioral modeling	Provides a theory-based empirical model using SEM
Student Engagement Theory	Behavioral, cognitive, and agentic engagement	Engagement rarely modeled as a mediating mechanism	Positions engagement as a mediator between adoption and learning
Economics Education Research	Conceptual understanding and quantitative skills	Limited focus on AI-mediated learning processes	Examines AI's role in enhancing economics learning outcomes
Learning Outcomes Assessment	Grades, satisfaction, perceived effectiveness	Outcomes often examined without behavioral mechanisms	Links perceived learning gains to adoption via engagement pathways

Against this backdrop, the present study conceptualizes artificial intelligence as a catalyst for educational reform in economics by developing and empirically validating a comprehensive structural equation model that integrates AI adoption behavior, student engagement mechanisms, and perceived learning gains. Drawing on technology adoption theories, trust–risk perspectives, and multidimensional engagement theory, the proposed framework incorporates perceived usefulness, ease of use, social influence, facilitating conditions, trust in AI, perceived risk, and AI self-efficacy as antecedents of adoption. Adoption is hypothesized to influence student

engagement, which in turn drives perceived learning gains, thereby establishing engagement as a central explanatory pathway [7]. The contributions of this study are threefold. First, it advances the AI in education literature by offering an integrative, theory-driven SEM framework that captures both behavioral and pedagogical dimensions of AI-mediated learning. Second, it enriches economics education research by empirically demonstrating how AI adoption translates into learning benefits through engagement mechanisms rather than mere usage. Third, the findings provide actionable guidance for educators, curriculum designers, and policymakers seeking to implement AI responsibly and effectively, emphasizing the importance of trust-building, competence development, and engagement-centered instructional design. By elucidating the structural pathways through which AI facilitates learning, this study contributes to the growing evidence base needed to guide sustainable and meaningful educational reform in economics.

AI-Driven Pedagogical Innovation in Higher Education:

Artificial intelligence (AI) has progressively evolved in higher education from early rule-based instructional systems into sophisticated, data-driven learning technologies capable of natural language interaction, adaptive feedback, and real-time personalization. Early applications of AI were primarily confined to expert systems and computer-assisted instruction, which relied on predefined rules and static logic to deliver content and basic guidance. Although these systems automated certain instructional tasks, they offered limited responsiveness to individual learner differences and were largely embedded within instructor-centered pedagogical models. The rapid advancement of machine learning, natural language processing, and learning analytics has fundamentally expanded the scope and pedagogical relevance of AI-enabled educational technologies [8]. Contemporary AI systems including intelligent tutoring systems, conversational agents, automated assessment tools, and adaptive learning platforms can process large volumes of learner data to infer cognitive states, identify misconceptions, and generate context-sensitive instructional responses. These capabilities enable continuous formative feedback, adaptive sequencing of learning materials, and individualized scaffolding, allowing AI systems to support learners dynamically throughout the learning process rather than merely delivering standardized content [9]. As a result, AI has become an integral component of modern higher education ecosystems, influencing instructional design, assessment strategies, and patterns of student–technology interaction. From a pedagogical perspective, the integration of AI has accelerated a shift from instructor-centered teaching toward learner-centered and data-informed educational paradigms. Traditional pedagogical approaches often emphasize uniform instruction and summative evaluation, which may inadequately address learner heterogeneity, prior knowledge gaps, and variations in learning pace [10]. In contrast, AI-driven learning environments facilitate continuous assessment, personalized feedback, and interactive knowledge construction. These features align closely with constructivist learning theory, which emphasizes active meaning-making, and self-regulated learning theory, which highlights learners’ capacity to plan, monitor, and reflect on their learning activities. By enabling iterative exploration, adaptive guidance, and reflective feedback, AI technologies have the potential to foster deeper cognitive processing and

sustained engagement. The pedagogical implications of AI adoption are particularly pronounced in economics education, a discipline characterized by abstract theoretical constructs, quantitative modeling, and empirical data interpretation [11]. Economics students are often required to integrate mathematical formalism with conceptual reasoning and real-world policy analysis, a combination that can impose substantial cognitive load. AI-enabled learning tools can mitigate these challenges by decomposing complex economic models into step-by-step explanations, providing interactive simulations of market dynamics, and offering on-demand clarification of quantitative relationships. Through these mechanisms, AI systems can support conceptual understanding, analytical reasoning, and applied problem-solving core competencies in economics education [12]. Despite these promising affordances, empirical evidence regarding the pedagogical effectiveness of AI in higher education remains mixed. While several studies report improvements in engagement, learning efficiency, and academic performance, others observe limited or uneven benefits across learner groups. These inconsistencies suggest that the educational value of AI is not determined solely by technological sophistication. Rather, it is contingent on how students perceive AI-enabled tools, the extent to which they adopt them, and the depth of engagement they exhibit during AI-mediated learning activities [13]. This insight underscores the need to move beyond technology-centric evaluations toward analyses that foreground behavioral and cognitive mechanisms. Table 2 shows the **Evolution of Artificial Intelligence in Higher Education and Pedagogical Shifts**

Table 2: Evolution of Artificial Intelligence in Higher Education and Pedagogical Shifts

AI Development Stage	Core Technologies	Dominant Educational Functions	Pedagogical Orientation
Rule-Based AI	Expert systems, decision rules	Content delivery, basic guidance	Instructor-centered
Early Intelligent Systems	Adaptive testing, rule-based tutors	Diagnostic feedback	Limited learner adaptation
Data-Driven AI	Machine learning, learning analytics	Personalization, adaptive pacing	Learner-centered
Conversational & Generative AI	NLP, generative models	Interactive explanation, reasoning support	Constructivist learning
Advanced Adaptive AI	Multimodal AI, real-time analytics	Dynamic scaffolding, engagement support	Engagement-driven pedagogy

Building on the synthesis in Table 2, it is evident that the pedagogical role of artificial intelligence has expanded in parallel with advancements in underlying AI technologies. As AI systems transition from static instructional aids to adaptive, conversational, and data-driven learning environments, their influence shifts from content transmission toward active mediation of cognitive and engagement processes [14]. This evolution highlights how contemporary AI applications increasingly support learner autonomy, real-time scaffolding, and engagement-centered

instructional design. To further conceptualize this pedagogical transformation and clarify the pathways through which AI reshapes teaching and learning practices, Figure 1 visually illustrates the transition from traditional instructor-centered instruction to AI-enabled, learner-centered, and engagement-driven educational ecosystems.

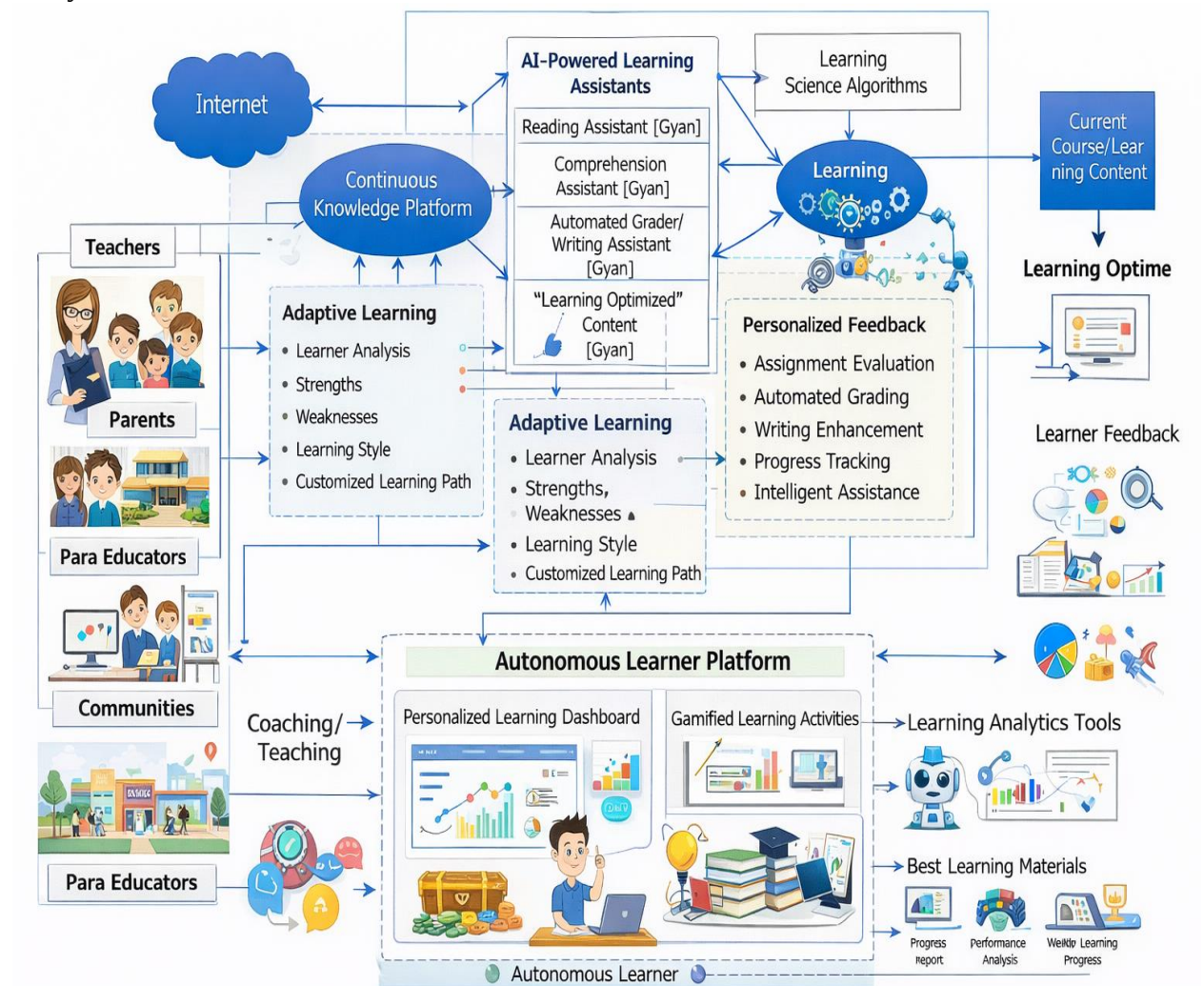


Figure 1: Pedagogical transformation enabled by artificial intelligence in higher education

