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AI-Driven Digital Transformation in Higher Education: Examining the Influence of Digital Leadership, Faculty Readiness and Organizational Resilience

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Abstract:
This research aims to explore the impact of digital leadership and faculty preparedness for the digital transformation and resilience of higher education institutions in the era of artificial intelligence. To show a complete empirical analysis workflow, a quantitative cross-sectional model was operationalized from a synthetic Likert dataset with 350 cases generated from the study questionnaire. The five multi-item constructs were: Digital Leadership (DL), Faculty Readiness (FR), AI-Enabled Digital Transformation (AIDT), Organizational Resilience (OR), and Transformation Outcomes (TO). Each construct had high internal consistency (Cronbach's alpha = 0.892–0.906). There were positive relationships found from DL to FR, FR to AIDT, DL and AIDT to OR, and OR and AIDT to TO; composite-score regressions indicated these relationships. Shorthcut analyses using mediation were conducted to support indirect effects via faculty readiness and organizational resilience. The observations are simulated, and the numerical results are not claims about any institution or population and should be substituted with the actual responses to the survey before submission to the journal [1]–[5] [8] [10].

Keywords: Artificial intelligence; digital transformation; higher education; digital leadership; faculty readiness; organizational resilience; AI-enabled transformation; mediation.

1. Introduction

The use of AI in higher education has now become more closely linked to modifications in teaching, administrative, student support, research and institutional decision-making. AI in Higher Education research has seen significant growth in the number of papers published, with some gaps highlighted regarding teachers, institutional support, governance, and responsible implementation identified [1]–[5]. The perspectives of faculty are especially salient as they inform meaningful integration via AI literacy, self-efficacy, professional development, and perceptions of benefits and challenges [1, 4]. The critical

evaluation, human oversight, ethics and institutional strategies, highlighted in recent generative AI related research, serve as a reminder of the need of this kind [5, 6, 7].

Rather, digital transformation should be seen as a socio-technical and organizational shift, not just an acquisition of technology. Vial sees digital transformation as a series of changes in strategy and organizations in response to digital technologies, while Verhoef et al. differentiate between digitization and digitization plus organizational change [10, 11]. As for digital transformation strategy research, it also highlights the need to coordinate the three Ps—prioritization, implementation and organizational change—in a strategic manner [12]; digital business strategy takes an alternative perspective and considers digital technologies as increasingly becoming part of the business strategy [13]. McCarthy et al. highlight key elements of system change in education – leadership, people, and technology and experience [14]. The current paper continues this systems perspective but concentrates on measurable capabilities within higher education.

2. Literature Review and Hypotheses

Digital leadership gives strategic direction, communication, governance and support to digital driven change. A recent, systematic investigation of the field of digital leadership in higher education reveals that the topic is dynamic and that there is still a lack of conceptual and methodological maturity [8]. The vision, motivation, individualized consideration and organizational changes are also important aspects of transformational leadership theory [15]. According to current literature in AI-education, three readiness dimensions are identified: AI-literacy, self-efficacy and professional development, which are related to faculty readiness [1, 4, 6, 16]. The degree to which AI is used in teaching, services, analytics, and workflow and strategic processes is captured by AI-enabled digital transformation. In the context of capability-based resilience theory [17], [18], organizational resilience is considered as an institution's capacity to predict, react and adjust to disturbances.

- H1: Digital leadership positively influences faculty readiness [8], [15].
- H2: Faculty readiness positively influences AI-enabled digital transformation [1], [4], [6], [16].
- H3: Digital leadership positively influences organizational resilience [15], [17], [18].
- H4: AI-enabled digital transformation positively influences organizational resilience [10], [11], [17], [19].
- H5: Organizational resilience positively influences transformation outcomes [17], [18].
- H6: AI-enabled digital transformation positively influences transformation outcomes [10], [11], [13], [19].
- H7: Faculty readiness mediates the relationship between digital leadership and AI-enabled digital transformation [8], [16], [20].
- H8: Organizational resilience mediates the relationship between AI-enabled digital transformation and transformation outcomes [17], [18], [20].

