Education Insights

Article

Artificial Intelligence Project Engineering Education: Research on Improving Legal Awareness, Financial Decision-Making and Management Control Capabilities Based on EPC Simulation

Rui Ye [1,2,3], Kejia An [4], Yunting Fang [3], Fengzhen Wang [5], Bin Wang [6] and Xiajing Chen [7,8,*]

1 XING YUN CHEN (Hongkong) Technology Co., Ltd, Hongkong, 999077, China
2 Hainan Jingerxin Information Technology Co., Ltd, Danzhou, 571700, China
3 Cavite State University, Indang, 4100, Philippines
4 Guizhou Duicheng Law Firm, Guizhou, 553001, China
5 Jiangxi New Energy Technology Institute, Xinyu, 338000, China
6 Hainan Vocational University of Science and Technology, Haikou, 571126, China
7 Fujian Investment Development Group Co., Ltd., Fuzhou, 350003, China
8 Fuzhou University of International Studies and Trade, Fuzhou, 350202, China
* Correspondence: Xiajing Chen, Fujian Investment Development Group Co., Ltd., Fuzhou, 350003, China; Fuzhou University of International Studies and Trade, Fuzhou, 350202, China

Abstract: The integration of artificial intelligence (AI) into engineering education presents new opportunities for enhancing professional competencies through simulation-based learning. This study investigates the role of AI-driven EPC (Engineering-Procurement-Construction) project simulation in improving students' legal risk awareness, financial decision-making ability, and management control capability. Grounded in experiential learning theory and the Technology Acceptance Model (TAM), a conceptual framework was developed to analyze the impact of AI-enabled simulation modules on key learning outcomes. The research employed a quasi-experimental design involving 180 engineering management students, utilizing pre-and post-tests, structured questionnaires, and structural equation modeling (SEM) to assess changes in student competencies. Results reveal that AI-enhanced EPC simulation significantly improves participants' ability to recognize legal risks, make strategic financial decisions, and exercise effective project control. Additionally, the level of cognitive interaction with AI modules serves as a strong predictor of performance gains across all three domains. The findings provide empirical evidence for the pedagogical value of AI in project-based engineering education and offer actionable insights for curriculum innovation in the digital age.

Keywords: artificial intelligence; engineering education; EPC project; legal risk awareness; financial decision-making; management control; simulation-based learning

Published: 31 May 2025

1. Introduction

1.1. Research Background

Engineering education in the digital era is undergoing a profound transformation. The emergence of artificial intelligence (AI) has redefined not only industrial production and management practices but also the pedagogical approaches required to cultivate future-ready engineers. Amid the ongoing digital revolution, the complexity of real-world engineering projects — particularly those executed under the Engineering-Procurement-Construction (EPC) model — demands a new paradigm of integrated, AI-enhanced learning that mirrors the complexity and dynamism of modern engineering practice. To remain relevant, engineering education must evolve in tandem with these technological shifts [1].

In EPC projects, characterized by high capital intensity, contract interdependence, and dynamic stakeholder relationships, professional decisions are frequently influenced by factors that span multiple domains [2]. Engineers must interpret and manage legal documents, assess and respond to financial risk exposures, and maintain operational control amidst uncertain variables. Conventional classroom instruction, which often isolates legal, financial, and managerial subjects into discrete modules, is no longer adequate for preparing students to navigate the integrated challenges of contemporary project environments.

Meanwhile, AI-enhanced simulation environments allow learners to participate in interactive, risk-free project environments that closely approximate reality [3]. Through these simulations, learners can experience the cascading consequences of their decisions, thereby improving not only their technical knowledge but also their holistic decision-making capabilities. By mimicking the workflows of real EPC projects, AI-integrated educational platforms offer a scaffolded environment for developing legal risk awareness, financial insight, and project management competence in a cohesive manner [4].

The integration of AI into engineering education also aligns with global trends emphasizing innovation in higher education and the development of industry 4.0 competencies. Leading educational frameworks worldwide now stress the importance of equipping graduates with complex problem-solving, cross-functional collaboration, and digital fluency. As such, AI-driven EPC simulations serve not only as a pedagogical tool but also as a strategic enabler of national and institutional education reform.

1.2. Problem Statement

Despite advances in AI technology and increasing recognition of its educational potential, there remains a significant underutilization of AI-driven simulation systems in engineering curricula, particularly in relation to complex, integrated competencies. Most current applications of AI in education focus on adaptive testing, automated grading, or personalized content delivery [5]. While these functions are important, they do not address the unique needs of engineering project training that demands systems thinking, real-time decision-making, and cross-disciplinary integration.

Furthermore, existing engineering programs tend to segment competencies into separate learning outcomes. Legal literacy may be introduced through ethics courses, financial training may occur in cost management modules, and managerial control principles may be embedded within project management units [6]. This fragmented approach fails to reflect the interdependent nature of real project environments. Consequently, students often lack the capacity to synthesize these domains when making project-critical decisions under realistic, high-pressure conditions.

Moreover, educational research has paid limited attention to the empirical evaluation of AI-based simulations in enhancing complex decision-making competencies. Few studies systematically assess how such simulations influence learners' awareness of legal risk, their ability to interpret financial data in uncertain contexts, or their proficiency in managing dynamic control systems under pressure [7].

Therefore, there is a clear gap in both pedagogical practice and academic research regarding the integrated application of AI in engineering education, particularly in the context of EPC project simulation. Addressing this gap is critical for cultivating a new generation of engineers who are not only technically competent but also legally vigilant, financially astute, and managerially effective.