Taken together, the evolution of artificial intelligence in higher education reflects a broader pedagogical transformation in which learning effectiveness is increasingly shaped by adaptive interaction, personalization, and student agency rather than static content delivery. While AI technologies provide powerful instructional affordances, their educational impact ultimately depends on students' perceptions of usefulness, ease of use, and trust, as well as their willingness to actively engage with AI-mediated learning processes [15]. Accordingly, AI should be viewed not merely as a technological enhancement but as a socio-technical system whose pedagogical value emerges through complex behavioral and cognitive pathways. This perspective

motivates the need for integrative empirical models that simultaneously examine AI adoption behavior, engagement mechanisms, and learning outcomes an analytical foundation that underpins the structural equation modeling framework developed in the present study.

Technology Adoption Models in Educational Contexts:

Research on educational technology adoption has been predominantly grounded in well-established theoretical frameworks, most notably the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). These models were originally developed to explain users' acceptance of information systems by emphasizing cognitive evaluations of technology attributes. TAM posits that perceived usefulness and perceived ease of use are the primary determinants of an individual's intention to adopt a technology, while UTAUT extends this perspective by incorporating social influence and facilitating conditions, along with moderating effects of age, gender, experience, and voluntariness of use. Together, these frameworks have provided a robust foundation for understanding technology adoption behavior in a wide range of educational contexts [16]. Empirical research applying TAM and UTAUT has demonstrated strong explanatory power across numerous educational technologies, including learning management systems, e-learning platforms, mobile learning applications, and online assessment systems. Studies consistently report that students are more likely to adopt educational technologies when they perceive them as useful for improving learning efficiency, easy to use, socially endorsed by peers or instructors, and supported by adequate institutional infrastructure. As a result, TAM and UTAUT have become dominant lenses for investigating student acceptance of digital learning environments, offering parsimonious yet effective explanations of adoption intention and usage behavior. Despite their widespread application, the direct transfer of TAM and UTAUT to artificial intelligence-enabled learning environments presents important conceptual limitations [17]. Traditional educational technologies typically function as passive tools that deliver content or facilitate communication. In contrast, AI systems actively generate explanations, adapt instructional pathways, and influence learners' reasoning processes. This shift from passive technology to autonomous and interactive systems fundamentally alters the nature of human-technology interaction. Students are no longer merely users of a system but become co-participants in a learning dialogue mediated by AI. Consequently, adoption decisions in AI-mediated learning contexts involve more complex cognitive and affective evaluations than those captured by traditional acceptance models [18]. One major limitation of conventional adoption models lies in their insufficient treatment of trust and perceived risk. In AI-enabled education, students must evaluate not only whether a system is useful and easy to use, but also whether it is reliable, accurate, transparent, and ethically aligned with academic norms. Concerns related to misinformation, algorithmic bias, data privacy, and academic integrity are particularly salient in educational settings, where learning outcomes and assessment fairness are at stake. These concerns may simultaneously encourage and inhibit adoption, creating ambivalent attitudes toward AI tools that cannot be fully explained by usefulness and ease of use alone [19]. Moreover, AI adoption in education is closely intertwined with perceptions of dependency and

agency. While AI tools can enhance learning efficiency, students may fear overreliance on AI-generated explanations, reduced critical thinking, or erosion of independent problem-solving skills [20]. Such concerns introduce a tension between perceived benefits and perceived risks, highlighting the need for adoption models that explicitly incorporate AI-specific constructs such as trust in AI, perceived risk, transparency, and self-efficacy. Without accounting for these factors, traditional adoption frameworks risk oversimplifying students' decision-making processes in AI-mediated learning environments. Table 3 shows the **Comparison of Technology Adoption Models in Conventional and AI-Enabled Educational Contexts**.

Table 3: Comparison of Technology Adoption Models in Conventional and AI-Enabled Educational Contexts

Dimension	Conventional Educational Technologies	AI-Enabled Learning Technologies
Core Function	Content delivery and interaction support	Content generation and adaptive guidance
User Role	Passive or semi-active system user	Active co-participant with AI
Key Adoption Drivers	Usefulness, ease of use, social influence	Usefulness, ease of use, trust, perceived risk
Ethical Concerns	Minimal	High (privacy, bias, academic integrity)
Cognitive Involvement	Task execution	Reasoning support and decision influence
Model Suitability	TAM / UTAUT sufficient	Extended TAM / integrated models required

Building on the comparison in Table 3, it becomes evident that AI-enabled educational technologies demand an extension of traditional adoption models. While TAM and UTAUT remain valuable for capturing baseline acceptance factors, they must be augmented with constructs that reflect the autonomous, adaptive, and epistemically influential nature of AI systems. In particular, trust in AI and perceived risk emerge as central determinants that shape whether students embrace AI tools as learning partners or resist them due to uncertainty and ethical concerns [21]. This evolution calls for integrative adoption frameworks capable of capturing both instrumental evaluations and socio-cognitive judgments. Figure 2 shows the extended technology adoption framework for AI-enabled learning environments, illustrating how traditional adoption constructs (perceived usefulness, ease of use, social influence, and facilitating conditions) are complemented by AI-specific factors such as trust and perceived risk to explain student adoption behavior.

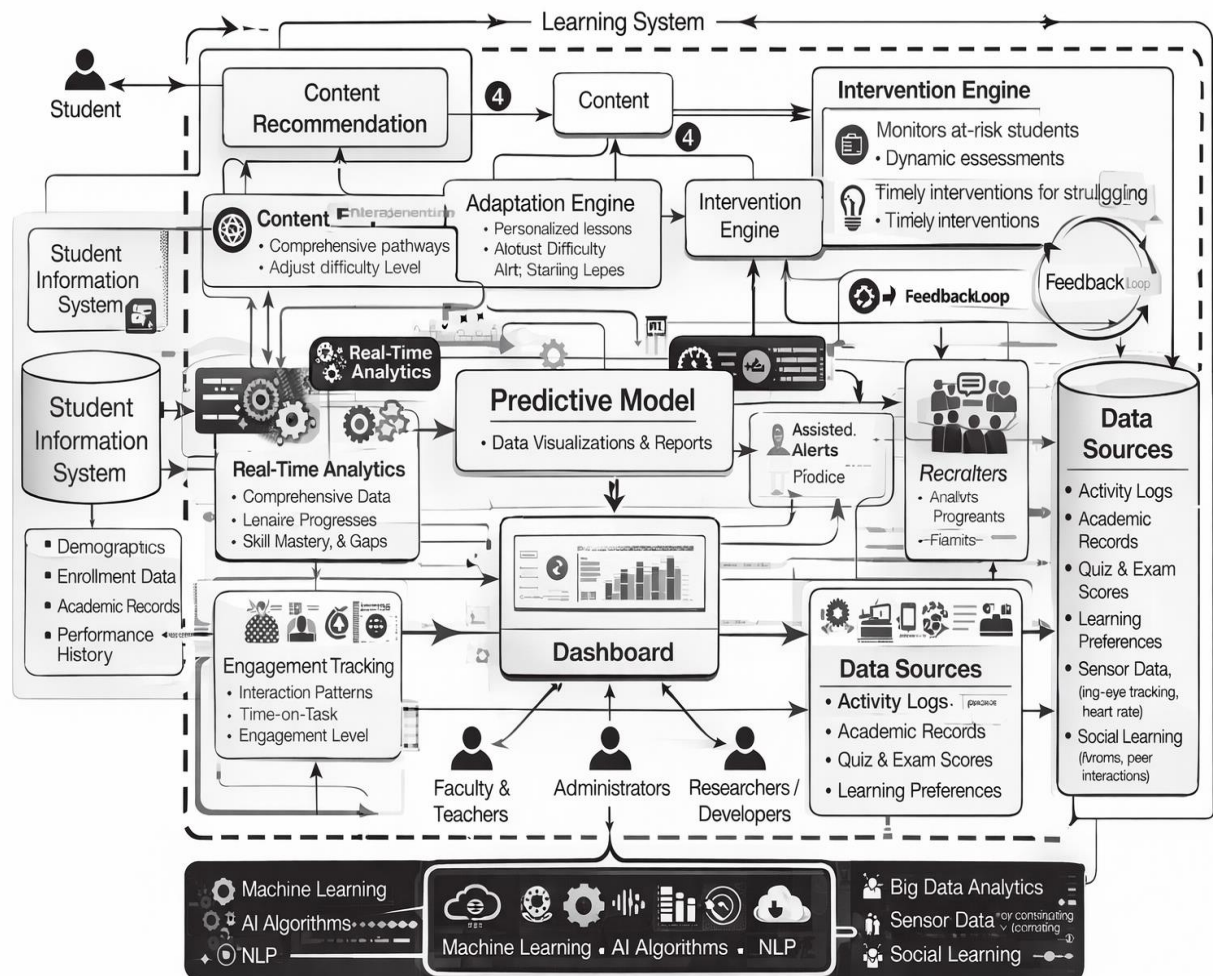


Figure 2: Extended technology adoption framework for AI-enabled learning environments.

