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Modeling Determinants of AI and Fiber-optic Integration in Technology Education Curricula: Evidence from Philippine University

Franklin M Ganancias[1,2]*, Jehu Roeh C Rubenial[2], Fae Mylene M Etchon[2], Sharon A Bucalon[2], Lyndon A Rosas[2]

[1]College of Engineering and Technology, North Eastern Mindanao State University, Rosario, Tandag City, Philippines, [2]College of Information Technology Education, North Eastern Mindanao State University, Rosario, Tandag City, Philippines. *Corresponding Author's Email: fmganancias@nemsu.edu.ph

Abstract

The integration of artificial intelligence (AI) and advanced networking technologies into higher education curricula requires a systemic understanding of how institutional conditions and instructional structures translate into measurable competency outcomes. This study develops and tests a structural equation model examining the determinants of AI and fiber-optic technology integration within a technology education curriculum at a Philippine state university. Drawing from Institutional Theory, the Resource-Based View and the Technological Pedagogical Content Knowledge (TPACK) framework, the proposed model links institutional readiness, instructional curriculum readiness, AI instructional integration, instructor competency in fiber-optic networks and students' competent skills. Data were collected from 317 undergraduate students enrolled in computing-related programs and analyzed using Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) in AMOS. The measurement model demonstrated strong convergent validity (AVE > 0.50) and high composite reliability (CR > 0.90), with acceptable global fit indices (χ^2/df = 2.912; RMSEA = 0.078). Structural analysis revealed that AI instructional integration significantly predicts instructor competency ($\beta = 0.804$, $p < 0.001$), which in turn strongly influences students' competent skills ($\beta = 1.000$, $p < 0.001$). Direct paths from institutional and instructional readiness to student skills were not supported; instead, their effects operate indirectly through a sequential pathway: Readiness → AI Integration → Instructor Competency → Student Skills. The findings highlight instructor competency as the critical mediating mechanism through which institutional and technological investments translate into technical skill development. This study contributes a validated readiness-driven framework for AI-supported technology education and offers practical implications for institutional curriculum development.

Keywords: Artificial Intelligence in Education, Fiber-optic Network Education, Institutional Readiness, Instructional Curriculum Readiness, Instructor Competency, Structural Equation Modeling.

Introduction

The rapid advancement of artificial intelligence (AI) and digital infrastructures is reshaping higher education, particularly in science, engineering and technology disciplines. AI-powered instructional systems, intelligent tutoring platforms, adaptive learning environments and learning analytics are increasingly used to enhance teaching effectiveness, personalize learning experiences and improve student engagement (1, 2). International initiatives have likewise highlighted AI as a strategic tool for improving educational quality and preparing learners for emerging workforce demands (3). Simultaneously, the expansion of Industry 4.0 technologies, cloud computing and digital communication systems has increased demand for graduates equipped with advanced networking competencies, particularly in fiber-optic communication technologies that underpin modern digital infrastructures (4). The convergence of AI and fiber-optic technologies presents significant opportunities for technology education. AI-supported instructional tools can facilitate adaptive learning, automate feedback and provide simulation-based experiences that strengthen technical understanding and practical competency development (1, 5). In engineering and networking education, AI-enhanced simulations and virtual laboratories have demonstrated effectiveness in improving conceptual understanding, problem-solving skills and hands-on learning outcomes (6,

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7). At the same time, fiber-optic networking remains a critical component of broadband connectivity, cloud services and digital transformation initiatives. Component of broadband connectivity, cloud services and digital transformation initiatives (8). Consequently, higher education institutions are increasingly expected to integrate both AI and advanced networking technologies into their curricula to ensure graduates possess industry-relevant competencies.

Despite these opportunities, effective technology integration requires organizational readiness, instructional preparedness and human capability in addition to technological resources (1, 9). Institutional leadership, infrastructure, policy support, strategic planning and resource allocation influence the adoption and sustainability of AI-supported educational initiatives (10, 11). Institutions that strategically align technology investments with curriculum development initiatives and faculty capacity-building efforts are more likely to achieve meaningful educational transformation and innovation (12, 13). Likewise, curriculum readiness plays a critical role in ensuring that learning objectives, laboratory activities, assessments and instructional approaches align with emerging technological requirements (6, 14). However, institutional and curriculum readiness alone may not guarantee improved student outcomes without instructors who possess the competencies necessary to effectively implement and facilitate technology-enhanced learning. Instructor competency has emerged as one of the most influential factors in technology-enabled education (15-17). Instructors serve as the link between institutional resources, curriculum design and student learning experiences. Their ability to integrate AI-supported tools, facilitate laboratory activities and connect theoretical concepts with practical applications directly influences students' competency development (14, 18). Previous studies have shown that instructor preparedness significantly affects the educational benefits derived from AI-enhanced learning environments and digital technologies (10, 19, 20). Similarly, research on generative AI highlights that the effectiveness of AI technologies depends largely on how instructors guide their pedagogical use within learning environments (21). These findings suggest that instructor competency may represent a critical mechanism through which institutional readiness and technological investments translate into meaningful student outcomes.

Although previous studies have examined AI adoption, technology readiness, instructor preparedness and digital transformation, these factors have largely been investigated in isolation. Limited empirical evidence explains how institutional readiness, instructional curriculum readiness, AI instructional integration and instructor competency collectively influence student competencies in specialized technology domains such as fiber-optic networking education. This gap is particularly important in developing-country contexts, where institutions must balance technological modernization with resource constraints while preparing graduates for increasingly digital industries (19, 22). The Philippine higher education sector provides a relevant context for examining these relationships. As universities respond to national digital transformation initiatives and workforce demands, they are increasingly expected to develop competencies in AI, networking technologies and related digital fields (4). However, variations in institutional readiness, curriculum implementation, technological infrastructure and faculty development may influence the effectiveness of these efforts (10, 11, 22). Understanding how these factors interact is therefore important for informing institutional planning, curriculum enhancement and technology integration strategies.

This study addresses these gaps by developing and empirically testing a structural equation model that examines the determinants of AI and fiber-optic technology integration within a technology education curriculum at a Philippine state university. Specifically, the study investigates how institutional readiness and instructional curriculum readiness influence AI instructional integration, instructor competency in fiber-optic networks and students' competent skills. Using Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM), the study provides an empirically validated framework explaining how organizational readiness and AI-supported instruction contribute to competency development. The findings extend the literature on AI integration in higher education by demonstrating the critical role of instructor competency in translating institutional and technological investments into meaningful student learning outcomes.

