Research in Education, Technology, and Multiculture
ISSN: 3025-6763 | Journal's DOI: 10.61436/rietm
Homepage: https://imrecsjournal.com/journals/index.php/rietm

A Big Data Analytics Adoption Model in Private Higher Education Institutions: Integrating Technology Readiness and Resource-Based Theory with the Mediation of Organizational Culture and Data Literacy

Yulison Herry Chrisnanto[1], Lala Septem Riza[2], Chairul Furqon[3], Julian Evan[4], & Munir[5,*]
[1,3]Department of Management, Universitas Pendidikan Indonesia, Indonesia
[2,5]Department of Computer Science, Universitas Pendidikan Indonesia, Indonesia
[4]Department of Bio-Functions and Systems Science, University of Agriculture and Technology, Japan

ARTICLE INFO
Article History:
Received: 13 July 2026
Accepted: 01 August 2026
Published: 22 September 2026

Keywords:
Big Data Analytics;
Technology Readiness Model;
Resource-Based Theory;
Data Literacy;
Organizational Culture.

Corresponding Author:
munir@upi.edu

ABSTRACT
Private higher education institutions (PHEIs) in Indonesia face growing pressure to adopt Big Data Analytics (BDA). However, adoption remains slow, and existing models treat technological capability and individual readiness as separate explanations. This study develops and empirically tests an integrative model of BDA adoption intention that positions Technology Readiness (TRM) and internal resource perceptions (RBT) within a Sociotechnical Systems (STS) framework, with Organizational Culture (OC) and Data Literacy (DL) as mediating mechanisms. A quantitative cross-sectional survey was administered to 285 lecturers, administrative staff, and institutional leaders drawn from 13 "Excellent"-accredited PHEIs in West Java (LLDIKTI Region IV). Eight latent constructs were measured with 25 reflective indicators on a five-point Likert scale and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4, with bootstrapping of 5,000 subsamples. The measurement model satisfied reliability and validity thresholds (Cronbach's Alpha 0.738–0.918; CR 0.884–0.944; AVE 0.703–0.870). All ten direct paths were significant, and all eight mediation paths were supported, with the model explaining 54.5% of the variance in adoption intention ($Q^2 = 0.430$; SRMR = 0.046). Organizational Culture was the dominant predictor of adoption intention ($\beta = 0.484$; $f^2 = 0.334$). Among the readiness dimensions, Discomfort was the strongest antecedent of Data Literacy ($\beta = -0.396$; $f^2 = 0.197$) and the only antecedent to depress both mediators. Psychological readiness and organizational resources translate into adoption intention only when converted by a supportive data culture and adequate data literacy. The principal impediment to that conversion is the difficulty staff experience with the information systems already in place. BDA adoption in higher education is therefore a sociotechnical outcome rather than a technological or psychological one.

To cite this article:
Chrisnanto, Y. H., Riza, L. S., Furqon, C., Evan, J., & Munir (2026). A big data analytics adoption model in private higher education institutions: Integrating technology readiness and resource-based theory with the mediation of organizational culture and data literacy. *Research in Education, Technology, and Multiculture*, *5*(3), 349-363. doi: https://doi.org/10.61436/rietm/v5i3.pp349-363

■ INTRODUCTION

The rapid development of Big Data technology has transformed modern organizational management, including higher education institutions. Big Data Analytics (BDA) refers not merely to data volume, but to the capacity to process its complexity, velocity, and variety to generate strategic insight (Chen et al., 2012; Gandomi & Haider, 2015). In higher education, data analytics draws on online learning systems, academic information systems, research repositories, and digitized administrative interactions. Effective use of BDA can improve decision quality, personalize academic services, and strengthen overall institutional competitiveness.

In Indonesia, the demand for BDA adoption has become increasingly urgent alongside the digitalization of higher education. However, empirical evidence indicates that the adoption of analytics technology in higher education institutions, particularly Private Higher Education Institutions (PHEIs), remains slow. The main barriers lie not only in technical infrastructure but also in human resource readiness, organizational culture, and the academic community's data literacy competence (SEVIMA, 2025). This condition underscores the need for a holistic understanding of the factors that drive or inhibit the intention to adopt BDA.

A review of the information systems literature identifies four significant theoretical gaps. First, prior research on Technology Readiness (TRM) tends to adopt a symmetrical approach, overlooking the Dual-Factor Theory, which posits that driver and inhibitor dimensions operate through distinct mechanisms (Cenfetelli, 2004). Second, most studies link organizational culture directly to performance without explaining the underlying operational mechanism, thereby creating a theoretical "black box." Third, BDA research remains polarized between the technical stream (infrastructure capability/RBT) and the behavioral stream (individual acceptance/ TRM) and rarely presents an integrative model. Fourth, the inhibitor dimensions are frequently aggregated with the drivers into a single readiness index, a specification that renders any distinct inhibitor mechanism invisible by construction.

This study addresses these gaps through three principal contributions: (1) integrating TRM and RBT within a single Sociotechnical Systems (STS) framework that views BDA adoption as the outcome of a dynamic interaction between technical and social subsystems; (2) simultaneously positioning Organizational Culture and Data Literacy as mediating variables that explain the causal mechanism; and (3) empirically testing the model in the context of PHEIs in a developing country, a setting that has been underrepresented in the literature. The study focuses on 13 "Excellent"-accredited PHEIs in West Java (LLDIKTI Region IV), with n = 285 respondents drawn from three strata of internal stakeholders. Accordingly, this study is guided by three research questions. RQ1: To what extent do the driver and inhibitor dimensions of technology readiness (optimism, innovativeness, discomfort, insecurity) and perceived internal resources shape organizational culture and data literacy within PHEIs? RQ2: Does data literacy mediate the relationship between these antecedents and BDA adoption intention? RQ3: Does organizational culture mediate that relationship, and which mediating mechanism dominates? These questions translate into three testable hypotheses (H1–H3) specified in the Method section, and the Conclusion synthesizes the answers.

Sociotechnical Systems (STS) as the Integrating Framework

Rather than arranging the theories in a hierarchy, this study treats Sociotechnical Systems (STS) as a conceptual umbrella, with TRM and RBT as two complementary lenses beneath it. STS holds that organizational performance emerges from jointly optimizing social and technical subsystems, and that optimizing either in isolation degrades the other (Trist, 1981; Bostrom & Heinen, 1977; Sarker et al., 2019). BDA adoption is a paradigmatic case: analytics platforms are inert without people who trust, understand, and are willing to use them, while motivated people cannot act without infrastructure and data governance. Within this umbrella, the technical subsystem is captured by perceived internal resources derived from Resource-Based Theory: technological infrastructure, human expertise in data management, and the organizational capability to configure both (Barney, 1991; Teece et al., 1997).