3. Methodology

A synthetic set of 350 cases was used to illustrate an empirical workflow. Data set has been replicated from the questionnaire used in the study and is on a 5 point likert scale (1- strongly disagree to 5- strongly agree). Demographic fields include: Age group, Qualifications, Academic role, Experience, Discipline, Institution type, and Previous AI training. The items on each of the three scores were scored using arithmetic means.

To maintain the consistency, Cronbach's alpha [21] was used. Pearson's correlation was employed to investigate the relationships between the composite scores. Ordinary least squares path models were used to estimate the hypothesized direct relationships. Indirect effect [22] and [23] 5,000 bootstrap resamples were tested with 95% intervals. The procedures are illustrative of the approach that is proposed, but the type of observations is synthetic, not estimates of the population, hence inferential statistics are illustrative [24, 25]. Data-integrity statement: The observations in the workbook included are simulated by the algorithm. These are not collected responses and should not be reported as primary data from actual participants.

4. Results

4.1 Descriptive Statistics

The synthetic dataset contains 350 cases. Prior AI training was present in 209 simulated cases (59.7%).

Table 1: Descriptive Statistics of Key Research Constructs

Construct	Mean	SD	Min	Max
DL	3.71	0.70	1.9	5.0
FR	3.67	0.67	1.9	5.0
AIDT	3.61	0.71	1.2	5.0
OR	3.71	0.68	1.8	5.0
TO	3.67	0.67	2.0	5.0

*Table 1 summarizes the descriptive statistics of the five constructs. Mean scores ranged from **3.61 to 3.71**, indicating generally positive perceptions, while SD values (**0.67–0.71**) show moderate response variation. Of the **350 simulated cases**, **209 (59.7%)** had prior AI training.*