Theoretical Framework and Hypotheses Development

This study integrates Institutional Theory, the Resource-Based View (RBV) and the Technological Pedagogical Content Knowledge (TPACK) framework to explain how organizational and technological factors influence instructor competency and student skill development in fiber-optic networking education. Institutional Theory highlights the role of leadership, governance, policies and organizational support in enabling innovation adoption (18, 23). RBV suggests that institutional resources, including laboratories, AI platforms and faculty development initiatives, create value when effectively utilized through human capital (5, 19, 24). Meanwhile, TPACK emphasizes the integration of technological, pedagogical and content knowledge in technology-intensive learning environments (13, 25). Collectively, these perspectives suggest that readiness and AI instructional integration strengthen instructor competency, ultimately influencing students' competent skills.

Previous studies indicate that institutional readiness significantly influences curriculum implementation, technology adoption and instructor capability (5, 22, 26). Similarly, instructional readiness supports effective instructional delivery through aligned learning objectives, practical laboratory experiences, assessment strategies and industry-relevant content (14, 20, 27, 28). AI instructional integration, including adaptive simulations, intelligent tutoring systems, automated feedback and learning analytics, has been shown to enhance instructional effectiveness and technical skill development (1, 5, 18, 24). Furthermore, instructor competency remains a key predictor of student learning outcomes and technical skill acquisition in applied educational settings (29, 30). Consistent with RBV and human capital perspectives, instructor competency may also serve as a mediating mechanism through which organizational readiness and technological resources influence student outcomes (31, 32).

Based on these theoretical foundations and empirical findings, the following hypotheses are proposed:

H1. Institutional readiness has a significant positive effect on instructional readiness.

H2. Institutional readiness has a significant positive effect on instructor competency in fiber-optic network instruction.

H3. Instructional readiness has a significant positive effect on instructor competency in fiber-optic network instruction.

H4. AI instructional integration has a significant positive effect on instructor competency in fiber-optic network instruction.

H5. Instructor competency in fiber-optic network instruction has a significant positive effect on students' competent skills in fiber-optic networking.

H6. Instructional readiness has a significant positive effect on students' competent skills in fiber-optic networking.

H7. AI instructional integration has a significant positive effect on students' competent skills in fiber-optic networking.

H8. Instructor competency in fiber-optic network instruction mediates the relationship between (a) institutional readiness and students' competent skills, (b) instructional readiness and students' competent skills and (c) AI instructional integration and students' competent skills.

The proposed relationships among the study variables are illustrated in Figure 1.

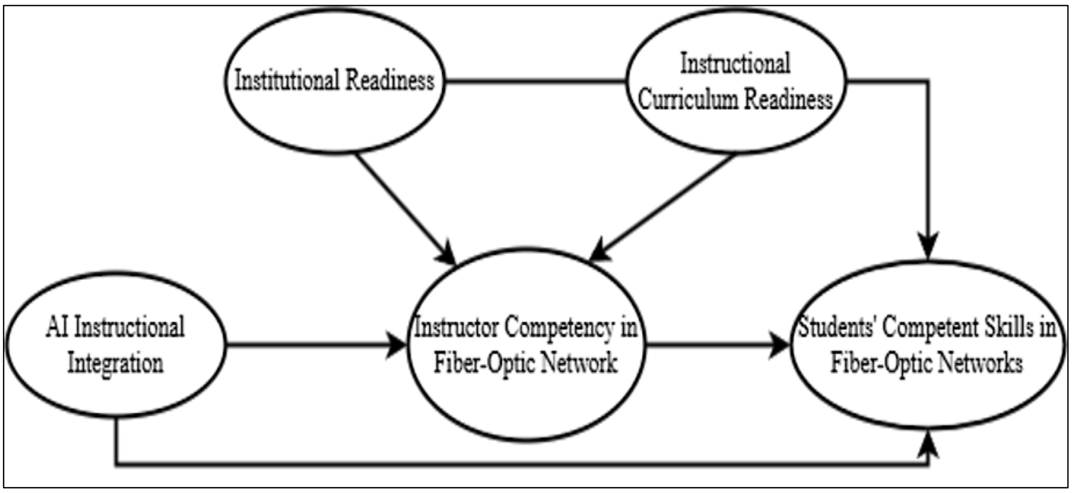

Figure 1: Proposed Conceptual Model

Methodology

Data and Respondents

Guided by the objective of modeling the determinants that shape AI and fiber-optic technology integration in technology education curricula, this study adopted a structural equation modeling approach to examine how institutional readiness, curriculum conditions, instructional practices and technological adoption mechanisms interact to influence competency development outcomes. The research follows a theory-driven explanatory perspective in which institutional readiness is assumed to enable AI-supported instructional practices that subsequently contribute to instructor competency and, ultimately, student technical skills. This analytical direction informed the development of the conceptual model and guided the selection of respondents to ensure that participants were situated in learning environments where such technological integration processes are meaningfully experienced. Data were gathered through a structured survey administered with the assistance of collaborating faculty members who maintain active links with computer-related programs in the university. Their involvement ensured appropriate access to students enrolled in programs classified under the Technology Education curriculum. Prior to participation, respondents were informed of data privacy provisions, assured that responses would be used solely for this study and provided with a clear explanation of the study's purpose and analytical direction so that their responses would reflect informed judgments about institutional readiness, AI use and competency development.

The resulting sample represents learners who are academically positioned to evaluate these processes. A substantial proportion of respondents were in their third year of study (68%), followed by second-year students (21%), indicating that most participants were already engaged in specialized technical coursework where exposure to laboratory-based instruction, curriculum alignment and instructional technologies is most pronounced. Program distribution further supports the relevance of the dataset, with the majority coming from Information Technology (55%) and Computer Technology (26%) programs, while smaller shares were drawn from Computer Science (11%) and Computer Engineering (8%), ensuring that the respondents collectively represent a broad spectrum of computing-oriented educational contexts. The gender composition is relatively balanced, with females representing 52% and males 48%, which helps reduce the likelihood of gender-based bias in perceptions of technology integration. Age distribution also reflects a typical undergraduate progression, with the largest share of respondents aged 21 (37%), followed by 20 years old (23%) and 22 years old (15%), suggesting that most participants are at a stage of academic maturity where they can meaningfully evaluate instructional practices and institutional support mechanisms. The detailed respondent profile is summarized in Table 1. Taken together, the dataset is composed primarily of mid-program computing students who are actively exposed to curriculum implementation, instructional technologies and laboratory-based learning environments.

Respondent selection was guided by predefined eligibility criteria. Participants were required to be currently enrolled in computer-related programs under the Technology Education curriculum, actively registered during the data collection period and willing to provide informed consent. These criteria ensured that respondents possessed sufficient exposure to instructional practices, technological resources and curriculum implementation processes relevant to the constructs under investigation. Responses that were incomplete, contained substantial missing data, or lacked consent were excluded from the analysis. This alignment between the respondents' academic positioning and the theoretical direction of the study strengthens the appropriateness of the sample for examining the readiness-driven pathways through which institutional conditions and AI-supported instruction contribute to competency development within technology education programs.