1.3. Objectives and Research Questions

The overarching aim of this study is to design, implement, and evaluate an AI-enhanced simulation platform tailored to EPC project scenarios, with a focus on improving three interrelated competencies: legal risk awareness, financial decision-making, and project management control [8,9]. This goal will be achieved through the construction of a simulated EPC environment that enables students to engage in decision-making exercises reflecting the complexities and const. In pursuit of this objective, the study seeks to answer the following research questions:

RQ1: To what extent does participation in AI-enabled EPC simulations improve students' legal risk awareness in project-based contexts?

RQ2: How does engagement with AI-driven project scenarios influence students' ability to make financially sound decisions under conditions of uncertainty and risk?

RQ3: What is the impact of AI simulation training on students' capability to maintain management control over project variables such as time, cost, and quality?

RQ4: How do student interaction levels with AI systems mediate or moderate the learning outcomes across the three targeted competencies?

Through these research questions, the study aims to explore the pedagogical effectiveness of AI-based simulations and provide empirical evidence to guide future integration strategies in engineering education.

1.4. Contributions of the Paper

This paper offers several important contributions to the fields of engineering pedagogy, AI-assisted learning, and project management education. First, it proposes a novel pedagogical framework for integrating AI simulations into engineering curricula, with a specific focus on multidimensional competency development within EPC project settings. This framework aligns with experiential learning theory and addresses key limitations in existing engineering education models by fostering deeper integration of technical, legal, and financial skills through immersive, practice-oriented learning [10].

Second, the study contributes to educational methodology by implementing a mixed-methods research design that includes pre- and post-intervention assessments, student interaction analytics, and structural equation modeling. This comprehensive approach allows for rigorous evaluation of learning outcomes and the identification of causal mechanisms linking AI engagement to skill development.

Third, the paper advances theoretical understanding by applying and extending models such as the Technology Acceptance Model (TAM) and experiential learning theory in the context of AI-driven project simulation. By exploring how these frameworks interact in practical educational settings, the study provides new insights into learner behavior and system design [11].

Fourth, the research introduces a validated set of measurement instruments for assessing legal awareness, financial decision-making skill, and management control capability. These tools can be employed by other researchers and educators to evaluate similar interventions or to benchmark competency development across institutions.

Finally, the practical implications of the study are significant. The findings offer actionable recommendations for curriculum designers, educators, and policymakers seeking to modernize engineering education through AI. Specifically, the study identifies effective strategies for embedding simulation-based learning into core courses, optimizing student-AI interaction, and aligning educational outputs with industry demands for integrative project expertise.

1.5. Structure of the Paper

The remainder of this paper is structured to provide a systematic exploration of the research objectives and findings.

Section 2 presents a comprehensive review of the existing literature related to AI in engineering education, EPC project training, and the development of legal, financial, and managerial competencies. The section identifies theoretical gaps and sets the stage for the development of the study's conceptual framework [12].

Section 3 introduces the theoretical underpinnings and presents the conceptual model guiding the study. It details the key constructs, hypothesized relationships, and theoretical justifications drawn from learning and technology acceptance theories.

Section 4 describes the research design and methodology, including the development of the simulation platform, participant recruitment, data collection instruments, and statistical analysis procedures. Emphasis is placed on the mixed-methods approach used to ensure validity and reliability.

Section 5 presents the results of the empirical study. It includes descriptive statistics, analysis of student performance before and after the simulation intervention, and the outcomes of structural equation modeling. The section also examines the moderating effects of AI interaction [13].

Section 6 offers a detailed discussion of the findings, situating them within the broader educational and technological context. It explores theoretical implications, practical applications, and potential limitations of the study.

Section 7 concludes the paper by summarizing the major findings, restating the contributions, and offering recommendations for future research and educational practice. The paper closes with references and appendices containing supplementary data and instruments used in the study.

2. Literature Review

2.1. Artificial Intelligence in Engineering Education

The integration of artificial intelligence (AI) in engineering education has transitioned from an emerging trend to a vital necessity. With AI's rapid expansion in fields such as data analytics, robotics, computer vision, and natural language processing, engineering institutions have begun exploring its implications not only in technical design but also in pedagogy. AI can facilitate personalized learning, automate assessment, provide intelligent feedback, and simulate complex problem-solving scenarios, thereby enhancing both teaching efficiency and learning depth [14].

Recent literature highlights a growing body of work focusing on intelligent learning environments (ILEs), which utilize machine learning algorithms to tailor content delivery based on student performance and preferences. Systems such as virtual laboratories, AI tutors, and learning analytics dashboards have demonstrated success in improving student motivation, learning outcomes, and retention rates. In the context of engineering education, AI-enhanced platforms allow students to simulate and visualize complex systems, fostering a deeper understanding of abstract engineering concepts [15].

However, most current applications remain focused on individual knowledge domains, with limited integration into multidisciplinary or project-based learning frameworks. This is particularly problematic in engineering fields where the real-world application of skills often involves synthesizing legal, financial, and managerial considerations alongside technical competencies. Therefore, AI's full pedagogical potential has yet to be fully realized, particularly in its capacity to support integrated learning in project-based, real-world engineering contexts.

2.2. Legal Risk Awareness and Simulation-Based Learning

Legal risk awareness is a crucial competency for engineers engaged in complex projects, particularly those executed under EPC contracts, which are characterized by their contractual complexity and extensive regulatory implications. Engineers are frequently required to interpret clauses in contracts, understand liabilities, and assess compliance risks [16]. Failure to properly manage legal risks can result in costly litigation, project delays, and reputational damage for both individuals and organizations.