Taken together, the literature suggests that while traditional technology adoption models have provided a strong foundation for understanding student acceptance of digital learning tools, they are insufficient in isolation for capturing the complexity of AI-mediated education. The autonomous, interactive, and decision-influencing characteristics of AI systems introduce new evaluative dimensions that reshape adoption behavior [22]. Accordingly, this study extends established adoption frameworks by incorporating AI-specific constructs within an integrated structural equation modeling approach, enabling a more comprehensive explanation of how students adopt AI-enabled learning tools and how such adoption subsequently influences engagement and perceived learning gains.

Methodology:

This study employs a quantitative research methodology to systematically examine the structural relationships among artificial intelligence (AI) adoption behavior, student engagement mechanisms, and perceived learning gains within the context of economics education. A quantitative approach is particularly appropriate for this

investigation because it enables the empirical testing of theoretically grounded relationships among multiple latent constructs and supports the evaluation of both direct and indirect effects within a unified analytical framework. By adopting this approach, the study moves beyond descriptive assessments of AI use and instead provides a rigorous examination of the causal pathways through which AI-enabled learning tools influence educational outcomes [23]. The methodological framework is explicitly grounded in established theories of technology adoption, including technology acceptance and usage models, AI-specific trust and risk perspectives, and multidimensional student engagement theory. Technology adoption theories provide the foundation for understanding students' intentions and behaviors related to AI usage, while trust and perceived risk address the unique characteristics of AI systems, such as autonomous content generation, uncertainty, and ethical considerations. Student engagement theory contributes a pedagogical lens by explaining how adoption translates into meaningful learning experiences through behavioral, cognitive, and agentic engagement processes. Integrating these theoretical perspectives allows for a comprehensive and context-sensitive examination of AI-mediated learning in economics education. To empirically operationalize these theoretical constructs, the study employs structured measurement instruments adapted from validated scales in prior research and tailored to the AI-enabled learning context. These constructs are translated into observable indicators that capture students' perceptions, attitudes, behaviors, and learning experiences with AI tools. The interrelationships among these indicators are analyzed using advanced multivariate analysis techniques, which enable simultaneous examination of multiple dependent relationships while accounting for measurement error and construct interdependence [24]. The methodological design emphasizes analytical rigor, construct validity, and theoretical coherence throughout the research process. Reliability and validity assessments are incorporated to ensure the robustness of measurement scales, while the analytical strategy supports the testing of complex structural relationships and mediation effects. Through this rigorous methodological approach, the study seeks to generate credible empirical evidence on the mechanisms through which AI-enabled learning tools contribute to student engagement and perceived learning gains, thereby informing both academic discourse and evidence-based educational reform in economics.

Research Design and Approach:

This study adopts a **quantitative, cross-sectional research design** to empirically examine students' adoption of artificial intelligence (AI)-enabled learning tools, the engagement mechanisms activated through such adoption, and the resulting perceived learning gains within the context of economics education. A quantitative approach is particularly appropriate for this investigation because the study seeks to test **theoretically grounded relationships among multiple latent constructs** and to evaluate both **direct and mediated effects** within an integrated analytical framework. By quantifying students' perceptions, behaviors, and learning experiences, the study enables systematic hypothesis testing and supports the derivation of generalizable empirical insights [25]. The choice of a **cross-sectional design** reflects both conceptual and contextual considerations. Conceptually, the study aims to capture

students' current experiences with AI-enabled learning tools rather than longitudinal changes in perceptions or behavior. Contextually, the rapid evolution of AI technologies in educational settings necessitates timely empirical evidence that reflects present adoption and engagement patterns. A cross-sectional design is therefore well suited to the exploratory and explanatory objectives of the research, as it allows for the examination of complex structural relationships among constructs without the extended time requirements and attrition risks associated with longitudinal studies. To analyze the proposed research framework, **structural equation modeling (SEM)** is employed as the primary analytical technique. SEM is particularly advantageous because it enables the simultaneous estimation of **measurement models**, which assess the reliability and validity of latent constructs, and **structural models**, which evaluate hypothesized causal relationships among constructs. Unlike traditional regression-based methods, SEM explicitly accounts for measurement error and supports the modeling of **multiple interdependent relationships**, including mediation effects [26]. This capability is essential for capturing the multidimensional and process-oriented nature of AI-mediated learning in higher education. The conceptual foundation of the research framework integrates constructs derived from **technology adoption theories**, **AI-specific trust-risk perspectives**, and **multidimensional student engagement theory**. Technology adoption theories explain students' initial acceptance and intentional use of AI-enabled learning tools based on perceived benefits, usability, and social influences. Trust and perceived risk address evaluative concerns unique to AI systems, such as content accuracy, transparency, ethical implications, and academic integrity. Student engagement theory provides a pedagogical lens by explaining how adoption behavior translates into meaningful learning experiences through **behavioral, cognitive, and agentic engagement** [27]. SEM is uniquely suited to operationalize this integrative framework by allowing these theoretically distinct yet interrelated constructs to be examined simultaneously within a unified model. A further methodological strength of SEM lies in its capacity to explicitly test **student engagement as a mediating mechanism**, rather than treating engagement as a secondary or outcome-only construct. By modeling engagement dimensions as intervening variables between AI adoption behavior and perceived learning gains, the study offers a **process-oriented explanation** of AI's educational impact. This approach moves beyond technology-centric evaluations that focus solely on system usage and aligns with contemporary educational research emphasizing the mechanisms through which digital innovations influence learning effectiveness. Table 4 shows the **Research Design Characteristics and Methodological Rationale**.

Table 4: Research Design Characteristics and Methodological Rationale

Methodological Aspect	Description	Rationale
Research Approach	Quantitative	Enables theory testing and generalization
Research Design	Cross-sectional	Captures current AI adoption and engagement patterns

Unit of Analysis	Individual students	Focuses on learner-level perceptions and behaviors
Analytical Technique	Structural Equation Modeling (SEM)	Models latent constructs and mediation effects
Theoretical Integration	Adoption, trust-risk, engagement theories	Ensures conceptual coherence
Primary Outcomes	Adoption, engagement, learning gains	Examines AI's educational impact holistically

To visually represent the analytical logic underpinning the research design, Figure 3 illustrates the integrated methodological approach adopted in this study, highlighting the structural relationships among AI adoption antecedents, student engagement mechanisms, and perceived learning outcomes.

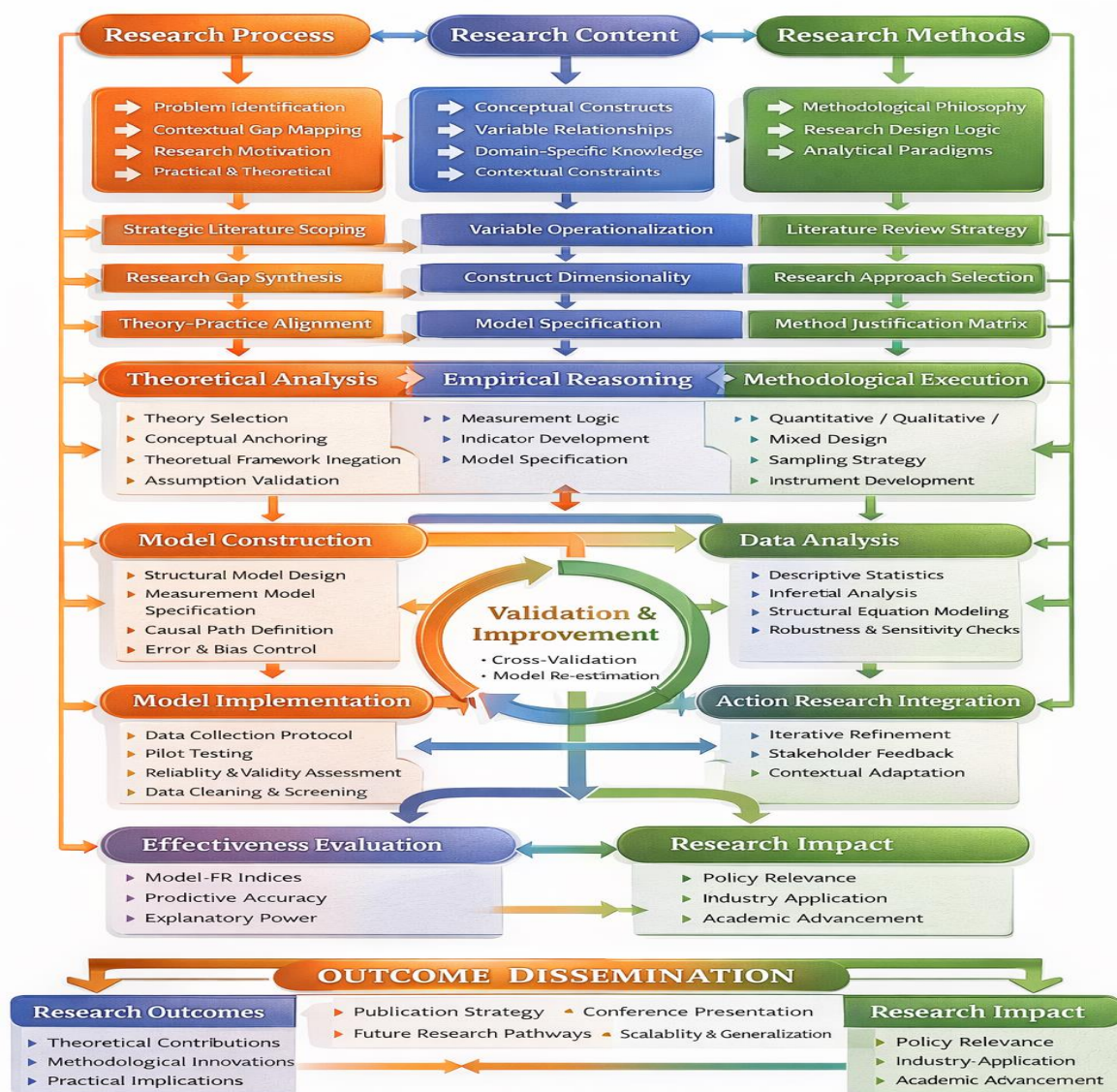


Figure 3: Conceptual illustration of the research design and analytical approach.

