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Data-Driven Decision-Making Capability and Strategic Decision Quality in Saudi Universities: A Contingency Perspective on Environmental Uncertainty

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ABSTRACT

Purpose: Purpose: This study examines the relationship between Data-Driven Decision-Making (DDDM) Capability and Strategic Decision Quality in Saudi higher education institutions and tests the moderating role of Environmental Uncertainty.
Design / Methodology: A quantitative cross-sectional survey was administered to 150 senior academic and administrative leaders across Saudi public and private universities. Partial Least Squares Structural Equation Modeling (PLS-SEM) with 5,000 bootstrap subsamples was employed for hypothesis testing.
Findings: DDDM Capability significantly and positively predicts Strategic Decision Quality ($\beta = 0.412$, $R^2 = 0.384$, $f^2 = 0.187$). Environmental Uncertainty significantly attenuates this relationship ($\beta = -0.187$, $p = .001$), with Dynamism and Complexity exerting the strongest constraining effects, indicating that data-driven governance yields its highest decision-quality premium under moderate rather than extreme uncertainty.
Originality / Value: This is the first empirical study to establish a multidimensional DDDM–decision quality nexus in higher education and to document a negative contingency moderation effect, advancing both contingency theory and the evidence base for evidence-based governance reform under Vision 2030.
Keywords: Data-driven decision-making; strategic decision quality; environmental uncertainty; higher education; Saudi Arabia; PLS-SEM; contingency theory.

INTRODUCTION

Despite substantial organizational investments in analytics infrastructure, the conditions under which data-driven decision-making (DDDM) capability translates into superior strategic decision quality remain poorly understood — particularly within higher education (Davenport & Harris, 2007; Mikalef et al., 2020). This gap is especially consequential in the Saudi context, where Vision 2030 has positioned universities as instruments of national economic transformation and catalysed far-reaching governance reform. Saudi institutions face acute pressure to demonstrate evidence-based strategic management, yet the relationship between their analytical capabilities and decision quality has received no direct empirical scrutiny.

Contingency theory holds that the effectiveness of organizational practices depends on fit with the environment (Lawrence & Lorsch, 1967; Donaldson, 2001). Applied here, it yields the proposition that the DDDM–decision quality relationship is moderated by environmental uncertainty: when the institutional environment is highly dynamic, complex, and resource-scarce, the marginal contribution of analytical capability to decision quality is heightened (Dess & Beard, 1984; Milliken, 1987). Three targeted gaps justify this study. First, DDDM capability is multidimensional — spanning data integration, analytics, interpretive communication, and organizational culture (Kiron et al., 2014; Vidgen et al., 2017) — yet its disaggregated effects on strategic decision quality subdimensions have not been examined (Dean & Sharfman, 1996; Elbanna & Child, 2007). Second, environmental uncertainty has been theorized as a boundary condition but not empirically tested in this configuration (Baum & Wally, 2003; Eisenhardt, 1989). Third, Saudi higher education is entirely absent from the DDDM literature.

This study addresses these gaps by: (1) assessing DDDM capability across Saudi universities; (2) evaluating strategic decision quality across theoretically grounded dimensions; (3) examining their direct relationship; and (4) testing environmental uncertainty as a contingency moderator. The study extends contingency theory to data-driven institutional governance, generates psychometrically rigorous evidence from an underrepresented national context, and offers actionable recommendations for higher education leaders and policymakers.

Research Objectives

RO1: To assess the level and profile of DDDM Capability across Saudi universities across four dimensions: data collection and integration, analytics capability, interpretive communication, and data-driven culture.

RO2: To evaluate strategic decision quality across four dimensions: comprehensiveness, rationality and evidence-basis, timeliness, and outcome effectiveness.

RO3: To examine the direct relationship between DDDM Capability and Strategic Decision Quality.

RO4: To test the moderating effect of Environmental Uncertainty — operationalized across dynamism, complexity, and munificence — on the DDDM–decision quality relationship.

RO5: To derive empirically supported recommendations for institutional leaders and policymakers.