The social subsystem is captured by the Technology Readiness Model, which specifies the psychological dispositions, optimism and innovativeness as drivers, and discomfort and insecurity as inhibitors, through which individuals appraise new technology (Parasuraman, 2000; Parasuraman & Colby, 2015). The two subsystems do not act on adoption intention independently. Organizational culture and data literacy are positioned as the interface at which they meet: culture is the collective mechanism that converts technical potential into shared intent (Schein, 2010; Gupta & George, 2016), whereas data literacy is the individual competence that makes technical resources usable (Ridsdale et al., 2015; Wolff et al., 2016). Framing the model this way makes explicit what a hierarchy of theories obscures: that TRM and RBT are not competing explanations at different levels of abstraction, but descriptions of the two subsystems whose joint optimization STS predicts to be decisive.

Technology Readiness Model (TRM)

The Technology Readiness Model, developed by Parasuraman (2000), measures individuals' psychological disposition toward accepting and using new technology through four dimensions: Optimism (OPT), Innovativeness (INV), Discomfort (DIS), and Insecurity (INS). Optimism and Innovativeness are driver dimensions that reflect an individual's positive beliefs about technology. Discomfort and Insecurity are inhibitor dimensions that may impede adoption. In the context of complex BDA adoption, these dimensions not only directly influence adoption intention but also operate through the development of cultural capability and individual competence.

Resource-Based Theory (RBT)

Resource-Based Theory (Barney, 1991) posits that sustainable competitive advantage originates from internal resources that satisfy the VRIO criteria: Valuable, Rare, Inimitable, and Organized. In the context of BDA in higher education, relevant resources include: (1) technology infrastructure and information systems; (2) human resource expertise and experience in data management; and (3) specific internal capabilities of a strategic nature. RBT emphasizes that resource ownership alone is insufficient; organizations must configure and integrate these resources effectively through dynamic capabilities (Teece et al., 1997).

Organizational Culture and Data Literacy as Mediators

Organizational Culture (Schein, 2010) is defined as the system of shared values, norms, and basic assumptions that shape the behavior of organizational members. A data-driven culture, characterized by a data orientation, cross-unit collaboration, and openness to experimentation, functions as a catalyst that converts the potential of individual readiness and organizational resources into actual adoption intention (Gupta & George, 2016). Data Literacy (Ridsdale et al., 2015) is defined as an individual's ability to read, analyze, interpret, and communicate effectively with data. In this study, Data Literacy mediates the path from the DIS and INV dimensions of TRM, as well as from RBT, toward BDA adoption intention, confirming the role of human competence as a bridge between antecedents and adoption behavior.

■ METHOD

Research Model and Hypotheses

Based on the literature review and the STS framework, the research model proposes three principal hypotheses: (H1) all dimensions of TRM (OPT, INV, DIS, INS) and RBT significantly influence Organizational Culture and/or Data Literacy; (H2) Data Literacy mediates the relationship between specific TRM dimensions (DIS, INV) and RBT toward BDA adoption intention; (H3) Organizational Culture mediates the relationship between TRM dimensions (OPT, INV, DIS, INS) and RBT toward BDA adoption intention. Figure 1 presents the research paradigm and illustrates the full set of hypothesized paths.

Relevant Prior Research

Research on BDA adoption has been examined from various theoretical perspectives, yet each leaves relevant gaps. (Alyoussef & Al-Rahmi, 2022) employed the Technology Acceptance Model with culture as a direct predictor, without incorporating TRM or RBT. Baig et al. (2023) identified the determinants of big data adoption in higher education using a multi-analytical SEM-ANN approach. However, they did not test data literacy or the mediating role of organizational culture. Al Hadwer et al. (2021) reviewed the organizational factors, including culture, that

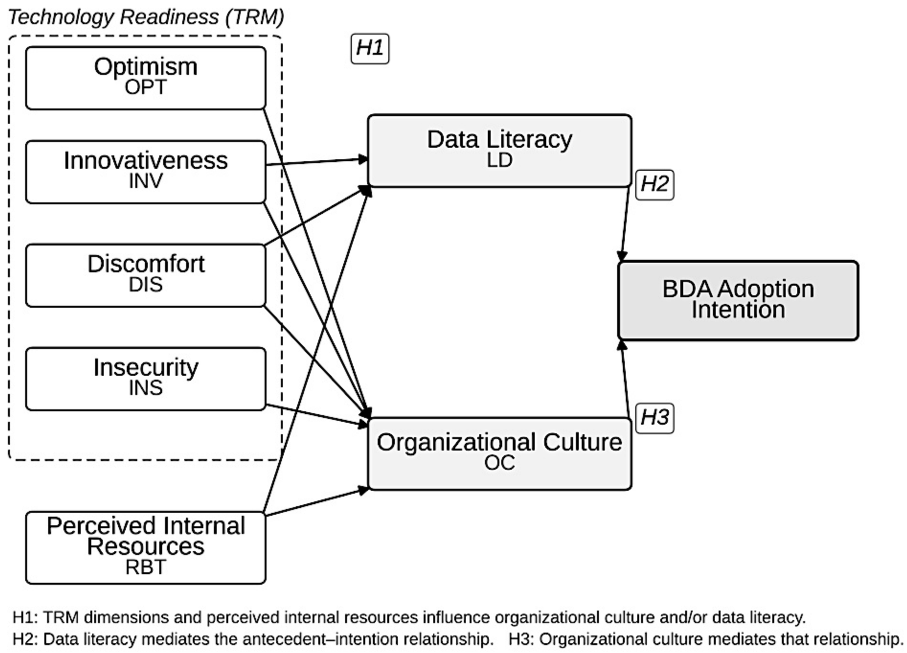

Figure 1. Research paradigm

shape cloud-based technology adoption within the Technology–Organization–Environment (TOE) framework, yet did not model individual readiness or data literacy. Chatterjee and Bhattacharjee (2020) modeled artificial intelligence adoption in higher education using technology acceptance constructs. However, they did not consider RBT or data literacy, as did Vrontis et al. (2022) in a manufacturing setting.