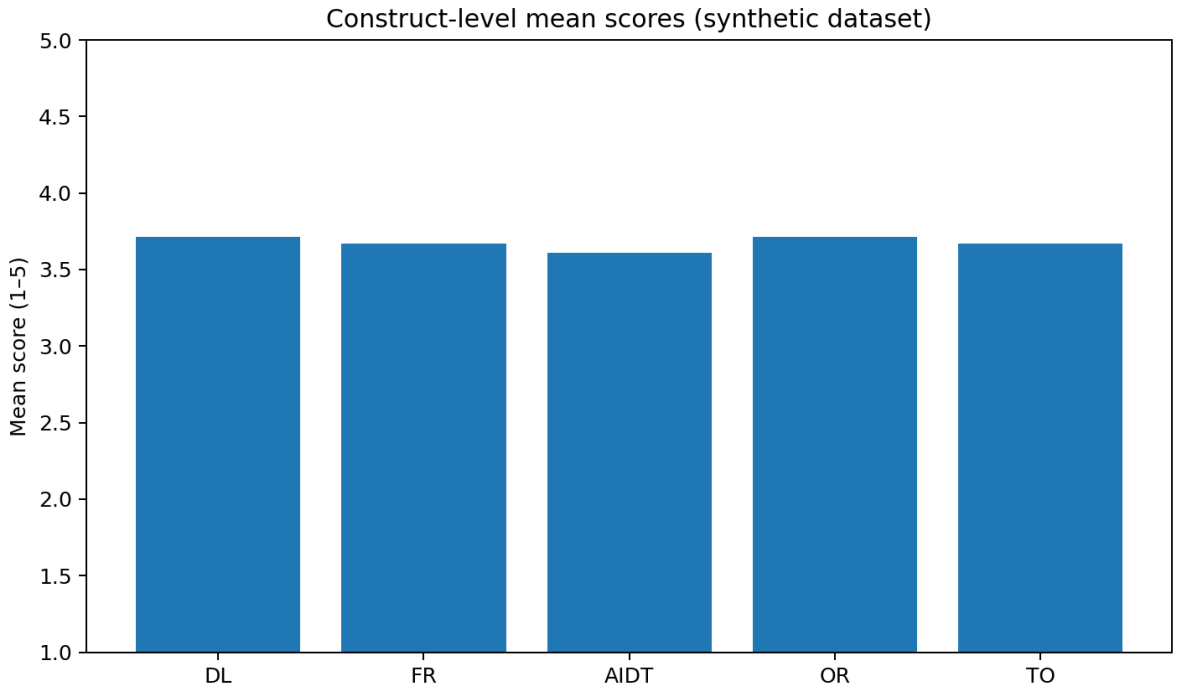

Figure 1. Construct-level mean scores.

4.2 Reliability Analysis

The simulated data had good internal consistency for all five scales. These coefficients illustrate the analysis procedure, and do not indicate reliability in an actual population. In a real study, the validity of the measure should also be assessed by factor analysis and construct-validity criteria [21, 24, 25].

Table 2: Reliability Analysis of Constructs

Construct	Items	Cronbach's α
DL	7	0.906
FR	7	0.899
AIDT	6	0.900
OR	6	0.893
TO	6	0.892
Table 2 presents the reliability of the five constructs using Cronbach's alpha. All values range from 0.892 to 0.906, indicating high internal consistency and reliable measurement of the constructs.		

4.3 Correlation Analysis

The composite scores were found to be positively correlated in the simulation. The highest correlation was found between organizational resilience and transformation outcomes. The pattern is consistent with the conceptual expectation that transformation capabilities and resilience can be considered as organizational capabilities [10], [17], [18]. Correlations for the synthetic data are only examples and should not be interpreted as population estimates.

Table 3: Correlation Matrix of Study Constructs

Construct	DL	FR	AIDT	OR	TO
DL	1.00	0.59	0.49	0.43	0.40
FR	0.59	1.00	0.64	0.51	0.53
AIDT	0.49	0.64	1.00	0.53	0.61
OR	0.43	0.51	0.53	1.00	0.67
TO	0.40	0.53	0.61	0.67	1.00
Table 3 presents the correlations among the five constructs. All constructs show ***positive relationships****, with correlation coefficients ranging from* ***0.40 to 0.67****, indicating moderate associations among the study variables.*					