Table 1: Demographic and Academic Profile of Respondents

Profile	Category	n	%
Age	18-19	30	9
	20	73	23
	21	117	37
	22	47	15
	23	23	7
	24 and above	27	9
Gender	Male	153	48
	Female	164	52
Year Level	1st	18	6
	2nd	67	21
	3rd	216	68
	4th	16	5
Degree Program	Computer Science	34	11
	Computer Engineering	26	8
	Information Technology	174	55
	Computer Technology	83	26

Note: n= Number of Respondents; %= Percentage.

Research Instruments

The study employed a structured survey questionnaire designed to measure the determinants of AI and fiber-optic technology integration in technology education curricula. The instrument consisted of three main sections. The first section presented an informed consent statement explaining the purpose of the research, voluntary participation and the confidentiality of respondents' data in accordance with institutional data privacy standards. The second section gathered the demographic profile of the respondents, including age, gender, year level and degree program, which were used to contextualize the analysis. The third section contained the measurement items corresponding to the study constructs, where respondents rated their level of agreement with each statement. The instrument comprised five latent constructs: Institutional Readiness, Instructional Curriculum Readiness, AI Instructional Integration, Instructor Competency in Fiber-Optic Networks and Students' Skills in Fiber-Optic Networks, each measured through multiple indicators as summarized in Table 2. All items were adapted from established literature to ensure content validity. Responses were recorded using a seven-point Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree), allowing for greater response sensitivity and variance suitable for structural equation modeling analysis.

Table 2: Measurement Constructs and Survey Items

Construct	Item Statement	No. of Items	References
Institutional Readiness (IR)	IR1. The university provides well-equipped fiber-optic laboratories. IR2. Modern fiber-optic instruments are available for student use.	8	(33)

	IR3. Laboratory equipment is sufficient for all students during practical sessions. IR4. The institution maintains up-to-date networking facilities. IR5. Technical support staff assist during laboratory activities. IR6. The university invests in upgrading fiber-optic technologies. IR7. Learning spaces support safe hands-on experimentation. IR8. Institutional resources enable effective technical training.		
Instructional Curriculum Readiness (ICR)	ICR1. The curriculum reflects current fiber-optic industry standards. ICR2. Courses include sufficient hands-on laboratory activities. ICR3. Learning materials clearly explain fiber-optic concepts. ICR4. Practical exercises reinforce theoretical lessons. ICR5. Assessments evaluate real networking skills. ICR6. Instruction integrates modern fiber-optic applications. ICR7. Course content prepares students for professional practice.	7	(6)
AI Instructional Integration (AI)	AI1. AI-based simulations help me understand fiber-optic systems. AI2. Virtual laboratories improve my technical practice. AI3. AI tools provide feedback during learning activities. AI4. Digital simulations support complex problem solving. AI5. AI technologies enhance laboratory instruction. AI6. Intelligent systems improve my learning efficiency.	6	(7)
Instructor Competency in Fiber-Optic Network (ICFON)	ICF1. The instructor demonstrates strong fiber-optic technical knowledge. ICF2. The instructor explains complex networking concepts clearly. ICF3. The instructor effectively demonstrates laboratory procedures. ICF4. The instructor guides troubleshooting activities competently. ICF5. The instructor connects theory with practical applications. ICF6. The instructor uses modern teaching technologies effectively. ICF7. The instructor manages laboratory sessions efficiently. ICF8. The instructor encourages hands-on experimentation. ICF9. The instructor provides useful technical feedback. ICF10. The instructor stays updated with industry advancements.	10	(29)
Students' Competent Skills in Fiber-Optic Networks (SCS)	SCS1. I can install basic fiber-optic components correctly. SCS2. I can perform fiber-optic cable testing procedures. SCS3. I can troubleshoot networking problems independently. SCS4. I can operate fiber-optic tools safely. SCS5. I can interpret measurement results accurately. SCS6. I can apply theory to real networking scenarios. SCS7. I can complete laboratory tasks independently. SCS8. I feel confident handling fiber-optic equipment. SCS9. I can collaborate effectively on technical projects.	9	(28)

Note: IR = Institutional Readiness; ICR = Instructional Curriculum Readiness; AI = AI Instructional Integration; ICFON = Instructor Competency in Fiber-Optic Networks; SCS = Students' Competent Skills in Fiber-Optic Networks.

Data Gathering Procedure

Data for this study were collected through an online survey administered via Google Forms from January to February 2026 among students enrolled in computer-related programs under the Technology Education curriculum. The survey distribution was facilitated with the assistance of collaborating faculty members who had direct coordination with the target respondents. Prior to participation, respondents were presented with an informed consent statement explaining the purpose of the study, the voluntary nature of involvement, confidentiality of responses and compliance with institutional data privacy standards; only those who agreed were allowed to proceed. The questionnaire link was shared through official academic communication channels, enabling students to complete the instrument at their convenience during the collection period. After the survey closed, responses were screened for completeness and consistency and valid entries were securely stored for subsequent use in the study, ensuring that the dataset was ethically obtained and suitable for examining the determinants of AI and fiber-optic technology integration in technology education curricula.

Data Analysis

Data analysis was conducted using IBM SPSS Statistics for Windows, Version 25.0 (IBM Corp., Armonk, NY, USA) and IBM SPSS AMOS Graphics, Version 20.0 (IBM Corp., Armonk, NY, USA) to examine both the measurement properties and structural relationships among the study variables. SPSS was first used to generate descriptive statistics, screen the dataset for missing values and inconsistencies and assess the internal reliability of the scales. Subsequently, Confirmatory Factor Analysis (CFA) was performed in AMOS to evaluate the measurement model, including indicator loadings, construct validity and overall model fit. After establishing acceptable measurement properties, Structural Equation Modeling (SEM) was employed to test the hypothesized relationships among institutional readiness, AI instructional integration, instructor competency in fiber-optic networks and student skill outcomes. Model fit indices, standardized regression paths and significance levels were examined to determine the adequacy of the proposed model and the strength of the structural relationships, ensuring a rigorous multivariate evaluation of the study framework.

