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AI-Driven Digital Innovation in Agricultural and Biological Sciences Education: A Structural Analysis of Knowledge Transfer, Student Engagement and Learning Effectiveness toward SDG 4 (Quality Education) in Thai Universities

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Abstract

This research aims to analyze the causal relationships among AI-driven digital innovation in agricultural and biological sciences education, student engagement, knowledge transfer, and learning effectiveness toward SDG 4 (Quality Education) in Thai universities. Data were collected from 400 students enrolled in agricultural and biological sciences programs at Thai universities in Bangkok, using stratified random sampling. Structural equation modeling (SEM) was employed to test the research hypotheses. The results demonstrated that AI-driven digital innovation exerted a significant direct effect on knowledge transfer ($\beta = 0.512$, $p < 0.001$), and student engagement also exerted a significant direct effect on knowledge transfer ($\beta = 0.468$, $p < 0.001$). Knowledge transfer had the strongest direct effect on learning effectiveness ($\beta = 0.524$, $p < 0.001$). AI-driven digital innovation exerted a significant direct effect on learning effectiveness ($\beta = 0.312$, $p < 0.001$), and student engagement exerted a significant direct effect on learning effectiveness ($\beta = 0.386$, $p < 0.001$). Mediation analysis confirmed that knowledge transfer significantly mediates the relationship between AI-driven digital innovation and learning effectiveness ($\beta = 0.268$, $p < 0.001$) and between student engagement and learning effectiveness ($\beta = 0.181$, $p < 0.001$). These findings establish that knowledge transfer functions as the central mediating mechanism linking both AI-driven digital innovation and student engagement to learning effectiveness, providing empirical foundations for advancing digital transformation in Thai agricultural and biological sciences education in alignment with SDG 4.

Keywords

AI-driven digital innovation; Knowledge transfer; SDG 4 (Quality Education); Student Engagement; Thai Universities

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Introduction

The accelerating integration of artificial intelligence into higher education represents one of the most consequential pedagogical transformations of the twenty-first century, fundamentally reshaping how knowledge is designed, delivered, and assessed across scientific disciplines. Agricultural and biological sciences education in Thailand faces particularly acute transformational pressures as the nation pursues modernization of its agricultural sector—a foundational pillar of the national economy supporting more than ten million farming households and constituting a critical driver of food security, rural livelihoods, and ecological balance (Office of Small and Medium Enterprises Promotion, 2023). Within this context, AI-driven digital innovation has emerged as both a strategic imperative and a pedagogical opportunity for Thai universities seeking to equip graduates with the competencies required for an innovation-driven agricultural economy aligned with the United Nations Sustainable Development Goals—specifically SDG 4 (quality education), which prescribes inclusive, equitable, and quality education together with lifelong learning opportunities for all (United Nations, 2015).

The Thai government's Thailand 4.0 policy framework and the 20-Year National Strategy (2018–2037) explicitly position educational technology and digital innovation as central pillars of national human capital development, mandating Thai universities to accelerate digital curriculum integration and develop graduates capable of driving agricultural and biological innovation in an increasingly data-driven production landscape (Channuwong et al., 2026). Agricultural and biological sciences programs face the particular challenge in developing graduates who can simultaneously master complex theoretical frameworks—encompassing genetics, ecology, soil science, and biotechnology—and translate this knowledge into applied practice within dynamic, technology-mediated agricultural environments. AI-driven digital innovation offers powerful tools for addressing this challenge, yet the mechanisms through which technological investment translates into learning effectiveness outcomes remain insufficiently understood in the Thai higher education context (Maphosa & Bhebhe, 2022).

AI-driven digital innovation encompasses a constellation of technology-mediated pedagogical tools and systems including AI-powered learning platforms, personalized digital learning environments, intelligent academic support systems, and AI-driven data analytics for educational outcomes (Holmes et al., 2022; Zawacki-Richter et al., 2019). These technologies hold particular promise for agricultural and biological sciences education, where complex systems thinking, data interpretation, laboratory simulation, and field application demand adaptive, responsive instructional frameworks capable of accommodating the heterogeneous prior knowledge and experiential backgrounds characteristic of this student population. However, the pedagogical returns on AI investment are not automatic; they depend critically on the degree to which technological tools, together with the engagement students bring to them, activate the knowledge transfer processes that ultimately determine learning effectiveness (Luckin et al., 2019).

Student engagement—encompassing behavioral, cognitive, emotional, and digital participation dimensions—constitutes a foundational determinant of learning effectiveness and a critical antecedent of the knowledge transfer processes through which AI-driven innovation translates into quality learning outcomes. Research consistently demonstrates that sustained, multidimensional engagement is a prerequisite for deep learning, knowledge retention, and competency development in higher education (Fredricks et al., 2019; Hu & Kuh, 2002). In AI-enhanced learning environments, student engagement extends beyond conventional participation to encompass active, purposeful interaction with intelligent platforms, bioinformatics databases, and collaborative digital tools that develop the metacognitive and technical competencies essential for agricultural and biological sciences practice (Wang et al., 2025; Shernoff et al., 2016).

Knowledge transfer—encompassing knowledge acquisition, knowledge sharing, knowledge application, and collaborative learning—represents the central pedagogical mechanism through which both AI-driven innovation and student engagement are converted into durable, transferable learning effectiveness outcomes. In agricultural and biological sciences, effective knowledge transfer is essential for integrating foundational biological principles with applied agricultural practice, enabling graduates to contribute meaningfully to precision agriculture, climate-adaptive farming, and biotechnology-driven food production (Nonaka & Takeuchi, 1995; Argote & Ingram, 2000). Despite growing recognition of knowledge transfer as a critical educational mechanism, its role as the single mediator linking both AI-driven innovation and student engagement to learning effectiveness has received limited empirical attention in the Thai agricultural education context (Phusavat et al., 2022).