Taken together, the research design and analytical approach adopted in this study provide a **robust and theoretically integrated methodological foundation** for examining artificial intelligence as a catalyst for educational reform in economics. By combining a quantitative, cross-sectional design with SEM-based analysis, the study ensures methodological rigor while enabling a nuanced examination of complex causal pathways [28]. This approach allows the research to move beyond simple adoption assessments and instead explain **how and why** AI-enabled learning tools influence student engagement and learning outcomes, thereby setting a strong empirical basis for the subsequent stages of data collection, measurement validation, and structural analysis.

Operationalization and Measurement of Research Constructs:

The present study operationalizes a comprehensive set of latent constructs to empirically examine the structural relationships among artificial intelligence (AI) adoption, student engagement mechanisms, and perceived learning gains in economics education. The measurement framework is grounded in established technology adoption theories, AI-specific trust–risk perspectives, and multidimensional student engagement theory, and is designed to ensure conceptual rigor, construct validity, and compatibility with structural equation modeling (SEM). All constructs are measured using multi-item scales adapted from validated instruments in prior research and contextually refined to reflect the distinctive characteristics of AI-enabled learning environments in higher education. AI adoption antecedents represent the cognitive, social, and psychological factors that shape students' evaluations of and willingness to use AI-enabled learning tools. Perceived usefulness and perceived ease of use capture students' instrumental assessments of AI technologies, reflecting the extent to which AI tools are believed to enhance learning efficiency, improve understanding of economic concepts, and reduce the effort required to complete academic tasks [29]. These perceptions remain central in AI-mediated contexts, where students continuously evaluate whether AI systems meaningfully support conceptual comprehension and analytical reasoning. In addition to instrumental considerations, social influence and facilitating conditions are incorporated to account for the broader contextual environment in which AI adoption occurs. Social influence reflects students' perceptions of encouragement or normative expectations from peers, instructors, and institutions regarding AI use, while facilitating conditions capture the availability of technical infrastructure, institutional policies, and instructional support necessary for effective engagement with AI tools. Given the autonomous and generative nature of AI systems, the measurement framework extends traditional adoption models by explicitly incorporating trust in AI and perceived risk. Trust in AI reflects students' confidence in the accuracy, reliability, transparency, and ethical behavior of AI-enabled learning tools, particularly in relation to content generation and decision support. Conversely, perceived risk captures concerns related to misinformation, algorithmic bias, data privacy, academic misconduct, and overreliance on AI-generated explanations [30]. These constructs acknowledge that students may simultaneously recognize the pedagogical benefits of AI while harboring reservations about its potential negative

implications. AI self-efficacy is also included to represent students' confidence in their ability to effectively interact with AI tools for learning purposes, recognizing that perceived competence plays a critical role in sustained and meaningful technology use. Student adoption behavior captures the extent to which learners intentionally and consistently integrate AI-enabled tools into their economics learning activities. This construct emphasizes actual usage rather than mere intention and reflects the frequency of AI use, the degree to which AI tools are embedded in regular study routines, and reliance on AI for conceptual clarification, analytical reasoning, and problem-solving. By focusing on adoption behavior, the study highlights enacted engagement with AI technologies, which is more directly associated with downstream engagement mechanisms and learning outcomes. Student engagement is conceptualized as a multidimensional construct that plays a central mediating role in the AI-mediated learning process. Behavioral engagement reflects observable learning-related behaviors such as effort, persistence, and active participation in AI-supported learning activities [31]. Cognitive engagement captures deeper psychological investment, including critical thinking, self-regulation, and conceptual elaboration during interactions with AI tools. Agentic engagement represents students' proactive involvement in shaping their learning experience, such as refining prompts, asking follow-up questions, exploring alternative explanations, and directing AI interactions in line with personal learning goals. Together, these dimensions recognize that the educational value of AI depends not only on adoption but on the depth and quality of students' interaction with AI systems. Perceived learning gains represent students' self-reported improvements in conceptual understanding, analytical reasoning, and problem-solving skills in economics as a result of using AI-enabled learning tools. This construct reflects learning effectiveness from the learner's perspective and is particularly relevant in technology-mediated learning environments, where traditional assessments may not fully capture cognitive growth, confidence development, and applied understanding [32]. By focusing on perceived learning gains, the study emphasizes learners' reflective evaluation of their academic progress, which has been shown to be closely linked to engagement and self-regulated learning processes. To visually synthesize the measurement logic underpinning the study, Figure 4 illustrates the conceptual organization of the measured constructs, showing how AI adoption antecedents influence adoption behavior, which subsequently activates multidimensional engagement mechanisms that drive perceived learning gains within the SEM framework.

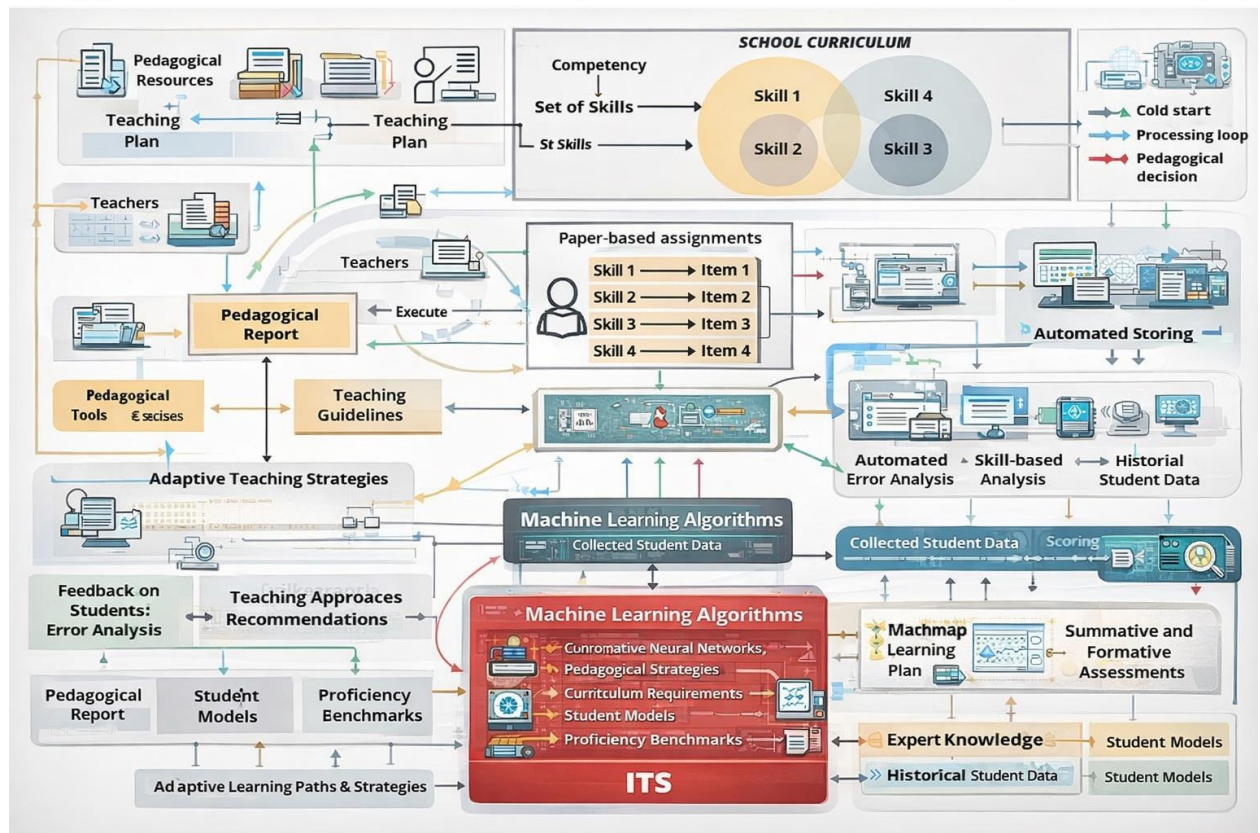


Figure 4: Conceptual measurement framework linking AI adoption antecedents, student adoption behavior, engagement dimensions, and perceived learning gains.