THEORETICAL FRAMEWORK AND LITERATURE REVIEW

Theoretical Foundations

The primary theoretical lens is contingency theory, which holds that organizational effectiveness is contingent upon alignment between organizational characteristics and the demands of the external environment (Lawrence & Lorsch, 1967; Donaldson, 2001). Donaldson (2001) formalized this into a rigorous analytical framework, specifying fit — the match between organizational practices and contextual factors — as the central mediating mechanism through which context shapes performance. Applied here, the contribution of DDDM capability to strategic decision quality is not invariant across institutional environments but is amplified under elevated environmental uncertainty, when information processing demands are highest. This contingency logic has found renewed empirical expression in recent research demonstrating that the value derived from analytics capabilities is fundamentally conditioned by the nature and intensity of the organizational context in which those capabilities are deployed (Laguir et al., 2023; Wong & Ngai, 2023). Specifically, Laguir et al. (2023), in a survey of 405 firms, demonstrated that analytics capability exerts differential effects on supply chain resilience and operational performance under varying degrees of environmental uncertainty, thereby reinforcing the proposition that organizational capabilities are not universally valuable but yield performance benefits in a contingency-consistent manner. These insights extend the foundational claim that fit, rather than the mere possession of resources, drives outcomes — a principle that the present study applies to the higher education context for the first time.

As a complementary foundation, this study draws on dynamic capabilities theory, which holds that sustained competitive advantage derives from an organization's capacity to sense, seize, and reconfigure capabilities in response to environmental change (Teece et al., 1997). Mikalef et al. (2018) explicitly theorize big data analytics capability as a dynamic capability; Mikalef et al. (2020) confirmed that its value is mediated by the breadth and reconfigurability of organizational capabilities, rather than arising from technological investment alone. Advancing this line of inquiry, Garmaki, Gharib, and Boughzala (2023) employed grounded theory methodology to develop a conceptual model demonstrating that BDA capability contributes to sustained competitive advantage through the mediating pathway of organizational learning, thereby formalizing the mechanism through which analytics-driven insight becomes embedded in institutional routines and performance. Karaboga, Zehir, Tatoglu, Karaboga, and Bouguerra (2023), drawing on dynamic capability view and survey data from 432 experts across 132 Turkish firms, further established that big data analytics management capability exerts significant positive effects on both operational and financial performance, and that this relationship is mediated by data-driven culture — a finding with direct implications for the cultural dimension of DDDM capability operationalized in the present study. The resource-based view further frames DDDM capability, when deeply institutionalized, as satisfying the criteria of rarity, value, inimitability, and non-substitutability (Barney, 1991). Xu and Lu (2026) extended this framework using AI-assisted language modeling across 2,873 Chinese listed firms, confirming that DDDM positively impacts international firm performance by enabling sustainable value creation across multiple competitive dimensions. Collectively, these theoretical perspectives converge on the proposition that DDDM capability, when culturally embedded and organizationally reconfigurable, constitutes a strategic asset capable of systematically elevating decision quality.

DDDM Capability: Conceptualization and Evidence

Data-driven decision-making (DDDM) capability refers to an organization's capacity to systematically collect, process, analyze, and interpret data to inform and improve the quality of its decisions (Davenport & Harris, 2007). Gupta and George (2016) advanced a multidimensional operationalization distinguishing tangible resources (data assets and technology infrastructure), human skills (technical expertise and managerial data literacy), and intangible resources (data-driven culture and organizational learning). Mikalef et al. (2018), through a systematic review of 57 empirical studies, further disaggregated these into six capability dimensions. The present study operationalizes DDDM Capability across four dimensions: (1) data collection and integration — systematic gathering and unification of high-quality data (Mikalef et al., 2018; Wamba et al., 2017); (2) analytics capability — deployment of advanced analytical methods (Gupta & George, 2016; Oesterreich et al., 2022); (3) data interpretation and communication — translation of analytical outputs into actionable intelligence (Vidgen et al., 2017); and (4) data-driven organizational culture — normative embedding of evidence-based reasoning (Mikalef et al., 2020). This multidimensional conceptualization has been empirically substantiated and refined in recent scholarship. Wong and Ngai (2023), combining strategic fit theory, dynamic capability view, and resource-based view in a structural equation model of 149 micro, small, and medium enterprises, demonstrated that both sensing and analytics capabilities have significant positive effects on operational performance, and that a data-driven culture moderates and amplifies these relationships — a finding directly consistent with the cultural dimension of DDDM capability developed here. Karaboga et al. (2023) similarly confirmed that data-driven culture mediates the analytics capability–performance link, suggesting that technical investments in analytics must be accompanied by normative organizational change to yield decision-relevant value. The human dimensions of DDDM capability have received sustained attention in emerging research. Korherr and Kanbach (2023) developed a comprehensive taxonomy of human-related capabilities in big data analytics, identifying technical expertise, managerial acumen, and cross-functional communication skills as distinct factors with measurable impact on firm performance — reinforcing the multi-domain operationalization adopted in the present study. Abdellatif et al. (2023) advanced this further by demonstrating, through partial least squares structural equation modeling, that business analytics capabilities improve strategic decision quality by enhancing both decision speed and comprehensiveness, with these process-level improvements serving as mediating mechanisms between technical capability and organizational outcomes.

