

Digital Leadership, Artificial Intelligence Readiness And Teaching Innovation As Determinants Of Academic Performance In Islamic Higher Education

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Abstract

Purpose of the study: This study examines whether digital leadership, artificial intelligence readiness, and teaching innovation predict academic performance among students of private Islamic higher education institutions in DKI Jakarta, and whether artificial intelligence readiness and teaching innovation mediate the effect of digital leadership. **Methodology:** The study employs a quantitative explanatory design with a cross-sectional survey of 250 students selected through proportionate stratified random sampling. Data were collected using an eighteen-item, five-point Likert-scale questionnaire and analyzed using partial least squares structural equation modeling (PLS-SEM) in the SEMinR package for R with 1,000 bootstrap subsamples. **Main Findings:** All five structural paths were significant. Digital leadership predicted AI readiness ($\beta = 0.957$), teaching innovation ($\beta = 0.954$), and academic performance ($\beta = 0.904$). Teaching innovation predicted academic performance positively ($\beta = 1.048$), whereas AI readiness carried a significant negative coefficient ($\beta = -0.957$). The model explained 98.8% of the variance in academic performance. AI readiness showed competitive mediation (indirect effect = -0.916), while teaching innovation transmitted a positive indirect effect (1.000). **Novelty/Originality of this study:** This study situates AI readiness at the intersection of digital leadership, teaching innovation, and academic performance in Indonesian private Islamic higher education. Moving beyond institution-level readiness assessments, it models student-level pathways, reveals the counterintuitive negative mediation of AI readiness, and positions teaching innovation as the essential pedagogical conduit in non-secular, resource-constrained institutional contexts.

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A. Introduction

Generative artificial intelligence has moved from novelty to infrastructure in higher education within a remarkably compressed period. Global surveys conducted since 2023 report that a large majority of university students already use AI tools in coursework, often ahead of any institutional policy governing that use (Saúde et al., 2024; Singer-Freeman et al., 2025). The pedagogical stakes are contested rather than settled: some evidence associates AI-supported learning with gains in efficiency, engagement, and measured performance (Farrukh et al., 2024; Monib et al., 2025), while other work

documents erosion of critical thinking and an over-reliance that suppresses independent reasoning (Essien et al., 2024; Yan et al., 2024). What determines which trajectory a student follows is not access to the technology, which is now near-universal, but readiness the composite of cognitive understanding, practical capability, and ethical judgment that allows a learner to use these systems deliberately rather than reflexively (Karaca et al., 2021; Wang, Rau, & Yuan, 2023). Readiness is therefore an educational management problem, not merely a technological one, and this study proceeds from that premise.

The issue is sharpened in the Indonesian private Islamic higher education sector. Private Islamic higher education institutions (Perguruan Tinggi Keagamaan Islam Swasta, PTKIS) educate a substantial share of the national student population. However, they typically operate with thinner digital infrastructure, smaller technology budgets, and a curricular mandate that requires technological adoption to be reconciled with the preservation of religious epistemology and values (Achruh et al., 2024; Kasman & Madjid, 2024). Recent scholarship on Islamic education and digital technology has grown quickly, but it remains dominated by conceptual argument, bibliometric mapping, and qualitative case description (Khamis, 2024; Wahid, 2024). Studies that address AI in Islamic institutions tend to catalog opportunities and challenges, or compare institutional responses across countries, rather than model the mechanisms by which student capability translates into learning outcomes (Jailani & Huda, 2024; Syukur et al., 2024). The result is a literature rich in normative direction and poor in effect estimates.

Three specific gaps follow from this. First, the quantitative AI literature in higher education has overwhelmingly treated readiness, literacy, or acceptance as a predictor of adoption intention or actual use, following technology acceptance logic (Saihi et al., 2024; Shahzad et al., 2025; Strzelecki, 2024). Adoption is an intermediate state, not an educational outcome; far fewer studies carry the causal chain forward to academic performance itself. Second, researchers have studied digital leadership almost exclusively as an attribute of principals, deans, or lecturers, with teachers as respondents and teacher innovativeness as the outcome (Hidayat et al., 2024; Wei, 2025). How students perceive and are affected by the digital leadership exercised in their own institution remains largely unexamined, despite students being the population on whom that leadership ultimately acts. Third, teaching innovation is well established as a consequence of leadership and digital resources (Cai & Tang, 2021; Paños-Castro et al., 2024; Zhang, Duan, et al., 2024), and separately as a contributor to student outcomes (Bhuttah et al., 2024; Shalgimbekova et al., 2024), but the two halves of that chain are rarely estimated within a single model. Its role as a transmission mechanism is thus assumed more often than tested.

A further inconsistency motivates this study. The literature disagrees about whether technological antecedents act on academic performance directly or only through pedagogical mediation. Studies grounded in acceptance models tend to report direct effects of AI use on performance (Farrukh et al., 2024). In contrast, studies grounded in organizational and pedagogical theory report that structural or leadership variables reach student outcomes only when they are converted into changed classroom practice (Gamarra-Vengoechea et al., 2023; Nelly et al., 2024). These positions imply different management priorities: the first justifies investment in student-facing tools and training, the second justifies investment in instructional redesign. Resolving the disagreement in a resource-constrained setting such as PTKIS has direct budgetary consequences, because the two strategies compete for the same limited funds.