On the resource side, Mikalef et al. (2019) applied RBT to examine BDA capability through PLS-SEM in a corporate context without TRM or data literacy, and Lai et al. (2018) developed a macro-level RBT–TOE model for supply chains that did not accommodate individual psychological factors or competence. Gupta and George (2016) developed a BDA capability model grounded in RBT that remained conceptual regarding adoption. Building on this mapping, the present study integrates TRM, RBT, organizational culture, and data literacy simultaneously through PLS-SEM, offering a micro–macro integration within an STS framework in the context of PHEIs in a developing country.

Research Design, Population, and Sample

This study employs a quantitative approach with a descriptive and verificative cross-sectional design. The population comprises members of the academic community, lecturers, administrative staff, and institutional leaders at "Excellent"-accredited PHEIs in the West Java region (LLDIKTI Region IV).

The sampling frame comprised all 19 PHEIs in West Java holding "Excellent" (Unggul) institutional accreditation from BAN-PT, retrieved from the LLDIKTI Region IV directory in April 2025. Institutional accreditation status was the sole inclusion criterion; no further selection criteria were applied, and no institution was excluded by design. Because accreditation status changes over time, the frame reflects the population at that date rather than at the time of publication. Invitations were extended to all 19 institutions; 13 granted access and returned usable responses, for an institutional participation rate of 68.4%.

Within the 13 participating institutions, a proportional stratified design was applied, with institution as the stratum. Lecturer counts obtained from PDDikti served as the measure of stratum size, giving a frame of 5,597 lecturers, from which a target of 353 questionnaires was allocated in proportion to stratum size. Questionnaires were distributed to lecturers, administrative staff, and institutional leaders within each institution; lecturer counts formed the basis for allocation because the national database does not include comparable enumerations of non-academic staff. A total of 285 valid responses were obtained, an overall response rate of 80.7%.

Institutional response rates varied considerably, from 35% at the largest institution to 171% at one of the smaller ones, and the realized distribution therefore departs significantly from the intended proportional allocation ($\chi^2 = 62.47$, df = 12, $p < 0.001$). The departure is driven almost entirely by a single institution, which accounts for 26.4% of the lecturer population but 11.6% of the realized sample; deviations for the remaining twelve institutions fall within ±4.5 percentage points. Consequently, the achieved sample is distributed more evenly across institutions than intended, with no institution contributing more than 11.6% of observations. The full allocation and realization are reported in Appendix A.

The achieved sample exceeds both conventional adequacy criteria for PLS-SEM. Under the ten-times rule, the construct with the most structural paths (organizational culture, with five antecedents) requires a minimum of 50 observations. Under the inverse square root method (Kock & Hadaya, 2018), detecting the smallest significant path in the model ($\beta = 0.157$) at the 5% significance level requires a minimum of 251 observations.

Instrument and Content Validity

The research instrument consisted of a questionnaire using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), covering 8 latent constructs and 25 indicators: TRM with 8 indicators (OPT1–2, INV1–2, DIS1–2, INS1–2), RBT with 6 indicators (RBT1–6), Organizational Culture with 3 indicators (OC1–3), Data Literacy with 4 indicators (LD1–4), and BDA Adoption Intention with 4 indicators (BDA1–4).

All 25 indicators were adapted from previously validated instruments rather than newly developed, and were adjusted in wording to the higher education context. Items for the four technology readiness dimensions were adapted from the Technology Readiness Index (Parasuraman, 2000; Parasuraman & Colby, 2015); perceived internal resource items from the BDA capability instruments of Gupta and George (2016) and Mikalef et al., 2020); organizational culture items from Schein (2010) conceptualisation as operationalised in the data-driven culture scale of Gupta and George (2016); data literacy items from the competency frameworks of Ridsdale et al. (2015) and Wolff et al., (2016); and adoption

Table 1. Operationalization of research variables

Variable	Dimension	Indicator	Scale	Source of adaptation
TRM (X1)	Optimism, Innovativeness, Discomfort, Insecurity	OPT1-2, INV1-2, DIS1-2, INS1-2	Interval (Likert 1–5)	Parasuraman (2000); Parasuraman and Colby (2015)
RBT (X2)	Technology resources, Human resources, Internal capability	RBT1-6	Interval (Likert 1–5)	Gupta and George (2016); Mikalef et al. (2020)
Organizational Culture (Z1)	Data orientation, Collaboration, Cultural innovation	OC1-3	Interval (Likert 1–5)	Schein (2010); Gupta and George (2016)
Data Literacy (Z2)	Interpretation, Identification, Communication, Critical data thinking	LD1-4	Interval (Likert 1–5)	Ridsdale et al. (2015); Wolff et al. (2016)
BDA Adoption Intention (Y)	Usage intention, Effort commitment, Behavioral prediction, Advocacy	BDA1-4	Interval (Likert 1–5)	Davis (1989); Ajzen (1991); Venkatesh et al. (2003)

intention items from the behavioural intention scales of Davis (1989), Ajzen (1991), and Venkatesh, Morris, Davis (2003). Table 1 summarizes the operationalization of the research variables together with the source of adaptation for each construct.

Content validity rests on adapting all 25 indicators from previously validated instruments, as detailed in Table 1, with wording adjusted to the higher education context. The adapted instrument was reviewed by the supervisory team prior to distribution. No separate pilot study was conducted; therefore, construct reliability was assessed in the full sample, and all constructs exceeded the 0.70 threshold for Cronbach's Alpha (Table 3). The absence of a pilot test is acknowledged as a limitation.

The discomfort and insecurity indicators were negatively worded, consistent with the Technology Readiness Index, and were analyzed in their original direction so that a higher score denotes greater discomfort and greater insecurity. No reverse coding was applied. Because the four readiness dimensions are modeled as distinct constructs rather than aggregated into a single readiness index, internal consistency was assessed within each dimension rather than against an aggregate readiness score. The inter-item correlations were 0.607 for optimism, 0.740 for innovativeness, 0.636 for discomfort, and 0.585 for insecurity, all satisfactory. Corrected item-total correlations computed against an aggregate readiness score fall below 0.30 for all eight indicators, including the two driver dimensions, reflecting the construct's multidimensional structure rather than any item deficiency; therefore, this statistic is not an appropriate basis for item retention decisions in a model of this specification.