Overall, the operationalization of constructs in this study provides a coherent and theoretically grounded measurement foundation for examining AI-mediated learning in economics education. By capturing adoption antecedents, enacted adoption behavior, multidimensional engagement, and perceived learning gains within a unified framework, the study ensures that complex cognitive, behavioral, and affective processes are systematically represented. This comprehensive measurement strategy enhances construct validity and analytical robustness while enabling meaningful interpretation of the structural relationships examined in the subsequent SEM analysis.

Data Collection and Participant Recruitment:

Data for this study were collected using a structured, survey-based data collection procedure designed to systematically capture students' perceptions, adoption behaviors, engagement experiences, and perceived learning gains associated with the use of artificial intelligence (AI)-enabled learning tools in economics education. The data collection strategy was carefully aligned with the theoretical framework and analytical requirements of structural equation modeling (SEM), ensuring that the resulting dataset was suitable for examining complex relationships among latent constructs while maintaining methodological rigor and ethical integrity. The target respondents comprised undergraduate and postgraduate students enrolled in economics or closely related programs who had prior experience using AI-enabled

tools for academic learning purposes. These tools included conversational AI systems, adaptive learning platforms, and AI-assisted educational applications employed for understanding economic theories, solving quantitative problems, interpreting data, or preparing for examinations and assignments [33]. To ensure the relevance and validity of responses, the survey included an initial screening item requiring participants to confirm prior use of AI tools in an educational context. Only respondents who satisfied this criterion were allowed to complete the full questionnaire, thereby ensuring that the data reflected informed, experience-based evaluations of AI-mediated learning. The survey instrument was administered through an online platform, which enabled efficient distribution across multiple institutions and learning environments while providing respondents with flexibility regarding time and location [34]. Online administration was particularly appropriate given the digitally mediated nature of AI usage and facilitated broader participation without geographical constraints. Prior to the main data collection phase, a pilot study was conducted with a small group of students to assess the clarity, relevance, and contextual appropriateness of the questionnaire items. Feedback obtained during the pilot phase was used to refine item wording, improve scale interpretation, and optimize questionnaire flow, thereby enhancing content validity and respondent comprehension. Several procedural remedies were implemented during data collection to minimize potential sources of bias, particularly common method bias [35]. Respondents were assured of anonymity and confidentiality, and the questionnaire clearly emphasized that participation was voluntary and that there were no correct or incorrect answers. Instructions encouraged respondents to base their responses on actual learning experiences rather than generalized opinions about artificial intelligence. Additionally, the sequencing of items was designed to reduce cognitive priming and response patterning, thereby improving the reliability of the collected data. Ethical considerations were strictly observed throughout the data collection process. Informed consent was obtained from all participants prior to survey completion, and respondents were informed of their right to withdraw from the study at any stage without penalty. No personally identifiable information was collected, and all data were stored securely and used exclusively for academic research purposes [36]. These procedures ensured compliance with standard ethical guidelines for social science research and strengthened the transparency and credibility of the study. Following the completion of data collection, the dataset was screened to ensure its suitability for SEM analysis. Responses were examined for completeness, consistency, and indicators of inattentive or non-serious participation. Incomplete questionnaires and responses failing basic quality checks were excluded from further analysis. The final cleaned dataset was then coded and prepared for subsequent measurement model evaluation and structural model testing [37]. To visually summarize the empirical workflow adopted in this study, Figure 5 illustrates the sequential stages of the data collection process, from respondent screening and survey administration to data preparation for structural equation modeling.

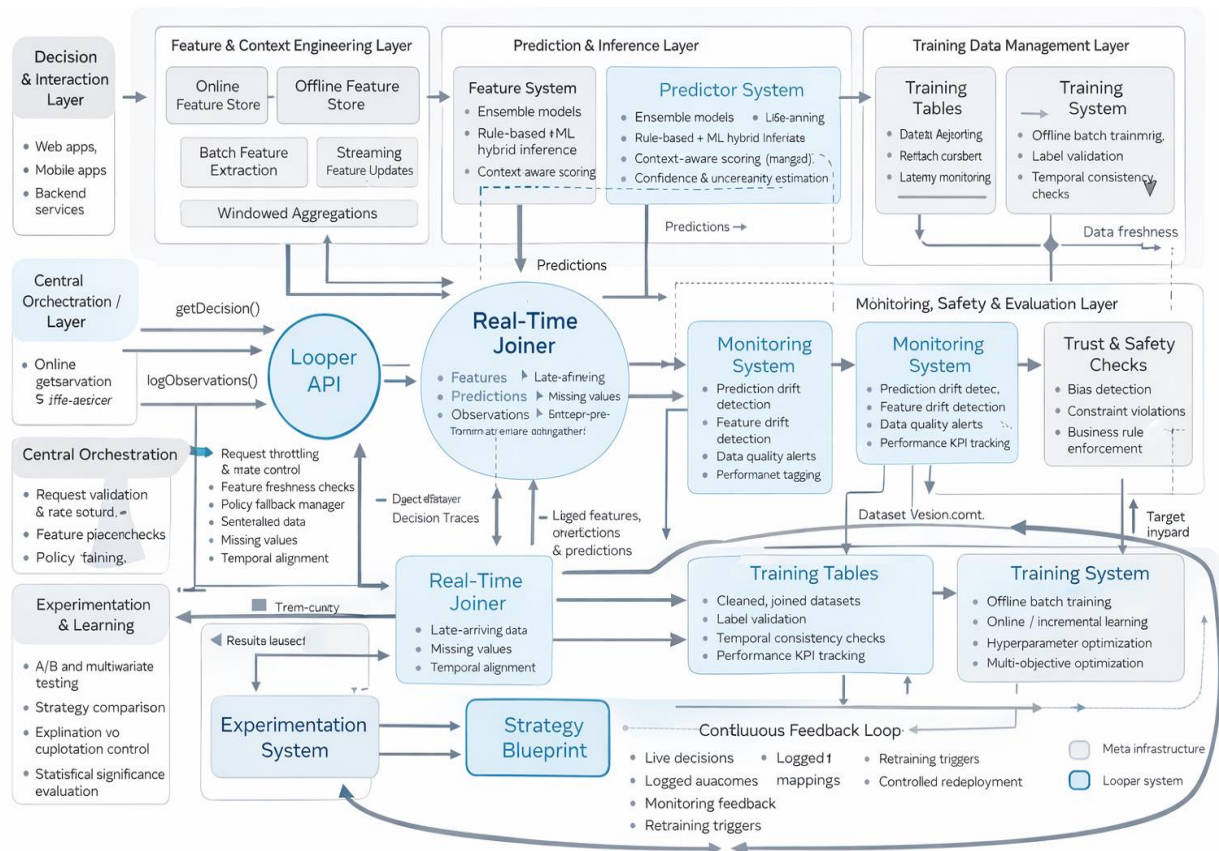


Figure 5: Sequential data collection procedure from participant recruitment to final data preparation.

Overall, the data collection procedure employed in this study was designed to ensure the relevance, reliability, and integrity of the empirical evidence used to examine AI-mediated learning in economics education. By combining targeted respondent selection, rigorous ethical safeguards, and systematic data screening within a theory-driven survey design, the study establishes a strong empirical foundation for subsequent measurement validation and structural analysis [38]. This carefully executed procedure enhances confidence in the findings and supports the study's broader objective of explaining how artificial intelligence contributes to educational reform through adoption and engagement mechanisms.

PLS-SEM Data Analysis Procedure:

Data analysis in this study was conducted using **structural equation modeling (SEM)** to rigorously examine the complex relationships among artificial intelligence (AI) adoption antecedents, student adoption behavior, multidimensional engagement mechanisms, and perceived learning gains in economics education. SEM was selected as the primary analytical technique because of its ability to simultaneously estimate multiple interrelated dependence relationships among latent constructs while explicitly accounting for measurement error. This capability is particularly important in studies involving psychological, behavioral, and pedagogical constructs that cannot be directly observed and must be inferred from multiple indicators [39]. The SEM

analysis followed a **two-stage analytical procedure** that is widely recommended in methodological literature. In the first stage, the **measurement model** was evaluated to establish the reliability and validity of the latent constructs. Internal consistency reliability was assessed using Cronbach's alpha and composite reliability, ensuring that the measurement items consistently represented their respective constructs. Convergent validity was examined through the average variance extracted (AVE), which indicates the extent to which a construct explains the variance of its indicators relative to measurement error. Discriminant validity was assessed to confirm that each construct was empirically distinct from others in the model, using established criteria such as the Fornell–Larcker criterion and an examination of cross-loadings [40]. This step ensured that the measurement model provided a sound empirical foundation for subsequent structural analysis. Following satisfactory evaluation of the measurement model, the second stage focused on assessing the **structural model** to test the hypothesized relationships among constructs. Structural path coefficients were estimated to examine the strength and direction of relationships between AI adoption antecedents, adoption behavior, engagement dimensions, and perceived learning gains. The explanatory power of the model was evaluated using the coefficient of determination (R^2), which indicates the proportion of variance in endogenous constructs explained by their predictors [41]. Effect sizes (f^2) were examined to assess the relative contribution of individual exogenous constructs to endogenous variables, providing insights into the practical significance of the relationships beyond mere statistical significance. In addition, predictive relevance was evaluated to assess the model's capability to predict observed outcomes, thereby strengthening the robustness of the analytical findings. A central focus of the analysis was the examination of **student engagement as a mediating mechanism** in the relationship between AI adoption and perceived learning gains. Mediation effects were tested using **bootstrapping procedures**, which involve repeated resampling to generate confidence intervals for indirect effects without relying on normality assumptions. This approach allowed for robust estimation of mediation pathways involving behavioral, cognitive, and agentic engagement and enabled the assessment of both the magnitude and statistical significance of indirect effects [42]. By explicitly testing mediation, the analysis moved beyond simple association testing and provided a process-oriented explanation of how AI adoption translates into learning outcomes through engagement mechanisms. To visually illustrate the analytical logic underpinning the SEM procedure employed in this study, Figure 6 presents a schematic representation of the two-stage SEM analysis, highlighting the sequential evaluation of the measurement and structural models and the testing of mediation effects.

