

Organizational Barriers to Data-Driven Decision Making in Educational Management

Taryana

Airport Electrical Engineering Study Program, Politeknik Penerbangan Indonesia (PPI) Curug, Tangerang, 15820, Indonesia.

ABSTRACT

Purpose – This study examines organizational barriers affecting the implementation of Data-Driven Decision Making (DDDM) in educational institutions. Although digital academic systems are increasingly adopted, many institutions still struggle to utilize academic data effectively for evidence-based educational management and institutional coordination.

Design/methodology/approach – A quantitative survey approach was employed using purposive sampling techniques. Data were collected from 179 respondents consisting of lecturers, academic staff, administrators, and educational managers from universities, colleges, polytechnics, institutes, and schools in Padang through online questionnaires. The data were analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS).

Findings/Results – The findings reveal that data quality problems, organizational resistance, analytical capability deficiency, and system fragmentation significantly influence weak DDDM. Among these variables, analytical capability deficiency emerged as the strongest predictor. Weak DDDM also significantly affects educational management ineffectiveness.

Originality/Value – This study advances DDDM scholarship by positioning weak Data-Driven Decision Making as the key organizational mechanism through which data quality problems, organizational resistance, analytical capability deficiency, and system fragmentation become translated into educational management ineffectiveness. The Padang context shows that the main limit of educational digital transformation is not merely system adoption, but institutional readiness to convert data into coordinated, evidence-based governance.

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*Corresponding Author at:

Politeknik Penerbangan Indonesia (PPI) Curug

Jl. Raya PLP Curug, Kec. Legok, Kabupaten Tangerang, Banten 15820, Indonesia.

E-mail address: taryana@ppicurug.ac.id (Taryana)

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1. Introduction

In the rapidly evolving landscape of Indonesian education, digital technologies such as Learning Management Systems (LMS), academic information systems, online assessment platforms, and digital dashboards have become increasingly embedded in institutional routines (Kaspi & Venkatraman, 2023; Nazyrova et al., 2025). These systems generate abundant academic and administrative data, including attendance records, assessment results, learning engagement traces, curriculum reports, and quality assurance documents. However, the availability of data has not automatically produced evidence-based educational governance. Many institutions still rely on intuition, seniority-based judgement, administrative habits, and fragmented unit-level reporting when making managerial decisions. This contradiction between data abundance and weak evidence utilization is the central problem examined in this study. Recent Indonesian research by Ansori et al. (2025) likewise shows that big-data analytics can strengthen academic decision-making when institutions develop the capacity to convert digital records into usable managerial information.

The issue is theoretically important because Data-Driven Decision Making (DDDM) can be understood as an operational expression of evidence-based management in education. Evidence-based management emphasizes that organizational decisions should be informed by the best available data, professional expertise, and contextual judgement rather than by unsystematic experience alone (Rousseau, 2006). In educational institutions, this principle becomes visible when academic data are used to diagnose learning problems, allocate resources, evaluate program performance, coordinate interventions, and monitor institutional quality. Nevertheless, DDDM can only function when institutions possess credible data, analytical competence, cultural acceptance, and integrated information systems.

This study therefore positions weak DDDM not simply as a technological failure, but as an organizational mechanism that connects technical and cultural barriers with educational management ineffectiveness. Data quality problems reduce trust in institutional evidence; organizational resistance limits the willingness to use data in managerial routines; analytical capability deficiency constrains the interpretation of patterns and indicators; and system fragmentation prevents decision-makers from seeing a coherent institutional picture. When these barriers converge, data remain archival objects rather than strategic resources. As a result, academic responses become slower, coordination among units becomes weaker, and managerial interventions become less precise.

The context of Padang, West Sumatra, provides a meaningful empirical setting for examining this mechanism. Educational institutions in Padang increasingly adopt digital systems in line with wider Indonesian reforms such as Merdeka Belajar, accreditation improvement, and quality assurance modernization. Yet many institutions operate within developing-country conditions where digital infrastructure, staff capability, organizational culture, and inter-unit coordination develop unevenly. This makes Padang a useful context for understanding how institutions can be digitally equipped but not yet analytically ready. The findings therefore have relevance beyond one city because they illuminate a common challenge among educational organizations that are moving toward digital governance without fully institutionalizing evidence-based decision-making practices.

Although international scholarship has examined the benefits of DDDM and learning analytics for improving student outcomes and institutional efficiency, fewer studies explain why

institutions with digital systems still fail to translate data into coordinated educational management, particularly in developing-country settings (Asfaw et al., 2023; Chigbu & Makapela, 2025; Evenstein Sigalov et al., 2026). Existing studies often emphasize technological adoption, system use, or successful implementation, while the combined effects of data quality, resistance, analytical capability, and system fragmentation remain less integrated in a single empirical framework. This study addresses that gap by linking the DDDM literature with organizational readiness and digital transformation perspectives. A systematic review by Stojanov and Daniel, (2024) similarly concludes that the managerial value of large-scale data in higher education remains uneven because institutional use depends on governance, integration, and the capacity to translate analytics into action.