The human analytical dimensions of DDDM capability are further nuanced by individual-level factors. Khan et al. (2025) examined the role of individual data-driven mindset (DDM) in enabling data-driven transformation, finding that expectancy beliefs and perceived values shape effort and persistence in data-driven behaviors, with direct implications for analytical culture formation at the institutional level. This individual-to-organizational link reinforces the proposition that DDDM capability cannot be reduced to its technological substrate but must be understood as a socio-technical configuration spanning individual cognition, organizational culture, and data infrastructure.

In higher education, Ashaari et al. (2021) demonstrated that big data analytics capability significantly improves institutional performance in Malaysian universities through direct and mediated pathways — emphasizing the critical role of managerial and human factors alongside technical infrastructure. Gaftandzhieva et al. (2023) confirmed that while analytical tools are increasingly adopted, their application to strategic institutional decision-making remains substantially underexplored. Khaw and Teoh (2023) provided further higher education-specific evidence, demonstrating in a study of private higher education institutions that big data analytics technological capabilities exercise a positive influence on institutional performance through the mediating mechanism of strategic agility — introducing agility as a critical translating mechanism between analytics capability and institutional outcomes. This finding indicates that the performance consequences of DDDM capability in higher education are not direct but require organizational responsiveness as an enabling condition, a nuance that the contingency framework of the present study is well-positioned to capture. A well-established empirical literature links DDDM capability to organizational performance across sectors: Wamba et al. (2017) demonstrated positive effects from analytics capabilities embedded in dynamic organizational routines; Raguseo and Vitari (2018) documented direct and knowledge-mediated pathways; Oesterreich et al. (2022), in a meta-analysis of 134 empirical studies, confirmed that both social and technical dimensions of big data analytics significantly predict firm performance. Garmaki et al. (2023) confirmed that organizational learning fully mediates the contribution of BDA capability to competitive advantage, while Karaboga et al. (2023) showed that data-driven culture plays an analogous mediating role for operational and financial performance. Awan et al. (2023) provided complementary cross-national evidence from Pakistan's banking sector, showing that DDDM significantly affects organizational productivity through both direct and innovation-mediated pathways, reinforcing the generalizability of analytics capability's performance effects beyond manufacturing contexts.

Strategic Decision Quality

Strategic decision quality is a multidimensional construct capturing both process and outcome quality. Dean and Sharfman (1996) established that systematic information gathering and rational analytical approach significantly predict decision effectiveness. Elbanna and Child (2007) distinguished decision rationality from comprehensiveness, while Shepherd and Rudd (2014) identified timeliness and outcome alignment as critical quality dimensions. Eisenhardt (1989) demonstrated that high-quality decisions in fast-moving environments combine analytical rigor with deliberate speed.