All CFA and SEM analyses were conducted using IBM SPSS Statistics for Windows, Version 25.0 (IBM Corp., Armonk, NY, USA) and IBM SPSS AMOS Graphics, Version 20.0 (IBM Corp., Armonk, NY, USA). Parameter estimation was performed using the Maximum Likelihood (ML) estimation method. Prior to model estimation, the dataset was screened for missing values, outliers and response inconsistencies and only complete responses were retained for analysis. Model convergence was assessed through the iterative estimation procedures implemented in AMOS and convergence was achieved when parameter estimates stabilized and acceptable model fit statistics were obtained. The adequacy of the measurement and structural models was evaluated using multiple goodness-of-fit indices, including the Chi-square to degrees of freedom ratio (χ^2/df), Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Incremental Fit Index (IFI) and Root Mean Square Error of Approximation (RMSEA). Statistical significance was assessed using standardized path coefficients, critical ratios (C.R.) and associated p-values at the 0.05 significance level.

Results

Measurement Model Analysis

The adequacy of the measurement model was evaluated through Confirmatory Factor Analysis (CFA) using AMOS, as illustrated in Figure 2, with detailed statistics reported in Table 3 and global fit indices in Table 4. Given the relatively large sample ($n = 317$), CFA provides robust parameter estimation and stable covariance structures, consistent with SEM recommendations that emphasize larger samples for model stability and generalizability (10, 34, 35). All observed indicators loaded significantly on their respective latent constructs ($p < 0.001$), with standardized factor loadings (SFL) ranging from 0.766 to 0.915 across constructs. Institutional Readiness (IR), Instructional Curriculum Readiness (ICR) and AI Instructional Integration (AI) demonstrated consistently strong loadings above the 0.78 threshold, while Instructor Competency in Fiber-Optic Networks (ICFON) and Students' Competent Skills (SCS) exhibited particularly high loadings, several exceeding 0.85. These results indicate strong indicator reliability and confirm that the observed variables meaningfully represent their underlying theoretical domains. In large-sample SEM contexts, high and stable loadings further strengthen confidence in construct representation because sampling variability is reduced and parameter estimates become more precise (35, 36).

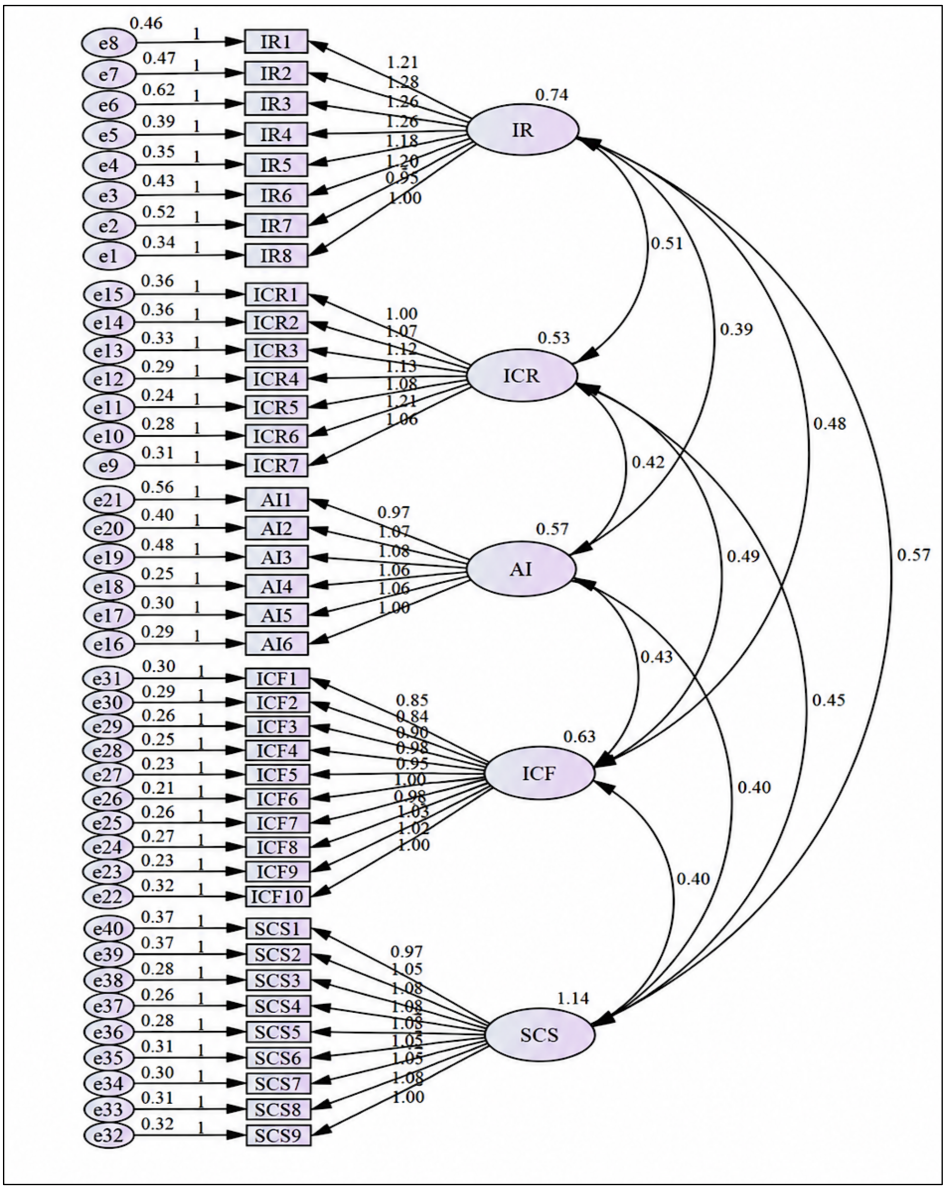

Figure 2: Confirmatory Factor Analysis Results

Table 3: Convergent Validity Results of the Measurement Model

Construct	Item	t-value	SFL	AVE	AVE²	CR
Institutional Readiness (IR)	IR1	16.304	0.839	0.694	0.833	0.947
	IR2	16.539	0.849			
	IR3	15.619	0.81			
	IR4	17.227	0.876			
	IR5	16.596	0.851			
	IR6	16.964	0.886			
	IR7	14.875	0.779			
	IR8		0.766			
Instructional Curriculum Readiness (ICR)	ICR1	15.940	0.779	0.669	0.818	0.934
	ICR2	16.284	0.791			
	ICR3	17.309	0.826			
	ICR4	17.083	0.818			
	ICR5	17.805	0.842			
	ICR6	18.358	0.859			
	ICR7		0.81			
	AI1	16.151	0.794	0.709	0.842	0.935