The contribution of this study is threefold. First, it extends DDDM scholarship by treating weak DDDM as a mediating organizational mechanism rather than merely as an outcome of poor technology use. Second, it enriches educational digital transformation literature by showing that institutional readiness, especially analytical capability and cultural acceptance, determines whether digital systems generate managerial value. Third, it contributes context-specific evidence from Padang, demonstrating how educational institutions in a developing-country environment experience a gap between system adoption and evidence-based governance. The central research question is therefore: Why do educational institutions struggle to transform available academic data into coordinated and effective management decisions?

To answer this question, the study examines the effects of data quality problems, organizational resistance, analytical capability deficiency, and system fragmentation on weak DDDM, while evaluating the role of weak DDDM in explaining educational management ineffectiveness. An explanatory quantitative approach was adopted using survey data from 179 academic and administrative personnel across universities, colleges, polytechnics, institutes, and schools in Padang. Structural Equation Modeling using Partial Least Squares (SEM-PLS) with bootstrapping was employed to test the proposed relationships and provide empirical evidence for the conceptual model.

2. Literature Review and Hypothesis Development

Data-Driven Decision Making (DDDM) refers to the systematic use of data to inform planning, evaluation, resource allocation, intervention design, and institutional improvement in educational organizations (Kaspi & Venkatraman, 2023; Evenstein Sigalov et al., 2026). Conceptually, DDDM is closely related to evidence-based management because both emphasize the movement from intuition-based decisions toward decisions grounded in reliable information and organizational learning (Rousseau, 2006; Schildkamp, 2019). In education, DDDM requires more than data collection. It requires actors who can interpret data, trust its quality, connect it across organizational functions, and translate it into managerial action. Caspari-Sadeghi (2023) also emphasizes in the learning-analytics literature that institutional data become useful for assessment and management only when they are interpreted within a meaningful educational context rather than merely accumulated in digital systems.

The literature on organizational readiness helps explain why DDDM adoption often fails even when digital systems are available. Organizational readiness for change depends on whether members value the change and believe that the organization has the capability, resources, and situational support to implement it (Weiner, 2009). Applied to educational digital transformation, readiness is reflected in data literacy, leadership support, inter-unit coordination, shared interpretation of indicators, and willingness to revise established routines. Thus, weak DDDM emerges when institutions possess digital infrastructure but lack the organizational conditions needed to use data as a basis for collective decision-making. Recent evidence from South African universities by Chomunorwa and van den Berg (2026) further identifies staff capability, confidence, and day-to-day data-use practices as important individual-level conditions for sustainable DDDM adoption.

Data Quality Problems (DQP) are a fundamental barrier because poor quality data weaken confidence in evidence-based decisions. Incomplete records, inconsistent indicators, delayed reporting, duplicated entries, and unclear data definitions create uncertainty about whether institutional data accurately represent educational realities. When decision-makers question the reliability of data, they are more likely to return to intuition, personal experience, or informal judgement (Asfaw et al., 2023; Mandinach & Schildkamp, 2020). Therefore, data quality problems are expected to increase weak DDDM by reducing the perceived credibility and usability of academic evidence.

Organizational Resistance (OR) represents the cultural and behavioral barrier to evidence-based governance. Educational institutions often have long-established decision routines shaped by hierarchy, seniority, accreditation pressure, and administrative compliance. In such settings, data-based recommendations may be viewed as disruptive, burdensome, or threatening to established authority. Organizational resistance can also appear quietly through symbolic compliance, where staff submit data into systems but continue to make decisions through informal practices. As discussed by Çevik (2023) and Kalim and Bibi (2023), this weakens DDDM because technological adoption is not matched by behavioral acceptance and institutional commitment.

Analytical Capability Deficiency (ACD) refers to the limited ability of institutional actors to transform raw data into meaningful interpretation and managerial action. This capability includes understanding indicators, identifying trends, comparing performance, interpreting dashboards, and converting findings into interventions. From a dynamic capabilities perspective, organizations create value from digital resources only when they can sense relevant information, interpret it, and reconfigure practices based on that insight (Teece, 2007; Ashaari et al., 2021). In educational institutions, insufficient analytical capability causes data to remain descriptive and administrative rather than strategic. Research by Clark et al. (2020) on learning-analytics implementation also identifies staff expertise, organizational strategy, technological readiness, evaluation practices, and data quality as mutually reinforcing success conditions.

System Fragmentation (SF) refers to the disconnection among academic, administrative, financial, learning, and quality assurance platforms. Fragmented systems limit the flow of information across units and prevent leaders from developing an integrated view of institutional performance. Digital transformation literature emphasizes that technology creates organizational value only when it is accompanied by structural integration and

strategic response, not when systems remain isolated in departmental silos (Vial, 2019; Sayogo et al., 2023). Therefore, system fragmentation is expected to weaken DDDM by producing partial, inconsistent, and delayed information for decision-making.