The present study adopts a four-dimensional operationalization: decision comprehensiveness (thoroughness of information search, alternative consideration, and stakeholder consultation); decision rationality (degree to which decisions are analytically grounded); decision timeliness (responsiveness within appropriate timeframes); and decision effectiveness and outcome alignment (degree to which strategic decisions achieve intended objectives aligned with broader institutional imperatives). This operationalization is consistent with recent developments in the strategic decision quality literature. Abdellatif et al. (2023), drawing on resource-based theory, demonstrated empirically that business analytics capabilities positively predict both decision comprehensiveness and decision speed, and that when firms utilize business analytics, these two dimensions are mutually inclusive rather than in tension — a significant departure from earlier assumptions of a speed–comprehensiveness trade-off. Alzghoul et al. (2022) similarly confirmed, using PLS-SEM on data from 236 Jordanian executives, that business intelligence capability enhances decision-making speed and comprehensiveness, which in turn improve organizational performance, with firm size moderating these relationships. Al-Hashimi, Weerakkody, Elbanna, and Schwarz (2022), in a landmark study of 170 strategic decisions across 38 public organizations in Qatar, developed and tested an integrative model demonstrating positive relationships between procedural rationality, participation, and constructive politics and the successful implementation of strategic decisions — and further showed that implementation fully mediates the relationships between these process dimensions and decision outcomes. This evidence underscores the necessity of treating decision quality as a process–outcome compound rather than as a purely evaluative post-hoc judgment. Scholtes, Trif, and Curseu (2024) added cognitive nuance, showing that the positive association between individual managerial rationality and organizational decision comprehensiveness holds only at low levels of dysfunctional cognition, reversing under high cognitive dysfunction — a finding with implications for how DDDM capability may compensate for individual cognitive limitations through structured analytical processes.

Environmental Uncertainty

Environmental uncertainty has been central to contingency theory since Lawrence and Lorsch (1967). Milliken (1987) provided the most influential typology, distinguishing state uncertainty, effect uncertainty, and response uncertainty. The present study operationalizes environmental uncertainty across three empirically validated dimensions: environmental dynamism (rate, volatility, and unpredictability of institutional change); environmental complexity (number, diversity, and interdependence of external factors); and environmental munificence (availability of critical external resources — low munificence intensifies competitive pressures). Dubey et al. (2020) demonstrated that environmental dynamism strengthens the positive relationship between analytics capability and performance. Wamba et al. (2020) confirmed that the performance premium from analytics capability is amplified by environmental dynamism.

Recent scholarship has substantiated and refined these contingency claims with greater theoretical and empirical precision. Laguir et al. (2023) provided confirmatory evidence that environmental uncertainty conditions the effects of analytics capability on supply chain resilience and operational performance, offering a compelling supply chain context analogue for the higher education dynamics examined here. Importantly, their findings showed that the moderating influence of environmental uncertainty is not uniform across all analytics-capability–outcome relationships, suggesting that future contingency research must be attentive to which dimensions of uncertainty interact with which dimensions of capability. Berkhout et al. (2024) revisited the construct of data-driven decision-making itself, identifying its antecedents, scope, and boundary conditions, and arguing that the performance consequences of DDDM are fundamentally contingent on the institutional context's capacity to absorb, interpret, and act on analytical outputs — a theoretical claim with direct implications for higher education institutions operating under asymmetric environmental pressures. Despite this evidence, no prior study has applied this contingency framework to higher education or tested strategic decision quality as the focal dependent variable. The present study thus addresses a substantive gap by examining, for the first time, whether environmental uncertainty moderates the DDDM capability–strategic decision quality relationship in higher education institutions, contributing to both the DDDM literature and to the contingency-theoretic understanding of institutional analytics.

Hypotheses

DDDM capability enhances decision comprehensiveness by expanding information fidelity; strengthens decision rationality by providing an empirical evidence base that constrains cognitive and political biases; supports decision timeliness through real-time data access and scenario modeling; and contributes to decision effectiveness through post-implementation outcome monitoring (Davenport & Harris, 2007; Mikalef et al., 2020; Raguseo & Vitari, 2018).

H1: DDDM Capability exerts a significant and positive direct effect on Strategic Decision Quality in Saudi universities.

Four disaggregated sub-hypotheses connect specific capability dimensions to quality subdimensions:

H1a: Data Collection and Integration is positively associated with Decision Comprehensiveness.