Data Analysis

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4 (Hair et al., 2022). PLS-SEM was selected for its predictive orientation, its capability to handle complex structural models with numerous constructs, its tolerance of non-normal data, and its flexibility in accommodating both reflective and formative measurement models (Hair et al., 2019). Model evaluation encompassed the outer model (internal consistency reliability, convergent validity assessed through AVE, and discriminant validity assessed through the Fornell–Larcker criterion and the HTMT ratio (Fornell & Larcker, 1981; Henseler et al., 2015) and the inner model (VIF collinearity, R^2, Q^2, f^2, and SRMR). Hypothesis testing was conducted through bootstrapping with 5,000 subsamples at a 5% significance level, with mediation assessed following the indirect-effect logic of Preacher and Hayes (2008) and Zhao et al. (2010). Predictive relevance was additionally assessed using PLSpredict (Shmueli et al., 2019). Common method bias was evaluated using a full collinearity assessment (Kock, 2015) in addition to the procedural remedies recommended by Podsakoff et al. (2003).

■ RESULT AND DISCUSSION

Respondent Profile and Variable Description

Of the 285 respondents distributed across 13 "Excellent"-accredited PHEIs in West Java, the largest group comprised lecturers (57.5%), followed by administrative staff (15.4%) and various levels of institutional leadership. In terms of length of service, the majority had 10–20 years of experience (42.1%), followed by 5–10 years (27.4%), less than 5 years (21.1%), and more than 20 years (9.5%). The gender distribution was 58.9% male and 41.1% female.

Table 2 reports the descriptive statistics, and Figure 2 visualizes the same information ordered by mean. The visualization makes the study's central tension immediately clear: adoption intention sits near the top of the distribution, while data literacy sits at the very bottom, below the scale midpoint. Willingness, in other words, currently outruns capability. The readiness dimensions are less polarised than this contrast might suggest. The driver dimensions cluster above the midpoint, while the two inhibitor dimensions sit close to it, indicating an academic community that reports moderate rather than acute discomfort and insecurity, a community in transition rather than one uniformly ready or resistant.

Measurement Model Evaluation (Outer Model)

To provide a concise and integrated assessment of the measurement model without fragmenting the data presentation, the construct reliability, convergent validity, and discriminant validity criteria are consolidated into Table 3. All constructs satisfied the recommended reliability thresholds, with Cronbach's alpha ranging from 0.738 to 0.918 and composite reliability (ρc) ranging from 0.884 to 0.942. Convergent validity was fully established, as all indicator outer loadings exceeded 0.70 and the average variance extracted (AVE) for every latent variable comfortably surpassed the 0.50 threshold (ranging between 0.704 and 0.870). Innovativeness showed the highest AVE, whereas internal resources (RBT) showed the lowest, consistent with RBT representing the most heterogeneous construct spanning infrastructure, human expertise, and organizational capability. As detailed in Table 3, the square root of the AVE for each construct (diagonal values) strictly exceeds its inter-construct correlations, confirming adequate distinction between latent variables.

Table 2. Descriptive statistics of research variables

Variable / Indicator	Mean	Md	Min	Max	Std. Dev.	Criterion
TRM – Optimism (OPT1)	3.253	3	1	5	0.934	Moderate
TRM – Optimism (OPT2)	3.614	4	1	5	1.141	High
TRM – Innovativeness (INV1)	3.337	3	1	5	0.867	Moderate
TRM – Innovativeness (INV2)	3.425	3	1	5	0.907	Moderate
TRM – Discomfort (DIS1)	3.018	3	1	5	0.898	Moderate
TRM – Discomfort (DIS2)	3.098	3	1	5	0.829	Moderate
TRM – Insecurity (INS1)	3.242	3	1	5	0.877	Moderate
TRM – Insecurity (INS2)	3.046	3	1	5	0.823	Moderate
Internal Resources – RBT (mean)	3.265	3	1	5	0.727	Moderate
Organizational Culture – OC (mean)	3.129	3	1	5	0.865	Moderate
Data Literacy – LD (mean)	2.977	3	1	5	0.845	Moderate
BDA Adoption Intention (mean)	3.453	4	1	5	0.837	High

Note: Discomfort and insecurity are scored in their original direction; a higher score denotes greater discomfort or insecurity

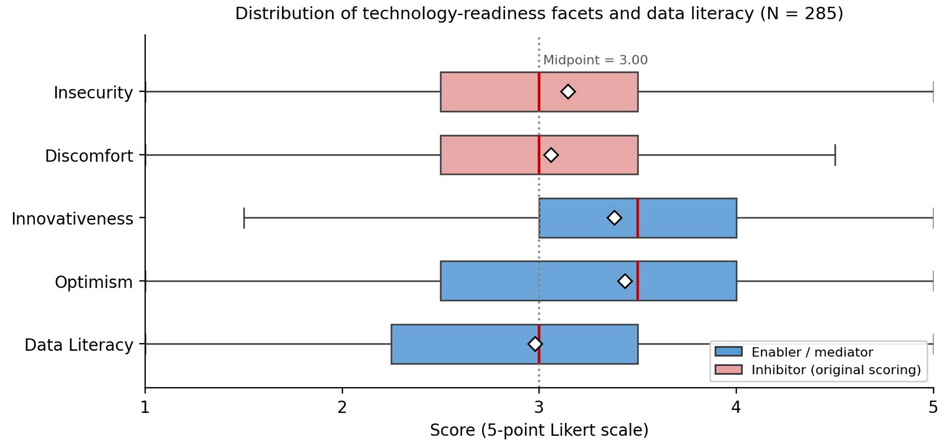

Figure 2. Boxplot of technology-readiness facets and data literacy (n = 285). box = interquartile range; line = median; diamond = mean; points = outliers. inhibitor facets (discomfort, insecurity) are shown in their original scoring, where higher values indicate greater discomfort or insecurity.

Furthermore, Discriminant validity was rigorously evaluated using both the Fornell–Larcker criterion and Heterotrait–Monotrait (HTMT) ratios. All HTMT ratios (Table 4) remained below the standard 0.90 threshold applicable to conceptually proximate constructs. Although two specific pairs, Discomfort with Insecurity (0.885) and Optimism with Adoption Intention (0.852), exceeded the more conservative 0.85 threshold, both fell within acceptable limits for closely related sociotechnical dimensions and are addressed in the study's limitations. Overall, the consolidated matrix confirms that the measurement properties are statistically robust and suitable for testing the structural model.