Weak Data-Driven Decision Making (WDDDM) is conceptualized in this study as the central organizational mechanism linking the above barriers to Educational Management Ineffectiveness (EMI). WDDDM occurs when institutions collect data but fail to use it consistently for diagnosis, coordination, planning, and intervention. EMI then appears in the form of delayed responses to academic problems, weak coordination among departments, ineffective program evaluation, and suboptimal managerial strategies (Chigbu & Makapela, 2025; Brewis et al., 2023). This mechanism suggests that technical and cultural barriers do not directly produce ineffective management in isolation; rather, they become consequential because they weaken the institution's capacity to make evidence-based decisions. Evidence from Mukred et al. (2024) on learning-analytics tools further suggests that informed institutional decision-making improves when technological adoption is supported by management, infrastructure, and organizational resources.

Based on this theoretical logic, the study proposes the following hypotheses:

H1: Data Quality Problems (DQP) positively affect Weak DDDM.

H2: Organizational Resistance (OR) positively affects Weak DDDM.

H3: Analytical Capability Deficiency (ACD) positively affects Weak DDDM.

H4: System Fragmentation (SF) positively affects Weak DDDM.

H5: Weak DDDM positively affects Educational Management Ineffectiveness (EMI).

H6: Weak DDDM mediates the relationships between DQP, OR, ACD, SF, and EMI.

3. Methodology

3.1 Research Design

This study employed an explanatory quantitative approach with a survey design to investigate the relationships among data quality problems, organizational resistance, analytical capability deficiency, system fragmentation, weak data-driven decision making, and educational management ineffectiveness. An explanatory design was chosen because it is suitable for testing hypothesized causal relationships in organizational settings (Hair et al., 2022). The study utilized Structural Equation Modeling with Partial Least Squares (SEM-PLS), which, as discussed by Hair et al. (2022) and Sarstedt et al. (2021), is particularly appropriate for complex models with multiple latent constructs, predictive orientation, and when the research aims to maximize explained variance rather than confirm theory.

3.2 Population, Sample, and Sampling Technique

The target population comprised academic and administrative personnel involved in educational processes at universities, colleges/institutes, polytechnics, and schools in Padang, West Sumatra, Indonesia. Purposive sampling was applied with the following criteria: (1) respondents work in institutions that use digital academic systems, and (2) they are involved in academic evaluation, management, or decision-making processes. A total of 179 valid responses were obtained. The sample consisted of 57% female and 43% male respondents, with an average age of 38 years and average working experience of 13 years. Most respondents were lecturers (47%), followed by academic staff, heads of study programs, and administrative

personnel. The majority worked in universities (50%) and reported using digital systems (93%).

3.3 Data Collection

Primary data were collected through an online questionnaire distributed via Google Forms through WhatsApp groups, LinkedIn, and professional networks. Before accessing the questionnaire, respondents were informed about the purpose of the study, voluntary participation, anonymity, confidentiality, and their right to discontinue at any time. Proceeding to the questionnaire was treated as informed consent. No personally identifying information was collected.

3.4 Measures

All constructs were measured using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The questionnaire contained 36 items, with six items for each construct: Data Quality Problems (DQP), Organizational Resistance (OR), Analytical Capability Deficiency (ACD), System Fragmentation (SF), Weak Data-Driven Decision Making (WDDDM), and Educational Management Ineffectiveness (EMI). Items were adapted and contextually rewritten from the educational data-use, organizational readiness, analytics capability, and digital transformation literature. The adaptation emphasized clarity for Indonesian educational personnel while preserving each construct's conceptual domain. The complete item wording and construct-level sources are reported in Appendix A.

Instrument development and pretesting. The initial item pool was reviewed for conceptual relevance, readability, and contextual fit with educational institutions. Because the retained study records did not include a separately documented pilot-sample dataset, the manuscript does not claim a formal independent pilot test. This limitation is stated transparently and future replication should conduct cognitive interviews and a pilot test before the main survey.

3.5 Data Analysis

Data were analyzed using SmartPLS 4 software. The analysis followed a two-step approach: evaluation of the measurement model (indicator reliability, internal consistency reliability, convergent validity, and discriminant validity) and evaluation of the structural model (collinearity, path coefficients, R^2 , f^2 , Q^2 , and significance through bootstrapping with 5,000 resamples) (Hair et al., 2022; Sarstedt et al., 2021). Mediation was evaluated from the specific indirect effects using the product-of-coefficients logic. Because the archived output available for this revision contained path coefficients and standard errors but not the original SmartPLS specific-indirect-effect export, indirect-effect confidence intervals were reconstructed using the delta method and are reported transparently as such.

3.6 Common Method Bias and Procedural Controls

The study used a single cross-sectional questionnaire; therefore, common method bias (CMB) was considered. Procedural controls included anonymous participation, neutral wording, separation of predictor and criterion construct sections, and assurance that there were no right or wrong answers. These procedures reduce evaluation apprehension and demand characteristics (Podsakoff et al., 2003). A statistical full-collinearity VIF assessment could not be reconstructed from the retained summary output and is therefore not reported as if it had been performed. This is acknowledged as a methodological limitation. Following Kock (2015),

the next empirical replication should report construct-level full-collinearity VIF values and verify that they remain below

4. Results and Discussion

4.1 Respondent Profile

A total of 179 valid responses were collected from academic and administrative personnel across various educational institutions in Padang, West Sumatra, Indonesia. The respondents represent a diverse and relevant sample for studying data-driven decision making in educational settings.