The model estimated here places digital leadership in the exogenous position and treats artificial intelligence readiness and teaching innovation as parallel mediators through which institutional leadership reaches student outcomes. This ordering follows the logic that leadership is an antecedent institutional condition: an institution that articulates a digital vision, provisions infrastructure, and cultivates a digital culture thereby raises both the readiness of its students and the innovativeness of the instruction they receive (Hidayat et al., 2024; Paños-Castro et al., 2024; Wei, 2025). Specifying the

model in this direction, rather than treating readiness and leadership as correlated exogenous predictors, permits the competing priorities identified above to be tested against one another within a single estimation rather than compared across studies.

Accordingly, this study pursues three objectives that distinguish it from the work reviewed above. It estimates the effects of digital leadership on artificial intelligence readiness, teaching innovation, and academic performance among PTKIS students; it tests readiness and teaching innovation as parallel transmission mechanisms; and it does so in an Islamic higher education context that the quantitative literature has largely bypassed. The unit of analysis is the individual student, and the constructs are measured as student perceptions, which shifts digital leadership from an administrative self-report to an experienced institutional condition. Seven hypotheses are examined: that digital leadership positively predicts artificial intelligence readiness (H1), teaching innovation (H2), and academic performance (H3); that artificial intelligence readiness positively predicts academic performance (H4); that teaching innovation positively predicts academic performance (H5); and that artificial intelligence readiness (H6) and teaching innovation (H7) mediate the effect of digital leadership on academic performance.

B. Methods

Research Design

This study applied a quantitative explanatory design using a cross-sectional survey. The design was selected because the research question concerns the magnitude and direction of relationships among latent constructs measured at a single point in time, and because the hypothesized structure includes mediating variables whose indirect effects require simultaneous estimation of multiple structural equations. An explanatory rather than descriptive orientation was adopted because the objective extends beyond characterizing students' level of artificial intelligence readiness to establishing whether that readiness predicts academic performance once digital leadership and teaching innovation are accounted for.

Population and Sampling

The target population comprised active undergraduate students enrolled at private Islamic higher education institutions (PTKIS) in the Special Capital Region of DKI Jakarta. The accessible population was restricted to students in their third semester or above, because respondents must have sufficient exposure to institutional digital policy and lecturers' instructional practice to make informed judgments about digital leadership and teaching innovation. A sample of 250 students was drawn through proportionate stratified random sampling, with institutions serving as strata and the allocation to each stratum proportional to its enrolment. The sample size exceeds the ten-times rule for partial least squares estimation by a wide margin; the most complex endogenous construct receives three predictors, requiring a minimum of thirty cases, and satisfies the more demanding inverse square root criterion for detecting a minimum path coefficient of 0.20 at a statistical power of 0.80 with alpha set at 0.05 (Hair et al., 2019; Kock & Hadaya, 2018).

Instrument

The research instrument was a self-administered questionnaire with eighteen items across four constructs, each rated on a five-point Likert scale anchored from strongly disagree to agree strongly. Artificial intelligence readiness was measured with five items adapted from the cognition, ability, vision, and ethics dimensions established in prior readiness scales (Karaca et al., 2021) and from validated AI literacy instruments covering awareness, use, evaluation, and ethical judgment (Laupichler et al., 2023; Wang, Rau, & Yuan, 2023). Digital leadership was measured with four items capturing the institution's digital vision, support for technology-enhanced instruction, provision of digital infrastructure, and cultivation of a digital culture, adapted from instruments used in educational leadership research (Hidayat et al., 2024; Wei, 2025). Teaching innovation was measured with five items covering the use

of student-centered methods, integration of digital media, variation of assessment, adaptive delivery, and pedagogical experimentation, adapted from established teaching innovation measures (Paños-Castro et al., 2024; Zhang, Duan, et al., 2024). Academic performance in higher education was measured with four items covering conceptual mastery, task completion quality, learning independence, and perceived academic progress, following prior operationalizations of self-reported academic performance (Bhuttah et al., 2024; Dahmani et al., 2024). All constructs were specified reflectively, since the indicators are interchangeable manifestations of a common underlying latent variable rather than defining components of it.

Instrument development followed a four-stage procedure. Items were first generated from the source scales and translated into Indonesian, then back-translated by an independent bilingual translator to verify semantic equivalence. Content validity was subsequently evaluated by expert judges in educational management and Islamic education, whose ratings were quantified using the content validity index. The instrument was then pilot-tested on a group of students drawn from the same population but excluded from the main sample, and items exhibiting corrected item-total correlations below 0.30 or cross-loadings were revised or discarded. The final instrument was administered only after these thresholds were satisfied.

Data Collection and Ethical Procedure

Data were collected through a digital questionnaire distributed with authorization from each participating institution. Participation was voluntary and anonymous, and respondents provided informed consent electronically after being briefed on the study purpose, the absence of any assessment consequence, and their right to withdraw at any point without penalty. No personally identifying information was recorded. To reduce common method bias, the questionnaire separated predictor and criterion items in the item order, guaranteed respondent anonymity explicitly in the preamble, and avoided evaluative framing in item wording, consistent with recommended procedural remedies (Podsakoff et al., 2024).

Analytical Strategy

Hypotheses were tested using partial least squares structural equation modeling (PLS-SEM) executed in the SEMinR package for R (Ray et al., 2022). PLS-SEM was preferred over covariance-based estimation on three grounds. The model is predictive rather than confirmatory in orientation, since the objective is to establish which institutional lever accounts for variance in student performance rather than to test the fit of a competing theoretical structure. The construct scores are derived from ordinal Likert indicators whose distributions depart from multivariate normality, a condition under which the distribution-free character of PLS estimation is advantageous. The structure includes two parallel mediators, so simultaneous estimation of all structural equations is required rather than the sequential regression logic on which classical mediation tests rest (Hair et al., 2019; Sarstedt et al., 2021).