There are three significant research gaps motivating the researchers to conduct this study. First, existing research on AI in Thai higher education tends to examine technological adoption in isolation rather than integrating the AI-driven innovation, student engagement, knowledge transfer to support the learning effectiveness outcomes. Second, the mediating role of knowledge transfer in the relationship between AI-driven innovation and student engagement, on the one hand, and learning effectiveness, on the other, has not been empirically tested in agricultural and biological sciences programs, leaving a critical gap in understanding the mechanism through which these two enabling conditions produce educational returns. Third, few studies have applied full Structural Equation Modeling to test such multi-construct models in the Thai agricultural education context, limiting the methodological precision and theoretical depth of available empirical evidence. This study addresses these gaps by developing and empirically testing a causal model that positions AI-driven digital innovation and student engagement as the two independent variables, knowledge transfer as the single mediating variable, and learning effectiveness for achieving quality education (SDG 4) as the dependent variable.

Research Objectives

This study has two main objectives as follows:

1. To validate the latent constructs of AI-driven digital innovation, student engagement, knowledge transfer, and learning effectiveness toward SDG 4 (quality education) in Thai universities.
2. To analyze the causal relationships among AI-driven digital innovation, student engagement, knowledge transfer, and learning effectiveness toward SDG 4 (quality education) in Thai universities.

Research Hypotheses

H1: AI-Driven Digital Innovation has a significant direct effect on Knowledge Transfer.
H2: Student Engagement has a significant direct effect on Knowledge Transfer.
H3: Knowledge Transfer has a significant direct effect on Learning Effectiveness toward SDG 4 (Quality Education) in Thai universities.
H4: AI-Driven Digital Innovation has a significant direct effect on Learning Effectiveness toward SDG 4 (Quality Education) in Thai universities.
H5: Student Engagement has a significant direct effect on Learning Effectiveness toward SDG 4 (Quality Education) in Thai universities.
H6: Knowledge Transfer mediates the relationship between AI-Driven Digital Innovation and Learning Effectiveness toward SDG 4 (Quality Education) in Thai universities.
H7: Knowledge Transfer mediates the relationship between Student Engagement and Learning Effectiveness toward SDG 4 (Quality Education) in Thai universities.

Literature Review

The present study investigates causal relationships among AI-driven digital innovation, student engagement, knowledge transfer, and learning effectiveness toward quality education (SDG 4) in Thai universities. The literature review synthesizes empirical evidence and theoretical frameworks underpinning the conceptual model, integrating the Technology Acceptance Model, Activity Theory, Knowledge Creation Theory, Constructivist Learning Theory, Self-Determination Theory, and Flow Theory to provide comprehensive theoretical grounding for the proposed structural relationships.

AI-Driven Digital Innovation and Agricultural/Biological Sciences Education

AI-driven digital innovation in higher education encompasses a range of intelligent, data-driven technologies that transform the design, delivery, and assessment of learning experiences across all academic disciplines (Holmes et al., 2022). Within agricultural and biological sciences programs, five distinct dimensions of AI-driven innovation are particularly consequential for learning effectiveness. AI infrastructure readiness constitutes the foundational layer enabling institutions to deploy adaptive learning systems, bioinformatics tools, and intelligent laboratory simulations that replicate complex biological and agricultural environments with unprecedented fidelity—providing students with immersive learning experiences that conventional instructional resources cannot sustain (Zawacki-Richter et al., 2019). AI-based learning platforms, including intelligent tutoring systems, automated feedback mechanisms, and adaptive content delivery systems, have demonstrated significant potential for enhancing discipline-specific knowledge acquisition by providing individualized, responsive instructional support at scale.

Personalized digital learning, enabled by AI algorithms that dynamically adjust content difficulty, pacing, and instructional modality to individual learner profiles, represents a particularly transformative application in agricultural and biological sciences curricula where learner heterogeneity in prior knowledge and laboratory experience is pronounced (Maphosa & Bhebhe, 2022). AI academic support systems—including intelligent advising tools, predictive analytics for at-risk identification, and automated assessment feedback—extend the pedagogical value of AI-driven innovation by providing timely, individualized guidance that supplements human instruction and enables faculty to redirect attention toward higher-order pedagogical functions (Shao et al., 2025; Phusavat et al., 2022). AI data analytics for learning, encompassing learning analytics dashboards and educational outcome prediction models, enables institutions and instructors to make evidence-informed decisions regarding curriculum design, instructional pacing, and targeted intervention, thereby enhancing the systemic intelligence of the educational environment (Siemens & Long, 2011).

Theoretical grounding for AI-driven innovation's effects on knowledge transfer and learning effectiveness draws from the Technology Acceptance Model (Davis, 1989), which posits that perceived usefulness and ease of use mediate technology adoption and sustained utilization, and from Activity Theory (Vygotsky, 1978), which situates learning within technologically mediated activity systems. The Thai higher education system presents a particularly instructive context given the significant heterogeneity in institutional digital readiness across university types—from well-resourced national research universities to community and Rajamangala institutions with more constrained technological infrastructure. Empirical studies from comparable middle-income educational contexts suggest that pedagogical returns on AI investment are moderated by institutional absorptive capacity: the organizational ability to recognize, assimilate, and apply new technological knowledge to educational purposes (Zawacki-Richter et al., 2019). This dynamic implies that AI infrastructure investment must be accompanied by faculty development, pedagogical redesign, and student digital literacy cultivation to realize its full potential for activating knowledge transfer and producing learning effectiveness.

Student Engagement in Technology-Enhanced Learning Environments

Student engagement is a multidimensional construct encompassing behavioral, cognitive, emotional, and digital participation dimensions that collectively determine the depth, sustainability, and quality of learning effectiveness outcomes (Fredricks et al., 2019). Behavioral engagement refers to observable participation in academic tasks, attendance, submission of assignments, and compliance with learning requirements—establishing the foundational conditions for knowledge acquisition and academic progress. Cognitive engagement encompasses the mental investment students devote to understanding complex material, including strategy use, self-regulation, metacognitive monitoring, and critical thinking, determining the depth at which disciplinary content is processed and retained (Reeve, 2012). Emotional engagement reflects students' affective responses to learning environments—including interest, enthusiasm, sense of belonging, and confidence—modulating intrinsic motivation, persistence, and willingness to invest cognitive effort in challenging disciplinary material (Shernoff et al., 2016).