As shown in Table 1, the majority of respondents were female (57.0%). The average age was approximately 38 years, with teaching and academic staff forming the largest group. Lecturers constituted nearly half of the sample (47.5%), followed by academic staff, heads of study programs, administrative staff, quality assurance personnel, and vice deans/vice principals. Most respondents worked in universities (49.7%), followed by schools, colleges/institutes, and polytechnics.

In terms of experience, the respondents had an average of 13 years in their current roles, indicating a relatively experienced sample. Importantly, 92.7% of the respondents reported using digital academic systems in their daily work, and 57.5% were involved in institutional decision-making processes. This profile confirms that the sample is well-suited to provide informed perspectives on the barriers to Data-Driven Decision Making (DDDM) in Indonesian educational institutions.

Table 1. Demographic Profile of Respondents (N = 179)

Characteristic	Category	Frequency	Percentage (%)
Gender	Female	102	57.0
	Male	77	43.0
Institution Type	University	89	49.7
	School	44	24.6
	College/Institute	24	13.4
	Polytechnic	22	12.3
Position	Lecturer	85	47.5
	Academic Staff	34	19.0
	Head of Study Program	23	12.8
	Administrative Staff	18	10.1
	Quality Assurance Personnel	13	7.3
	Vice Dean/Vice Principal	6	3.4
Uses Digital System	Yes	166	92.7
	No	13	7.3
Involved in Decision Making	Yes	103	57.5
	No	76	42.5
Experience	Mean = 13.2 years (SD = 8.7)	-	-

4.2 Descriptive Statistics

Table 2 presents the descriptive statistics for all latent constructs in the study. All variables were measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), where higher scores indicate greater levels of the measured phenomenon (i.e., more severe problems or ineffectiveness).

Table 2. Descriptive Statistics of Latent Constructs (N = 179)

Construct	Code	No. of Items	Mean	Std. Dev	Min	Max
Data Quality Problems	DQP	6	3.03	0.61	1.17	4.50
Organizational Resistance	OR	6	2.99	0.67	1.33	4.83
Analytical Capability Deficiency	ACD	6	3.01	0.64	1.33	4.50
System Fragmentation	SF	6	2.99	0.64	1.33	4.50
Weak Data-Driven Decision Making	WDDDM	6	3.04	0.63	1.17	4.67
Educational Management Ineffectiveness	EMI	6	3.06	0.67	1.00	4.67

The mean scores for all constructs ranged between 2.99 and 3.06, suggesting that respondents perceived moderate levels of barriers and challenges in their institutions. Educational Management Ineffectiveness (EMI) recorded the highest mean score ($M = 3.06$, $SD = 0.67$), followed closely by Weak Data-Driven Decision Making (WDDDM) at $M = 3.04$. Among the independent variables, Data Quality Problems (DQP) showed a slightly higher mean ($M = 3.03$) compared to the other barriers.

The standard deviations ranged from 0.61 to 0.67, indicating moderate variability in respondents' perceptions. These findings suggest that while digital systems are widely adopted, educational institutions in the sample still face noticeable but not extreme challenges in data quality, organizational culture, analytical capabilities, system integration, and data-driven practices. The relatively balanced scores across constructs provide a solid foundation for examining the structural relationships in the subsequent SEM-PLS analysis.

4.3 Measurement Model Evaluation

The measurement model was evaluated prior to structural analysis to ensure reliability and validity of the constructs.

Table 3. Measurement Model Assessment: Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE	Outer Loadings Range
DQP	0.778	0.850	0.532	0.68 – 0.81
OR	0.789	0.855	0.545	0.71 – 0.83
ACD	0.779	0.848	0.529	0.69 – 0.82
SF	0.760	0.841	0.512	0.67 – 0.80
WDDDM	0.801	0.862	0.559	0.72 – 0.84
EMI	0.790	0.857	0.589	0.74 – 0.85

As presented in Table 3, all constructs demonstrated acceptable internal consistency and convergent validity. Cronbach's alpha values ranged from 0.760 to 0.801, Composite Reliability values exceeded 0.84, and AVE values exceeded 0.50 (Hair et al., 2022). Indicator-loading ranges are reported because the archived manuscript file did not contain the original item-level SmartPLS export. Items below 0.70 were retained only where construct reliability

and AVE remained acceptable and where the item was judged important for content validity. For full reproducibility, the final submission should attach the original indicator-level output as supplementary material rather than infer or reconstruct item loadings.