Structural Model Evaluation (Inner Model)

All VIF values ranged from 1.416 to 2.163, well below the 5.00 threshold (Hair et al., 2019), confirming that the model is free from multicollinearity; this assessment also indicates that common method bias is unlikely to be substantive (Kock, 2015). Table 4 reports R^2 and Q^2 for the endogenous variables. The model explains 54.5% of the variance in adoption intention, and Q^2 values above zero for all endogenous constructs confirm predictive relevance. The saturated model SRMR of 0.046 meets the good-fit criterion of below 0.080. Figure 3 presents the estimated structural model. Figure 3 shows the final estimated structural model, including

Table 3. Construct reliability and convergent validity

Construct	Cronbach's α	ρc (CR)	AVE	√AVE
Optimism (OPT)	0.756	0.891	0.804	0.896
Innovativeness (INV)	0.850	0.930	0.870	0.933
Discomfort (DIS)	0.778	0.900	0.818	0.905
Insecurity (INS)	0.738	0.884	0.792	0.890
Internal Resources (RBT)	0.916	0.934	0.704	0.839
Organizational Culture (OC)	0.904	0.940	0.838	0.916
Data Literacy (LD)	0.915	0.940	0.796	0.892
BDA Adoption Intention (BDA)	0.918	0.942	0.803	0.896

Note: α = Cronbach's Alpha; ρc = Composite Reliability; AVE = Average Variance Extracted.

Table 4. Fornell–larcker criterion and htmt ratios

	OPT	INV	DIS	INS	RBT	OC	LD	BDA
Optimism (OPT)	**0.896**	0.779	0.682	0.653	0.704	0.690	0.597	0.852
Innovativeness (INV)	0.625	**0.933**	0.641	0.555	0.586	0.623	0.568	0.663
Discomfort (DIS)	−0.523	−0.521	**0.905**	0.885	0.481	0.489	0.692	0.495
Insecurity (INS)	−0.488	−0.439	0.671	**0.890**	0.467	0.334	0.507	0.424
Internal Resources (RBT)	0.586	0.517	−0.406	−0.384	**0.839**	0.656	0.541	0.728
Organizational Culture (OC)	0.571	0.546	−0.410	−0.273	0.597	**0.916**	0.642	0.747
Data Literacy (LD)	0.497	0.501	−0.584	−0.416	0.495	0.583	**0.892**	0.681
BDA Adoption Intention (BDA)	0.710	0.586	−0.418	−0.349	0.668	0.681	0.624	**0.896**

Note: Bold diagonal values are the square root of the AVE (Fornell–Larcker criterion); values below the diagonal are inter-construct correlations; values above the diagonal are Heterotrait–Monotrait (HTMT) ratios.

Table 5. Inner model evaluation: r², q², and SRMR

Endogenous variable	R²	R² category	Q²	SRMR (saturated)
Organizational Culture (OC)	0.477	Moderate	0.395	0.046
Data Literacy (LD)	0.439	Moderate	0.344	–
BDA Adoption Intention	0.545	Moderate–Strong	0.430	–

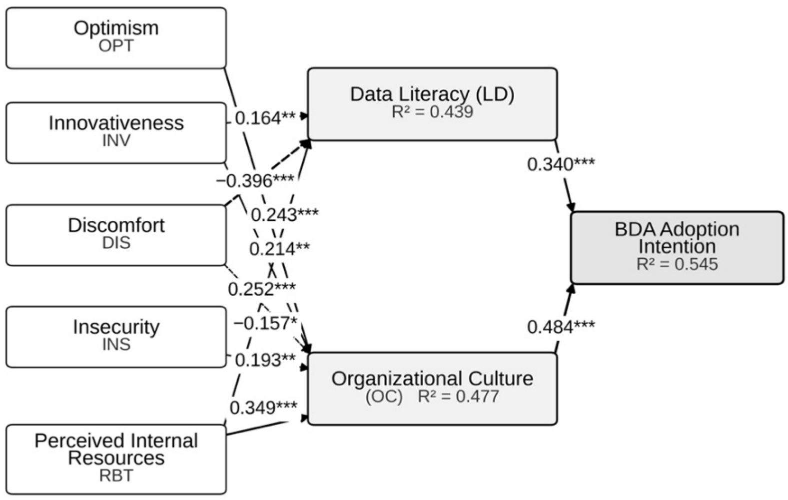

Figure 3. Structural model with standardized path coefficients (n = 285; 5,000 bootstrap subsamples, two-tailed). dashed arrows denote negative coefficients; values in endogenous constructs are r². *p < 0.05; **p < 0.01; ***p < 0.001.

standardized path coefficients (β), significance levels, and coefficient of determination (R^2) for each endogenous construct. Overall, the model demonstrates strong explanatory power, accounting for 54.5% of the variance in Big Data Analytics (BDA) Adoption Intention (R^2 = 0.545). Regarding direct drivers of adoption, both Organizational Culture (OC) (β = 0.484, p < 0.001) and Data Literacy (LD) (β = 0.340, p < 0.001) exert a positive and highly significant impact on BDA Adoption Intention, with Organizational Culture serving as the primary direct determinant. Together, these two endogenous variables explain 47.7% of the variance in Organizational Culture (R^2 = 0.477) and 43.9% of the variance in Data Literacy (R^2 = 0.439).

Hypothesis Testing – Direct Effects

Table 6 and Figure 4 report the direct effects. All ten hypothesized paths were significant at the 5% level. Two patterns are worth reading beyond the coefficients themselves. First, the structural model is asymmetric in where explanatory weight accumulates: the single strongest path runs from organizational culture to adoption intention, and it is roughly one and a half times stronger than culture's strongest antecedent. Adoption intention is therefore governed less by what individuals bring to the technology than by what the institution has already normalized around it.

Second, the four readiness dimensions do not behave as a single latent tendency. The driver dimensions act principally through culture, whereas discomfort acts principally through data literacy and is the only antecedent in the model to depress both mediators. Insecurity carries a positive coefficient on culture that reverses its negative zero-order correlation; this suppression effect, addressed in the note to Table 7, is not interpreted as a substantive finding. The asymmetry between drivers and inhibitors is precisely what the dual-factor perspective anticipates (Cenfetelli, 2004) and what a symmetrical treatment of technology readiness would have concealed: inhibitors here are not weak drivers carrying a negative sign, but antecedents operating through a different mediating mechanism altogether.