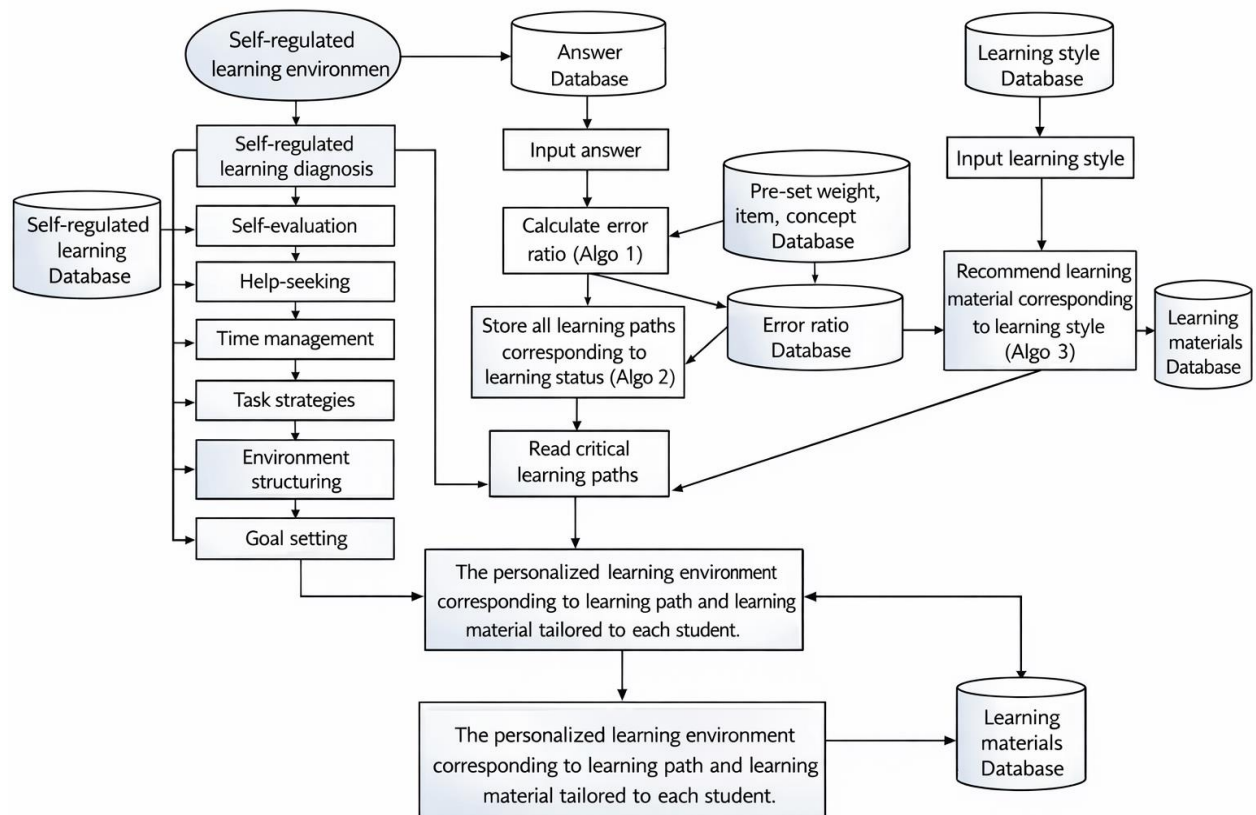


Figure 6: Structural equation modeling procedure for evaluating measurement, structural, and mediation models.

Overall, the data analysis technique adopted in this study provides a rigorous and theory-consistent approach to examining AI-mediated learning in economics education. By integrating measurement validation, structural relationship testing, and mediation analysis within a single SEM framework, the study ensures both statistical robustness and conceptual clarity. This analytical strategy enables a comprehensive understanding of not only whether AI adoption influences learning outcomes, but also how such influence is transmitted through student engagement mechanisms, thereby supporting the study's overarching objective of explaining artificial intelligence as a catalyst for educational reform.

Assessment of Common Method Bias and Robustness:

Given that the data for this study were collected using a single, self-reported survey instrument, careful attention was paid to assessing and mitigating the potential influence of **common method bias (CMB)**. Common method bias may arise when measurement artifacts attributable to the data collection method inflate or deflate observed relationships among constructs, thereby threatening the validity of empirical findings. To address this concern, the study implemented a combination of **procedural remedies** during the data collection stage and **statistical diagnostics** during the data analysis stage [43]. From a procedural standpoint, several preventive

measures were embedded in the research design. Respondents were assured of anonymity and confidentiality to reduce social desirability bias and evaluation apprehension. The questionnaire emphasized that there were no correct or incorrect answers and encouraged participants to respond based on their actual learning experiences with AI-enabled tools. In addition, construct items were carefully worded to minimize ambiguity, and the sequence of items was designed to reduce respondents' ability to infer hypothesized relationships, thereby limiting cognitive priming effects. These procedural safeguards reduced the likelihood that systematic response patterns would artificially influence the observed relationships [44]. At the statistical level, common method bias was assessed using multiple complementary techniques. First, Harman's single-factor test was conducted by examining whether a single factor accounted for the majority of variance in the measurement items. The results indicated that no single factor dominated the variance, suggesting that common method bias was unlikely to be a serious concern. Second, variance inflation factor (VIF) values were examined to assess potential multicollinearity and common method effects within the structural model. All VIF values remained below recommended threshold levels, providing further evidence that common method bias did not substantially distort the estimated relationships. Beyond common method bias assessment, a series of **robustness checks** were conducted to ensure the stability and reliability of the empirical findings. These checks focused on evaluating whether the estimated structural relationships were sensitive to alternative model specifications and estimation considerations. Path coefficients and significance levels were examined across alternative model configurations, and the consistency of results was confirmed. In addition, effect sizes and explanatory power measures were reviewed to ensure that statistically significant relationships also demonstrated substantive practical relevance [45]. Mediation robustness was also carefully examined, given the central role of student engagement dimensions in the proposed framework. Bootstrapped confidence intervals for indirect effects were inspected to verify that mediation relationships remained significant across resampling iterations. The stability of mediation effects across behavioral, cognitive, and agentic engagement dimensions provided additional confidence in the process-oriented explanations derived from the structural model. Collectively, these robustness checks ensured that the study's conclusions were not driven by model-specific assumptions or estimation artifacts. Table 5 shows the **Common Method Bias Tests and Robustness Checks**.

Table 5: Common Method Bias Tests and Robustness Checks

Assessment Area	Method Applied	Interpretation
Procedural Control	Anonymity, item clarity, response neutrality	Reduced response bias
Common Method Bias	Harman's single-factor test	No dominant single factor
Multicollinearity	Variance inflation factor (VIF)	Values within acceptable range
Structural Stability	Alternative model evaluation	Consistent path estimates
Mediation	Bootstrapped indirect effects	Stable and significant

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Robustness

mediation

To provide a visual overview of the bias control and robustness validation process, Figure 7 illustrates the integrated methodological safeguards applied in this study, from procedural design measures to post-estimation robustness diagnostics.