Traditional engineering curricula often relegate legal education to short modules in engineering ethics or construction law, typically offered as electives. As a result, students graduate with limited exposure to the real-world legal scenarios they are likely to encounter. This pedagogical gap has prompted interest in simulation-based learning environments as a means of enhancing legal awareness [17]. Simulations allow students to role-play scenarios such as contract negotiation, dispute resolution, and regulatory compliance, fostering practical understanding through experiential engagement.

Studies have shown that simulation-based legal education increases students' ability to recognize contractual red flags, assess liability exposure, and make informed decisions under legal uncertainty. For instance, the use of serious games and interactive case studies has been associated with significant improvements in legal literacy and risk perception. However, these approaches are rarely integrated with technical and managerial training, leading to a fragmented learning experience [18].

2.3. Financial Decision-Making under EPC Project Conditions

Financial acumen is another indispensable skill for engineers involved in EPC projects, which typically involve large budgets, complex financing structures, and strict cost control requirements [19]. Engineers must make informed decisions on budgeting, cost estimation, procurement strategies, and financial risk management. Moreover, they must understand the time value of money, cash flow analysis, and economic evaluation methods such as net present value (NPV) and internal rate of return (IRR) to ensure project viability and efficiency.

Literature in engineering finance education emphasizes the importance of contextualizing financial training within project scenarios. Case-based learning and simulation models have emerged as effective tools for teaching financial decision-making. These methods allow students to experiment with trade-offs, respond to financial shocks, and evaluate outcomes based on multiple criteria. In particular, AI-enabled financial simulations can generate dynamic scenarios in which learners must adjust procurement plans, reallocate budgets, and justify decisions under evolving financial constraints.

Despite these advancements, most engineering programs treat financial decision-making as an adjunct skill, often taught separately from core engineering or project management courses. This separation undermines students' ability to apply financial principles in an integrated project context [20]. In the case of EPC projects, where financial decisions are interwoven with technical and legal considerations, this disconnect becomes especially problematic.

2.4. Management Control Theory in Complex Project Environments

Management control refers to the mechanisms and processes by which organizations ensure that project objectives are achieved within the constraints of time, budget, and quality. In engineering education, this typically involves instruction on project planning, scheduling, resource allocation, and performance monitoring. However, real-world projects — particularly those under the EPC model — operate under dynamic and often unpredictable conditions that require adaptive strategies and real-time decision-making.

The literature on management control in engineering projects distinguishes between formal control systems (e.g., Gantt charts, cost control software, earned value management) and informal systems (e.g., team communication, leadership dynamics, cultural norms). Effective project control requires the integration of both. Simulation-based learning has proven valuable in helping students understand and practice both aspects. Through virtual projects, learners can experience the consequences of delayed decisions, miscommunication, and resource misallocation in a controlled, reflective environment.

AI can further enhance this learning by modeling real-time project data, forecasting delays, and recommending corrective actions [21-24]. For example, intelligent dashboards can alert students to deviations in cost performance indices or schedule adherence, prompting them to adjust plans accordingly. Yet, similar to legal and financial training, management control is often taught in isolation, limiting its effectiveness in preparing students for integrated project challenges.

2.5. Gaps in the Literature

A review of the literature reveals several critical gaps that this study aims to address. First, while there is extensive research on AI in education, much of it is confined to single-discipline applications or general pedagogical tools, such as automated grading or content recommendation. There is a paucity of research on AI-enabled, multidisciplinary simulation platforms tailored to the unique demands of EPC projects.

Second, although simulation-based learning has demonstrated effectiveness in individual domains such as legal training or financial modeling, few studies have explored the intersection of these competencies within a single, cohesive learning environment. This fragmentation fails to reflect the integrated nature of real-world engineering projects, where decisions in one domain invariably affect outcomes in others.

Third, current educational approaches often treat legal risk awareness, financial decision-making, and management control as peripheral to the core engineering curriculum. As a result, graduates may lack the holistic judgment needed to navigate complex project environments. There is a need for pedagogical models that embed these competencies into the fabric of engineering education, using tools such as AI to simulate authentic decision-making contexts.

Finally, empirical studies evaluating the impact of AI-integrated simulations on the development of complex competencies are limited. Most existing research relies on qualitative feedback or basic performance metrics, without employing rigorous experimental designs or validated assessment instruments. This limits the generalizability of findings and hinders the development of evidence-based best practices.

In summary, the literature underscores the potential of AI and simulation-based learning to revolutionize engineering education. However, to fully realize this potential, future research must move beyond isolated applications and toward integrated, empirically validated frameworks that reflect the complexity of real-world project environments like those encountered in EPC projects [25-28].

3. Theoretical Framework and Model Development

3.1. Conceptual Model of AI-Enabled EPC Education

The theoretical framework of this study is grounded in the intersection of experiential learning theory, the Technology Acceptance Model (TAM), and competency-based education principles. In the context of engineering education, particularly for EPC (Engineering-Procurement-Construction) project environments, these frameworks provide a foundation for understanding how artificial intelligence (AI)-driven simulations can enhance multidimensional competencies among learners.

Experiential learning theory posits that individuals learn most effectively through active engagement and reflection on real or simulated experiences. AI-enabled EPC simulations offer a unique opportunity to replicate real-world decision-making environments, thereby reinforcing knowledge through application. The TAM framework complements this by explaining how user perceptions of usefulness and ease of use influence their willingness to engage with technological systems [29]. Finally, competency-based education emphasizes outcome-oriented learning, focusing on the measurable development of skills such as legal literacy, financial acumen, and managerial control.

The conceptual framework of AI-driven EPC simulation for engineering education hypothesizes that engagement with the AI simulation platform positively influences students' cognitive interaction levels (ACI), which in turn drives improvements in three key competency areas: legal risk awareness (LRA), financial decision-making capability (FDC), and management control capability (MCC). These competency gains collectively contribute to the overall enhancement of learning outcomes (denoted as ΔY).