H1b: Data Analytics Capability is positively associated with Decision Rationality.

H1c: Data Interpretation and Communication is positively associated with Decision Timeliness.

H1d: Data-Driven Organizational Culture is positively associated with Decision Effectiveness and Outcome Alignment.

Under conditions of high environmental uncertainty, decision-makers face elevated information processing demands: the number of relevant variables increases, the rate of change accelerates, and the cost of decisional errors grows. DDDM capability directly addresses these heightened demands by supplying timely, analytically grounded institutional intelligence. Accordingly, its marginal contribution to decision quality should be greatest when uncertainty is highest — a logic empirically anchored in Dubey et al. (2020), Wamba et al. (2020), and Elbanna and Child (2007).

H2: Environmental Uncertainty positively moderates the DDDM Capability–Strategic Decision Quality relationship. Sub-hypotheses H2a–H2c specify positive moderation for Dynamism, Complexity, and Munificence respectively.

Research Model

Figure 1 presents the conceptual research model. DDDM Capability — operationalized across four dimensions — constitutes the independent variable. Strategic Decision Quality — operationalized across four dimensions — constitutes the dependent variable. Environmental Uncertainty — across dynamism, complexity, and munificence — is the moderating variable. Institutional characteristics and top management team analytical orientation serve as control variables.

FIGURE 1. CONCEPTUAL RESEARCH MODEL

Independent Variable   Dependent Variable

DDDM Capability ——— **H1** ———▶ **Strategic Decision Quality**

DCI · DA · DIC · DDC   H1a–H1d   Comprehensiveness · Rationality · Timeliness · Effectiveness

▲ **H2 / H2a–H2c**
Moderator: Environmental Uncertainty
Dynamism · Complexity · Munificence
Controls: Institutional Type · Size · IT Maturity · TMT Analytical Orientation

METHODOLOGY

Research Design

The study is grounded in a positivist epistemological position, which holds that social phenomena can be studied through objective measurement and that causal relationships can be identified through systematic empirical testing (Creswell & Creswell, 2018). A deductive research approach is adopted, in which theoretically derived hypotheses are subjected to empirical verification through primary data collection. A cross-sectional quantitative survey design is employed — appropriate for examining relationships between latent constructs such as perceived decision quality and institutional capability at a defined point in time (Kline, 2016).

Population, Sampling, and Sample Size

The target population comprises senior academic and administrative leaders across Saudi public and private universities holding formal responsibility for institutional strategic decision-making — including full professors serving on governance committees, deans, department heads, directors of strategic planning and institutional research units, and senior administrative officials. A stratified proportional random sampling procedure was employed, stratifying by institutional type (public/private), region, and size. The final achieved sample was $n = 150$. A G*Power analysis (Cohen, 1988) confirmed a minimum required sample of $n = 103$ to detect a medium effect size ($f^2 = 0.15$) with 80% statistical power; the achieved sample provides approximately 95% power. The sample also satisfies PLS-SEM guidelines recommending a minimum of ten times the largest number of structural paths directed at any single latent variable (Hair et al., 2019).

Data Collection

Primary data were collected via a structured, self-administered questionnaire distributed electronically. A pilot phase administered to 20 academic and administrative leaders not in the main sample assessed item clarity and face validity. Data collection spanned eight weeks with two follow-up reminders. To assess non-response bias, early versus late respondents were compared across key demographic variables and construct means using independent samples t-tests (Armstrong & Overton, 1977); no significant differences were observed (all $p > 0.05$). A total of 178 questionnaires were returned, of which 150 were retained after excluding 28 responses failing eligibility criteria or exhibiting excessive missing data.

Measurement Instrument

All constructs were measured using reflective, multi-item scales adapted from validated instruments, with a seven-point Likert response format (1 = Strongly Disagree; 7 = Strongly Agree). Table 1 summarizes the measurement instrument.