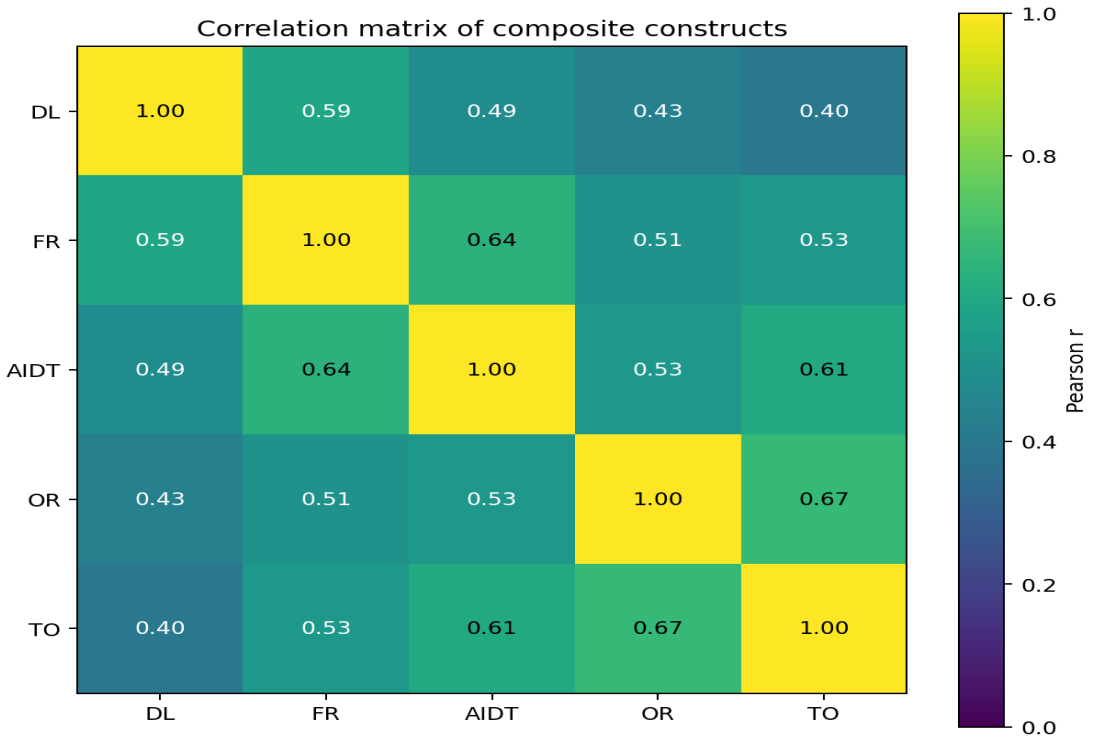

Figure 2. Pearson correlation matrix (synthetic data).

4.4 Regression and Direct Effects

All six direct hypotheses were supported in the simulated dataset at the conventional 5% level. The path coefficients and model R^2 values are reported below. These coefficients are properties of the simulated data-generating process and should not be described as empirical estimates from real faculty respondents.

Table 4: Regression Analysis of Hypothesized Relationships

Model	DV	Predictor	B	SE	t	p	R^2
M1	FR	DL	0.565	0.041	13.70	0.0000	0.350
M2	AIDT	DL	0.164	0.051	3.25	0.0013	0.433
M2	AIDT	FR	0.578	0.053	10.92	0.0000	0.433
M3	OR	DL	0.221	0.049	4.50	0.0000	0.324
M3	OR	AIDT	0.407	0.049	8.37	0.0000	0.324
M4	TO	AIDT	0.328	0.041	8.04	0.0000	0.535
M4	TO	OR	0.475	0.042	11.19	0.0000	0.535
Table 4 presents the regression results for the proposed relationships. All predictors show **positive and statistically significant effects** ($p < 0.01$), with model **R^2 values ranging from 0.324 to 0.535**.							