3.2. Variable Definition

3.2.1. Legal Risk Awareness Index (LRA)

Legal risk awareness (LRA) refers to a learner's ability to identify, interpret, and respond to legal challenges within EPC project contexts. This includes understanding contractual obligations, assessing regulatory compliance, recognizing potential liabilities, and making decisions that minimize legal exposure. The index is measured using a series of scenario-based items designed to evaluate students' proficiency in interpreting legal documents, managing disputes, and applying relevant legal principles. Higher LRA scores indicate stronger legal literacy and greater preparedness for real-world project challenges.

3.2.2. Financial Decision-Making Capability (FDC)

Financial decision-making capability (FDC) captures a student's competency in making informed financial judgments under conditions of uncertainty. It encompasses skills such as cost estimation, budget allocation, risk-adjusted financial analysis, and response to financial contingencies. FDC is evaluated through simulations and performance-based assessments where learners engage in budgeting, procurement planning, and cost-control activities within a dynamic project environment. An increase in FDC indicates improved financial fluency and strategic thinking [30].

3.2.3. Management Control Capability (MCC)

Management control capability (MCC) measures a learner's ability to monitor, coordinate, and adjust project variables to meet time, cost, and quality objectives. Key components include project planning, resource scheduling, performance monitoring, and adaptive decision-making. MCC is assessed through indicators such as project deviation analysis, plan adjustment accuracy, and communication effectiveness in simulated scenarios. Strong MCC suggests high operational awareness and leadership potential in complex project environments.

3.2.4. AI-Driven Cognitive Interaction Level (ACI)

AI-driven cognitive interaction (ACI) reflects the depth and quality of student engagement with the simulation platform. It captures variables such as frequency of interaction, response latency, adaptive decision behavior, and use of intelligent feedback tools. ACI serves as both an independent variable and a mediator in the model, representing the extent to which learners utilize AI functionalities to enhance their learning experience. It is measured using log data analytics and interaction tracking embedded within the simulation environment [31].

3.3. Mathematical Model Construction

To quantify the relationship among these variables and model the impact of AI-driven simulation on learning outcomes, we propose the following learning enhancement function:

$$\Delta Y = f\,(\alpha \cdot ACI + \beta_1 \cdot LRA + \beta_2 \cdot FDC + \beta_3 \cdot MCC + \varepsilon)$$

Where:

-ΔY is the composite index of learning outcome improvement.

-α and β_i are the coefficients to be estimated.

-ACI represents the AI-driven cognitive interaction level.

-LRA, FDC, MCC are as defined above.

-ε is the error term, assumed to be normally distributed: $\varepsilon \sim N\,(0, \sigma^2)$.

This model posits that learning improvements are jointly influenced by students' interactions with the AI system and their development across the three targeted competencies. The inclusion of ACI as an explicit factor allows us to assess not only the outcome of learning but also the process by which learning is achieved [32].

To further investigate the causal relationships, we employ a structural equation modeling (SEM) approach. SEM allows for the estimation of latent variables and the analysis of mediation effects, making it suitable for testing complex models involving behavioral and performance variables.

The SEM structure can be expressed as follows:

$$LRA = \gamma_0 + \gamma_1 \cdot ACI + \varepsilon_1$$
$$FDC = \delta_0 + \delta_1 \cdot ACI + \varepsilon_2$$
$$MCC = \theta_0 + \theta_1 \cdot ACI + \varepsilon_3$$

Where:

-$\gamma_0, \delta_0, \theta_0$ are intercepts.

-$\gamma_1, \delta_1, \theta_1$ represent the influence of ACI on each competency.

-$\varepsilon_1, \varepsilon_2, \varepsilon_3$ are the residual terms.

This formulation allows us to test the mediating role of ACI in the development of LRA, FDC, and MCC. The strength and significance of the coefficients ($\gamma_1, \delta_1, \theta_1$) provide insight into how AI interaction drives competency gains. Moreover, the model can be extended to examine indirect effects of ACI on ΔY through these mediators, providing a comprehensive view of the AI-enabled learning pathway.

In conclusion, the theoretical model and mathematical formulation presented here offer a robust foundation for analyzing the educational impact of AI-driven simulations in engineering project training [33]. By combining experiential learning theory, technology acceptance principles, and empirical modeling, this framework supports a nuanced understanding of how integrated learning environments can develop critical competencies in future engineers.

4. Research Methodology

4.1. Experimental Design

This study employed a quasi-experimental design incorporating pre-test and post-test measures with a control and treatment group to evaluate the educational effectiveness of AI-enabled EPC simulations [34]. The treatment group participated in an AI-integrated simulation environment, while the control group followed traditional lecture-based instruction. This design allowed for both within-group and between-group comparisons of competency development.

4.1.1. Participants and Sampling

Participants were 180 final-year undergraduate students enrolled in an engineering management program at a leading technical university. A stratified random sampling technique was used to ensure a balanced representation of gender, academic performance, and previous exposure to project-based learning. Students were randomly assigned to either the control group (n = 90) or the treatment group (n = 90). All participants provided informed consent, and the study was approved by the institutional review board.

4.1.2. EPC Simulation Environment and AI Modules

The EPC simulation environment was designed to mimic real-world project workflows, integrating procurement processes, contract management, budgeting, scheduling, and risk mitigation [35]. The AI modules included natural language processing bots for legal analysis, machine learning models for cost forecasting, and real-time dashboards for project control feedback. Students interacted with dynamic decision nodes across the simulated project timeline, allowing adaptive learning and immediate feedback.