AI Instructional Integration (AI)	AI2	14.590	0.895			
	AI3	16.714	0.814			
	AI4	18.788	0.883			
	AI5	17.812	0.851			
	AI6		0.81			
Instructor Competency in Fiber-Optic Network (ICFON)	ICF1	16.672	0.78	0.690	0.830	0.957
	ICF2	17.612	0.808			
	ICF3	17.270	0.798			
	ICF4	18.664	0.838			
	ICF5	18.649	0.838			
	ICF6	19.298	0.855			
	ICF7	19.340	0.857			
	ICF8	18.609	0.837			
	ICF9	19.542	0.862			
	ICF10		0.833			
Students' Competent Skills in Fiber-Optic Networks (SCS)	SCS1	23.093	0.878	0.798	0.893	0.972
	SCS2	23.093	0.878			
	SCS3	23.520	0.885			
	SCS4	24.939	0.907			
	SCS5	25.430	0.915			
	SCS6	24.858	0.906			
	SCS7	23.537	0.886			
	SCS8	24.454	0.9			
	SCS9		0.885			

Note: SFL = Standardized Factor Loading; AVE = Average Variance Extracted; CR = Composite Reliability; IR = Institutional Readiness; ICR = Instructional Curriculum Readiness; AI = AI Instructional Integration; ICFON = Instructor Competency in Fiber-Optic Networks; SCS = Students' Competent Skills in Fiber-Optic Networks.

Global model fit statistics are presented in Table 4. The baseline measurement model demonstrated acceptable overall fit, with $\chi^2/df = 2.912$ and RMSEA = 0.078, both within recommended thresholds ($\chi^2/df < 3.00$; RMSEA < 0.08). Incremental fit indices (CFI = 0.896; TLI = 0.889; IFI = 0.897) were marginally below the conventional 0.90 benchmark but remained close to acceptable levels. Given the relatively large sample size (n = 317) and the complexity of the model with multiple constructs and indicators, slight attenuation in incremental indices is not uncommon, as fit statistics are known to be sensitive to model size and sample characteristics. Modification indices were subsequently examined; however, re-specification resulted in deterioration of global fit ($\chi^2/df = 5.28$; RMSEA = 0.116; CFI = 0.857). Because the modified model did not improve overall fit and introduced additional complexity without theoretical justification, the baseline theoretically grounded measurement model was retained. This decision aligns with best-practice SEM recommendations emphasizing theoretical parsimony over data-driven overfitting. Overall, the combination of strong standardized loadings, high composite reliability, satisfactory AVE values and acceptable absolute fit indices supports the adequacy of the measurement model for structural testing.

Table 4: Measurement Model Data Fit Indices Results

Model Fit Indices	Proposed Threshold Value	Results before Modification	Results After Modification	References
CFI	> 0.90	0.896	0.857	(35)
TLI	> 0.90	0.889	0.841	(35)
RMSEA	< 0.08	0.078	0.116	(35)
IFI	≥0.90	0.897	0.858	(35)
Chi-square/df	< 3.00	2.912	5.28	(35)

Note: CFI = Comparative Fit Index; TLI = Tucker–Lewis Index; RMSEA = Root Mean Square Error of Approximation; IFI = Incremental Fit Index; χ^2/df = Chi-square divided by degrees of freedom.

The discriminant validity results presented in Table 5 indicate that most constructs satisfy the Fornell–Larcker criterion, as the square root of the Average Variance Extracted (AVE) for each construct generally exceeds its correlations with other constructs. Specifically, Students' Competent Skills (√AVE = 0.893), Instructor Competency (√AVE = 0.831), Institutional Readiness (√AVE = 0.830), Instructional Curriculum Readiness (√AVE = 0.818) and AI Instructional Integration (√AVE = 0.816) demonstrate adequate discriminant separation in most pairwise comparisons. However, the correlation between Instructional Curriculum Readiness and Instructor Competency (r = 0.846) exceeds the square root of AVE for Instructional Curriculum Readiness [0.818] and the Maximum Shared Variance (MSV) for Instructor Competency [0.716] slightly exceeds its AVE [0.691], indicating substantial shared variance between these constructs.

To further assess discriminant validity beyond the Fornell–Larcker criterion, the Heterotrait–Monotrait (HTMT) ratio was examined. The HTMT value between Instructional Curriculum Readiness and Instructor Competency remained below the conservative threshold of 0.90, indicating that the constructs retain empirical distinctiveness despite their strong association. The elevated correlation is theoretically defensible, as structured curriculum preparedness directly supports instructional execution quality in technical domains such as fiber-optic networking. Given this conceptual proximity and acceptable HTMT results, both constructs were retained as separate yet related dimensions within the measurement model.

Despite this overlap, all constructs maintain high composite reliability and acceptable AVE values, suggesting that while certain constructs are strongly related, the overall measurement model retains acceptable discriminant validity for subsequent structural analysis. The substantial covariance between Institutional Readiness and Instructional Curriculum Readiness supports the conceptualization of readiness as a multi-dimensional organizational construct, which informed the subsequent higher-order modeling in the structural phase.

Table 5: Discriminant Validity Results

Variables	CR	AVE	MSV	ASV	ICF	IR	ICR	AI	SCS
ICF	0.957	0.691	0.716	0.483	0.831				
IR	0.947	0.689	0.669	0.477	0.700	0.830			
ICR	0.934	0.670	0.716	0.578	0.846	0.818	0.818		
AI	0.923	0.666	0.587	0.422	0.707	0.599	0.766	0.816	
SCS	0.973	0.798	0.389	0.299	0.475	0.624	0.583	0.491	0.893

Note: CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Variance; ASV = Average Shared Variance; ICF = Instructor Competency in Fiber-Optic Networks; IR = Institutional Readiness; ICR = Instructional Curriculum Readiness; AI = AI Instructional Integration; SCS = Students' Competent Skills in Fiber-Optic Networks.

Structural Model Analysis

The structural model was examined using Structural Equation Modeling (SEM) in AMOS to test the hypothesized relationships among the constructs. As shown in Figure 3 and summarized in Table 6, the relationship between Institutional Readiness (IR) and Instructional Curriculum Readiness (ICR) was statistically significant at the measurement level as shown in Table 5, indicating strong covariance between the two constructs (r = 0.818, $p < .001$). Given their high empirical association and conceptual alignment under organizational preparedness, IR and ICR were subsequently modeled as complementary dimensions of a higher-order Readiness construct in the final structural specification. Therefore, H1 is considered supported at the correlational level; however, it was not retained as a direct regression path in the final SEM model. The retained structural sequence reflects a theoretically parsimonious pathway in which Readiness predicts AI instructional integration, AI integration predicts Instructor Competency in Fiber-Optic Networks (ICFON) and Instructor Competency predicts Students' Competent Skills (SCS).