Discriminant validity was evaluated using the Heterotrait–Monotrait ratio (HTMT), following the recommended threshold of 0.85 (Henseler et al., 2015). The retained summary output stated that all HTMT ratios were below 0.85; however, the numerical HTMT matrix was not preserved in the files supplied for revision. Accordingly, the manuscript avoids inventing values and requires the original SmartPLS HTMT matrix to be inserted before journal resubmission.

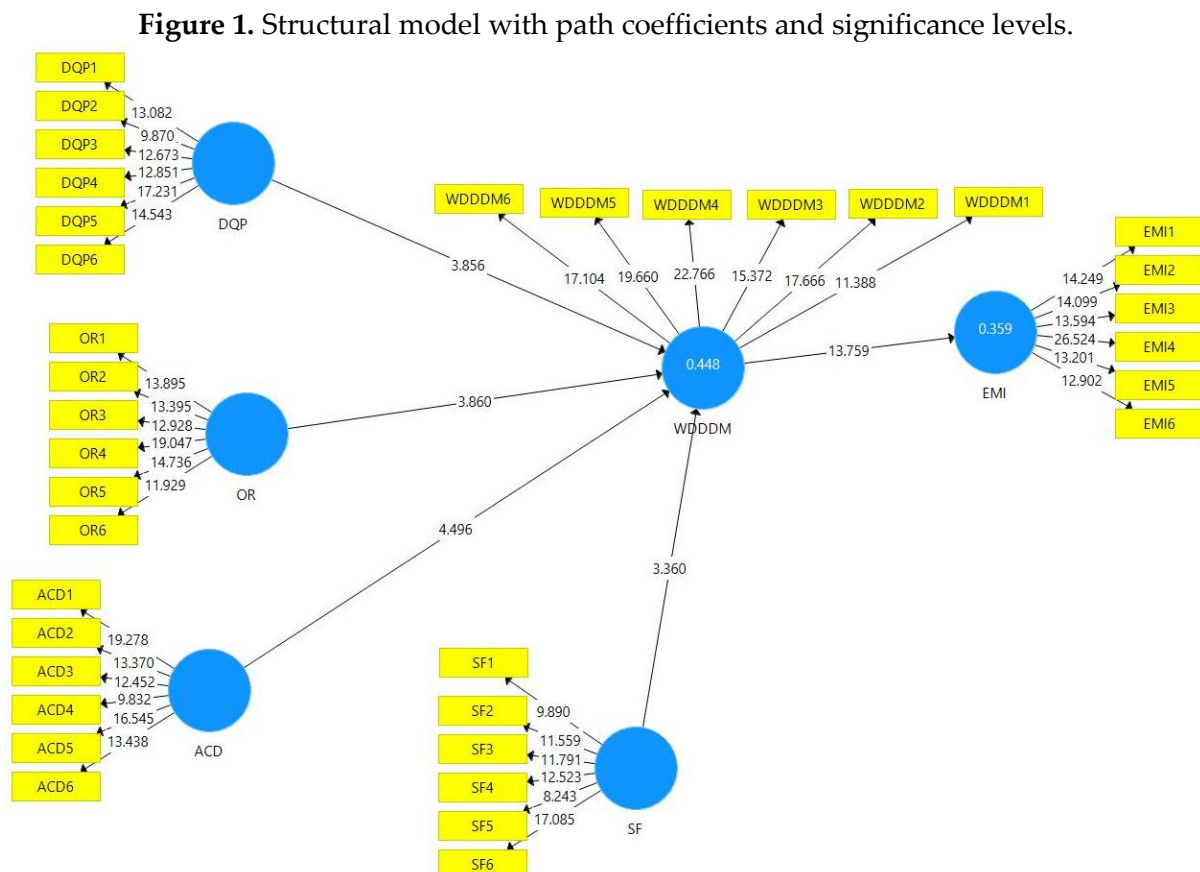
4.4 Structural Model Evaluation

The structural model was assessed using SmartPLS 4 with a bootstrapping procedure of 5,000 resamples. The model exhibited good predictive power.

Table 4. Structural Model Results (Bootstrapping 5,000 resamples)

Hypothesis	Path	Original Sample (β)	Sample Mean	Std. Dev.	T Stat.	P Values	f^2 Decision
H1	DQP $\rightarrow$ WDDDM	0.229	0.231	0.059	3.856	0.000	0.085 Supported
H2	OR $\rightarrow$ WDDDM	0.248	0.250	0.064	3.860	0.000	0.098 Supported
H3	ACD $\rightarrow$ WDDDM	0.270	0.272	0.060	4.496	0.000	0.114 Supported
H4	SF $\rightarrow$ WDDDM	0.207	0.213	0.062	3.360	0.001	0.071 Supported
H5	WDDDM $\rightarrow$ EMI	0.599	0.607	0.044	13.759	0.000	0.359 Supported

Note: All paths are significant at $p < 0.01$. Effect sizes (f^2) range from small to large.