Table 6. Summary of structural model test results: direct effects and effect sizes

Path	β (O)	t-stat	p-value	95% BCa CI for β	f²	95% CI for f²	Result
OC → BDA	0.484	8.995	0.000	[0.369; 0.581]	0.334	[0.189; 0.523]	Supported (H1)
DIS → LD	−0.396	6.901	0.000	[−0.503; −0.276]	0.197	[0.092; 0.356]	Supported (H1)
RBT → OC	0.349	5.568	0.000	[0.230; 0.471]	0.142	[0.058; 0.281]	Supported (H1)
LD → BDA	0.340	6.028	0.000	[0.230; 0.452]	0.165	[0.079; 0.303]	Supported (H1)
RBT → LD	0.252	5.193	0.000	[0.155; 0.343]	0.080	[0.029; 0.156]	Supported (H1)
OPT → OC	0.243	3.671	0.000	[0.113; 0.372]	0.052	[0.011; 0.124]	Supported (H1)
INV → OC	0.214	3.278	0.001	[0.080; 0.340]	0.046	[0.008; 0.124]	Supported (H1)
INS → OC	0.193	3.172	0.002	[0.076; 0.313]	0.037	[0.002; 0.085]	Supported (H1)
INV → LD	0.164	2.758	0.006	[0.046; 0.280]	0.030	[0.003; 0.089]	Supported (H1)
DIS → OC	−0.157	2.395	0.017	[−0.291; −0.037]	0.023	[0.001; 0.065]	Supported (H1)

Note: Bias-corrected and accelerated (BCa) intervals from 5,000 bootstrap subsamples; all direct and indirect paths exclude zero. Effect-size thresholds: small $f^2 \geq 0.02$; medium ≥ 0.15; large ≥ 0.35 (Cohen, 1988).

Table 6. Mediation effects

Mediation path	Indirect β (O)	t-stat	p-value	Result
DIS → LD → BDA	−0.135	5.139	0.000	Supported (H2)
INV → LD → BDA	0.056	2.345	0.019	Supported (H2)
RBT → LD → BDA	0.086	3.461	0.001	Supported (H2)
DIS → OC → BDA	−0.076	2.384	0.017	Supported (H3)
INV → OC → BDA	0.104	3.042	0.002	Supported (H3)
OPT → OC → BDA	0.117	3.193	0.001	Supported (H3)
RBT → OC → BDA	0.169	4.743	0.000	Supported (H3)
INS → OC → BDA	0.093	3.071	0.002	Supported (H3)

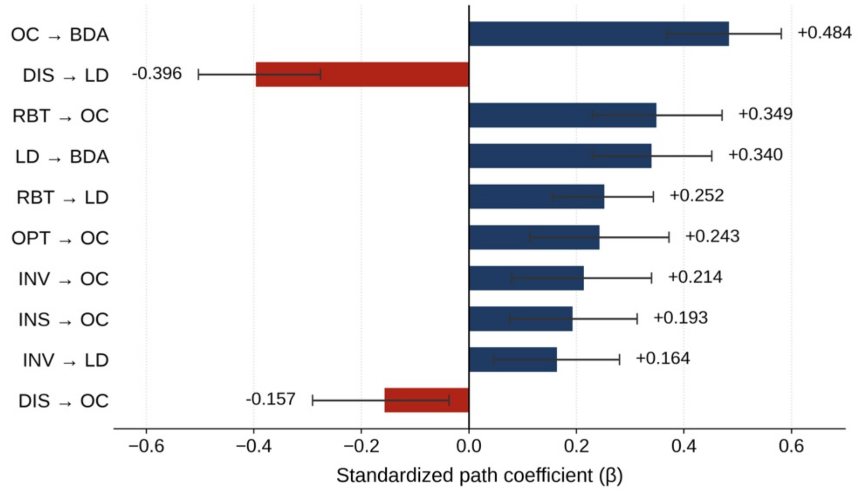

Figure 4. Direct effects with 95% bootstrap confidence intervals. bars are sorted by absolute effect size; negative paths are shown in red.

Taken together, the direct effects locate the bottleneck of BDA adoption at the sociotechnical interface rather than at either subsystem in isolation. Perceived internal resources reach adoption intention only after passing through culture and literacy, and their contribution to culture exceeds that of any single readiness dimension, indicating that, in these institutions, staff read resources as a signal of institutional commitment as much as a technical enabler.

Effect Size (f²)

The f² column in Table 5 reports effect sizes. Organizational culture is the only path reaching a medium-to-large effect on adoption intention; data literacy and the discomfort–literacy path reach medium effects, and the remainder fall in the small range. Read alongside the path coefficients, the effect sizes reinforce rather than merely restate the structural finding: the model does not distribute explanatory power evenly across antecedents but concentrates it at the cultural mediator, which is where intervention would yield the greatest marginal return, and at the discomfort–literacy path, which is where the largest single impediment is located.

Robustness Check: Consistent PLS (PLSc)

Because each technology-readiness dimension was measured with only two indicators, a consistent PLS (PLSc) estimation was performed to check whether the standardized path coefficients remain stable once measurement error is removed through disattenuation. The full comparison is reported in Appendix B. Two results are noteworthy. First, the coefficients that carry the study's substantive conclusions are essentially invariant: LD → BDA (0.344 vs 0.342), OC → BDA (0.480 vs 0.528), RBT → OC (0.354 vs 0.337), and RBT → LD (0.248 vs 0.234) all retain their sign, magnitude, and ordering, so the dominance of organizational culture and the resource–culture route are not artifacts of measurement error. Second, the coefficients linking the two inhibitor dimensions to culture are sensitive to disattenuation: DIS → OC and INS → OC change markedly under PLSc. This sensitivity is expected rather than anomalous: discomfort and insecurity are empirically close (HTMT = 0.885; disattenuated correlation ≈ 0.89), and each is measured with two items, so removing measurement error inflates their collinearity and destabilizes their individual coefficients. The PLSc check therefore corroborates the paper's principal findings while reinforcing the existing caution that the separate contributions of discomfort and insecurity to culture should be treated as provisional; confirm the exact PLSc estimates in SmartPLS.

Hypothesis Testing - Indirect Effects (Mediation)

Table 6 reports the indirect effects. All eight mediation paths were supported. The two mediators are not interchangeable: culture carries the larger share of the transmission from perceived resources and from the driver dimensions, whereas literacy carries the larger share from discomfort. Discomfort mediation is the analytically distinctive case. Discomfort has no direct path to adoption intention and reaches the outcome exclusively through the two mediators, with the larger share traveling through data literacy (−0.135) rather than culture (−0.076). Following Zhao et al. (2010), this is indirect-only mediation, with a specific managerial implication: measures that reduce the difficulty staff experience with existing systems will move adoption intention mainly by raising competence, not by changing collective norms. The indirect effect of insecurity is reported for completeness but is not interpreted substantively, for the reason given in the note to Table 5.