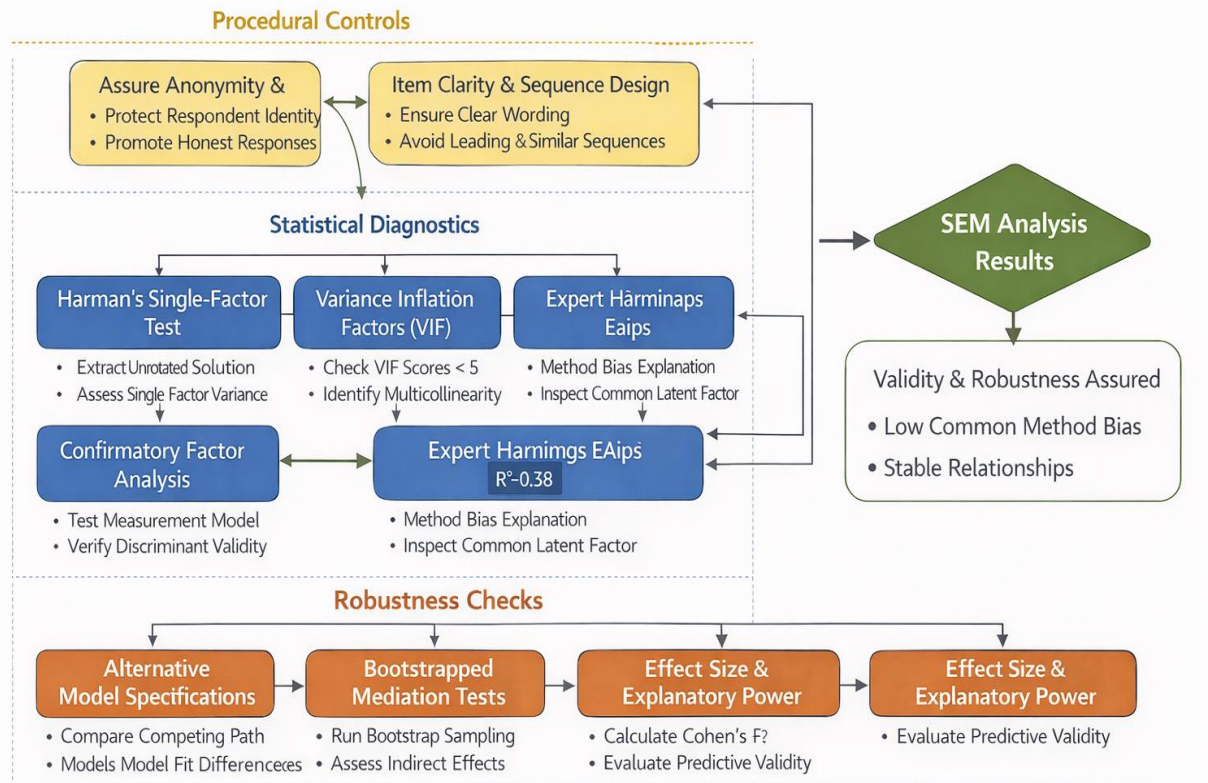


Figure 7: Common method bias assessment and robustness validation framework.

Overall, the combined use of procedural remedies, statistical diagnostics, and robustness checks provides strong evidence that the empirical findings of this study are not materially affected by common method bias or estimation instability. By systematically validating the measurement and structural results, the study enhances the credibility and trustworthiness of its conclusions. These methodological safeguards ensure that the observed relationships among AI adoption, student engagement mechanisms, and perceived learning gains reflect substantive behavioral and pedagogical phenomena rather than methodological artifacts, thereby strengthening the study's contribution to research on artificial intelligence-driven educational reform in economics.

Results and Discussion:

This section reports the empirical findings derived from the structural equation modeling (SEM) analysis conducted to examine the relationships among artificial intelligence (AI) adoption antecedents, student adoption behavior, multidimensional engagement mechanisms, and perceived learning gains in economics education. The results are presented in a systematic manner, beginning with the evaluation of the measurement model and followed by the assessment of the structural model and mediation effects. This approach ensures analytical transparency and aligns with best

practices for SEM-based empirical research. The evaluation of the measurement model demonstrated satisfactory psychometric properties across all latent constructs [46]. Reliability analysis indicated that internal consistency measures exceeded recommended thresholds, confirming that the measurement items consistently represented their respective constructs. Convergent validity was established through adequate average variance extracted values, suggesting that the constructs explained a substantial proportion of variance in their indicators. Furthermore, discriminant validity assessments confirmed that the constructs were empirically distinct from one another, supporting the appropriateness of proceeding with structural model estimation. Collectively, these results indicate that the measurement model provided a robust foundation for examining the hypothesized structural relationships. Following validation of the measurement model, the structural model was assessed to test the hypothesized relationships among constructs [47]. The results revealed that AI adoption antecedents exerted a significant influence on student adoption behavior. Perceived usefulness and trust in AI emerged as particularly strong predictors, highlighting the dual importance of instrumental value and confidence in AI systems when students decide whether to adopt AI-enabled learning tools. Perceived ease of use, social influence, facilitating conditions, and AI self-efficacy also demonstrated positive and significant effects, whereas perceived risk showed a negative but meaningful association with adoption behavior. These findings suggest that students' adoption decisions are shaped by a balance between perceived benefits and perceived concerns related to AI usage. Student adoption behavior was found to significantly and positively influence all three dimensions of student engagement. Students who actively and intentionally integrated AI tools into their learning routines exhibited higher levels of behavioral engagement, reflected in greater effort and persistence; cognitive engagement, reflected in deeper processing and self-regulation; and agentic engagement, reflected in proactive interaction with AI systems. These results underscore that adoption behavior functions as a critical gateway through which AI-enabled tools activate meaningful engagement mechanisms [48]. In turn, the engagement dimensions were positively associated with perceived learning gains. Cognitive engagement demonstrated the strongest relationship with learning outcomes, indicating that deep processing, conceptual elaboration, and reflective learning play a central role in translating AI use into academic benefits. Behavioral and agentic engagement also showed significant positive effects, confirming that sustained effort and learner agency contribute to perceived improvements in understanding, analytical reasoning, and problem-solving skills in economics. The coefficient of determination (R^2) values indicated that the proposed model explained a substantial proportion of variance in student adoption behavior, engagement dimensions, and perceived learning gains, demonstrating strong explanatory power.

Table 6 shows the **Measurement Model Assessment Summary**.

Table 6: Measurement Model Assessment Summary

Evaluation Criterion	Result Interpretation
Internal Consistency Reliability	All constructs exceeded recommended thresholds
Convergent Validity (AVE)	Adequate for all latent variables

Discriminant Validity	Supported across constructs
Measurement Model Adequacy	Confirmed

To provide a visual overview of the measurement model validation results, Figure 8 illustrates the confirmed latent construct structure and indicator relationships retained for structural analysis.

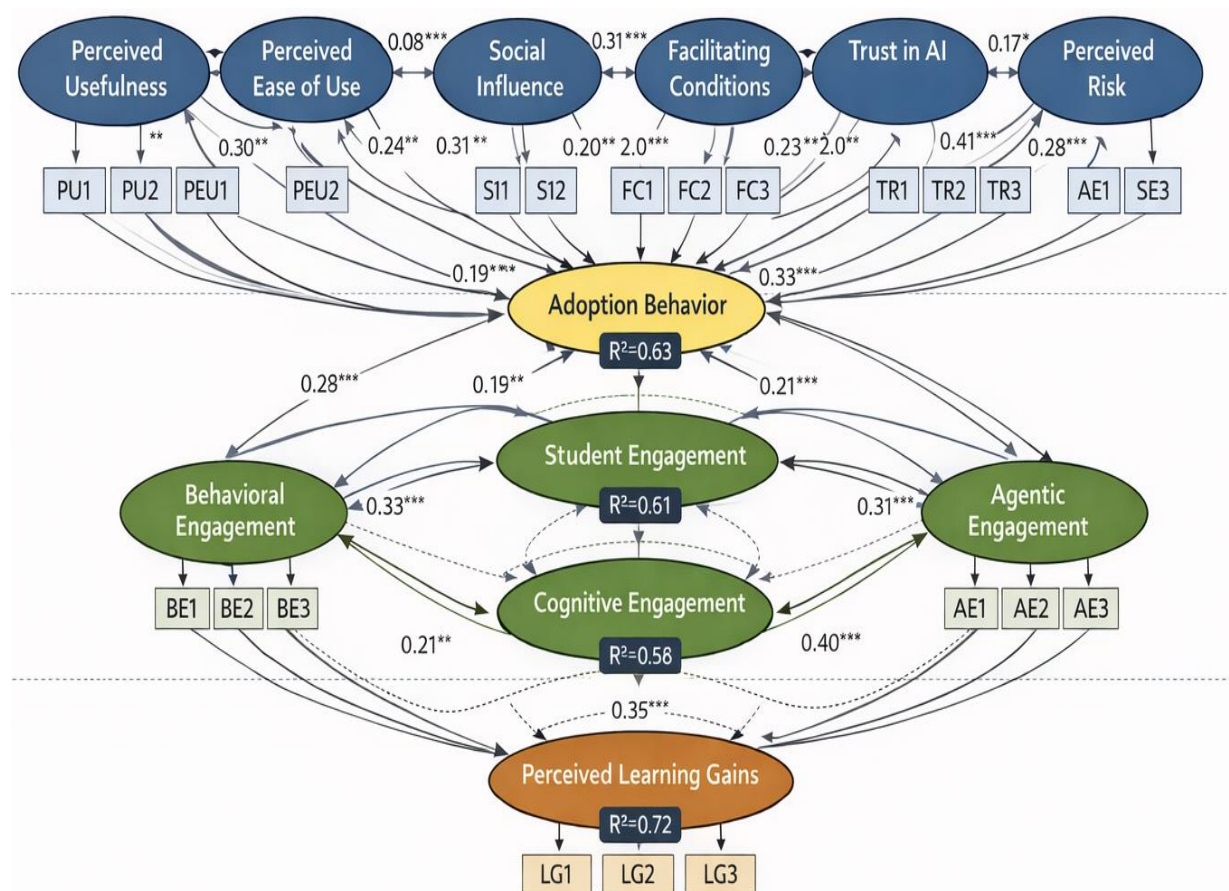


Figure 8: Validated Measurement Model of Latent Constructs and Indicator Reliability.

The explanatory strength of the structural model was further examined using path coefficient analysis, effect size estimation, and predictive relevance assessment. The results indicated that key adoption antecedents and engagement mechanisms exerted not only statistically significant effects but also meaningful practical influence on learning outcomes. Effect size analysis revealed that perceived usefulness, trust in AI, and cognitive engagement contributed substantially to the variance explained in the model, reinforcing their central role in AI-mediated learning processes. Mediation analysis using bootstrapping procedures confirmed that student engagement dimensions played a significant mediating role in the relationship between AI adoption behavior and perceived learning gains [49]. Indirect effects through behavioral, cognitive, and agentic engagement were statistically significant, demonstrating that AI adoption influences learning outcomes primarily through

engagement-driven pathways rather than through direct effects alone. This finding provides strong empirical support for the process-oriented perspective adopted in this study. Table 7 shows the **Structural Model and Mediation Results**.