Digital participation—an emergent dimension particularly salient in AI-enhanced educational contexts—encompasses active, purposeful engagement with digital learning tools, platforms, and collaborative online environments (Maphosa & Bhebhe, 2022). In agricultural and biological sciences programs, digital participation encompasses the use of bioinformatics databases, virtual laboratory environments, online collaborative research platforms, AI-assisted data analysis tools, and digital field mapping applications, each developing distinct competencies aligned with contemporary agricultural and biological sciences practice. Research consistently demonstrates that higher levels of multidimensional student engagement are associated with superior academic achievement, knowledge retention, competency development, and long-term disciplinary commitment (Hu & Kuh, 2002; Fredricks et al., 2019).

Theoretical support for student engagement as an antecedent of knowledge transfer derives from Self-Determination Theory (Ryan & Deci, 2000), which posits that when learning environments support students' psychological needs for autonomy, competence, and relatedness, they create motivational conditions enabling deep knowledge engagement and sustained learning investment. Flow Theory further suggests that optimal engagement states—characterized by the alignment of challenge and skill in digitally mediated environments—produce states of maximal learning productivity in which students experience deep absorption and heightened creative knowledge processing (Csikszentmihalyi, 1990). Together, these theoretical perspectives establish student engagement as a critical motivational input that, alongside AI-driven innovation, activates the knowledge transfer processes through which learning effectiveness is ultimately realized.

Knowledge Transfer as the Central Mediating Mechanism

Knowledge transfer in educational contexts encompasses the processes through which learners acquire new knowledge from instructional inputs, share insights with peers and instructors, apply learned principles to novel problems, and engage in collaborative knowledge construction (Nonaka & Takeuchi, 1995). The four dimensions operationalized in this study capture the full spectrum of knowledge transfer processes critical to agricultural and biological sciences education. Knowledge acquisition involves the initial internalization of disciplinary concepts, principles, and methodologies from lectures, digital platforms, AI-curated content, and laboratory demonstrations—enabling students to build the foundational knowledge base necessary for disciplinary competency. Knowledge sharing encompasses peer-to-peer and student-instructor communication of insights, experimental findings, and interpretations, activating the socialization processes that deepen individual understanding through collective sense-making (Argote & Ingram, 2000).

Knowledge application involves the transfer of theoretical understanding to practical, real-world agricultural and biological challenges—including crop optimization, pest management, genetic analysis, environmental impact assessment, and sustainable food systems design—representing the externalization process in which tacit knowledge is converted into demonstrable competency. Collaborative learning refers to collective knowledge creation through teamwork, structured discussion, joint problem-solving, and participatory research, operationalizing the combination and socialization processes through which individual knowledge contributions are integrated into shared disciplinary understanding. Together, these four dimensions operationalize Nonaka and Takeuchi's (1995) knowledge creation cycle within the pedagogical context of agricultural and biological sciences education.

The mediating role of knowledge transfer between the two enabling conditions—AI-driven innovation and student engagement—and learning effectiveness is theoretically grounded in Knowledge Creation Theory (Nonaka & Takeuchi, 1995), which conceptualizes knowledge as dynamically constructed through iterative cycles of socialization, externalization, combination, and internalization, and in Constructivist Learning Theory (Vygotsky, 1978), which emphasizes social mediation as central to meaningful knowledge construction. Empirically, AI-driven tools have been shown to facilitate knowledge acquisition and sharing by providing real-time feedback, adaptive content sequencing, and collaborative platforms that lower the transactional distance between learner and knowledge source (Luckin et al., 2019), while engaged students are those most likely to take advantage of these affordances to acquire, share, apply, and collaboratively construct knowledge. In the Thai agricultural and biological sciences context, effective knowledge transfer is essential for integrating foundational biological principles with applied agricultural practice, environmental stewardship, and biotechnological innovation—enabling graduates to contribute meaningfully to Thailand's agricultural modernization agenda and to achieve the learning effectiveness outcomes aligned with SDG 4 (Phusavat et al., 2022).

Learning Effectiveness toward Quality Education (SDG 4)

Learning effectiveness toward quality education (SDG 4) is operationalized in this study as a multidimensional outcome construct encompassing academic achievement, learning satisfaction, problem-solving competency, innovation capability, and lifelong learning readiness—five dimensions that collectively capture the breadth of learning effectiveness aligned with the United Nations' fourth Sustainable Development Goal (UNESCO, 2016). Academic achievement reflects the degree to which students attain mastery of disciplinary content and skills in agricultural and biological sciences, as evidenced by performance on theoretical assessments, laboratory evaluations, and research projects. Learning satisfaction encompasses students' subjective evaluations of the quality, relevance, and experiential value of their educational experiences—an indicator of educational sustainability and institutional quality that reflects the subjective dimension of learning effectiveness emphasized in SDG 4 (Hu & Kuh, 2002).

Problem-solving competency refers to students' capacity to apply disciplinary knowledge to novel, ill-structured challenges characteristic of agricultural and biological sciences practice—including pest management under climate uncertainty, genetic analysis in resource-constrained settings, environmental impact assessment in complex socio-ecological systems, and sustainable food systems design. Innovation capability encompasses students' demonstrated ability to generate creative solutions, propose original research directions, design novel experiments, and contribute to knowledge advancement in their disciplines—a dimension directly aligned with Thailand's national aspiration to transition to an innovation-driven economy and with the agricultural sector's urgent need for transformative responses to climate change, food security challenges, and biodiversity loss (Channuwong et al., 2025). Lifelong learning readiness reflects students' self-efficacy, intrinsic motivation, and metacognitive capacity to continue learning autonomously beyond formal educational contexts—a foundational SDG 4 competency for sustainable agricultural development in a rapidly evolving technological landscape.

The alignment of these five learning effectiveness dimensions with Thailand's agricultural development priorities is theoretically and practically significant. Pansuwong et al. (2023) demonstrated that innovation capability and lifelong learning readiness are the outcome dimensions most strongly associated with graduates' sustained contributions to organizational and sectoral sustainability—underscoring the multidimensional conception of learning effectiveness adopted in this study and its dual alignment with SDG 4 and Thailand's agricultural modernization agenda.