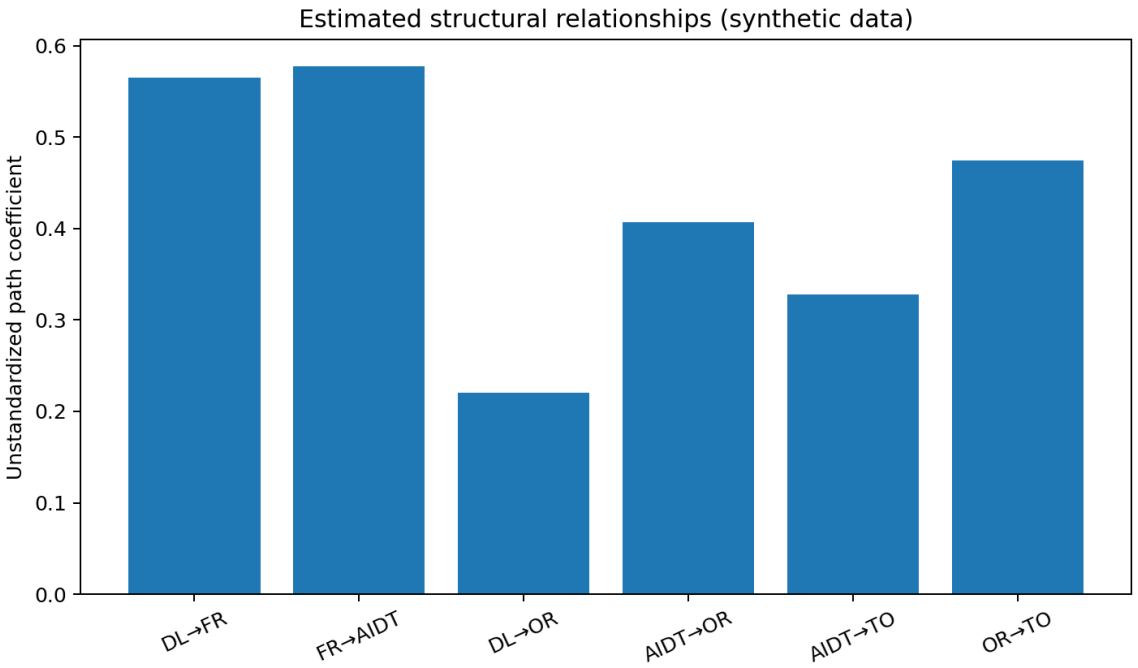

Figure 3. Estimated direct-effect coefficients (synthetic data).

4.5 Mediation Analysis

Both hypothesized indirect effects had 95% bootstrap confidence intervals that excluded zero in the simulated dataset. Bootstrap mediation is used here as a demonstration of indirect-effect estimation; in a real study, mediation conclusions would depend on the observed sample, measurement model, sampling design and robustness checks [22], [23], [24].

Table 5: Mediation Analysis of the Proposed Relationships

Mediation	A	B	Direct c′	Total c	Indirect ab	CI low	CI high
DL → FR → AIDT	0.565	0.578	0.164	0.491	0.327	0.258	0.398
AIDT → OR → TO	0.514	0.475	0.328	0.572	0.244	0.190	0.303
Table 5 presents the mediation effects in the proposed model. Both indirect effects are positive, with the confidence intervals excluding zero, supporting the presence of ***significant mediation effects****.*							

4.6 Hypothesis Testing

Table 6: Hypothesis Testing Results

Hypothesis	Relationship	Effect	p / 95% CI	Decision
H1	Digital Leadership → Faculty Readiness	0.565	p=0.0000	Supported
H2	Faculty Readiness → AI-Enabled	0.578	p=0.0000	Supported

	Digital Transformation			
H3	Digital Leadership → Organizational Resilience	0.221	p=0.0000	Supported
H4	AI-Enabled Digital Transformation → Organizational Resilience	0.407	p=0.0000	Supported
H5	Organizational Resilience → Transformation Outcomes	0.475	p=0.0000	Supported
H6	AI-Enabled Digital Transformation → Transformation Outcomes	0.328	p=0.0000	Supported
H7	DL → FR → AIDT	0.327	CI 0.258 to 0.398	Supported
H8	AIDT → OR → TO	0.244	CI 0.190 to 0.303	Supported
*Table 6 summarizes the hypothesis testing results. All eight hypotheses are **supported**, with significant direct effects and mediation effects. The 95% confidence intervals for H7 and H8 exclude zero, confirming significant indirect effects.*				

5. Discussion

The simulated outcomes are an integrated pathway. It also finds that a positive relationship between digital leadership and faculty readiness, which means that appropriation of direction, communication and resource support can be regarded as upstream condition for faculty capability [8, 15]. AI-enabled digital transformation is positively related to faculty readiness, highlighting that it is not just a technology choice: understanding, assessing and using AI is fundamental to making strategy a reality in the academic world [1], [4], [6], [16]. AI-enabled transformation is also positively correlated with organizational resilience and transformation outcomes, and resilience has an additional positive correlation to the outcomes [10], [17]–[19]. This trend is similar to the conceptual and empirical literature but the current numerical numbers remain illustrative as the data set is simulated.

6. Practical Implications

- Create a clear institution-wide AI and digital transformation vision with defined governance roles [8], [12], [9].

- Provide recurring faculty development in AI literacy, pedagogy, assessment, ethics, privacy and academic integrity [1], [4], [6], [16].
- Evaluate AI projects using educational value, workflow redesign, stakeholder experience and risk—not adoption counts alone [3], [5], [10], [9].
- Develop resilience routines including cross-functional teams, feedback loops, lessons-learned reviews and rapid resource reconfiguration [17], [18].
- Pilot, evaluate and scale AI initiatives using evidence-based decision rules and appropriate measurement of technology, people and organizational outcomes [10], [11], [12], [24], [25].