The initially specified structural model, derived from the proposed conceptual framework in Figure 1, included direct paths from Institutional Readiness (IR), Instructional Curriculum Readiness (ICR) and AI Instructional Integration (AI) to Instructor Competency (ICFON), as well as direct effects on Students' Competent Skills (SCS). This full structural model was first estimated to test all hypothesized relationships simultaneously. The results indicated that several direct paths (H2, H3, H6 and H7) were not statistically significant. Consistent with established SEM practice emphasizing theoretical coherence and model parsimony, non-significant paths were removed sequentially and the model was re-estimated. The resulting specification as discussed in Figure 4 demonstrated improved theoretical clarity and structural stability, revealing a sequential mechanism in which Readiness influences AI instructional integration, AI strengthens instructor competency and instructor competency directly predicts students' competent skills. This refinement does not alter the theoretical foundations of the study but rather clarifies the mechanism through which institutional and instructional readiness operate via AI integration to influence student competency outcomes.

The results indicate that AI Instructional Integration has a significant positive effect on Instructor Competency in Fiber-Optic Networks (β = 0.804, C.R. = 16.932, p < .001), supporting H4. Furthermore, Instructor Competency significantly predicts Students' Competent Skills in Fiber-Optic Networks (β = 1.000, C.R. = 8.809, p < 0.001), supporting H5. These findings confirm that instructor competency functions as a key explanatory mechanism in the model. The remaining direct paths hypothesized from Institutional Readiness and Instructional Curriculum Readiness to Instructor Competency (H2 and H3), as well as direct effects from Instructional Curriculum Readiness and AI Integration to Students' Competent Skills (H6 and H7), were not retained in the final structural model after re-specification, as indicated in Table 6. Instead, their influence operates indirectly through the retained structural sequence.

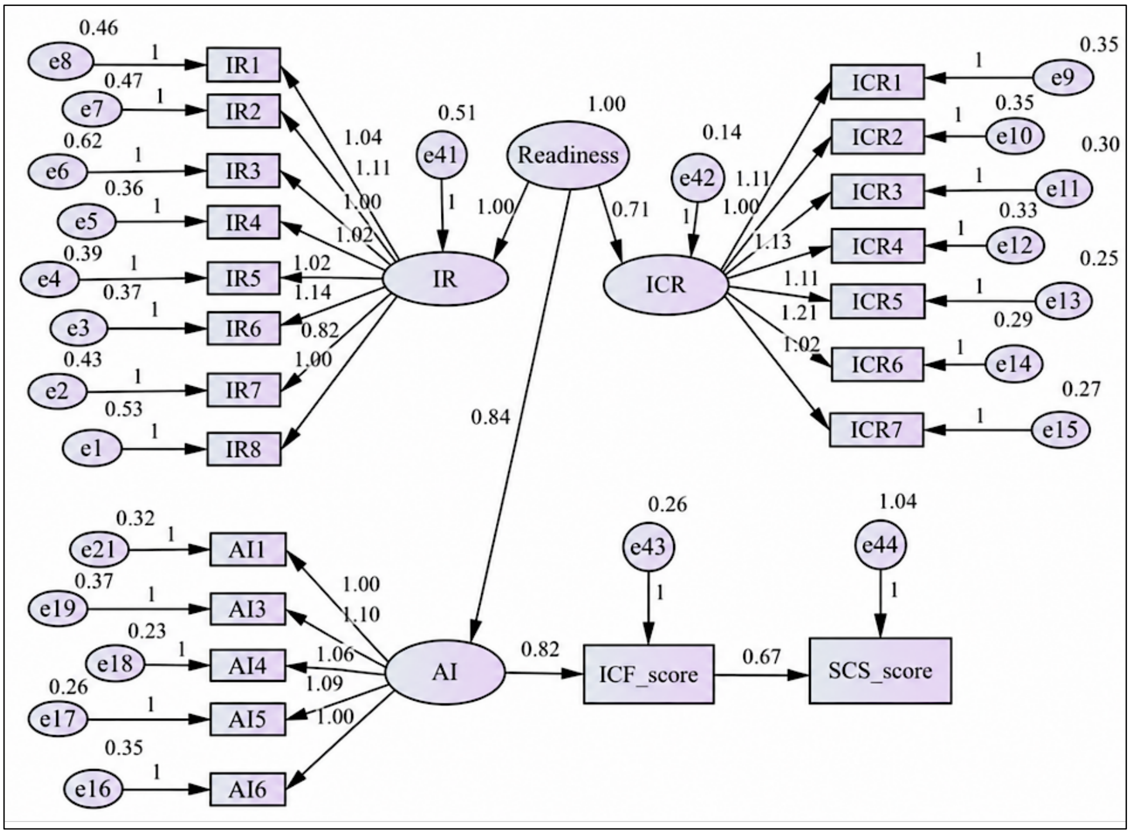

Figure 3: Structural Equation Modeling Results

Table 6: Structural Model Estimates

Hypothesis	Path	Standardized β	t-value (C.R.)	p-value	Result	Interpretation
H1	IR ↔ ICR	r = 0.818 (Table 5)	—	< 0.001	Supported (Correlation Level)	Strong covariance justified higher-order Readiness construct

H2	IR → ICFON	—	—	—	Not Supported	Effect absorbed into Readiness–AI pathway
H3	ICR → ICFON	—	—	—	Not Supported	Influence operates indirectly via AI integration
H4	AI → ICFON	0.804	16.932	< 0.001	Supported	Strong predictor of instructor competency
H5	ICFON → SCS	1.000	8.809	< 0.001	Supported	Competent instructors strongly influence student skills
H6	ICR → SCS	—	—	—	Not Supported	Only indirect through instructor competency
H7	AI → SCS	—	—	—	Not Supported	Fully mediated by instructor competency
H8	Mediation	Present	—	—	Supported	Sequential mediation confirmed

Note: β = Standardized Path Coefficient; C.R. = Critical Ratio; IR = Institutional Readiness; ICR = Instructional Curriculum Readiness; AI = AI Instructional Integration; ICFON = Instructor Competency in Fiber-Optic Networks; SCS = Students' Competent Skills in Fiber-Optic Networks.