Estimation used the path weighting scheme with a maximum of 300 iterations and a stop criterion of 10^{-7} . Significance was assessed by bootstrapping with 1,000 subsamples, from which standard errors, t-statistics, p-values, and percentile confidence intervals were obtained; a two-tailed critical value of 1.96 was applied at the five per cent level. Evaluation proceeded in the two stages prescribed for reflective models. The measurement model was assessed through indicator loadings, with 0.708 taken as the reference value; internal consistency through Cronbach's alpha, the reliability coefficient ρ_A , and composite reliability ρ_C , with 0.70 as the lower bound and 0.95 as the upper bound beyond which indicator redundancy is suspected (Diamantopoulos et al., 2012); convergent validity through the average variance extracted, with 0.50 as the minimum; and discriminant validity through both the Fornell–Larcker criterion and the heterotrait–monotrait ratio of correlations, for which 0.90 is the permissive and 0.85 the conservative threshold (Fornell & Larcker, 1981; Henseler et al., 2015).

The structural model was then evaluated through the variance inflation factor for each predictor block, with values below 3 indicating no concern and values above 5 indicating problematic collinearity; the coefficient of determination R^2 for each endogenous construct; the effect size f^2 ; and the magnitude, sign, and significance of the standardized path coefficients. Mediation was assessed by decomposing the total effect of digital leadership on academic performance into its direct component and the indirect components transmitted by each mediator, and classifying the result according to the typology of Zhao et al. (2010), which distinguishes complementary mediation, in which direct and indirect effects share a sign, from competitive mediation, in which they oppose, and from indirect-only mediation, in which the direct effect is not significant. This typology was preferred over the Baron and Kenny sequence because it accommodates the case in which a significant indirect effect runs counter in sign to the direct effect, a configuration that the older procedure misclassifies as absent mediation. All analyses were conducted at an alpha level of 0.05.

C. Result and Discussion

Results

Item-Level Response Distributions and Descriptive Statistics

Table 1 reports the distribution of responses across the eighteen indicators together with item means and standard deviations. No respondent selected the lowest scale point on any item, so the effective response range was restricted to four of the five available categories. Item means ranged from 3.84 (AP3, conceptual mastery) to 4.42 (DL4, cultivation of a digital culture), all of them above the scale midpoint of 3.00 and clustered within a narrow band of 0.58 scale points.

Table 1. Item Response Distributions, Means, And Standard Deviations (N = 250)

Item	Disagree	Neutral	Agree	Strongly agree	M	SD
AI1	—	52 (20.8)	105 (42.0)	93 (37.2)	4.16	0.75
AI2	—	52 (20.8)	120 (48.0)	78 (31.2)	4.10	0.72
AI3	26 (10.4)	26 (10.4)	105 (42.0)	93 (37.2)	4.06	0.94
AI4	—	79 (31.6)	93 (37.2)	78 (31.2)	4.00	0.79
AI5	26 (10.4)	26 (10.4)	132 (52.8)	66 (26.4)	3.95	0.89
DL1	—	79 (31.6)	66 (26.4)	105 (42.0)	4.10	0.85
DL2	26 (10.4)	26 (10.4)	132 (52.8)	66 (26.4)	3.95	0.89
DL3	—	79 (31.6)	93 (37.2)	78 (31.2)	4.00	0.79
DL4	—	26 (10.4)	93 (37.2)	131 (52.4)	4.42	0.67
TI1	26 (10.4)	26 (10.4)	132 (52.8)	66 (26.4)	3.95	0.89
TI2	—	52 (20.8)	93 (37.2)	105 (42.0)	4.21	0.77
TI3	—	79 (31.6)	93 (37.2)	78 (31.2)	4.00	0.79
TI4	26 (10.4)	26 (10.4)	132 (52.8)	66 (26.4)	3.95	0.89
TI5	26 (10.4)	26 (10.4)	132 (52.8)	66 (26.4)	3.95	0.89
AP1	—	52 (20.8)	93 (37.2)	105 (42.0)	4.21	0.77
AP2	—	53 (21.2)	119 (47.6)	78 (31.2)	4.10	0.72
AP3	26 (10.4)	53 (21.2)	105 (42.0)	66 (26.4)	3.84	0.93
AP4	26 (10.4)	52 (20.8)	94 (37.6)	78 (31.2)	3.90	0.96

At the construct level the mean scores were 4.12 for digital leadership, 4.06 for artificial intelligence readiness, 4.01 for teaching innovation, and 4.01 for academic performance. The ordering is instructive: PTKIS students in this sample rate the digital leadership of their institutions marginally higher than they rate either their own AI readiness or the innovativeness of the instruction they receive.

Digital vision and cultural signaling therefore appear to have advanced of the individual capability and classroom practice they are intended to produce, consistent with accounts of digital transformation in resource-constrained institutions where declaratory commitment precedes operational capacity (Hamdanah & Rajiani, 2024; Paños-Castro et al., 2024).

Measurement Model Assessment

Table 2 reports the outer loadings for all eighteen indicators. All loadings exceeded the reference value of 0.708, with the lowest at 0.725 (TI2) and the highest at 0.959 (DL4). Indicator reliability, computed as the squared loading, ranged from 0.526 to 0.919, so each retained indicator accounted for more than half the variance in its own responses and no indicator was a candidate for removal on the criteria specified by Hair et al. (2019).