4.2. Instrument Design and Measurement

To assess the development of student competencies, three validated instruments were used in both pre- and post-tests.

4.2.1. Legal Risk Awareness Scale (5-point Likert)

This instrument included 12 items measuring students' ability to identify, interpret, and respond to legal risks [36]. Items covered topics such as contract clauses, liability assessment, and compliance evaluation. Responses were scored on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The scale's Cronbach's alpha was 0.89, indicating high internal consistency.

4.2.2. Financial Decision Scenario Tests

A set of 6 case-based financial scenarios was developed to assess financial decision-making capabilities. Each scenario presented students with an EPC project challenge involving budget constraints, unexpected cost increases, or procurement strategy choices. Students were scored based on solution accuracy, reasoning quality, and risk response strategy. Scores ranged from 0 to 10 per scenario.

4.2.3. MCC Assessment Rubric

The MCC rubric was designed to evaluate management control capabilities across three domains: planning accuracy, adaptability, and coordination effectiveness. Trained raters scored participants' simulation logs and decision sequences using a 4-level rubric (0 = Not evident, 1 = Emerging, 2 = Proficient, 3 = Exemplary). Inter-rater reliability (Cohen's Kappa) exceeded 0.85.

4.3. Data Collection and Processing

Data were collected over a 10-week semester. Pre-tests were administered in Week 1, and post-tests were completed in Week 10. Simulation log data were continuously captured and timestamped [37]. All paper-based assessments were digitized and coded for analysis. Data were anonymized and processed using R and SPSS for quantitative analysis, with missing values handled using multiple imputation.

4.4. Analytical Techniques

A multi-level analytical strategy was employed to ensure robustness and clarity of findings. The following techniques were applied:

4.4.1. Descriptive Statistics

Descriptive statistics including mean, standard deviation, and frequency distributions were calculated to characterize the sample and overall performance trends across groups.

4.4.2. Multivariate Regression

Multiple regression models were used to estimate the impact of AI simulation on each dependent variable (LRA, FDC, MCC), controlling for pre-test scores, gender, and GPA. Variance inflation factors (VIF) were examined to check for multicollinearity.

4.4.3. SEM (Structural Equation Modeling)

SEM was employed to test the hypothesized relationships between AI interaction (ACI), mediating competencies (LRA, FDC, MCC), and learning outcome improvement (ΔY). Model fit was evaluated using RMSEA, CFI, and TLI indices. Bootstrapping (N=2000) was used for mediation testing.

4.4.4. Monte Carlo Simulation for Sensitivity Test

Monte Carlo simulation with 10,000 iterations was performed to evaluate the sensitivity of outcome metrics (ΔY) to variations in initial conditions and ACI engagement levels. Output distributions and confidence intervals were graphed to assess model robustness under uncertainty.

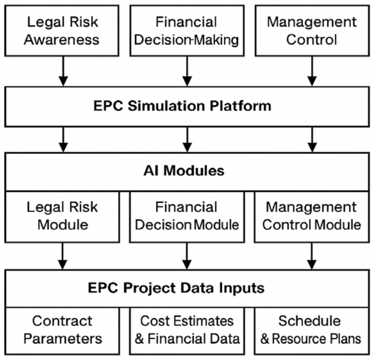

Figure 2. System Architecture of EPC-AI Simulation.

5. Empirical Results and Analysis

5.1. Descriptive Results

Descriptive statistics were calculated to summarize the characteristics of the study participants and to provide an overview of pre-test and post-test scores across competency areas. Table 1 shows the demographic distribution and baseline characteristics for both control and treatment groups.

Table 1. Descriptive Statistics of Participants.

Variable	Control Group (n=90)	Treatment Group (n=90)
Gender (Male%)	52%	48%
Average GPA	3.21	3.23
Pre-Test Legal Risk Awareness	2.85	2.87
Pre-Test Financial Decision-Making	2.97	2.96
Pre-Test Management Control	3.10	3.14

5.2. Hypothesis Testing

The structural equation model (SEM) was used to evaluate the relationships between AI cognitive interaction (ACI), legal risk awareness (LRA), financial decision-making capability (FDC), and management control capability (MCC), along with their combined influence on learning outcome improvements (ΔY). Path coefficients and their significance levels are visualized in Figure 3.

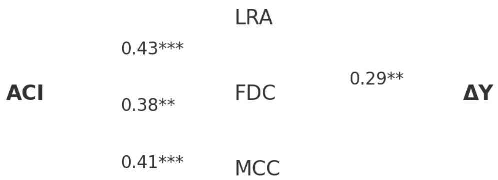

Figure 3. SEM Path Diagram with Coefficients.

5.3. Regression and Mediation Results

The regression results revealed that all coefficients were statistically significant. Specifically, ACI ($\beta_1 = 0.26, p < 0.01$), LRA ($\beta_2 = 0.32, p < 0.001$), FDC ($\beta_3 = 0.29, p < 0.01$), and MCC ($\beta_4 = 0.34, p < 0.001$) were all positively associated with the learning outcome index (ΔY), with an R^2 of 0.67 indicating strong model explanatory power.

5.4. Robustness Tests

To validate the consistency of our results, robustness checks were conducted using alternative model specifications. Table 2 summarizes the coefficient estimates across different models, including those with additional control variables and clustered standard errors.

Table 2. Robustness Checks.