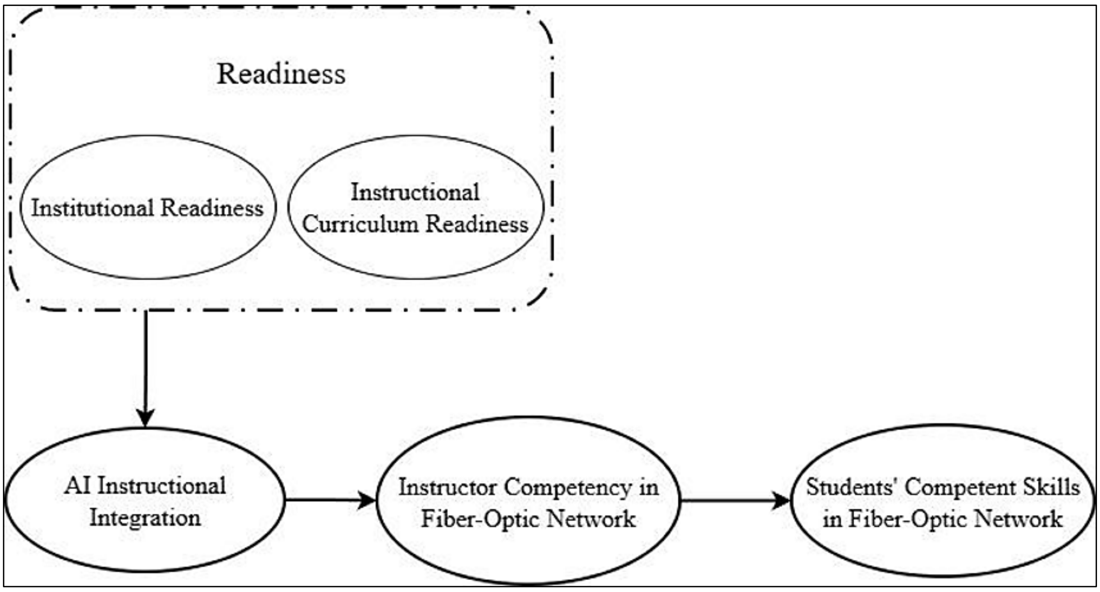

Figure 4: Final Structural Model

Discussion

This study sought to model the determinants of AI and fiber-optic technology integration in technology education curricula using a theory-driven SEM approach. We first validated the measurement model through CFA as shown in Figure 2; Table 3 and then tested the structural sequence linking Readiness → AI Integration → Instructor Competency (ICFON) → Students' Competent Skills (SCS) as illustrated in Figure 3 and Table 6. The multi-stage procedure (CFA → structural testing) allowed us to ensure that indicator reliability, convergent validity (AVE) and composite reliability (CR) were established prior to hypothesis testing as illustrated in Table 3. Given the relatively large sample used in this study, as presented in Table 1, the CFA estimates and CR/AVE statistics were stable and provide reasonable confidence that the observed measures faithfully represent the intended latent constructs. The results shown in Table 3 further support the reliability and validity of the measurement model and are consistent with established recommendations regarding sample size adequacy and SEM stability (37, 38).

The CFA findings show uniformly strong standardized factor loadings and high composite reliabilities (CR > 0.92), while the average variance extracted (AVE) exceeded the recommended threshold of 0.50 for all constructs. As presented in Table 3, these results indicate robust convergent validity for Institutional Readiness (IR), Instructional Curriculum Readiness (ICR), AI Integration (AI), Instructor Competency in Fiber-Optic Networks (ICFON) and Students' Competent Skills (SCS). These psychometric results are consistent with best practices in measurement for complex educational SEMs and align with recent large-sample studies that emphasize the importance of ensuring measurement quality before interpreting structural relations (20, 35, 39). Despite the generally strong measurement evidence, the overall fit indices revealed a mixed pattern. Table 4 shows that the baseline measurement model achieved acceptable RMSEA and χ^2/df values, whereas the incremental fit indices (CFI, TLI and IFI) were slightly below the commonly recommended cutoff value of 0.90. This pattern is not unusual in complex models with many indicators; simulation and applied work show that large models and larger samples can produce conservative incremental fit measures while RMSEA and χ^2/df remain informative (36). In practical terms, the combination of strong indicator loadings and high CR and AVE values justify proceeding with structural model testing while transparently acknowledging the observed fit limitations. The detailed model fit statistics are presented in Table 4 and the final measurement model is illustrated in Figure 2.

Discriminant validity was generally supported based on the Fornell–Larcker criterion. As presented in Table 5, most constructs demonstrated satisfactory discriminant validity; however, the relationship between Instructional Curriculum Readiness (ICR) and Instructor Competency in Fiber-Optic Networks (ICFON) exhibited relatively high shared variance ($r = 0.846$), which slightly exceeded the square root of the AVE for ICR (0.818). Given this empirical overlap and consistent with contemporary recommendations, we advocate the complementary use of HTMT (Heterotrait–Monotrait) and bootstrapped HTMT confidence intervals as a sensitivity check because HTMT often detects discriminant concerns that Fornell–Larcker can miss (40, 41). Several recent applied studies using SEM in educational technology have taken this combined approach (42, 43), advising researchers to interpret construct proximity in light of theory. As shown in Table 5, curriculum readiness and instructor competency are conceptually adjacent and may legitimately share variance; however, transparency about construct overlap and potential remedies remains essential for theoretical clarity.

Turning to the structural results, Figure 4 illustrates the final structural model, while Table 6 presents the corresponding path estimates. The retained model reveals a clear sequential mechanism in which Readiness (the higher-order configuration of IR and ICR) significantly predicts AI instructional integration. AI instructional integration, in turn, strongly predicts instructor competency ($\beta = 0.804$, C.R. = 16.932, $p < 0.001$), while instructor competency subsequently predicts students' competent skills ($\beta = 1.000$, C.R. = 8.809, $p < 0.001$), as shown in Table 6. These results support the mediating role of instructor competency in transmitting the effects of readiness and AI integration to learner outcomes (H8 supported), while direct paths from ICR or AI to students' skills were not retained in the final specification (H6 and H7 not supported directly; their influence is indirect via ICFON). This pattern mirrors findings in recent published work where instructor capacity mediates the relationship between institutional/technological inputs and student learning gains in technology-rich settings (31). Put differently, readiness and AI create enabling conditions, but actual student competencies materialize primarily when instructors possess the technical and pedagogical capability to operationalize those conditions. An important finding of this study is that neither instructional curriculum readiness nor AI instructional integration demonstrated a direct effect on students' competent skills in the final structural model. This result differs from several previous studies that reported direct positive relationships between technology-enhanced learning environments and student performance outcomes (9, 19, 33). A possible explanation is that the effectiveness of AI-supported instructional tools in highly technical domains such as fiber-optic networking depends substantially on how instructors translate technological resources into meaningful learning experiences. In contrast to more general educational settings, technical competency development often requires guided laboratory practice, troubleshooting activities and contextualized demonstrations that cannot be fully replaced by technology alone. Consequently, the present findings suggest that AI and curriculum readiness function primarily as enabling mechanisms whose effects are realized through instructor competency rather than through direct influence on student skills. This highlights the critical role of human expertise in maximizing the educational value of emerging technologies within technology-intensive curricula.