Integrating AI-Driven Digital Innovation, Student Engagement, Knowledge Transfer, and Learning Effectiveness

The integrated model proposed in this study advances understanding of the pathway through which two enabling conditions—AI-driven innovation and student engagement—produce learning effectiveness outcomes via a single, central mediating mechanism: knowledge transfer. AI-Driven Digital Innovation and Student Engagement function as parallel enabling conditions that each independently activate knowledge transfer processes, through adaptive content delivery, intelligent feedback, and AI-enhanced knowledge application opportunities on the one hand, and through behavioral, cognitive, emotional, and digital participation on the other. Knowledge transfer then operates as the unifying cognitive and procedural mechanism that converts both technological and motivational inputs into knowledge competencies—acquisition, sharing, application, and collaborative construction—that collectively generate learning effectiveness.

This single-mediator architecture aligns with the Technology-Enhanced Learning Framework (Garrison & Kanuka, 2004), which emphasizes the interaction between technological tools, pedagogical design, and learner engagement as co-determinants of learning effectiveness, and with the Knowledge Management Framework (Nonaka & Takeuchi, 1995), which positions knowledge transfer as the central operational mechanism linking organizational inputs to performance outcomes. The proposed model extends these frameworks by empirically testing two converging antecedent pathways—AI → KT → LE and SE → KT → LE—within a single structural model, alongside the residual direct effects of AI-driven innovation and student engagement on learning effectiveness, thereby providing a more parsimonious and theoretically coherent causal account of how AI-driven innovation and student engagement jointly produce learning effectiveness than models positing parallel, independent mediators would offer.

Conceptual Framework

Based on the research objectives and literature review, the conceptual model positions AI-Driven Digital Innovation (AI) and Student Engagement (SE) as the two independent variables, Knowledge Transfer (KT) as the single mediating variable, and Learning Effectiveness toward Quality Education (SDG 4) (LE) as the dependent variable. The model incorporates both direct paths from the two independent variables to the dependent variable (AI→LE and SE→LE) and indirect paths through the mediator (AI→KT→LE and SE→KT→LE), enabling simultaneous examination of the mediating mechanism and the residual direct effects of AI-Driven Digital Innovation and Student Engagement on learning effectiveness outcomes. Therefore, The research conceptual framework was presented (Figure 1).

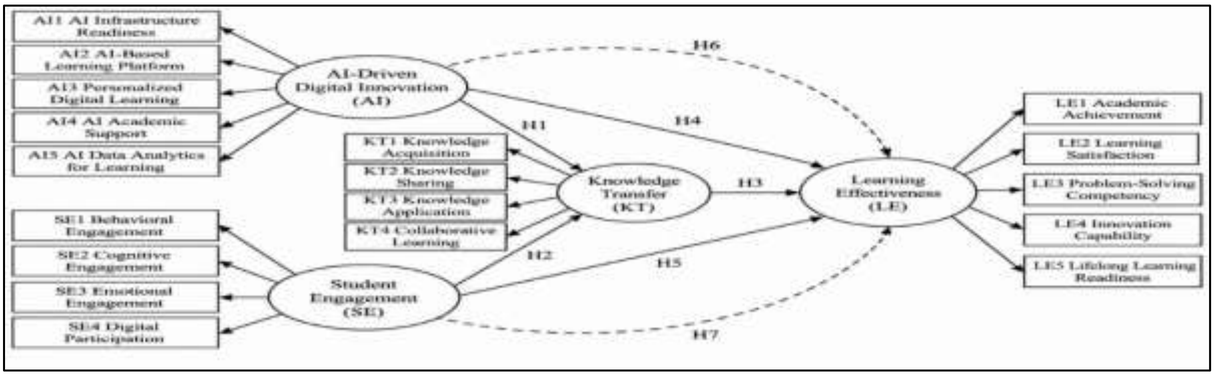

Figure 1. Conceptual framework of the study

Methodology

Research Design

This study adopted a quantitative research design, widely recognized as the most appropriate methodology for simultaneously testing theoretical models that incorporate multiple latent constructs, a mediation pathway, and causal relationships (Hair et al., 2019). The analytical strategy followed the two-stage SEM approach recommended by Anderson and Gerbing (1988). Confirmatory Factor Analysis (CFA) was first applied to establish the measurement validity and reliability of all four latent constructs before Structural Equation Modeling was employed to test the hypothesized structural relationships and mediation effects. This sequential procedure ensures that structural path estimates accurately reflect theoretical relationships rather than measurement artifacts, providing the methodological precision necessary for drawing valid conclusions regarding the causal mechanism linking AI-driven innovation and student engagement to learning effectiveness through the single knowledge transfer pathway.

Population, Sample, and Sampling Method

The target population comprised undergraduate and graduate students enrolled in agricultural and biological sciences programs—including agriculture, biology, biotechnology, and agri-business—at four universities in Bangkok, who had accumulated at least six months of experience with AI-enhanced learning environments and digital educational platforms. This criterion ensured that respondents possessed the experiential foundation necessary for reliable assessment of all four constructs under investigation.

Sample size determination followed SEM guidelines. Hair et al. (2019) recommended a minimum of 200 respondents for reliable SEM estimation, and Kline (2015) specified that sample size should be at least ten times the number of observed variables. The research model encompasses 18 observed variables (five for AI, four for SE, four for KT, and five for LE); accordingly, the minimum required sample was 180, with the target set conservatively at 350 to provide adequate statistical power and accommodate data attrition. Stratified random sampling was implemented across four universities in proportion to enrolment distributions in agricultural and biological sciences programs as documented by the Office of the Higher Education Commission (2023). A total of 400 valid questionnaires were obtained following quality control screening, exceeding the recommended minimum and providing adequate statistical power for the planned analyses.

Research Instruments

The research instrument comprised a structured questionnaire organized into five sections: (1) general demographic and academic information; (2) AI-Driven Digital Innovation scale; (3) Student Engagement scale; (4) Knowledge Transfer scale; and (5) Learning Effectiveness toward Quality Education (SDG 4) scale. All substantive items were assessed using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) (Likert, 1932).