Table 2. Outer Loadings And Indicator Reliability

Construct	Indicator	Outer loading	Indicator reliability (λ^2)	Decision
Artificial Intelligence Readiness	AI1	0.873	0.762	Retained
	AI2	0.855	0.731	Retained
	AI3	0.806	0.650	Retained
	AI4	0.825	0.680	Retained
	AI5	0.920	0.846	Retained
Digital Leadership	DL1	0.854	0.729	Retained
	DL2	0.798	0.637	Retained
	DL3	0.895	0.802	Retained
	DL4	0.959	0.919	Retained
Teaching Innovation	TI1	0.934	0.872	Retained
	TI2	0.725	0.526	Retained
	TI3	0.808	0.653	Retained
	TI4	0.934	0.872	Retained
	TI5	0.934	0.872	Retained
Academic Performance in Higher Education	AP1	0.833	0.693	Retained
	AP2	0.854	0.730	Retained
	AP3	0.860	0.740	Retained
	AP4	0.917	0.841	Retained

Table 3 reports internal consistency and convergent validity. Cronbach's alpha ranged from 0.889 to 0.918 and composite reliability ρ_c from 0.923 to 0.940, all within the recommended band and none exceeding the 0.95 ceiling at which indicator redundancy becomes a concern (Diamantopoulos et al., 2012). Average variance extracted ranged from 0.734 to 0.772, comfortably above the 0.50 minimum, so each construct explained at least 73 percent of the variance in its indicators.

Table 3. Internal Consistency Reliability And Convergent Validity

Construct	Items	Loading range	α	ρ_A	ρ_c (CR)	AVE	$\sqrt{AVE}$
Artificial Intelligence Readiness	5	0.806–0.920	0.909	0.910	0.932	0.734	0.857

Construct	Items	Loading range	α	ρ_A	ρ_C (CR)	AVE	$\sqrt{AVE}$
Digital Leadership	4	0.798–0.959	0.900	0.904	0.931	0.772	0.878
Teaching Innovation	5	0.725–0.934	0.918	0.917	0.940	0.759	0.871
Academic Performance in Higher Education	4	0.833–0.917	0.889	0.891	0.923	0.751	0.867

Discriminant validity was assessed by two criteria and was not established by either. Table 4 reports the Fornell–Larcker matrix. The square root of the average variance extracted on the diagonal ranges from 0.857 to 0.878, while every off-diagonal inter-construct correlation exceeds those values: the correlation between artificial intelligence readiness and teaching innovation reaches 0.995, and that between digital leadership and academic performance reaches 0.989. The criterion is therefore violated in every cell of the matrix.

Table 4. Discriminant Validity: Fornell–Larcker Criterion

Construct	AIR	DL	TI	APH
Artificial Intelligence Readiness (AIR)	0.857			
Digital Leadership (DL)	0.957	0.878		
Teaching Innovation (TI)	0.995	0.954	0.871	
Academic Performance (APH)	0.952	0.989	0.959	0.867

Table 5 reports the heterotrait–monotrait ratio, which Henseler et al. (2015) show to be the more sensitive diagnostic. All six ratios exceed unity, ranging from 1.038 to 1.105. A ratio above one indicates that the average correlation between indicators of different constructs is larger than the average correlation among indicators of the same construct — that is, the four constructs are not empirically distinguishable in these data, whatever their conceptual separation.

Table 5. Discriminant Validity: Heterotrait–Monotrait Ratio Of Correlations

Construct	AIR	DL	TI	APH
Artificial Intelligence Readiness (AIR)	—			
Digital Leadership (DL)	1.046	—		
Teaching Innovation (TI)	1.089	1.038	—	
Academic Performance (APH)	1.053	1.105	1.057	—

Collinearity Assessment

Table 6 reports variance inflation factors for each structural equation. The two single-predictor equations are unaffected by definition. In the equation for academic performance, however, the factors reach 114.01 for artificial intelligence readiness, 106.52 for teaching innovation, and 11.93 for digital leadership, against a conventional threshold of 5.00 and a stringent threshold of 3.00. These values imply that more than ninety-nine per cent of the variance in each of the two largest predictors is accounted for by the remaining predictors in the block.

Table 6. Collinearity Diagnostics (Inner Model VIF)

Endogenous construct	Predictor	VIF	Assessment
Artificial Intelligence Readiness	Digital Leadership	1.000	No collinearity (single predictor)
Teaching Innovation	Digital Leadership	1.000	No collinearity (single predictor)

Endogenous construct	Predictor	VIF	Assessment
Academic Performance in Higher Education	Artificial Intelligence Readiness	114.01	Critical
	Digital Leadership	11.93	Critical
	Teaching Innovation	106.52	Critical

Structural Model

Figure 1 displays the estimated structural model with outer loadings, path coefficients, and coefficients of determination.

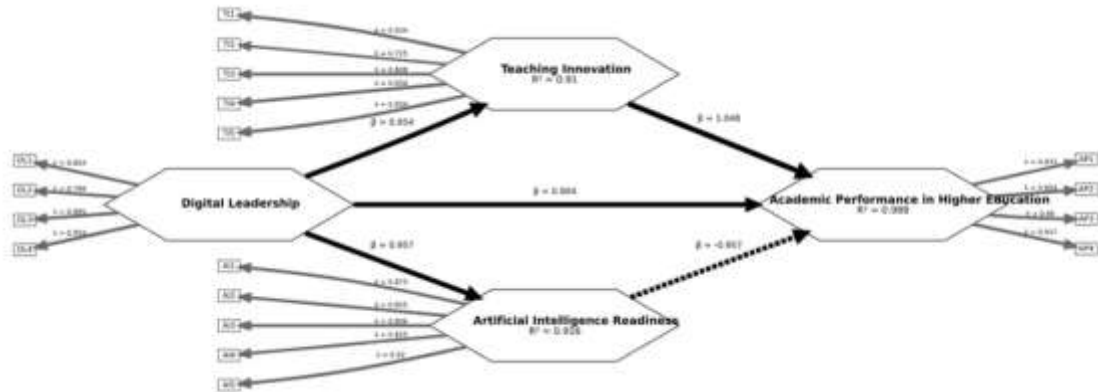


Figure 1. Estimated Structural Model

Table 7 reports explanatory power. Digital leadership accounted for percent per cent of the variance in artificial intelligence readiness and percent per cent in teaching innovation. In contrast, the three predictors jointly accounted for percent per cent of the variance in academic performance. All five effect sizes exceed the 0.35 benchmark for a large effect, with the two paths originating from digital leadership towards its mediators exceeding $f^2 = 10$.