Robustness Check: Partial Mediation

The hypothesized model specifies full mediation, with no direct paths from the antecedents to adoption intention. To test whether this specification is warranted, we estimated a competing model in which direct paths from optimism and perceived internal resources to adoption intention were freed. Both were significant (β = 0.356 and β = 0.224, respectively), and R^2 for adoption intention rose from 0.545 to 0.689. In that specification, the two mediating paths weakened substantially, with organizational culture falling from 0.484 to 0.230 and data literacy from 0.340 to 0.199. The full-mediation assumption is therefore not fully satisfied: optimism and perceived resources retain direct associations with adoption intention that the mediators do not absorb, and the mediating coefficients reported in Table 5 should be read as upper bounds. The conclusion that culture is the stronger of the two mediating mechanisms is unaffected, since it holds under both specifications.

The results confirm the relevance of the sociotechnical framework in explaining BDA adoption in higher education. The integrative TRM–RBT model explains a substantial share of the variance in adoption intention in a behavioral model within a complex organizational domain, and it does so through mediating mechanisms rather than direct effects.

The first and most prominent finding is that organizational culture is the strongest predictor of adoption intention. This supports Gupta and George (2016) that a data-driven culture is a prerequisite for BDA capability, not a by-product. Conceptually, culture functions as the shared system of meaning Schein (2010) that converts individual potential and technical resources into collective intent. The practical implication is direct: investing in BDA infrastructure without accompanying cultural transformation produces capacity the institution will not use.

A second finding concerns the inhibitor dimensions. Discomfort exerts the strongest single effect on data literacy in the model (β = −0.396; f^2 = 0.197): the more staff report being overwhelmed by the information systems already in place and needing technical assistance to use them, the lower their self-assessed capability to work with data. This aligns with cognitive load theory, in which extraneous load from poorly designed interfaces consumes working-memory resources that would otherwise support schema construction, leaving less capacity for acquiring analytical competence (Sweller et al., 2019). The finding also carries a practical implication that distinguishes it from a generic call for training. The barrier lies in the usability of already deployed systems rather than in the absence of new technology, suggesting that improving interfaces and support around existing academic information systems may yield more literacy gain per unit of investment than procuring additional analytics capacity.

The asymmetry between the two inhibitor dimensions lies in their targets rather than in their signs. Discomfort operates on the capability channel and additionally depresses perceptions of organizational culture, whereas the association between insecurity and culture does not survive partialling and is not interpreted here. Treating technology readiness as a single balance of positive and negative dispositions would conceal this difference entirely, since aggregation would attribute the discomfort effect to the readiness construct as a whole and obscure the mediating channel through which it travels. This is the concrete sense in which the dual-factor perspective (Cenfetelli, 2004) earns its place in an adoption model: not because inhibitors are stronger than drivers, but because they reach the outcome by a different route.

A third finding concerns the role of perceived internal resources. Resources significantly shaped both organizational culture and data literacy, supporting Barney's (1991) contention that strategic resources are valuable not only in technical terms but in their capacity to shape a conducive socio-cultural environment, and echoing findings on the mediating role of organizational capabilities in the BDA literature (Mikalef et al., 2020). The resource–culture–adoption path was the strongest mediated route, indicating that resource investment translates into adoption intention most effectively through culture-building rather than directly. PLS predictive results also indicate strong out-of-sample predictive capability for the culture and literacy constructs, confirming that the model not only explains the current data but also generalizes to new observations (Shmueli et al., 2019). Overall, these findings support the sociotechnical claim that successful BDA adoption requires joint optimization of the technical and social subsystems; neither alone is sufficient.

■ CONCLUSION

This study set out to explain why BDA adoption in Indonesian private higher education lags behind the availability of the technology itself, and it answers that question in three connected ways. First, adoption intention in these institutions is not constrained by willingness. The academic community reports a clear appetite for analytics, yet the two capabilities that would make that appetite operational, a data-oriented culture and the literacy to work with data, both sit below the level of the intention they are meant to support. The gap that matters, therefore, is not between reluctance and enthusiasm but between enthusiasm and capability, and institutional intervention must close the latter.

Second, the empirical model confirms that psychological readiness and perceived internal resources reach adoption intention largely through conversion by culture and by competence. Culture proved the dominant of the two conversion mechanisms, which reframes the practical problem: an institution that invests in analytics infrastructure without simultaneously changing what its members treat as normal practice is investing in capacity it will not use. This is the study's central theoretical contribution, and it is sociotechnical: neither subsystem explains adoption alone, and the interface between them carries the explanatory weight.

Third, the inhibitor dimensions do not operate as the mirror image of the drivers. Discomfort acts principally on competence rather than on collective conditions, and it is the single largest impediment to data literacy in the model. In contrast, insecurity contributes no independently interpretable effect once discomfort is accounted for. Treating technology readiness as a single balance of positive and negative dispositions therefore misses the mechanism. For research on technology adoption in developing-country higher education, this implies that models built on driver dimensions alone, or on an aggregate readiness index, will systematically misattribute where adoption stalls.

Practically, three priorities follow. PHEIs should pursue data-based cultural transformation through leadership policies that foster experimentation and knowledge sharing. They should design continuous, staged data literacy programs for all strata of the academic community. Most immediately, they should reduce the difficulty staff encounter with the academic information systems already in operation, through interface simplification, embedded guidance, and responsive technical support, since that difficulty is the largest single impediment to the competence on which adoption depends.

Several limitations qualify these conclusions. The realized sample departs significantly from the intended proportional allocation, with the largest institution substantially under-represented. Descriptive statistics should therefore be read as characterizing the participating respondents rather than as unbiased estimates of the lecturer population of “Excellent”-accredited PHEIs in West Java. Structural coefficients are less affected, since the study tests relationships among constructs rather than estimating population parameters; nevertheless, the possibility that the structural model operates differently across institutional contexts could not be examined, because the number of respondents per institution is too small for multi-group analysis. Six of the 19 eligible institutions did not participate and may differ systematically from those that did, for instance, in digital infrastructure or administrative openness.

Further limitations concern scope and measurement. The scope is limited to “Excellent”-accredited PHEIs in West Java, so generalization to public institutions or other regions requires further research. Adoption intention was measured as a proxy for behavior rather than actual adoption, and the cross-sectional design precludes causal inference. Two measurement limitations warrant particular attention. The HTMT ratio between discomfort and insecurity is 0.885, above the 0.85 criterion for conceptually distinct constructs, which reflects the fact that both sets of items refer to the respondent’s experience of currently deployed campus systems rather than to general dispositions toward technology; the separation of their unique contributions should therefore be treated as provisional. The HTMT ratio between optimism and adoption intention is 0.852, attributable to overlap in item wording, so the association between these two constructs may be partly definitional. Each readiness dimension was measured with only two indicators, which limits the stability of these estimates. Future research should measure each dimension with the full four-item Technology Readiness Index scales, use word inhibitor items that refer to technology in general rather than specific institutional systems, examine actual adoption as the dependent variable, and consider moderating variables such as regulatory pressure and leadership support.