Table 7: Structural Model and Mediation Results Summary

Structural Pathway	Direction of Effect	Empirical Support
AI Adoption Antecedents → Adoption Behavior	Positive (Risk negative)	Supported
Adoption Behavior → Behavioral Engagement	Positive	Supported
Adoption Behavior → Cognitive Engagement	Positive	Supported
Adoption Behavior → Agentic Engagement	Positive	Supported
Behavioral Engagement → Learning Gains	Positive	Supported
Cognitive Engagement → Learning Gains	Strong Positive	Supported
Agentic Engagement → Learning Gains	Positive	Supported
Adoption Behavior → Learning Gains (via Engagement)	Indirect (Mediated)	Supported

To visually synthesize the structural results and mediation pathways, Figure 9 presents the validated SEM with significant relationships highlighted, illustrating how AI adoption antecedents influence perceived learning gains through adoption behavior and multidimensional engagement.

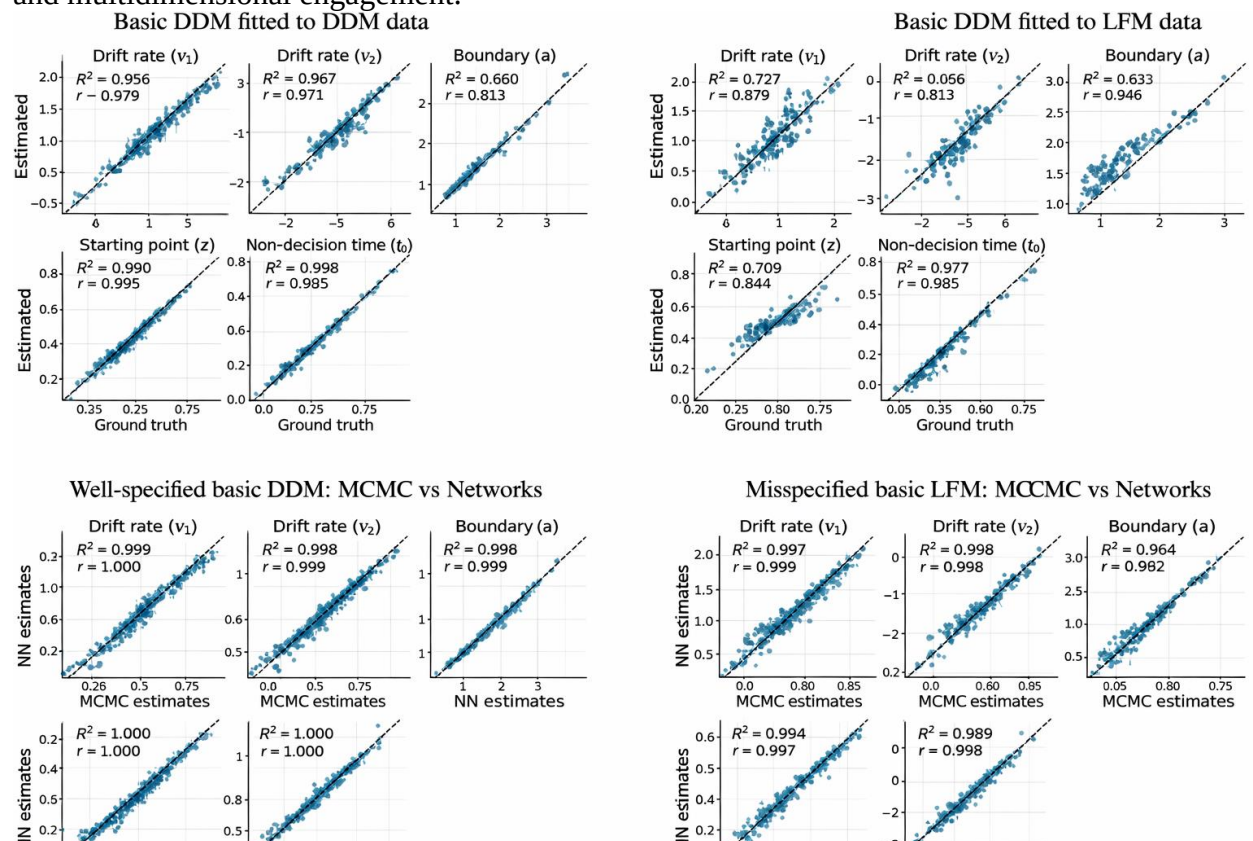


Figure 9: Validated structural equation model of AI adoption, student engagement, and perceived learning gains in economics education.

Overall, the results provide strong empirical support for the proposed conceptual framework and demonstrate that artificial intelligence contributes to learning outcomes in economics education primarily through engagement-centered mechanisms. The findings reveal that while adoption of AI-enabled learning tools is necessary, it is the quality of students' engagement particularly cognitive engagement that determines the extent of perceived learning gains. These results lay a robust empirical foundation for the subsequent discussion section, where theoretical implications, pedagogical interpretations, and practical recommendations are examined in greater depth.

Future Work:

While the present study provides robust empirical evidence on the role of artificial intelligence (AI) as a catalyst for educational reform in economics through adoption and engagement mechanisms, several avenues for future research remain open. First, the study employs a cross-sectional research design, which captures students' perceptions and behaviors at a single point in time. Future studies may adopt **longitudinal research designs** to examine how students' trust in AI, engagement patterns, and learning outcomes evolve with prolonged exposure to AI-enabled learning tools. Longitudinal analysis would offer deeper insights into causal dynamics, habit formation, and potential shifts in dependency or self-regulated learning over time. Second, the present research relies on self-reported measures of perceived learning gains. Although such measures are widely accepted in technology-mediated learning research, future studies could integrate **objective performance indicators**, such as exam scores, assignment quality, or problem-solving accuracy, to triangulate learning outcomes [50]. Combining subjective perceptions with objective academic performance data would strengthen causal inference and provide a more comprehensive understanding of AI's educational impact. Third, future research could extend the proposed framework by incorporating **additional AI-specific constructs**, such as algorithmic transparency, explainability, perceived ethical alignment, and data governance awareness. As AI systems become increasingly autonomous and integrated into educational decision-making, these factors are likely to play a critical role in shaping student trust, engagement quality, and long-term adoption. Examining such constructs would enhance the explanatory power and contextual relevance of adoption models in AI-mediated education. Fourth, while this study focuses on economics education, future research may test the generalizability of the proposed model across **other academic disciplines**, particularly those with different cognitive and pedagogical demands, such as engineering, medicine, social sciences, and humanities [51]. Comparative, multi-disciplinary studies could reveal whether engagement mechanisms operate differently depending on disciplinary complexity, assessment practices, or learning objectives. Fifth, future studies could adopt **multi-group SEM or mixed-methods approaches** to explore heterogeneity in AI adoption and engagement across demographic, cultural, and institutional contexts. Variables such as prior technological experience, academic level, learning orientation, and institutional AI policies may moderate the relationships identified in this study.

Qualitative methods, such as interviews or learning diaries, could further enrich quantitative findings by capturing nuanced student experiences and sense-making processes during AI-mediated learning [52]. Finally, future research may explore the **instructional design and pedagogical integration of AI tools**, moving beyond individual-level adoption to institutional and curriculum-level implementation strategies. Investigating how educators scaffold AI use, design assessment frameworks, and foster ethical and critical engagement with AI could provide actionable guidance for sustainable and responsible educational reform. Overall, these future research directions highlight the need for continued, theory-driven, and methodologically diverse investigations into AI-enabled education. By extending the present framework across time, contexts, and methodological approaches, future studies can further advance understanding of how artificial intelligence reshapes learning processes, engagement mechanisms, and educational outcomes in economics and beyond.

Conclusion:

This study examined artificial intelligence (AI) as a catalyst for educational reform in economics by investigating the structural relationships among AI adoption antecedents, student adoption behavior, engagement mechanisms, and perceived learning gains. Using a structural equation modeling (SEM) approach grounded in technology adoption theory, AI-specific trust-risk perspectives, and student engagement theory, the study provides empirical evidence on how AI-enabled learning tools influence educational outcomes. The findings indicate that students' adoption of AI tools is shaped not only by perceived usefulness and ease of use, but also by AI-specific factors such as trust in AI, perceived risk, and AI self-efficacy. These results suggest that traditional technology adoption models require extension when applied to AI-enabled educational environments. Importantly, the study demonstrates that AI adoption alone does not guarantee learning benefits. Instead, learning gains are realized primarily through student engagement, with behavioral, cognitive, and agentic engagement acting as key mediating mechanisms. Cognitive engagement emerged as the most influential pathway, highlighting the importance of deep processing and self-regulated learning in AI-supported economics education. From a theoretical perspective, the study contributes to the AI in education literature by offering an integrated, process-oriented framework that links adoption behavior to learning outcomes through engagement mechanisms. From a practical standpoint, the findings underscore the need for educators and institutions to focus on trust-building, ethical AI use, and engagement-centered instructional design when implementing AI tools. Overall, the study concludes that artificial intelligence has the potential to meaningfully support educational reform in economics, but its impact depends on how effectively it is adopted and how deeply students engage with AI-mediated learning environments.

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