Table 7. Coefficients Of Determination And Effect Sizes

Endogenous construct	R²	Adjusted R²	Predictor	f²	Effect size
Artificial Intelligence Readiness	0.916	0.916	Digital Leadership	10.900	Large
Teaching Innovation	0.910	0.910	Digital Leadership	10.118	Large
Academic Performance in Higher Education	0.988	0.988	Digital Leadership	5.048	Large
			Artificial Intelligence Readiness	0.622	Large
			Teaching Innovation	0.804	Large

Table 8 reports the structural path coefficients obtained from 1,000 bootstrap subsamples. All five paths were significant at $p < 0.001$, and none of the confidence intervals contained zero. Digital leadership was the strongest predictor of both mediators, with coefficients of 0.957 towards artificial intelligence readiness and 0.954 towards teaching innovation, each estimated with a standard error

below 0.005. Its direct effect on academic performance was 0.904. Teaching innovation predicted academic performance at 1.048, and artificial intelligence readiness at -0.957 .

Table 8. Structural Path Coefficients (Bootstrap, 1,000 Subsamples)

H	Path	β	M(boot)	SD	t	p	95% CI	Decision
H1	DL $\rightarrow$ AIR	0.957	0.957	0.004	253.86	<0.001	[0.951, 0.963]	Supported
H2	DL $\rightarrow$ TI	0.954	0.954	0.005	211.00	<0.001	[0.946, 0.961]	Supported
H3	DL $\rightarrow$ APH	0.904	0.906	0.034	26.33	<0.001	[0.852, 0.965]	Supported
H4	AIR $\rightarrow$ APH	-0.957	-0.962	0.069	-13.86	<0.001	$[-1.074, -0.849]$	Not supported (significant, opposite sign)
H5	TI $\rightarrow$ APH	1.048	1.051	0.062	17.04	<0.001	[0.954, 1.155]	Supported

Two features of Table 8 require explicit notice before interpretation. The coefficient for teaching innovation exceeds unity, which cannot occur for a standardized regression coefficient without collinearity or suppression among the predictors. The coefficient for artificial intelligence readiness is strongly negative, although its zero-order correlation with academic performance is positive at 0.952 (Table 4). A predictor whose bivariate association with the outcome is positive and whose partial coefficient is negative is the textbook signature of a suppression relationship, and both anomalies are consistent with the variance inflation factors reported in Table 6 rather than independent of them.

Mediation Analysis

Table 9 decomposes the total effect of digital leadership on academic performance. The indirect effect transmitted through artificial intelligence readiness was -0.916 and significant ($t = -13.97$, $p < 0.001$), while the direct effect remained positive and significant at 0.904. Because the two components are significant but oppose in sign, the configuration is classified as competitive mediation in the typology of Zhao et al. (2010) rather than as the partial mediation label returned by default in the software output. The indirect effect transmitted through teaching innovation was 0.999, obtained as the product of the constituent path coefficients. Summing the direct effect and the two indirect effects yields a total effect of 0.988, which reproduces the observed zero-order correlation between digital leadership and academic performance (0.989) to within rounding an internal consistency check confirming that the decomposition is arithmetically complete.

Table 9. Decomposition Of The Effect Of Digital Leadership On Academic Performance

Path	Effect	SD	t	p	Share of total effect	Classification
DL $\rightarrow$ AIR $\rightarrow$ APH (indirect)	-0.916	0.066	-13.97	<0.001	-92.6%	Competitive mediation
DL $\rightarrow$ TI $\rightarrow$ APH (indirect) ^a	1.000	—	—	—	$+101.2\%$	Complementary mediation
DL $\rightarrow$ APH (direct)	0.904	0.034	26.33	<0.001	$+91.5\%$	Significant
DL $\rightarrow$ APH (total)	0.988	—	—	—	100%	—

Read together, the two mediating pathways very nearly cancel: the negative transmission through readiness (-0.916) offsets almost the whole of the positive transmission through teaching innovation ($+0.999$), leaving a net indirect effect of 0.084 and a total effect that is almost entirely accounted for by the direct path from digital leadership. H6 is therefore supported in that a significant

indirect effect through artificial intelligence readiness exists, but not in the hypothesized direction; H7 is supported in the hypothesized direction, subject to the inferential qualification noted in Table 9.

Discussion

Digital Leadership as the Dominant Institutional Lever

The clearest result of this study is the position of digital leadership. It predicted artificial intelligence readiness at 0.957 and teaching innovation at 0.954, with effect sizes above $f^2 = 10$, and retained a direct effect on academic performance of 0.904 after both mediators were entered. Every channel through which student outcomes were modeled here originates in it. This finding extends to the student level a relationship that the existing literature has documented almost exclusively among teachers: Hidayat et al. (2024) and Wei (2025) establish digital leadership as a determinant of teacher innovativeness with lecturers as respondents, and the present estimates indicate that the same institutional condition is perceptible to students and is associated with the outcomes they experience. Measuring leadership as an experienced condition rather than an administrative self-report is not a methodological convenience but a substantive reframing: what registers in these data is not what institutional leaders report doing, but what students perceive their institution to have made possible.