The theoretical and practical implications are multiple. First, the results reinforce readiness as an upstream systemic enabler. As shown in Table 6, investments in infrastructure, institutional policies and curricular preparedness create favorable conditions for AI instructional integration, providing conceptual support for H1. Second, AI instructional integration is pedagogically meaningful only when accompanied by instructor capacity building investments in AI tools should therefore be paired with targeted professional development and curriculum alignment to translate potential into practice (14, 44, 45). Third, the finding that instructor competency fully mediates the effects of AI and instructional readiness on student outcomes suggests policy priorities: funding and planning should allocate resources not only for technology acquisition but for instructor training and ongoing curricular redesign (46, 47). These recommendations are consistent with broader evidence in several studies showing that technology investments without parallel instructor supports yield limited learning improvements (48, 49).

Conclusion

This study developed and empirically tested a structural equation model to examine how institutional and instructional readiness influence AI instructional integration, instructor competency in fiber-optic network instruction and ultimately students' competent skills within a technology education curriculum. Following a rigorous two-stage SEM procedure, the measurement model was first validated using the results, followed by structural model testing using the model and the path estimates. The findings confirm that readiness operates as a foundational enabler that supports AI instructional integration, which in turn significantly strengthens instructor competency. Instructor competency emerged as the strongest direct predictor of students' competent skills, serving as the primary transmission mechanism linking institutional conditions and AI practices to learner outcomes. The measurement model demonstrated strong convergent validity and internal consistency, with high composite reliability and AVE values across all constructs. Although the incremental fit indices were marginal in certain stages, the results indicate that the factor loadings, reliability statistics and acceptable RMSEA and χ^2/df values supported the adequacy of the measurement structure. Discriminant validity was largely satisfactory. The substantial association between instructional curriculum readiness and instructor competency suggests a close conceptual alignment between these domains. This empirical proximity reinforces the systemic nature of instructional preparedness and instructional performance in technology-based curricula.

Structurally, the final model supports a sequential pathway in which Readiness influences AI Integration, AI Integration enhances Instructor Competency and Instructor Competency subsequently improves Students' Competent Skills. Direct paths from readiness and AI integration to student skills were not retained, indicating that technological and institutional inputs influence learner outcomes primarily through instructor capability. This finding underscores the central role of instructor competency in translating institutional investments and AI-enabled tools into measurable student technical performance. The study therefore contributes a refined empirical framework that positions instructor competency as the critical mediator in AI-supported technology education environments. Practically, the results suggest that institutions aiming to integrate AI into technical curricula should adopt a capacity-centered strategy. Investments in infrastructure and AI technologies must be accompanied by structured curriculum alignment and instructor professional development to produce meaningful student skill acquisition. Without strengthening instructional capacity, technological enhancements alone may not directly yield improvements in learner competency. The study thus provides actionable guidance for policymakers, curriculum designers and academic leaders seeking to operationalize AI within technology education programs.

Limitations

Notwithstanding its contributions, this study has several limitations that should be considered when interpreting the findings. First, the study relied exclusively on self-reported student perceptions, which may be influenced by social desirability bias, perceptual bias and inaccuracies associated with self-assessment. Respondents may unintentionally overestimate or underestimate their competencies, perceptions of instructional effectiveness, or evaluations of institutional readiness and AI integration practices. Furthermore, the use of a single-source survey instrument may increase the possibility of common method variance. Second, the cross-sectional design captures perceptions at a single point in time, limiting the ability to establish causal relationships among the constructs. Third, the study was conducted within a single Philippine state university, which may limit the generalizability of the findings to other institutional, disciplinary, or national contexts. Despite these limitations, the study provides valuable insights into the readiness-driven mechanisms through which AI-supported instruction and instructor competency contribute to competency development in technology education and offers a foundation for future research in this emerging field.

Future Work

Future research should extend this model in several directions. First, longitudinal designs are recommended to validate the temporal stability of the sequential relationships identified in this study and to strengthen causal inference. Second, multi-group SEM could examine whether the structural relationships differ across program specializations (e.g., computer science, information technology, engineering technology), year levels, or institutional types. Such analysis would clarify whether readiness and AI integration function uniformly across contexts or vary by disciplinary emphasis.

Third, future studies should incorporate objective performance indicators such as laboratory assessments, certification outcomes, project-based evaluations and instructor assessments to complement self-reported measures of student competency. The inclusion of multiple data sources would help mitigate potential social desirability bias, perceptual bias and self-assessment inaccuracies while providing a more comprehensive evaluation of competency development. This would enhance construct robustness and reduce potential common method bias. Fourth, bootstrapped mediation analysis with confidence intervals should be conducted to quantify indirect effects more precisely and to provide stronger statistical evidence for the mediating role of instructor competency.

Finally, given the rapid evolution of AI technologies, future models may include additional constructs such as AI self-efficacy, perceived pedagogical usefulness, institutional innovation climate, or digital governance policies. Expanding the framework to cross-institutional or cross-national samples would further strengthen generalizability and allow comparative insights into how readiness and AI integration shape technology education curricula globally. Together, these extensions would build upon the present study's validated framework and contribute to a more comprehensive understanding of AI-driven transformation in technical education.

Abbreviations

AI: Artificial Intelligence, CFA: Confirmatory Factor Analysis, ICFCON: Instructor Competency in Fiber-Optic Network, ICR: Instructional Curriculum Readiness, IR: Institutional Readiness, RBV: Resource-Based View, SCS: Students' Competent Skills in Fiber-Optic Networks, SEM: Structural Equation Modeling, TPACK: Technological-Pedagogical-Content Knowledge.

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Author Contributions

Franklin M Ganancias: Conceptualization, Analysis, Methodology, Writing – Review Editing, Jehu Roeh C Rubenial: Validation, Formal analysis, Fae Mylene M Etchon: Data Curation, Writing - Original Draft Preparation, Sharon A Bucalon: Resources, Analysis, Writing – Review Editing, Lyndon A Rosas: Visualization, Writing – Review Editing.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

Declaration of Artificial Intelligence (AI) Assistance

The authors acknowledge the use of ChatGPT and Grammarly to support the editing process by improving grammar, spelling, sentence structure and overall readability. All scholarly contributions, including the study design, data analysis, interpretation and conclusions, were independently developed by the authors. The authors remain fully accountable for the content presented in this manuscript.

Ethics Approval

This research was conducted with the permission of the Campus Director of North Eastern Mindanao State University, as evidenced by the approved permission letter (Reference No. RD-2026-004) dated January 12, 2026. All participants were provided with informed consent prior to their participation in the study and participation was entirely voluntary. The study was conducted in accordance with institutional ethical guidelines and data privacy requirements.

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