DECLARATION OF GENERATIVE AI USAGE IN THE WRITING PROCESS

During the preparation of this manuscript, the authors used Claude (Anthropic) to assist with language refinement, structuring tables and figures, verifying statistical computations against the dataset, and formatting the reference list. All analytical decisions, the interpretation of results, and the substantive content were determined by the authors. After using this tool, the authors reviewed and edited the content as needed and accept full responsibility for the article's final content.

REFERENCES

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Al Hadwer, A., Tavana, M., Gillis, D., & Rezania, D. (2021). A systematic review of organizational factors impacting cloud-based technology adoption using technology-organization-environment framework. *Internet of Things*, *15*, 100407. https://doi.org/10.1016/j.iot.2021.100407

Alyoussef, I., & Al-Rahmi, W. (2022). Big data analytics adoption via lenses of Technology Acceptance Model: empirical study of higher education. *Entrepreneurship and Sustainability Issues*, 9(3), 399–413. https://doi.org/10.9770/jesi.2022.9.3(24)

Baig, M. I., Yadegaridehkordi, E., Shuib, L., & Sallehuddin, H. (2023). Identifying determinants of big data adoption in the higher education sector using a multi-analytical SEM-ANN approach. *Education and Information Technologies*, *28*(12), 16457–16484. https://doi.org/10.1007/s10639-023-11875-6

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17(1), 99–120. https://doi.org/10.1177/014920639101700108*

Bostrom, R. P., & Heinen, J. S. (1977). MIS Problems and Failures: A Socio-Technical Perspective. Part I: The Causes. *MIS Quarterly*, *1*(3), 17–32. https://doi.org/10.2307/248710

Cenfetelli, R. T. (2004). Inhibitors and enablers as dual factor concepts in technology usage. *Journal of the Association for Information Systems*, *5*(11), 472–492. https://doi.org/10.17705/1jais.00059

Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. *Education and Information Technologies*, *25*(5), 3443–3463. https://doi.org/10.1007/s10639-020-10159-7

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: from big data to big impact. *MIS Quarterly*, *36(4), 1165–1188. https://doi.org/10.2307/41703503*

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13(3), 319–340. https://doi.org/10.2307/249008*

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312

Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, *35*(2), 137–144. https://doi.org/10.1016/j.ijinfomgt.2014.10.007

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information and Management*, *53*(8), 1049–1064. https://doi.org/10.1016/j.im.2016.07.004

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2022). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook. Springer. https://doi.org/10.1007/978-3-030-80519-7*

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31(1)*, 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of E-Collaboration*, *11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Kock, N., & Hadaya, P. (2018). Minimum

sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal*, *28*(1), 227–261. https://doi.org/10.1111/isj.12131

Lai, Y., Sun, H., & Ren, J. (2018). Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management: An empirical investigation. *The International Journal of Logistics Management*, *29*(2), 676–703. https://doi.org/10.1108/IJLM-06-2017-0153

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big Data Analytics Capabilities and Innovation: The Mediating Role of Dynamic Capabilities and Moderating Effect of the Environment. *British Journal of Management*, *30*(2), 272–298. https://doi.org/10.1111/1467-8551.12343

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information and Management*, *57*(2), 103169. https://doi.org/10.1016/j.im.2019.05.004

Parasuraman, A. (2000). Technology Readiness Index (Tri): A Multiple-Item Scale to Measure Readiness to Embrace New Technologies. *Journal of Service Research*, *2*(4), 307–320. https://doi.org/10.1177/109467050024001

Parasuraman, A., & Colby, C. L. (2015). An Updated and Streamlined Technology Readiness Index: TRI 2.0. *Journal of Service Research*, *18*(1), 59–74. https://doi.org/10.1177/1094670514539730

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*(3), 879–891. https://doi.org/10.3758/BRM.40.3.879

Ridsdale, C., Rothwell, J., Smit, M., Ali-Hassan, H., Bliemel, M., Irvine, D., Kelley, D., Matwin, S., & Wuetherick, B. (2015). *Strategies and Best Practices for Data Literacy Education: Knowledge synthesis report. Dalhousie University. https://doi.org/10.13140/RG.2.1.1922.5044*

Sarker, S., Chatterjee, S., Xiao, X., & Elbanna, A. (2019). The sociotechnical axis of cohesion for the IS discipline: Its historical legacy and its continued relevance. *MIS Quarterly*, *43*(3), 695–719. https://doi.org/10.25300/MISQ/2019/13747

Schein, E. H. (2010). *Organizational culture and leadership* (4th ed.). Jossey-Bass.

SEVIMA. (2025). *Tren Digitalisasi Kampus di 2025: hasil survey 300+ Institusi Pendidikan*. SEVIMA. https://sevima.com/ebook/tren-digitalisasi-kampus-di-2025-hasil-survei-300-institusi-pendidikan/

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing*, *53*(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189

Sweller, J., Van Merriënboer, J. J. G., & Paas, F. (2019). Cognitive architecture and instructional design: 20 years later. *Educational Psychology Review*, *31*(2), 261–292. https://doi.org/10.1007/s10648-019-09465-5

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

Trist, E. (1981). The evolution of socio-technical system. *Ontario Ministry of Labour, Ontario Quality of Working Life Centre*.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27(3), 425–478. https://doi.org/10.2307/30036540*

Vrontis, D., Chaudhuri, R., & Chatterjee, S. (2022). Adoption of Digital Technologies by SMEs for Sustainability and Value Creation: Moderating Role of Entrepreneurial Orientation. *Sustainability*, 14(13), 7949. https://doi.org/10.3390/su14137949

Wolff, A., Gooch, D., Cavero Montaner, J. J., Rashid, U., & Kortuem, G. (2016). Creating an understanding of data literacy for a data-driven society. *The Journal of Community Informatics*, *12*(3), 9–26. https://doi.org/10.15353/joci.v12i3.3275

Zhao, X., Lynch, J. G., & Chen, Q. (2010).

Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research*, *37*(2), 197–206. https://doi.org/10.1086/651257