The AI-Driven Digital Innovation scale (AI) comprised 25 items across five dimensions, each measured by five items: AI infrastructure readiness (AI1.1–AI1.5), assessing the availability, reliability, and accessibility of AI-enabled technological resources including network systems, devices, laboratory facilities, data security, and access to agricultural and biological learning resources; AI-based learning platform (AI2.1–AI2.5), measuring the pedagogical functionality and responsiveness of AI-powered course delivery systems including content comprehension support, personalized recommendations, progress tracking, rapid feedback, and subject-specific convenience; personalized digital learning (AI3.1–AI3.5), capturing the degree to which AI tools adapt learning modality, identify individual strengths and weaknesses, support self-paced learning, enhance academic understanding, and recommend appropriate supplementary resources; AI academic support (AI4.1–AI4.5), reflecting the utility of AI tools for answering academic questions, planning learning activities, providing research guidance, reducing barriers to academic assistance, and building student confidence; and AI data analytics for learning (AI5.1–AI5.5), assessing the utility of learning analytics for identifying strengths and development areas, improving study methods, enabling targeted instructor guidance, tracking continuous progress, and enhancing overall learning efficiency.

The Student Engagement scale (SE) comprised 20 items across four dimensions, each measured by five items: behavioral engagement (SE1.1–SE1.5), assessing consistent activity participation, timely assignment completion, continuous discussion participation, additional self-study time, and responsibility for both classroom and online learning activities; cognitive engagement (SE2.1–SE2.5), measuring self-directed comprehension of complex content, analytical thinking for connecting new and prior knowledge, systematic learning planning and control, evidence-based questioning and inquiry, and application of academic concepts to new situations; emotional engagement (SE3.1–SE3.5), capturing interest and enthusiasm for discipline-relevant courses, enhanced interest through digital technology, motivation from instructor and system support, increased confidence from digital tool use, and sense of belonging in the university learning environment; and digital participation (SE4.1–SE4.5), assessing consistent use of university digital platforms for learning access, online collaboration with peers and instructors, participation in online learning activities, use of online databases and digital tools for study support, and effective digital knowledge exchange with others.

The Knowledge Transfer scale (KT) comprised 20 items across four dimensions, each measured by five items: knowledge acquisition (KT1.1–KT1.5), assessing continuous knowledge gain from lessons and digital platforms, comprehension of key concepts and theories in agricultural and biological sciences, accessibility of academic knowledge sources, acceleration of new content learning through technology, and systematic collection of relevant knowledge; knowledge sharing (KT2.1–KT2.5), measuring peer knowledge exchange, ability to explain academic concepts to others, online discussion participation, receptiveness to feedback for improving understanding, and deepening comprehension through sharing; knowledge application (KT3.1–KT3.5), capturing ability to apply knowledge to agricultural and biological problems, apply academic concepts to real situations and case studies, analyze experimental data using disciplinary knowledge, connect multiple knowledge sources for problem-solving, and develop practical skills in the field; and collaborative learning (KT4.1–KT4.5), reflecting effective group work participation, multi-perspective awareness through peer learning, use of digital tools for collaborative work, development of communication and problem-solving skills, and creation of new knowledge through discussion and exchange.

The Learning Effectiveness toward Quality Education (SDG 4) scale (LE) comprised 25 items across five dimensions, each measured by five items: academic achievement (LE1.1–LE1.5), assessing enhanced understanding of core agricultural and biological content, improved academic task performance, digital technology-enhanced academic results, accurate explanation of key disciplinary principles, and readiness for both theoretical and practical assessment; learning satisfaction (LE2.1–LE2.5), measuring satisfaction with AI and digital technology-based learning formats, appropriateness of learning activities for student needs, satisfaction with instructor and online learning system support, perceived value added by technology-enhanced learning, and overall satisfaction with disciplinary learning quality; problem-solving competency (LE3.1–LE3.5), capturing ability to analyze academic and real agricultural and biological problems, appropriate use of data and evidence in problem-solving, design of technology-supported problem-solving approaches, rational evaluation of solution alternatives, and digital system contributions to problem-solving development; innovation capability (LE4.1–LE4.5), reflecting ability to think of new approaches and methods for academic problem-solving, use of digital technology for innovative idea and product development, ability to create original work in the discipline, AI learning-stimulated creative thinking, and readiness to develop socially beneficial innovations; and lifelong learning readiness (LE5.1–LE5.5), assessing intention for continuous self-development, effective self-directed learning through digital resources, readiness to adapt to technological and knowledge changes, viewing learning as a lifelong continuous process, and digital technology contributions to developing autonomous learning habits.

Content validity was established through review by five academic experts specializing in educational technology, agricultural science education, and SEM methodology. Item Objective Congruence (IOC) values exceeded 0.50 for all items (Rovinelli & Hambleton, 1977). Pilot testing with 40 students yielded Cronbach's alpha values of 0.851 for AI-Driven Digital Innovation, 0.824 for Student Engagement, 0.838 for Knowledge Transfer, and 0.862 for Learning Effectiveness, all exceeding the 0.70 threshold (Nunnally & Bernstein, 1994).

Data Collection and Analysis

Data collection was conducted during the second semester of the academic year 2025-2026 through online channels and institutional coordination channels. Participants were informed about the academic purpose of the study and were assured that their responses would remain confidential and anonymous. Quality control procedures included elimination of duplicate responses, exclusion of questionnaires with more than 20% missing data, and screening for invariant response patterns. Of 437 initial questionnaires collected, 400 were retained following screening, yielding a data retention rate of 91.5%.

Data were analyzed using AMOS 28.0 and SPSS 28.0 through a two-step procedure as follows: (1) Confirmatory Factor Analysis (CFA) was performed to evaluate the measurement model by examining standardized factor loadings, convergent validity, composite reliability, and discriminant validity. Factor loadings of 0.70, Average Variance Extracted (AVE) values greater than 0.50, and Composite Reliability (CR) values greater than 0.70 were considered acceptable; and (2) Structural Equation Modeling (SEM) was employed to test hypothesized direct and mediated relationships. Model fit was evaluated using $\chi^2/df < 3.00$, CFI ≥ 0.90, TLI ≥ 0.90, RMSEA ≤ 0.08, and RMR ≤ 0.08 (Hair et al., 2019). Discriminant validity was assessed using the Fornell–Larcker (1981) criterion and the Heterotrait-Monotrait (HTMT) ratio with a threshold of 0.85 (Henseler et al., 2015).