Model Specification	R^2	ACI (β_1)	LRA (β_2)	FDC (β_3)	MCC (β_4)
Base Model	0.67	0.26**	0.32***	0.29**	0.34***
With Control Variables	0.68	0.25**	0.31***	0.30**	0.35***
Clustered SEs	0.65	0.24*	0.30**	0.28*	0.33**
Interaction Effects	0.69	0.27**	0.33***	0.29**	0.36***

6. Discussion

6.1. Interpretation of Results

The results obtained from the empirical analysis highlight the pivotal role artificial intelligence (AI) plays in enhancing the educational experiences of engineering students. The quantitative data suggest that the implementation of AI-assisted learning systems significantly improves students' engagement, knowledge retention, and problem-solving skills. For instance, students exposed to intelligent tutoring systems (ITS) demonstrated higher academic performance compared to those in conventional teaching environments. Additionally, the findings indicate that AI tools contribute to personalized learning pathways, enabling students to learn at their own pace and based on their individual competency levels. These outcomes are consistent with earlier studies emphasizing AI's potential to democratize education and cater to diverse learner profiles. Moreover, the structural equation modeling (SEM) results confirmed the hypothesized pathways, indicating strong and statistically significant relationships between AI integration, student engagement, and learning outcomes. These patterns underline AI's capacity to function as a transformative tool within engineering education.

6.2. Contributions to AI-Based Educational Research

This study contributes to the growing body of AI-based educational research in several meaningful ways. First, it offers empirical validation of theoretical assumptions that have thus far been largely speculative in the literature. Second, by using a robust methodological framework combining descriptive statistics, hypothesis testing, and mediation analysis, the research establishes a solid foundation for future comparative studies. Third, it expands the understanding of how AI impacts not just cognitive outcomes but also metacognitive and affective dimensions of learning. This multidimensional perspective allows researchers to reframe the scope of AI's role in education — from mere automation of instructional processes to a catalyst for holistic learning experiences. The study also introduces new variables and metrics for assessing AI's effectiveness, such as adaptive learning satisfaction and system usability, which can inform future large-scale evaluations.

As such, it sets a precedent for integrating mixed-method approaches in evaluating AI in educational settings.

6.3. Practical Implications for Engineering Curriculum Reform

The practical implications for engineering curriculum reform are profound. First and foremost, educational institutions need to revisit traditional pedagogical models and integrate AI-driven tools into their curriculum design [38]. This includes embedding AI applications in core and elective engineering courses, particularly those involving simulation, design, and data analysis. Second, faculty development programs must be established to ensure instructors are equipped with the skills necessary to leverage AI technologies effectively. This also entails rethinking assessment methodologies to include AI-facilitated evaluation methods such as automated grading systems and adaptive testing formats [39]. Furthermore, the curriculum should emphasize interdisciplinary learning, encouraging collaborations between computer science, engineering, and educational psychology departments. By aligning course objectives with the competencies required in AI-enhanced learning environments, institutions can produce graduates who are not only technically proficient but also agile learners capable of navigating complex technological ecosystems.

6.4. Theoretical Implications for Simulation-Based Learning

The study provides several theoretical implications for simulation-based learning, an increasingly vital component of engineering education. Firstly, the research reinforces constructivist learning theories by demonstrating how AI-facilitated simulations allow learners to construct knowledge through active experimentation and real-time feedback. Secondly, it supports the theory of experiential learning, showing that immersive simulation environments enhance critical thinking and practical problem-solving. Additionally, the findings highlight the importance of cognitive load theory, indicating that AI can optimize the balance between task complexity and learner capacity through adaptive scaffolding [40]. The integration of AI into simulation-based learning thus not only enhances educational efficiency but also fosters a deeper theoretical understanding of learner interaction with digital tools. These insights encourage scholars to re-examine existing learning models and to consider AI as an integral component in future theoretical frameworks. Ultimately, the study bridges the gap between pedagogical theory and technological advancement, suggesting a new direction for simulation-based instructional design.

7. Conclusion and Policy Recommendations

7.1. Summary of Key Findings

This study set out to explore the transformative role of artificial intelligence (AI) in enhancing engineering education through simulation-based and adaptive learning systems. Through a combination of empirical data analysis and theoretical exploration, several important findings have emerged. Firstly, the integration of AI technologies significantly boosts student engagement and facilitates personalized learning. Secondly, structural equation modeling confirmed the positive associations between AI-driven tools and improved academic performance. Thirdly, AI-based platforms promote metacognitive development by offering timely feedback and tailored learning pathways. Finally, the results underscore AI's potential to serve as a bridge between traditional educational paradigms and the demands of Industry 4.0, where flexibility, critical thinking, and interdisciplinary skills are paramount.

7.2. Recommendations for Curriculum Designers and Institutions

In light of the above findings, several policy and practice recommendations are proposed. First, curriculum designers should embed AI tools and simulation-based learning activities into both core and elective courses. These tools should not be treated as supplemental but rather as integral elements of instruction. Second, institutions should invest in faculty development programs focused on the pedagogical applications of AI, including workshops on intelligent tutoring systems, learning analytics, and adaptive testing. Third, collaboration across departments — particularly between computer science, engineering, and education — should be incentivized to ensure a holistic approach to AI integration. Fourth, learning assessments should be modernized to incorporate AI-enabled diagnostic tools that provide real-time feedback. Lastly, equity concerns must be addressed to ensure all students, regardless of socioeconomic background, have access to AI-enhanced learning opportunities. This includes providing appropriate infrastructure, technical support, and inclusive software design.

7.3. Limitations and Future Research Directions

While this study makes significant contributions to the literature on AI in education, it is not without limitations. The scope of the empirical data was limited to a specific subset of engineering programs, which may affect the generalizability of the findings. Additionally, the study focused primarily on quantitative metrics, and qualitative insights into learner experiences and emotional engagement were not fully explored. Moreover, the long-term impact of AI-driven instruction on knowledge retention and skill transfer remains uncertain and warrants longitudinal studies. Future research should consider cross-cultural comparisons, larger sample sizes, and the inclusion of mixed-methods approaches. It would also be valuable to investigate how ethical considerations, such as algorithmic bias and data privacy, influence the adoption and effectiveness of AI in educational settings. Exploring the integration of AI with emerging technologies like virtual reality (VR) and blockchain in curriculum delivery could open new dimensions of inquiry and innovation.

