



ORIGINAL RESEARCH ARTICLE

<https://doi.org/10.61650/ajis.v4i3.1380>

Artificial Intelligence Readiness and Educational Management Effectiveness: The Role of Digital Leadership

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Article History: 20 September 2026 • Revised: 05 October 2025 • Accepted: 10 October 2026 • Published: 20 October 2026 date pending

ABSTRACT

This quantitative explanatory study examines relationships among artificial intelligence readiness (AIR), digital leadership (DL), and educational management effectiveness (EME) in questionnaire responses from 78 people involved in educational management or administration. In the supplied results, AIR was positively associated with DL (standardized coefficient = 0.292, $t = 2.663$, $p = .009$; $R^2 = .085$). AIR was strongly associated with EME after adjustment for DL ($\beta = 0.951$, $t = 26.460$, $p < .001$), whereas the adjusted DL–EME coefficient was 0.012 ($t = 0.328$, $p = .744$); EME model R^2 was .911. The source reports an indirect estimate near 0.0033, calculated from unstandardized paths, but no bootstrapped confidence interval or direct test of the indirect effect. A non-significant DL–EME path alone does not establish the significance of mediation. Furthermore, EME had Cronbach's alpha of .665, and the measurement model, institutional sampling frame, and item wording are not provided. These cross-sectional self-reports support associations within this sample, not a causal effect or a verified absence of mediation. The measurement evidence and indirect-effect interval should be supplied before submission.

Keywords: Artificial Intelligence Readiness; Digital Leadership; Educational Management; Mediation; Measurement Validity



ABSTRAK

Studi kuantitatif eksplanatori ini mengkaji hubungan antara kesiapan kecerdasan buatan (AIR), kepemimpinan digital (DL), dan efektivitas manajemen pendidikan (EME) berdasarkan kuesioner dari 78 responden yang terlibat dalam manajemen atau administrasi pendidikan. Hasil sumber menunjukkan hubungan positif AIR dengan DL (koefisien terstandar = 0,292; $t = 2,663$; $p = 0,009$; $R^2 = 0,085$). AIR berhubungan sangat kuat dengan EME setelah memperhitungkan DL ($\beta = 0,951$; $t = 26,460$; $p < 0,001$), sedangkan koefisien DL–EME setelah penyesuaian sebesar 0,012 ($t = 0,328$; $p = 0,744$); R^2 model EME = 0,911. Sumber menyebut estimasi efek tidak langsung sekitar 0,0033 dari hasil perkalian jalur tidak terstandar, tetapi tidak menyediakan interval kepercayaan bootstrap atau pengujian langsung efek tidak langsung. Jalur DL–EME yang tidak signifikan saja tidak menentukan signifikansi mediasi. Selain itu, alpha Cronbach EME sebesar 0,665, sedangkan hasil model pengukuran, kerangka sampel institusi, dan butir instrumen tidak tersedia. Data potong lintang berupa laporan diri ini mendukung hubungan dalam sampel, bukan pengaruh sebab-akibat ataupun bukti pasti ketiadaan mediasi. Bukti pengukuran dan interval efek tidak langsung perlu dilengkapi sebelum pengujian.

Kata kunci: Kesiapan Kecerdasan Buatan; Kepemimpinan Digital; Manajemen Pendidikan; Mediasi; Validitas Pengukuran

How to cite: Setiawan, Kuswadi, A., Sugianikl, D., Dinata, F. R., & Qomarudin, M. (2026). Artificial Intelligence Readiness and Educational Management Effectiveness: The Role of Digital Leadership. *Assyfa Journal of Islamic Studies*, 4(3), 22–28. Retrieved from <https://journal.assyfa.com/index.php/ajis/article/view/1380>

1. INTRODUCTION

Artificial intelligence (AI) is being considered for administrative work, information handling, and decision support in education. The possibility of using a system does not establish whether an institution has the data, skills, safeguards, and processes to use it well. Organizational AI readiness addresses these conditions before adoption (Jöhnk et al., 2021; Nazari Tehrani et al., 2024).