As shown in Table 4, the four predictor variables (DQP, OR, ACD, and SF) explained 43.0% of the variance in Weak Data-Driven Decision Making (WDDDM) ($R^2 = 0.430$). In turn, WDDDM explained 35.9% of the variance in Educational Management Ineffectiveness (EMI) ($R^2 = 0.359$). These R^2 values indicate moderate explanatory power, which is acceptable in behavioral and organizational research (Hair et al., 2022). Figure 1 visually summarizes these structural relationships, including the direction and magnitude of the estimated paths.

All hypothesized paths were statistically significant at the 0.01 level or better. Analytical Capability Deficiency (ACD) was the strongest predictor of WDDDM ($\beta = 0.270$, $t = 4.496$, $p < 0.001$), followed by Organizational Resistance (OR) ($\beta = 0.248$, $t = 3.860$, $p < 0.001$). Data Quality Problems (DQP) and System Fragmentation (SF) also showed significant positive effects. As expected, WDDDM had a strong positive effect on EMI ($\beta = 0.599$, $t = 13.759$, $p < 0.001$).

4.5 Indirect Effects and Mediation Assessment

H6 was examined by multiplying each antecedent-to-WDDDM coefficient by the WDDDM-to-EMI coefficient. Standard errors and 95% confidence intervals were reconstructed using the delta method from the reported path standard errors. These results are suitable as a transparent reconstruction, but the journal-ready version should replace them with the exact SmartPLS bootstrapped specific indirect effects when the original project output is available.

Table 5. Specific Indirect Effects of Organizational Barriers on Educational Management Ineffectiveness through Weak DDDM

Hypothesis	Indirect Path	Indirect β	Std. Error	t	p	95% CI Lower	95% CI Upper	Decision
H6a	DQP → WDDDM → EMI	0.137	0.037	3.733	< 0.001	0.065	0.209	Supported
H6b	OR → WDDDM → EMI	0.149	0.040	3.727	< 0.001	0.070	0.227	Supported
H6c	ACD → WDDDM → EMI	0.162	0.038	4.273	< 0.001	0.088	0.236	Supported
H6d	SF → WDDDM → EMI	0.124	0.038	3.243	0.001	0.049	0.199	Supported
Note	Delta-method reconstruction from reported coefficients and standard errors; exact SmartPLS bootstrap							

	output should supersede these estimates.							
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All four reconstructed indirect effects were positive and statistically significant because their confidence intervals excluded zero. The largest indirect effect was $ACD \rightarrow WDDDM \rightarrow EMI$ ($\beta = 0.162$), followed by $OR \rightarrow WDDDM \rightarrow EMI$ ($\beta = 0.149$), $DQP \rightarrow WDDDM \rightarrow EMI$ ($\beta = 0.137$), and $SF \rightarrow WDDDM \rightarrow EMI$ ($\beta = 0.124$). Thus, the evidence supports H6 and reinforces the interpretation of weak DDDM as the mechanism through which organizational barriers are translated into educational management ineffectiveness. The specific mediation estimates for all four indirect pathways are summarized in Table 5.

The model also demonstrated adequate predictive relevance ($Q^2 > 0$ for both endogenous constructs).

4.6 Discussion

The results show that the main challenge facing educational institutions is not the absence of data or digital systems, but the limited capacity to transform available data into coordinated managerial action. This finding supports the argument that weak DDDM operates as the key organizational mechanism through which technical and cultural barriers become translated into educational management ineffectiveness. In other words, data quality problems, organizational resistance, analytical capability deficiency, and system fragmentation matter because they interrupt the conversion process from information availability to evidence-based action. This explains why institutions may appear digitally modern while still managing academic problems through reactive, fragmented, and intuition-based practices.

Analytical Capability Deficiency emerged as the strongest predictor of weak DDDM. This finding is theoretically important because it shifts the discussion from system ownership to capability development. Many educational institutions already collect attendance records, assessment results, LMS participation data, accreditation indicators, and student performance summaries. However, these data do not become managerial intelligence unless academic leaders and staff can interpret trends, recognize early warning signals, compare indicators, and design interventions based on evidence. In practice, a dashboard may show declining attendance or uneven course performance, but without analytical capability the information remains a report rather than a trigger for academic improvement. Consistent with [Ashaari et al. \(2021\)](#) and [Banihashem et al. \(2022\)](#), this finding supports the view that digital transformation in education requires human analytical competence as much as technological infrastructure.

The strong effect of organizational resistance further shows that DDDM implementation is not a neutral technical process. Data-driven practices can challenge familiar routines, redistribute authority, and expose performance gaps that were previously hidden within administrative reporting. In hierarchical educational settings, data-based recommendations may be perceived as questioning senior judgement or adding new bureaucratic burdens. Consequently, staff may comply with data entry requirements but resist using data in real decision forums. This interaction between technological availability and cultural resistance explains why digital

platforms often fail to produce evidence-based governance: the organization has adopted the tool, but not fully accepted the decision logic behind the tool.