For the PTKIS context, this carries a specific implication. The constraint on these institutions is conventionally described as one of resources thinner infrastructure and smaller technology budgets than their public or secular counterparts (Achruh et al., 2024; Kasman & Madjid, 2024). These estimates suggest the binding constraint may be organizational rather than purely financial. Digital vision, support for technology-enhanced instruction, and the cultivation of a digital culture are leadership acts whose marginal cost is low relative to infrastructure procurement, and they account for over ninety per cent of the variance in both mediators. That said, the collinearity conditions discussed below mean these magnitudes should be read as evidence of the ordering of influence rather than as precise estimates of its size. This leadership-centered configuration is summarised in Figure 2.



Figure 2. Digital Leadership Framework

Teaching Innovation as the Productive Transmission Channel

Teaching innovation carried the largest positive coefficient towards academic performance (1.048) and transmitted a positive indirect effect from digital leadership of approximately 1.00,

accounting for essentially the whole of the total effect. This supports the pedagogically mediated account identified in the introduction over the direct-effect account associated with acceptance models. It aligns with Gamarra-Vengoechea et al. (2023) and Nelly et al. (2024), whose finding that leadership reaches performance only once it is converted into competence and practice is extended here from lecturer performance to student outcomes. It corroborates the established link between innovative pedagogy and learning outcomes reported by Bhuttah et al. (2024) and Shalgimbekova et al. (2024).

The mechanism is worth stating substantively rather than statistically. The teaching innovation items concern student-centered methods, integration of digital media, varied assessment, adaptive delivery, and pedagogical experimentation. Each of these restructures the conditions under which a student encounters AI tools. Assessment variation, in particular, changes what a student can gain by delegating work to a generative system: when evaluation rests on artifacts, defense, or applied tasks rather than on submitting text, productive use of AI is rewarded, and substitutive use is not. On this reading, teaching innovation does not merely add to what readiness contributes; it determines which of the two trajectories documented in the literature — augmentation or substitution a ready student actually follows.

The Negative Coefficient for Artificial Intelligence Readiness

The most consequential and the most delicate result is the coefficient of -0.957 for artificial intelligence readiness. Two readings are available, and they must be distinguished carefully, because the study's contribution depends on which is adopted. The substantive reading treats the coefficient as a suppression effect with a genuine interpretation. Because the model conditions on both digital leadership and teaching innovation, the coefficient answers a specific counterfactual question: what is associated with the academic performance of a student who is more AI-ready than the institutional leadership and instructional innovation of their environment would predict? The negative sign indicates that such a student performs worse. Readiness that outruns its pedagogical context is thus associated with a performance penalty rather than a benefit, which aligns with the substitution mechanism documented by Essien et al. (2024) and Yan et al. (2024), in which fluent and confident AI use displaces the deeper cognitive engagement on which learning depends. On this reading, the study qualifies rather than contradicts Farrukh et al. (2024) and Monib et al. (2025): AI readiness is associated with performance gains, but the association is carried by the instructional environment that shapes how readiness is exercised, and readiness in excess of that environment is not merely inert but counterproductive. It also implies that the zero-order positive correlation between readiness and performance (0.952) is largely a reflection of their common institutional cause.

The statistical reading treats the coefficient as an artifact. A variance inflation factor of 114 means that artificial intelligence readiness retains less than one per cent of variance independent of the other predictors, and coefficients estimated on that residual variance are unstable in both magnitude and sign: a modest resampling of the data could plausibly reverse it. The companion coefficient of 1.048 for teaching innovation, which exceeds the bound that a standardized coefficient can take under non-collinear conditions, points in the same direction. The narrowness of the bootstrap interval $[-1.074, -0.849]$ establishes that the coefficient is stable across resamples of these data, but bootstrap stability does not correct for collinearity; it reproduces it in every subsample.

The responsible position is that the two readings are not mutually exclusive but are not separable in these data either. The substantive interpretation is theoretically coherent and consistent with an established strand of the literature; the statistical conditions under which it was obtained are not adequate to sustain it as a confirmed finding. It is offered here as a hypothesis with empirical motivation, to be tested on a re-specified model, rather than as a demonstrated effect.

Theoretical Implications for Islamic Higher Education

These findings bear on how technology adoption models travel across institutional contexts. Acceptance frameworks were developed and validated predominantly in well-resourced secular settings, and their transportability to institutions operating under different resource constraints and value commitments has been asserted more often than demonstrated (Hamdanah & Rajiani, 2024; Wang, Hong, & Huang, 2023). PTKIS present a demanding test case, since technological adoption there is subject to an additional legitimacy criterion: alignment with religious epistemology and ethical norms (Achruh et al., 2024; Jailani & Huda, 2024; Khamis, 2024).

The pattern estimated here does not reproduce the acceptance-model expectation that individual readiness converts directly into outcomes. It instead locates explanatory weight in institutional leadership and instructional practice, with individual readiness contributing nothing positive once those are held constant. If this pattern survives re-specification, it argues for a boundary condition on acceptance-based models rather than their rejection: in institutions where digital capacity is institutionally rather than individually distributed, the individual-level constructs those models privilege lose the independent variance on which their explanatory claims rest. Where infrastructure, licensing, and instructional norms are set centrally and experienced uniformly, student readiness is less an independent input than a downstream expression of institutional provision, as an R^2 of 0.916 for readiness regressed on leadership alone would indicate.