Leadership may influence how a school or educational organization sets priorities, prepares staff, and governs digital tools. Research on digital leadership in higher education identifies both growing interest and unsettled concepts and measures (Jameson et al., 2022). Readiness and leadership could therefore be related, but their separate links with educational management effectiveness need empirical examination rather than assumption.

AI in education research reports promising uses as well as persistent questions about pedagogical value, transparency, and organizational implementation (Zawacki-Richter et al., 2019; Wang et al., 2023). Educational management effectiveness in the present manuscript refers to perceived planning, coordination, service, and evaluation. Because these variables are measured using self-report at one time, relationships among them cannot establish that AI implementation caused improvement.

The supplied study tests whether AIR predicts EME and whether DL transmits some of that relationship using 78 questionnaire responses. This revision retains reported descriptive statistics, reliability coefficients, correlations, and adjusted paths. It also distinguishes the reported mediation claim from the evidence needed to evaluate an indirect effect and examines the unusually high AIR–EME correlation.

2. RESEARCH METHODS

The source describes a quantitative explanatory survey involving 78 respondents active in educational management or administration. Participation was voluntary, and respondents answered five-point Likert items. Neither the identities and number of institutions nor the recruitment frame, response rate, fieldwork dates, respondent characteristics, or questionnaire wording are provided. The institution is therefore the subject of respondents' perceptions, not an independently observed unit of analysis.

Three constructs were defined: AIR as perceived technical and organizational preparedness; DL as perceived leadership vision and support for digital change; and EME as perceived ability to plan, coordinate, decide, monitor, and evaluate. The source reports Cronbach's alpha for the three constructs. Although it states that outer loadings, average variance extracted, composite reliability, heterotrait–monotrait ratios, and variance inflation factors were assessed, the corresponding values are not supplied (Hair et al., 2019; Henseler et al., 2015).

The results supplied include means, standard deviations, Pearson correlations, and coefficients from regressions of DL on AIR and EME on AIR and DL. The manuscript labels the analysis PLS-SEM, but provides no indicator model, algorithm setting, software output, bootstrapping replication count, or path confidence intervals. We present the available coefficients without claiming that all PLS measurement and structural checks have been demonstrated.

The source computes an indirect point estimate as the product of the unstandardized AIR–DL and adjusted DL–EME paths ($0.316 \times 0.010 \approx 0.0032$; the source rounds this to 0.0033). Testing mediation requires the sampling distribution or a confidence interval of that product, normally obtained by bootstrap (Preacher & Hayes, 2008). The p-value of either component alone does not substitute for that test. No raw responses were provided for recomputation.

3. RESULTS AND FINDINGS

For 78 respondents, the supplied means (SD) are AIR 3.272 (0.190), DL 3.256 (0.206), and EME 3.276 (0.181) on five-point scales. Cronbach's alpha is .698 for AIR, .707 for DL, and .665 for EME. The last two figures, and especially EME, warrant careful interpretation; they cannot be assessed further without the number and content of items and composite reliability estimates.

The reported Pearson correlations are AIR–DL $r = .292$, AIR–EME $r = .955$, and DL–EME $r = .290$. The AIR–EME relationship is unusually high for distinct self-report constructs. The manuscript provides no item-level or discriminant-validity evidence to exclude overlapping wording, common method effects, or nearly redundant measures.

In the reported model of DL, AIR had an unstandardized coefficient of 0.316 and a standardized coefficient of .292 ($t = 2.663$, $p = .009$); R^2 was .085. In the adjusted model of EME, AIR had an unstandardized coefficient of .905 and a standardized coefficient of .951 ($t = 26.460$, $p < .001$). The adjusted coefficient for DL was 0.010 unstandardized and .012 standardized ($t = 0.328$, $p = .744$). Model R^2 for EME was .911. These values are reported as supplied; standard errors and confidence intervals are absent.

The source calculates an indirect point estimate of about 0.0033 from unstandardized paths and interprets it as unsupported mediation because the adjusted DL–EME path was not significant. Without an indirect-effect standard error or bootstrap confidence interval, however, the significance of mediation is undetermined. The reported evidence does show that the adjusted DL coefficient is small and imprecisely tested relative to AIR in this sample; it does not establish a zero indirect effect.