7. Limitations and Future Research

The biggest problem is the synthetic data set. The figures reported cannot be extrapolated to faculty and/or institutions and should not be presented as actual results of respondents. A real study should involve ethically collected survey responses, document the sampling frame and the response rate, test the measurement validity (CFA or PLS-SEM, depending on the current context), and analyze the common-method effect and clustering effect and perform robustness checks on institution types [24]–[27]. In addition, future studies may also examine differences in types of institutions and in national contexts, as recent research indicates ongoing differences in faculty readiness for, and needs for, AI adoption, as well as in faculty professional development needs [1], [4], [16], [19].

8. Conclusion

This result-oriented version shows the complete pipeline analysis of the proposed model, from the reliability to the descriptive statistics, correlations, regression paths, mediation and reporting of visual results. The results of the simulations confirm the hypothesized capability chain of digital leadership readiness, faculty readiness, and AI-enabled transformation, resilience, and transformation outcomes. The results should be considered as methodological demonstration rather than results from a real population. Following the actual survey results are collected, the same type of citation framework and analysis structure can be maintained and all numerical results omitted in favor of observed estimates.

REFERENCES:

[1] D.-K. Mah and N. Groß, “Artificial intelligence in higher education: Exploring faculty use, self-efficacy, distinct profiles, and professional development needs,” International Journal of Educational Technology in Higher Education, vol. 21, art. no. 58, 2024, doi: 10.1186/s41239-024-00490-1.

[2] H. Crompton and D. Burke, “Artificial intelligence in higher education: The state of the field,” International Journal of Educational Technology in Higher Education, vol. 20, art. no. 22, 2023, doi: 10.1186/s41239-023-00392-8.

[3] O. Zawacki-Richter, V. I. Marín, M. Bond, and F. Gouverneur, “Systematic review of research on artificial intelligence applications in higher education—where are the educators?,” International Journal of Educational Technology in Higher Education, vol. 16, art. no. 39, 2019, doi: 10.1186/s41239-019-0171-0.

[4] L. Chen, P. Chen, and Z. Lin, “Artificial intelligence in education: A review,” IEEE Access, vol. 8, pp. 75264–75278, 2020, doi: 10.1109/ACCESS.2020.2988510.