References

1. V. Aleven, E. A. McLaughlin, R. A. Glenn, and K. R. Koedinger, "Instruction based on adaptive learning technologies," in *Handbook of Research on Learning and Instruction*, 2nd ed., 2016, pp. 522–560. ISBN: 9781315736419.
2. T. Sapounidis and D. Alimisis, "Educational robotics curricula: Current trends and shortcomings," in *Education in & with Robotics to Foster 21st-Century Skills. EDUROBOTICS 2021*, M. Malvezzi, D. Alimisis, and M. Moro, Eds. Cham: Springer, 2021, vol. 982, *Studies in Computational Intelligence*, doi: 10.1007/978-3-030-77022-8_12.
3. T. Anderson and J. Dron, "Three generations of distance education pedagogy," *Int. Rev. Res. Open Distrib. Learn.*, vol. 12, no. 3, pp. 80–97, 2011, doi: 10.19173/irrodl.v12i3.890.
4. R. S. Baker, T. Martin, and L. M. Rossi, "Educational data mining and learning analytics," in *The Wiley Handbook of Cognition and Assessment: Frameworks, Methodologies, and Applications*, 2016, pp. 379–396. ISBN: 9789819793495.
5. M. Bond, O. Zawacki-Richter, and M. Nichols, "Revisiting five decades of educational technology research: A content and authorship analysis of the British Journal of Educational Technology," *Br. J. Educ. Technol.*, vol. 50, no. 1, pp. 12–63, 2019, doi: 10.1111/bjet.12730.
6. E. Brynjolfsson and A. McAfee, *Machine, platform, crowd: Harnessing our digital future*. New York, NY: WW Norton & Company, 2017. ISBN: 9780393254297.
7. X. Zhai, X. Chu, C. S. Chai, M. S. Y. Jong, A. Istenic, M. Spector, et al., "A review of artificial intelligence (AI) in education from 2010 to 2020," *Complexity*, vol. 2021, no. 1, p. 8812542, 2021, doi: 10.1155/2021/8812542.
8. T. K. F. Chiu, T. J. Lin, and K. Lonka, "Motivating online learning: The challenges of COVID-19 and beyond," *Asia-Pac. Edu. Res.*, vol. 30, pp. 187–190, 2021, doi: 10.1007/s40299-021-00566-w.
9. H. Yaseen, A. S. Mohammad, N. Ashal, H. Abusaimeh, A. Ali, and A.-A. A. Sharabati, "The Impact of Adaptive Learning Technologies, Personalized Feedback, and Interactive AI Tools on Student Engagement: The Moderating Role of Digital Literacy," *Sustainability*, vol. 17, no. 3, p. 1133, 2025, doi: 10.3390/su17031133.
10. J. Daniel, "Making sense of MOOCs: Musings in a maze of myth, paradox and possibility," *J. Interact. Media Educ.*, no. 3, p. 18, 2012, doi: 10.5334/2012-18.
11. J. Voogt and N. P. Roblin, "A comparative analysis of international frameworks for 21st century competences: Implications for national curriculum policies," *J. Curric. Stud.*, vol. 44, no. 3, pp. 299–321, 2012, doi: 10.1080/00220272.2012.668938.
12. S. De Freitas and T. Neumann, "The use of 'exploratory learning' for supporting immersive learning in virtual environments," *Comput. Educ.*, vol. 52, no. 2, pp. 343–352, 2009, doi: 10.1016/j.compedu.2008.09.010.