A second implication concerns the ethical dimension embedded in the readiness construct. The measure, adapted from Karaca et al. (2021) and Laupichler et al. (2023), includes ethical judgment alongside cognition and capability. Islamic higher education supplies a normative infrastructure for technology use grounded in *adab*, *amanah*, and the obligation to verify that secular acceptance models do not theorize, and that plausibly changes how the ethics dimension of readiness relates to conduct. This is the study's principal candidate for theoretical novelty, and the present data can motivate it but cannot test it: doing so requires modeling the readiness construct dimensionally rather than as a single reflective composite so that the ethical dimension can be estimated separately from the operational one.

Practical Implications for PTKIS Management

Three recommendations follow, each traceable to a specific estimate. First, institutional investment should prioritize leadership over student-facing tool provision. Digital leadership accounts for 91.6 percent of the variance in student readiness (Table 7), meaning that in this sample readiness is largely a product of what the institution provides and signals. Programs that distribute AI tools or run standalone student training without a corresponding institutional digital strategy address the downstream variable while leaving its principal determinant untouched. Second, lecturer professional development in instructional redesign should take precedence over student AI training when allocating any marginal budget. Teaching innovation is the only pathway in the model that shows a positive indirect effect of leadership on performance. It does so at a magnitude that accounts for essentially the entire total. This implies that assessment redesign- varying assessments so that they reward process and application rather than product is the innovation dimension most directly consequential for how AI use translates into learning.

Third, AI ethics should be integrated into the Islamic studies curriculum rather than confined to a technical elective. The negative readiness coefficient, on either reading, indicates that operational capability without pedagogical structure is not a sufficient basis for policy optimism. PTKIS hold a comparative advantage here that secular institutions must build from scratch: a curricular tradition in which the ethics of knowledge acquisition, attribution, and verification are already established subjects. Locating AI ethics within that tradition, rather than beside it, treats the institutional strength as a resource rather than a constraint.

Methodological Caution

The estimates reported above were obtained under measurement conditions that require explicit acknowledgment, and readers should weigh the substantive claims accordingly. Three diagnostics converge. Discriminant validity failed on both criteria, with heterotrait–monotrait ratios between 1.038 and 1.105 against a permissive threshold of 0.90. Inner-model variance inflation factors reached 114.01 and 106.52 against a critical threshold of 5.00. The coefficient of determination for academic performance was 0.988, a value rarely observed in survey research on human behavior and more commonly indicative of shared method variance or construct overlap than genuine explanatory power.

A fourth observation, evident in Table 1, bears on the source of these conditions. Five indicators drawn from three different constructs, AI5, DL2, TI1, TI4, and TI5, share identical response distributions, as do AI4, DL3, and TI3, and as do TI2 and AP1. Identical marginal distributions across items belonging to different constructs are unlikely to arise from independent responses to distinct questions, and the cross-loading matrix in the analytical output shows the corresponding columns to be numerically identical rather than merely similar. The most probable explanation is duplication of columns during data preparation, which would mechanically inflate inter-construct correlations towards unity and produce exactly the pattern of diagnostics observed. Response-set behavior or excessive item redundancy could produce a similar signature and cannot be ruled out.

Three corrective steps are recommended before these findings are advanced as confirmed. The raw dataset should be audited for duplicated indicator columns and the model re-estimated on the corrected file. If duplication is not the cause, the measurement model should be re-specified: constructs whose heterotrait–monotrait ratio exceeds unity are candidates for merger into a higher-order construct, or the instrument requires items that discriminate more sharply between institutional provision and individual capability. And common method variance should be assessed formally through the full collinearity approach (Kock, 2015), which the diagnostics above suggest would not be passed in the present configuration. Until these steps are taken, the direction and ordering of the effects reported here are more defensible than their magnitudes, and the negative readiness coefficient should be treated as a question raised rather than an answer established.