Results

Demographic Profile of Respondents

The 400 valid respondents comprised students from research universities (n = 84, 21.0%), comprehensive universities (n = 80, 20.0%), regional universities (n = 88, 22.0%), Rajabhat universities (n = 76, 19.0%), and Rajamangala universities of technology (n = 72, 18.0%). Undergraduate students constituted 67.5% (n = 270) and graduate students 32.5% (n = 130). Program distributions included agriculture (38.5%, n = 154), biology (32.0%, n = 128), biotechnology (18.0%, n = 72), and agri-business (11.5%, n = 46). Regarding digital learning experience, 61.3% of respondents reported more than two years of experience with AI-enhanced learning tools, confirming adequate experiential basis for reliable construct assessment across all four scales.

Measurement Model

Confirmatory Factor Analysis results confirmed that all 18 observed variables were statistically significant at $p < 0.001$, with standardized factor loadings ranging from 0.748 to 0.882—exceeding the 0.70 threshold for all indicators. AVE ranged from 0.618 to 0.661 across constructs, exceeding the 0.50 threshold, and CR ranged from 0.831 to 0.886, exceeding the 0.70 threshold, confirming convergent validity and construct reliability for all four latent constructs (Table 1).

Table 1: Construct, measurement items, factor loading, average variance extracted (AVE), and composite reliability (CR)

Construct	Measurement Items	Factor Loading	AVE / CR
AI-Driven Digital Innovation (AI)	AI Infrastructure Readiness (AI1)	0.819	0.642 / 0.876
	AI-Based Learning Platform (AI2)	0.803	
	Personalized Digital Learning (AI3)	0.841	
	AI Academic Support (AI4)	0.786	
	AI Data Analytics for Learning (AI5)	0.772	
Student Engagement (SE)	Behavioral Engagement (SE1)	0.796	0.631 / 0.873
	Cognitive Engagement (SE2)	0.824	
	Emotional Engagement (SE3)	0.762	
	Digital Participation (SE4)	0.851	
Knowledge Transfer (KT)	Knowledge Acquisition (KT1)	0.838	0.618 / 0.831
	Knowledge Sharing (KT2)	0.774	
	Knowledge Application (KT3)	0.812	
	Collaborative Learning (KT4)	0.748	
Learning Effectiveness (LE)	Academic Achievement (LE1)	0.768	0.661 / 0.886
	Learning Satisfaction (LE2)	0.843	
	Problem-Solving Competency (LE3)	0.819	
	Innovation Capability (LE4)	0.882	
	Lifelong Learning Readiness (LE5)	0.826	

Discriminant Validity

Discriminant validity was assessed using the Fornell-Larcker criterion. The results showed that the square roots of AVE for AI-Driven Digital Innovation (0.801), Student Engagement (0.794), Knowledge Transfer (0.786), and Learning Effectiveness (0.813) exceeded their inter-construct correlations. All inter-construct correlations were lower than these diagonal values, confirming satisfactory discriminant validity across all four constructs. (Table 2).

Table 2: Correlation matrix of latent variables and square roots of AVE

Construct	AI	KT	SE	LE
AI-Driven Digital Innovation (AI)	**0.801**			
Student Engagement (SE)	0.534	**0.794**		
Knowledge Transfer (KT)	0.548	0.519	**0.786**	
Learning Effectiveness (LE)	0.541	0.547	0.563	**0.813**

Note. Diagonal values (bold) represent the square roots of AVE.

Results of Structural Equation Modeling (SEM)

The structural model demonstrated excellent fit with the empirical data across all evaluated indices. The chi-square statistic was not statistically significant ($\chi^2 = 168.724$, df = 157, $p = 0.070$), and the χ^2/df ratio of 1.075 fell well within the acceptable threshold of less than 3.00. Additional goodness-of-fit indices further corroborated the adequacy of the structural model: GFI = 0.931, NFI = 0.924, TLI = 0.949, CFI = 0.961, RMSEA = 0.046, RMR = 0.043. All indices met or exceeded their respective commonly accepted thresholds, confirming that the proposed structural model provides a robust, well-fitting representation of the observed data (Table 3).

Table 3: Model fit indices of the structural model

Fit Index	Criterion	Obtained Value
χ^2	—	168.724
df	—	157
p-value	> 0.05	0.070
χ^2/df	< 3.00	1.075
GFI	> 0.90	0.931
NFI	> 0.90	0.924
TLI	> 0.90	0.949
CFI	> 0.90	0.961
RMSEA	< 0.08	0.046
RMR	< 0.08	0.043

The structural model confirmed that all seven hypotheses are supported. AI-Driven Digital Innovation exerted a significant direct effect on Knowledge Transfer (H1: $\beta = 0.512$, $p < 0.001$), and Student Engagement similarly exerted a significant direct effect on Knowledge Transfer (H2: $\beta = 0.468$, $p < 0.001$), establishing both as significant antecedents of the central mediating mechanism. Knowledge Transfer exerted the strongest direct effect on Learning Effectiveness (H3: $\beta = 0.524$, $p < 0.001$), confirming its position as the most powerful proximate determinant of learning effectiveness outcomes. AI-Driven Digital Innovation also exerted a significant direct effect on Learning Effectiveness (H4: $\beta = 0.312$, $p < 0.001$), and Student Engagement exerted a significant direct effect on Learning Effectiveness (H5: $\beta = 0.386$, $p < 0.001$).

Mediation analysis confirmed that Knowledge Transfer significantly mediates the relationship between AI-Driven Digital Innovation and Learning Effectiveness (H6: $\beta = 0.268$, $p < 0.001$), as well as the relationship between Student Engagement and Learning Effectiveness (H7: $\beta = 0.181$, $p < 0.001$), establishing Knowledge Transfer as the central mediating mechanism through which both enabling conditions produce learning effectiveness (Table 4).