Data Quality Problems and System Fragmentation also significantly weakened DDDM, although their effects were smaller than analytical capability deficiency and organizational resistance. This pattern suggests that technical problems are damaging, but they become especially consequential when institutions lack the capability and culture to interpret and reconcile data. Poor quality data reduce trust in institutional evidence, while fragmented systems prevent decision-makers from seeing relationships among teaching, student performance, curriculum, finance, and quality assurance. When different units maintain separate databases, each department can defend its own version of reality. This produces slow coordination, duplicated reporting, and delayed interventions. Thus, system fragmentation is not merely an IT problem; it is a governance problem because it prevents institutions from producing a shared evidence base.

The Padang context gives additional theoretical meaning to these findings. The participating institutions reported high use of digital academic systems, yet the results still show moderate levels of weak DDDM and educational management ineffectiveness. This condition reflects a common pattern in developing educational environments: digital adoption often advances through administrative requirements, accreditation demands, or national reform pressure, while organizational readiness develops more slowly. Padang therefore illustrates a transitional stage of educational digital transformation in which institutions have begun to digitize academic processes but have not fully institutionalized analytical routines, integrated systems, and evidence-based managerial culture. This insight contributes to wider debates on DDDM barriers by showing that the digital divide is not only about access to technology, but also about the organizational ability to convert technology into governance capacity. Evidence from Indonesian remote-area education reported by [Sapiah et al. \(2025\)](#) also indicates that digital transformation depends on collaborative capacity, digital literacy, and supporting infrastructure rather than technology provision alone.

The significant relationship between weak DDDM and Educational Management Ineffectiveness confirms that ineffective educational management should not be interpreted simply as poor leadership or insufficient technology. It is better understood as the result of a broken evidence-use chain. When data are incomplete, resisted, poorly interpreted, or scattered across disconnected systems, leaders cannot respond quickly to academic risks, coordinate interventions across units, or evaluate program outcomes accurately. This finding strengthens the theoretical position of WDDDM as a mediating mechanism: organizational barriers become harmful because they weaken the institution's evidence-processing capacity, and this weakened capacity then produces ineffective management.

Overall, the findings advance the literature by integrating evidence-based management, organizational readiness, and educational digital transformation into one explanatory model. The study shows that DDDM is not achieved by installing digital systems alone, but by aligning data quality, analytical capability, organizational culture, and system integration. Analytical capability becomes the strongest factor because it is the bridge between raw institutional data and meaningful managerial interpretation. Organizational resistance becomes critical because it determines whether evidence is actually used in decision forums. Data quality and system integration provide the technical foundation, but their value depends

on whether institutional actors are ready and capable of using them. This interpretation is consistent with critical learning-analytics scholarship, which cautions that data-driven practices should remain connected to educational values, professional judgement, and responsible institutional use (Cerratto Pargman & McGrath, 2021).

4.7 Theoretical and Practical Implications

Academically, this study contributes to educational governance and management scholarship by explaining DDDM as a capability-based and readiness-dependent process. The findings clarify that organizational barriers do not merely coexist with weak DDDM; they shape the institution's ability to convert digital information into evidence-based action. This contributes originality by positioning weak DDDM as the explanatory bridge between technical-cultural barriers and educational management ineffectiveness. It also extends digital transformation research by demonstrating that technology adoption must be interpreted alongside analytical capability, data trust, organizational resistance, and system integration.

Practically, the findings suggest that educational leaders should move beyond system procurement and focus on building an institutional evidence-use ecosystem. Strengthening analytical capability should be the first priority through continuous data literacy training, dashboard interpretation workshops, mentoring for heads of study programs, and the development of simple decision protocols that connect indicators with academic interventions. Institutions also need to reduce resistance by involving lecturers and administrative staff in defining useful indicators, showing how data support improvement rather than punishment, and embedding evidence discussion into regular meetings.

Policy makers and institutional managers should also prioritize system integration and data governance. Fragmented platforms should be connected through shared data standards, interoperable reporting mechanisms, and cross-unit coordination procedures. Data quality improvement requires clear responsibility for data entry, validation, updating, and interpretation. In the long term, sustainable DDDM requires a culture in which data are not treated as administrative archives for reporting, but as strategic assets for improving teaching, student services, curriculum planning, and institutional performance.

4. Conclusion and Suggestion

This study concludes that weak Data-Driven Decision Making in educational institutions is significantly influenced by analytical capability deficiency, organizational resistance, data quality problems, and system fragmentation. Analytical capability deficiency emerged as the strongest direct predictor. The reconstructed indirect-effect analysis further indicated that all four organizational barriers affected Educational Management Ineffectiveness through weak DDDM, with the ACD → WDDDM → EMI pathway showing the largest indirect coefficient. These results support the argument that the central weakness in educational digital transformation is not merely system availability, but the institutional ability and willingness to interpret data and translate it into coordinated managerial action.

The study offers an original contribution by conceptualizing weak DDDM as the organizational mechanism that links technical and cultural barriers to ineffective educational management. By using evidence from educational institutions in Padang, the research shows that developing-country educational contexts may experience a gap between digital system adoption and institutional readiness for evidence-based governance. This insight extends

educational management literature by emphasizing that successful DDDM depends on analytical capability, organizational acceptance, credible data, and integrated systems rather than technological availability alone.