4. DISCUSSION

The positive AIR–DL relationship suggests that respondents perceiving greater institutional preparedness also tended to perceive stronger digital leadership. Its standardized coefficient of .292 and R^2 of .085 indicate that most variation in reported leadership remained unexplained by AIR. Research on AI readiness treats technology, skills, management support, and organizational context as related components (Jöhnk et al., 2021; Nazari Tehrani et al., 2024). This survey does not establish whether readiness preceded leadership or developed alongside it.

The AIR–EME association is striking: $r = .955$ and an adjusted standardized path of .951. Although the supplied model R^2 of .911 is arithmetically compatible with these coefficients, a near-unity association raises a measurement question. If readiness items ask whether planning, coordination, and data systems are effective, and effectiveness items ask similar questions, the constructs may overlap. Discriminant validity requires evidence from the actual indicators, such as HTMT and item content (Henseler et al., 2015). The source does not report either.

The adjusted DL–EME path is .012 with $p = .744$, while its bivariate correlation with EME is .290. Controlling for AIR largely removes the shared association in this sample. Such a pattern can occur when the predictors share variance with the outcome, without proving leadership is unimportant in practice. A review of higher education digital leadership finds considerable variation in conceptualization and measurement (Jameson et al., 2022). The DL items and their reliability need inspection before interpreting the coefficient as a substantive null result.

The mediation claim needs a separate inferential step. The product of two fitted paths is a point estimate; its distribution is often asymmetric, so a bootstrap interval for the indirect effect is preferable to an inference from the second path's p -value (Preacher & Hayes, 2008; Hair et al., 2019). The supplied estimate near 0.0033 appears small compared with the direct path, but its uncertainty is unknown. A revised analysis should report the original and adjusted direct effects and the interval around the indirect effect.

Internal consistency also limits interpretation. The EME alpha of .665 is below the commonly used .70 reference value, while AIR alpha is .698 and DL alpha .707. A threshold should not replace item-level judgment, and alpha depends on scale length and assumptions about item covariance (Cronbach, 1951; Sijtsma, 2009). Reporting the questionnaire, item counts, loadings, and composite reliability would clarify whether the latent measures are adequate for the proposed model.

The questionnaire measures respondents' perceptions of preparedness and managerial performance at the same time. Shared respondents, response format, and favorable institutional evaluations can

amplify observed associations (Podsakoff et al., 2003). The study contains no independently observed management outcomes, time sequence, or experimental variation. Consequently, statements that readiness improved effectiveness or leadership failed as a mechanism exceed the evidence. A later design could use records of service quality and AI use from separate sources.

Context is also underreported. The sample of 78 is a count of people, but the source does not identify institutions, sampling method details, or clustering of responses within institutions. If several respondents describe the same organization, their answers may not be independent. Research on AI implementation emphasizes differences in data governance, infrastructure, and local capacity (Holmes et al., 2022; Selwyn, 2019). These differences cannot be evaluated or generalized from the current case description.

The practical implication is to assess actual preparedness and governance before drawing strong conclusions from self-reported correlations. Institutions can inventory data quality, staff competence, authorized use, and decision responsibilities, while recording specific management outcomes. For publication, the authors should supply full item wording, measurement checks, recruitment details, and a bootstrap confidence interval for the indirect effect. With those additions, the proposed model can be evaluated on its own terms without treating this unusually high cross-sectional association as causal proof.

5. CONCLUSION AND SUGGESTIONS

In the supplied survey of 78 respondents, AIR was associated with DL ($\beta = .292$, $p = .009$) and strongly associated with EME after adjustment ($\beta = .951$, $p < .001$). The adjusted DL–EME path was small ($\beta = .012$, $p = .744$). These are sample associations from self-reported cross-sectional data. The significance of the proposed indirect effect through DL cannot be determined from the reported statistics because no interval or direct inferential test is available.

Before submission, report the institution and respondent sampling frame, the questionnaire and measurement model, and a bootstrap interval for mediation. Give particular attention to the AIR–EME correlation of .955 and EME alpha of .665. Independent management indicators and longitudinal data would strengthen future evaluation.

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