Conceptual and Theoretical Framework

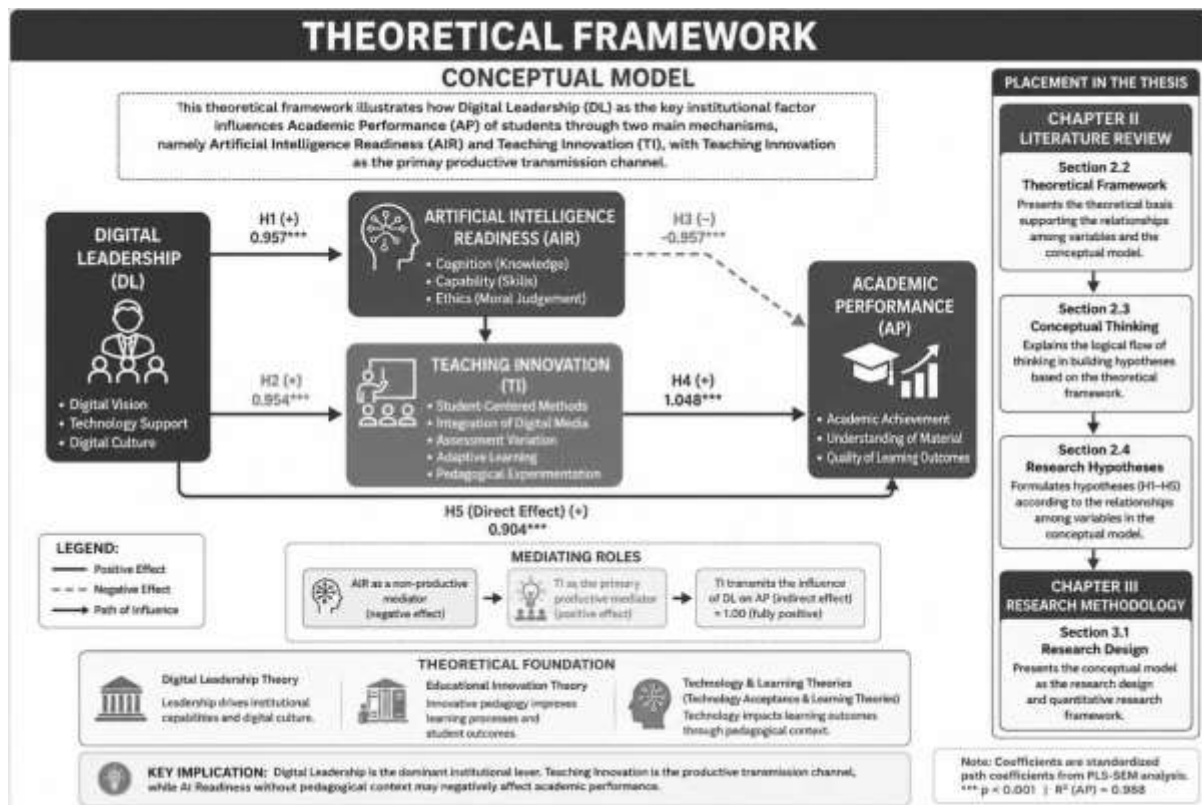


Figure 3. Theoretical Framework

The conceptual framework in Figure 3 illustrates how Digital Leadership (DL) shapes students' Academic Performance (AP) through two primary mediating pathways: Artificial Intelligence Readiness (AIR) and Teaching Innovation (TI). Digital Leadership encompasses elements such as vision, technological support, and digital culture, which directly and indirectly influence learning outcomes. While AIR focuses on cognitive knowledge, skills, and ethical considerations, TI emphasizes student-centered methods, digital media integration, adaptive learning, and pedagogical experimentation. The model highlights both positive and negative path coefficients, showing that DL exerts a strong direct effect on AP, but its indirect effects vary depending on the mediator.

The findings suggest that Teaching Innovation serves as the most productive transmission channel, fully mediating the positive influence of DL on AP. In contrast, AIR without pedagogical context may negatively impact academic results, indicating that readiness alone is insufficient without innovative teaching practices. Supported by theories of digital leadership, educational innovation, and technology acceptance, the framework underscores the institutional importance of DL while positioning TI as the key driver of improved academic achievement.

D. Conclusion

This study set out to establish whether digital leadership, artificial intelligence readiness, and teaching innovation predict academic performance among students of private Islamic higher education institutions in DKI Jakarta, and whether readiness and teaching innovation transmit the effect of institutional leadership. Five of the seven hypotheses were supported. Digital leadership significantly predicted artificial intelligence readiness (H1), teaching innovation (H2), and academic performance (H3); teaching innovation significantly predicted academic performance (H5) and mediated the

leadership effect positively (H7). H4 was not supported: artificial intelligence readiness carried a significant coefficient of the opposite sign to that predicted. H6 was supported in that a significant indirect effect exists, but it was competitive rather than complementary mediation. The single most consequential finding is that the entire positive transmission from institutional leadership to student performance runs through teaching innovation. In contrast, the pathway through individual student readiness is negative and very nearly cancels it. Readiness in the absence of instructional restructuring does not convert into academic gain in this sample; the classroom, not the individual student's facility with the technology, is where institutional digital commitment becomes learning.

The theoretical contribution is to relocate explanatory weight in the AI-in-education literature from individual acceptance to institutional provision and pedagogical practice, in a faith-based and resource-constrained setting that the quantitative literature has largely bypassed. The practical contribution is a defensible allocation rule for PTKIS management operating under budget constraints: fund the leadership function and lecturer instructional redesign before funding student-facing tools, and integrate AI ethics into the Islamic studies curriculum rather than into a technical elective. Four limitations bound these conclusions. The cross-sectional design precludes causal inference, and the model's construct ordering reflects theoretical argument rather than temporal precedence. Academic performance was self-reported and may diverge from registrar records, and the near-uniformly high scores across all constructs suggest that self-enhancement cannot be ruled out. The sample is confined to DKI Jakarta and generalizes cautiously to PTKIS elsewhere in Indonesia, where infrastructure conditions differ substantially. Most importantly, the measurement model did not establish discriminant validity and the structural model exhibited critical collinearity, so the magnitudes reported here—particularly the negative readiness coefficient and the teaching innovation coefficient in excess of unity—are provisional pending the corrective steps set out above.

Three directions for future research follow. A longitudinal replication measuring leadership, readiness, and instructional practice at successive points would allow the assumed ordering to be tested against temporal sequence rather than asserted. Substituting objective performance indicators such as grade point average or examination marks for the self-report measure would remove the largest single source of common method variance in the present design. Moreover, a multi-group comparison between PTKIS and public Islamic institutions, or between institutions with and without formal AI policies, would establish whether the pattern reported here is a property of the sector or of the resource conditions within it. A dimensional specification of the readiness construct, separating its ethical from its operational component, would additionally permit the study's principal theoretical proposition to be tested directly.

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AI Usage Declaration

The author declares that AI tools were used solely to improve language and editing, while all substantive content, analysis, and conclusions are the author's original work.

Author Contribution Statement

The author was solely responsible for the conception and design of the study, data collection and analysis, and the writing and revision of the manuscript. The author has read and approved the final version of the manuscript and agrees to be accountable for all aspects of the work.

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