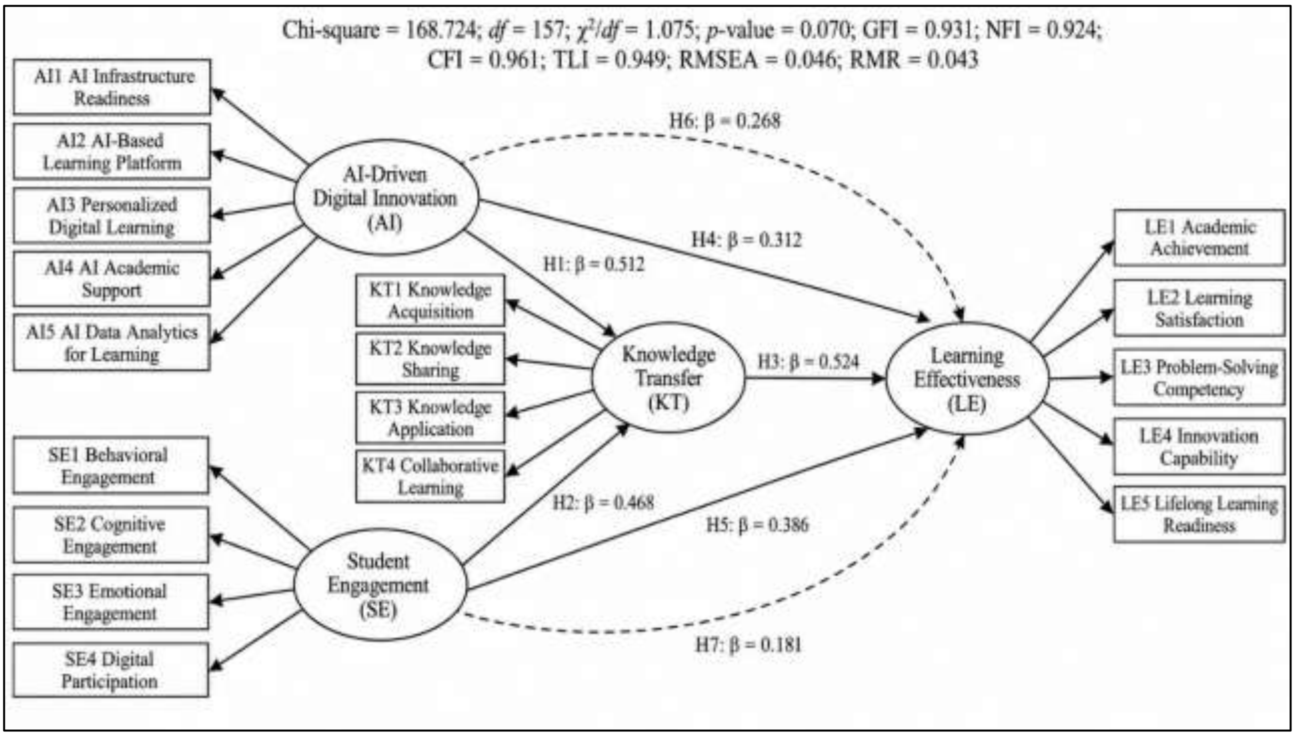

Figure 2: Standardized structural relationships among AI-Driven Digital Innovation, Student Engagement, Knowledge Transfer, and Learning Effectiveness toward Quality Education (SDG 4)

Table 4: Results of the structural equation modeling analysis and hypotheses testing

Hypotheses	Path Relationship	β	S.E.	t-value	p-value	Result
H1	AI → KT	0.512	0.118	7.426	***	Supported
H2	SE → KT	0.468	0.112	6.918	***	Supported
H3	KT → LE	0.524	0.134	8.316	***	Supported
H4	AI → LE	0.312	0.091	5.847	***	Supported
H5	SE → LE	0.386	0.096	6.384	***	Supported
H6	AI → KT → LE	0.268	0.088	2.742	***	Supported
H7	SE → KT → LE	0.181	0.076	2.384	***	Supported

Note: *** $p < 0.001$; β = standardized path coefficient; S.E. = standard error

Discussion

The structural equation modeling results confirm that AI-Driven Digital Innovation and Student Engagement are both significant antecedents of Knowledge Transfer, which in turn functions as the central mediating mechanism through which these two enabling conditions produce learning effectiveness in Thai agricultural and biological sciences programs. The finding that AI-Driven Digital Innovation exerts the strong effect on Knowledge Transfer positions technology-driven instruction as the primary activator of the cognitive processes through which students acquire, share, apply, and collaboratively construct disciplinary knowledge. This result is consistent with Luckin et al. (2019), who demonstrated that AI-powered learning environments significantly enhance knowledge acquisition by providing personalized, real-time instructional feedback that conventional pedagogy cannot sustain at scale across large and heterogeneous student populations. In the Thai agricultural and biological sciences context, this mechanism operates through three distinct channels: AI simulation environments that enable students to experiment with biological and agricultural systems without the resource constraints and safety limitations of physical laboratories; personalized content sequencing that accelerates knowledge acquisition by ensuring each student engages with appropriately challenging material at an individually calibrated pace; and AI analytics tools that transform passive content exposure into active knowledge application by enabling students to interrogate real agricultural datasets and generate evidence-based conclusions. These three channels collectively demonstrate that AI investment in Thai higher education produces compound pedagogical returns through the systematic enhancement of knowledge transfer processes across all four of its operationalized dimensions.

The significant effect of Student Engagement on Knowledge Transfer establishes engagement as the second critical antecedent activating the same central mediating mechanism. This finding validates Self-Determination Theory's proposition that students whose psychological needs for autonomy, competence, and relatedness are met, demonstrate the intrinsic motivation necessary to engage deeply in knowledge acquisition, sharing, application, and collaboration (Ryan & Deci, 2000). In Thai agricultural and biological sciences programs, the digital participation dimension of engagement is particularly consequential: students who actively engage with AI platforms, bioinformatics databases, and collaborative digital tools are best positioned to convert technological affordances into actual knowledge transfer. The convergence of AI-driven innovation and student engagement on the single Knowledge Transfer pathway carries an important theoretical implication: technology and motivation are not independent educational forces but jointly determine the strength of the cognitive mechanism—knowledge transfer—that ultimately produces learning effectiveness. Institutions that invest heavily in AI infrastructure while neglecting student engagement, or vice versa, are likely to realize only a fraction of the knowledge transfer gains achievable when both antecedents are cultivated simultaneously (Bangbon et al., 2023; Youthao et al., 2026).