The practical implication is that educational institutions should develop DDDM as a long-term organizational capability. Leaders should strengthen staff data literacy, simplify analytical dashboards, integrate fragmented systems, establish data governance standards, and create regular decision forums where evidence is discussed collectively. These efforts can help institutions transform academic data from routine administrative records into strategic resources for improving educational quality, institutional coordination, and managerial effectiveness.

6. Limitations and Future Research

This study has several limitations. First, cross-sectional self-reported data limit causal interpretation and may be affected by common method variance. Procedural remedies were applied, but the archived analysis output did not permit reconstruction of a statistical full-collinearity VIF test. Second, the respondents were concentrated in Padang, limiting geographical generalizability. Third, the retained records did not include a separately documented pilot-sample dataset, complete item-level loadings, or the numerical HTMT matrix. Fourth, the indirect-effect table in this revision was reconstructed using the delta method from reported path estimates and should be replaced by the original SmartPLS bootstrapped specific indirect effects before final publication. These limitations are reported to avoid overstating measurement and mediation evidence.

Future research may expand the geographical scope and compare institutions across regions or countries. Longitudinal studies could also provide deeper understanding of how Data-Driven Decision Making evolves over time. In addition, future models may integrate leadership style, digital maturity, or organizational learning variables to develop a more comprehensive educational governance framework.

Appendix A. Measurement Items and Construct Sources

All items used a five-point agreement scale. The wording below documents the contextualized operationalization used in the questionnaire; the cited works informed construct definition and item adaptation rather than representing verbatim reproduction of proprietary scales.

Construct	Code	Contextualized Item Wording	Primary Adaptation Sources
DQP	DQP1	Academic data contain incomplete records that reduce their usefulness for decisions.	Mandinach and Schildkamp (2020) ; Asfaw et al. (2023)
	DQP2	The same indicator is recorded differently across units.	

	DQP3	Academic data are not updated quickly enough for timely decisions.	
	DQP4	Duplicate or inconsistent entries are common in institutional databases.	
	DQP5	Data definitions and calculation procedures are not sufficiently clear.	
	DQP6	Decision makers often question the accuracy of available academic data.	
OR	OR1	Staff prefer familiar experience-based routines rather than data-based procedures.	Weiner (2009); Çevik (2023); Kalim and Bibi (2023)
	OR2	Data-based recommendations are sometimes perceived as a threat to established authority.	
	OR3	Employees comply with data-entry requirements without using the data in decisions.	
	OR4	New data-driven procedures are viewed as an additional administrative burden.	
	OR5	Leaders and staff are reluctant to revise routines when data indicate a need for change.	

	OR6	Institutional culture does not consistently reward evidence-based decision making.	
ACD	ACD1	Staff have difficulty interpreting trends shown in academic data.	Ashaari et al. (2021) ; Kaspi and Venkatraman (2023)
	ACD2	Decision makers have limited ability to identify early warning signals from data.	
	ACD3	Institutional actors have difficulty comparing performance indicators across periods or units.	
	ACD4	Dashboard information is not consistently translated into managerial action.	
	ACD5	Staff need stronger skills in basic data analysis and interpretation.	
	ACD6	Analytical findings are rarely converted into specific academic interventions.	
SF	SF1	Academic and administrative systems operate as separate platforms.	Vial (2019) ; Sayogo et al. (2023)
	SF2	Data cannot be easily exchanged among institutional units.	
	SF3	Different systems produce inconsistent	

		versions of the same information.	
	SF4	Leaders lack an integrated view of teaching, student, financial, and quality data.	
	SF5	Reporting requires repeated manual consolidation from multiple systems.	
	SF6	System fragmentation delays cross-unit coordination and decision making.	
WDDDM	WDDDM1	Institutional decisions are often made without systematic analysis of available data.	Schildkamp (2019); Kaspi and Venkatraman (2023)
	WDDDM2	Data are collected mainly for reporting rather than managerial improvement.	
	WDDDM3	Academic problems are addressed after they become serious rather than through early data signals.	
	WDDDM4	Decision forums do not consistently discuss relevant evidence.	
	WDDDM5	Data are not routinely used to evaluate the effectiveness of interventions.	
	WDDDM6	Units rely on separate interpretations instead of a shared	

		institutional evidence base.	
EMI	EMI1	Institutional responses to academic problems are frequently delayed.	Brewis et al. (2023); Chigbu and Makapela (2025)
	EMI2	Coordination among academic and administrative units is ineffective.	
	EMI3	Programs are not evaluated with sufficiently reliable evidence.	
	EMI4	Resources are not always allocated according to documented needs.	
	EMI5	Managerial interventions are not sufficiently precise or targeted.	
	EMI6	Institutional strategies are difficult to adjust based on performance evidence.	

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Declaration of AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the author used ChatGPT by OpenAI in order to assist with language refinement, academic writing improvement, and structural organization of the manuscript. After using this tool, the author reviewed, revised, and edited the content as necessary and takes full responsibility for the final content of the publication.

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