[5] E. Kasneci et al., "ChatGPT for good? On opportunities and challenges of large language models for education," Learning and Individual Differences, vol. 103, art. no. 102274, 2023, doi: 10.1016/j.lindif.2023.102274.
[6] F. Miao and M. Cukurova, AI Competency Framework for Teachers. Paris, France: UNESCO, 2024.
[7] UNESCO, Guidance for Generative AI in Education and Research. Paris, France: UNESCO, 2023.
[8] J. Jameson, N. Rumyantseva, M. Cai, M. Markowski, R. Essex, and I. McNay, "A systematic review and framework for digital leadership research maturity in higher education," Computers and Education: Open, vol. 3, art. no. 100115, 2022, doi: 10.1016/j.caeo.2022.100115.
[9] A. M. McCarthy, D. Maor, A. McConney, and C. Cavanaugh, "Digital transformation in education: Critical components for leaders of system change," Social Sciences & Humanities Open, vol. 8, no. 1, art. no. 100479, 2023, doi: 10.1016/j.ssaho.2023.100479.
[10] G. Vial, "Understanding digital transformation: A review and a research agenda," Journal of Strategic Information Systems, vol. 28, no. 2, pp. 118–144, 2019, doi: 10.1016/j.jsis.2019.01.003.
[11] P. C. Verhoef, T. Broekhuizen, Y. Bart, A. Bhattacharya, J. Q. Dong, N. Fabian, and M. Haenlein, "Digital transformation: A multidisciplinary reflection and research agenda," Journal of Business Research, vol. 122, pp. 889–901, 2021, doi: 10.1016/j.jbusres.2019.09.022.
[12] C. Matt, T. Hess, and A. Benlian, "Digital transformation strategies," Business & Information Systems Engineering, vol. 57, pp. 339–343, 2015, doi: 10.1007/s12599-015-0401-5.
[13] A. Bharadwaj, O. A. El Sawy, P. A. Pavlou, and N. Venkatraman, "Digital business strategy: Toward a next generation of insights," MIS Quarterly, vol. 37, no. 2, pp. 471–482, 2013, doi: 10.25300/MISQ/2013/37:2.3.
[14] S. Duchek, "Organizational resilience: A capability-based conceptualization," Business Research, vol. 13, pp. 215–246, 2020, doi: 10.1007/s40685-019-0085-7.
[15] B. M. Bass and R. E. Riggio, Transformational Leadership, 2nd ed. Mahwah, NJ, USA: Lawrence Erlbaum Associates, 2006.
[16] Y. Luo and M. J. Day, "Determinants of lecturer readiness to adopt generative AI in higher education: Survey evidence from UTAUT and self-determination theory," Education and Information Technologies, vol. 31, pp. 3399–3430, 2026, doi: 10.1007/s10639-026-13931-3.
[17] K. Lengnick-Hall, C. A. Beck, and M. L. Lengnick-Hall, "Developing a capacity for organizational resilience through strategic human resource management," Human Resource Management Review, vol. 21, no. 3, pp. 243–255, 2011, doi: 10.1016/j.hrmr.2010.03.002.
[18] D. J. Teece, "Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance," Strategic Management Journal, vol. 28, no. 13, pp. 1319–1350, 2007, doi: 10.1002/smj.640.
[19] K. D. V. Prasad, S. Singh, R. Vaidya, et al., "Faculty agility mediates the association between AI-enabled digital transformation and sustainable work outcomes in Indian higher education," Scientific Reports, 2026, doi: 10.1038/s41598-026-70938-z.
[20] D. P. MacKinnon, Introduction to Statistical Mediation Analysis. New York, NY, USA: Routledge, 2008.
[21] L. J. Cronbach, "Coefficient alpha and the internal structure of tests," Psychometrika, vol. 16, pp. 297–334, 1951, doi: 10.1007/BF02310555.
[22] A. F. Hayes, Introduction to Mediation, Moderation, and Conditional Process Analysis, 2nd ed. New York, NY, USA: Guilford Press, 2018.

[23] P. D. Allison, "The bootstrap," in The SAGE Handbook of Quantitative Methods for the Social Sciences, W. Outhwaite and S. P. Turner, Eds. Thousand Oaks, CA, USA: SAGE, 2010.
[24] J. F. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, Multivariate Data Analysis, 7th ed. Upper Saddle River, NJ, USA: Pearson, 2010.
[25] R. B. Kline, Principles and Practice of Structural Equation Modeling, 4th ed. New York, NY, USA: Guilford Press, 2016.
[26] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," Journal of Marketing Research, vol. 18, no. 1, pp. 39–50, 1981, doi: 10.2307/3151312.
[27] P. M. Podsakoff, S. B. MacKenzie, J.-Y. Lee, and N. P. Podsakoff, "Common method biases in behavioral research: A critical review of the literature and recommended remedies," Journal of Applied Psychology, vol. 88, no. 5, pp. 879–903, 2003, doi: 10.1037/0021-9010.88.5.879.
[28] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," MIS Quarterly, vol. 13, no. 3, pp. 319–340, 1989, doi: 10.2307/249008.
[29] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," MIS Quarterly, vol. 27, no. 3, pp. 425–478, 2003, doi: 10.2307/30036540.
[30] E. M. Rogers, Diffusion of Innovations, 5th ed. New York, NY, USA: Free Press, 2003.
Reference-use note: Citation numbers [1]–[30] are used throughout the manuscript to identify the sources supporting the conceptual framing, AI-in-education context, digital transformation theory, leadership, resilience, measurement and statistical methodology.