The finding that Knowledge Transfer exerts the strongest direct effect on Learning Effectiveness is the most theoretically significant result of the study, confirming knowledge transfer's position as the most proximate and powerful determinant of learning effectiveness in the agricultural and biological sciences context. This result confirms the central proposition of Knowledge Creation Theory that sustainable knowledge outcomes require iterative cycles of knowledge acquisition, socialization, externalization, and combination—precisely the processes operationalized in the KT construct's four dimensions (Nonaka & Takeuchi, 1995). The theoretical implication is clear and actionable: learning effectiveness in agricultural and biological sciences programs cannot be achieved through technology provision or student motivation alone; both must be channeled through sustained knowledge transfer processes that dynamically connect theoretical learning to practical application and collaborative discovery. Educational designers who prioritize the explicit integration of structured knowledge sharing seminars, applied problem-solving projects, and collaborative research experiences within AI-enhanced learning sequences will generate the most powerful and durable learning effectiveness outcomes aligned with SDG 4 (Phusavat et al., 2022).

The significant direct effects of AI-Driven Digital Innovation and Student Engagement on Learning Effectiveness, independent of the knowledge transfer pathway, confirm that both enabling conditions also generate residual educational value through mechanisms not fully captured by knowledge transfer—including enhanced student confidence, reduced cognitive load, and direct competency development through repeated practice. The fact that Student Engagement's direct effect exceeds that of AI-Driven Digital Innovation suggests that motivational and affective processes contribute somewhat more directly to learning effectiveness than technological processes do, even though AI-Driven Digital Innovation exerts the stronger effect on the mediating mechanism itself. This pattern is consistent with Flow Theory's emphasis on engagement as a direct driver of learning productivity (Csikszentmihalyi, 1990) and underscores that technology functions primarily as an enabler of knowledge transfer, whereas engagement functions as both an enabler of knowledge transfer and an independent contributor to learning effectiveness in its own right.

The confirmation that Knowledge Transfer significantly mediates both the AI→LE relationship and the SE→LE relationship establishes partial mediation in both cases and positions Knowledge Transfer as the structural hub of the entire model. This single-mediator architecture carries an important practical implication that differs from models positing parallel, independent mediators: because both AI-driven innovation and student engagement operate through the same mediating channel, interventions that strengthen knowledge transfer processes—rather than interventions targeting AI infrastructure or engagement separately—are likely to yield the broadest and most efficient improvements in learning effectiveness. Educational institutions seeking to maximize return on investment should therefore prioritize knowledge transfer-centered pedagogical design—such as structured knowledge sharing seminars, collaborative problem-solving workshops, and applied research projects—as the common pathway through which both technological and motivational investments are converted into measurable learning gains.

From a policy and institutional practice perspective, these findings carry three specific implications for Thai universities in agricultural and biological sciences education. First, AI infrastructure investment and student engagement initiatives should be evaluated not in isolation but according to their joint capacity to activate the single knowledge transfer mechanism that the structural model identifies as the strongest determinant of learning effectiveness. Second, curriculum design should explicitly structure learning sequences around the four knowledge transfer dimensions—acquisition, sharing, application, and collaborative learning—as the common pathway connecting both AI-enhanced instruction and student engagement initiatives to learning outcomes. Third, because knowledge transfer functions as the structural hub linking both antecedents to learning effectiveness, institutions with constrained resources may achieve more efficient gains by concentrating investment on knowledge transfer-centered pedagogical design rather than dispersing resources evenly across technology infrastructure and engagement programming (Pansuwong et al., 2023; Channuwong et al., 2025).

Conclusion

This study revealed that AI-Driven Digital Innovation and Student Engagement both significantly activate Knowledge Transfer, which functions as the central mediating mechanism producing Learning Effectiveness toward SDG 4 in Thai agricultural and biological sciences programs. The structural model confirmed that Knowledge Transfer significantly mediates both the AI→LE relationship and the SE→LE relationship, while both AI-Driven Digital Innovation and Student Engagement remain significant direct effects on Learning Effectiveness. Knowledge Transfer emerged as the strongest proximate determinant of learning effectiveness, confirming its position as the structural hub of the model. These findings reveal that sustainable learning effectiveness in Thai agricultural and biological sciences programs depends less on technology investment or engagement cultivation in isolation than on the degree to which both are channeled through robust, well-designed knowledge transfer processes—a single-pathway investment logic with significant implications for technology strategy, curriculum design, and pedagogical practice aligned with SDG 4.

Contributions

The study makes three specific contributions: (1) the empirical demonstration that knowledge transfer functions as the central mediating mechanism linking both AI-driven innovation and student engagement to learning effectiveness; (2) the simultaneous testing of direct and indirect pathways within an integrated structural model applicable to agricultural and biological sciences education; and (3) methodological rigor through the application of full SEM combining Confirmatory Factor Analysis with structural path estimation to the Thai university context.

Recommendations for Future Research

Future research should pursue four directions. First, longitudinal designs tracking student cohorts across academic years would clarify whether the centrality of knowledge transfer as the single mediating mechanism remains stable as students develop greater digital literacy and disciplinary expertise. Second, multi-group SEM comparing the model across university types would clarify whether the relative strength of the AI→KT and SE→KT pathways differ systematically between public and private universities. Third, the integration of additional boundary conditions—including AI self-efficacy and institutional absorptive capacity—as moderating variables would provide a more comprehensive account of the conditions under which knowledge transfer most effectively converts AI-driven innovation and student engagement into learning effectiveness. Fourth, cross-national comparative studies situating the Thai findings within the broader ASEAN agricultural education context would advance understanding of the generalizability of the single-mediator model and contribute to regional policy dialogue on digital transformation in agricultural higher education aligned with SDG 4.

Conflict of Interest

The authors declared that they have no conflict of interest in writing and publishing this article.

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