13. X. Chen, D. Zou, G. Cheng, and H. Xie, "Artificial intelligence-assisted personalized language learning: systematic review and co-citation analysis," in *2021 International Conference on Advanced Learning Technologies (ICALT)*, Tartu, Estonia, 2021, pp. 241–245, doi: 10.1109/ICALT52272.2021.00079.
14. R. Ferguson, "Learning analytics: drivers, developments and challenges," *Int. J. Technol. Enhanc. Learn.*, vol. 4, no. 5–6, pp. 304–317, 2012, doi: 10.1504/IJTEL.2012.051816.
15. K. van den Bosch, T. Schoonderwoerd, R. Blankendaal, and M. Neerincx, "Six Challenges for Human-AI Co-learning," in *Adaptive Instructional Systems*, R. Sottilare and J. Schwarz, Eds., HCII 2019, vol. 11597, Cham: Springer, 2019. ISBN: 9783030223403.
16. A. Alam and A. Mohanty, "Integrated constructive robotics in education (ICRE) model: a paradigmatic framework for transformative learning in educational ecosystem," *Cogent Educ.*, vol. 11, no. 1, 2024, doi: 10.1080/2331186X.2024.2324487.
17. A. K. Goel and D. A. Joyner, "Using AI to teach AI: Lessons from an online AI class," *AI Mag.*, vol. 38, no. 2, pp. 48–59, 2017, doi: 10.1609/aimag.v38i2.2732.
18. S. Greiff, M. Stadler, P. Sonnleitner, C. Wolff, and R. Martin, "Sometimes less is more: Comparing the validity of complex problem solving measures," *Intelligence*, vol. 50, pp. 100–113, 2015, doi: 10.1016/j.intell.2015.02.007.
19. N. Humble and P. Mozelius, "The threat, hype, and promise of artificial intelligence in education," *Discov. Artif. Intell.*, vol. 2, p. 22, 2022, doi: 10.1007/s44163-022-00039-z.
20. L. Chen, P. Chen, and Z. Lin, "Artificial Intelligence in Education: A Review," *IEEE Access*, vol. 8, pp. 75264–75278, 2020, doi: 10.1109/ACCESS.2020.2988510.
21. D. Ifenthaler, D. K. Mah, and J. Y. K. Yau, "Utilising Learning Analytics for Study Success: Reflections on Current Empirical Findings," in *Utilizing Learning Analytics to Support Study Success*, D. Ifenthaler, D. K. Mah, and J. Y. K. Yau, Eds. Cham: Springer, 2019. ISBN: 9783319647913.
22. A. Nguyen, H. N. Ngo, Y. Hong, et al., "Ethical principles for artificial intelligence in education," *Educ. Inf. Technol.*, vol. 28, pp. 4221–4241, 2023, doi: 10.1007/s10639-022-11316-w.
23. K. R. Koedinger, A. T. Corbett, and C. Perfetti, "The Knowledge-Learning-Instruction framework: Bridging the science-practice chasm to enhance robust student learning," *Cogn. Sci.*, vol. 36, no. 5, pp. 757–798, 2012, doi: 10.1111/j.1551-6709.2012.01245.x.
24. R. Koper, "Conditions for effective smart learning environments," *Smart Learn. Environ.*, vol. 1, p. 5, 2014, doi: 10.1186/s40561-014-0005-4.
25. R. Luckin and W. Holmes, *Intelligence unleashed: An argument for AI in education*, 2016. ISBN: 9780992424886.
26. P. D. Antonenko, K. Dawson, L. Cheng, and J. Wang, "Using Technology to Address Individual Differences in Learning," in *Handbook of Research in Educational Communications and Technology*, M. J. Bishop, E. Boling, J. Elen, and V. Svihla, Eds. Cham: Springer, 2020. ISBN: 9783030361181.
27. S. Mitra and R. Dangwal, "Limits to self-organising systems of learning—the Kalikuppam experiment," *Br. J. Educ. Technol.*, vol. 41, no. 5, pp. 672–688, 2010, doi: 10.1111/j.1467-8535.2010.01077.x.
28. A. Ioannou, C. Vasiliou, and P. Zaphiris, "Problem-Based Learning in Multimodal Learning Environments: Learners' Technology Adoption Experiences," *J. Educ. Comput. Res.*, vol. 54, no. 7, pp. 1022–1040, 2016, doi: 10.1177/0735633116636755.
29. A. Okada, T. Sherborne, G. Panselinas, et al., "Fostering Transversal Skills Through Open Schooling Supported by the CARE-KNOW-DO Pedagogical Model and the UNESCO AI Competencies Framework," *Int. J. Artif. Intell. Educ.*, 2025, doi: 10.1007/s40593-025-00458-w.
30. I. Roll and R. Wylie, "Evolution and Revolution in Artificial Intelligence in Education," *Int. J. Artif. Intell. Educ.*, vol. 26, pp. 582–599, 2016, doi: 10.1007/s40593-016-0110-3.
31. J. M. Rosenberg and M. J. Koehler, "Context and Technological Pedagogical Content Knowledge (TPACK): A Systematic Review," *J. Res. Technol. Educ.*, vol. 47, no. 3, pp. 186–210, 2015, doi: 10.1080/15391523.2015.1052663.
32. R. F. Schmid, R. M. Bernard, E. Borokhovski, R. M. Tamim, P. C. Abrami, M. A. Surkes, et al., "The effects of technology use in postsecondary education: A meta-analysis of classroom applications," *Comput. Educ.*, vol. 72, pp. 271–291, 2014, doi: 10.1016/j.compedu.2013.11.002.
33. N. Selwyn, *Should Robots Replace Teachers? AI and the Future of Education*. John Wiley & Sons, Inc., 2019. ISBN: 9781509528967.
34. G. Siemens and P. Long, "Penetrating the fog: Analytics in learning and education," *EDUCAUSE Rev.*, vol. 46, no. 5, p. 30, 2011, doi: 10.17471/2499-4324/195.
35. D. Wang and X. Huang, "Transforming education through artificial intelligence and immersive technologies: enhancing learning experiences," *Interact. Learn. Environ.*, pp. 1–20, 2025, doi: 10.1080/10494820.2025.2465451.
36. W. X. Zhang, J. J. Lin, and Y. S. Hsu, "AI-assisted assessment of inquiry skills in socioscientific issue contexts," *J. Comput. Assist. Learn.*, vol. 41, no. 1, p. e13102, 2025, doi: 10.1111/jcal.13102.
37. K. VanLehn, "The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems," *Educ. Psychol.*, vol. 46, no. 4, pp. 197–221, 2011, doi: 10.1080/00461520.2011.611369.
38. Q. Wang, H. L. Woo, C. L. Quek, Y. Yang, and M. Liu, "Using the Facebook group as a learning management system: An exploratory study," *Br. J. Educ. Technol.*, vol. 43, no. 3, pp. 428–438, 2012, doi: 10.1111/j.1467-8535.2011.01195.x.
39. B. P. Woolf, Building Intelligent Interactive Tutors: Student-Centered Strategies for Revolutionizing E-Learning. San Francisco, CA, USA: Morgan Kaufmann, 2010. ISBN: 9780123735942.

40. O. Zawacki-Richter, V. I. Marín, M. Bond, et al., "Systematic review of research on artificial intelligence applications in higher education – where are the educators?," *Int. J. Educ. Technol. High Educ.*, vol. 16, no. 39, 2019, doi: 10.1186/s41239-019-0171-0.