Table 1: Measurement Instrument Summary

Construct	Dimension	Items	Source Scale
DDDM Capability	Data Collection & Integration	4	Mikalef et al. (2018); Wamba et al. (2017)
	Data Analytics Capability	4	Gupta & George (2016); Oesterreich et al. (2022)
	Interpretive Communication	3	Vidgen et al. (2017); Mikalef et al. (2020)
	Data-Driven Culture	3	Mikalef et al. (2020)
Strategic Decision Quality	Decision Comprehensiveness	4	Dean & Sharfman (1996); Elbanna & Child (2007)
	Decision Rationality	4	Elbanna & Child (2007); Shepherd & Rudd (2014)
	Decision Timeliness	3	Eisenhardt (1989); Baum & Wally (2003)
	Decision Effectiveness	4	Shepherd & Rudd (2014)
Environmental Uncertainty	Dynamism	4	Miller & Friesen (1983); Dess & Beard (1984)
	Complexity	3	Duncan (1972); Dess & Beard (1984)
	Munificence (R)	3	Dess & Beard (1984); Milliken (1987)
Control Variables	IT Maturity, TMT Orientation, Institutional Age	6	Established literature

Note. (R) denotes reverse-scored items.

Analytical Strategy

Hypothesis testing was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM), implemented in SmartPLS 4.0. PLS-SEM was selected over covariance-based SEM on four grounds: (1) the model is predictive and exploratory in orientation; (2) the structural model is complex, incorporating four second-order constructs and a three-dimensional moderating variable; (3) the sample size of n = 150, while adequate for PLS-SEM, falls below conservative thresholds for CB-SEM; and (4) PLS-SEM is more robust to deviations from multivariate normality (Hair et al., 2022). The measurement model was evaluated for indicator reliability (outer loadings ≥ 0.70), internal consistency (Cronbach's α and CR ≥ 0.70), convergent validity (AVE ≥ 0.50), and discriminant validity using HTMT < 0.85 (Henseler et al., 2015). Structural assessment employed bootstrapping with 5,000 BCa subsamples, R^2, f^2, Q^2, and SRMR < 0.08. Moderation interaction terms were operationalized using the product-indicator approach with standardized scores (Hair et al., 2022). Common method bias was assessed using Harman's single-factor test and the unmeasured latent method factor procedure (Podsakoff et al., 2003).

RESULTS

Overview

Findings are presented in four sequential stages: sample characteristics, common method bias (CMB) assessment, measurement model evaluation, and structural model estimation with hypothesis testing. All analyses were conducted in SmartPLS 4.0 using 5,000 BCa bootstrap subsamples (Hair et al., 2019; 2022).

Sample Characteristics

Of 178 returned questionnaires, 150 were retained for analysis after excluding 28 incomplete responses (retention rate: 84.3%). Table 1 presents the full demographic profile and Figure 1 provides a graphical summary.

Table 2: Demographic Profile of the Sample (N = 150)

Variable	Category	n	%
Gender	Male	96	64.0
	Female	54	36.0
Age Group	Under 30	6	4.0
	30–39	42	28.0
	40–49	56	37.3
	50–59	40	26.7
	60 or above	6	4.0
Current Position	Vice Rector / Deputy President	5	3.3
	Dean	20	13.3
	Director	43	28.7
	Department Head	48	32.0
	Faculty Member	23	15.3
	Other	11	7.3
Qualification	Bachelor's Degree	3	2.0
	Master's Degree	25	16.7
	Doctoral Degree	116	77.3
	Other	6	4.0
Total Experience	Less than 5 years	13	8.7
	5–10 years	34	22.7
	11–15 years	32	21.3
	16–20 years	42	28.0
	More than 20 years	29	19.3
	Less than 2 years	20	13.3

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Years in Current Role	2–5 years	44	29.3
	6–10 years	50	33.3
	More than 10 years	36	24.0
Institution Type	Governmental	91	60.7
	Private	59	39.3
Decision-Making Involvement	Core member of committee	30	20.0
	Regular strategic participant	30	20.0
	Occasional consultant	50	33.3
	Implementation role only	27	18.0
	No direct involvement	13	8.7
Analytics / IR Unit	Fully operational and integrated	31	20.7
	Established, limited scope	63	42.0
	In development	33	22.0
	No unit	23	15.3

Note. Percentages may not sum to 100% due to rounding.

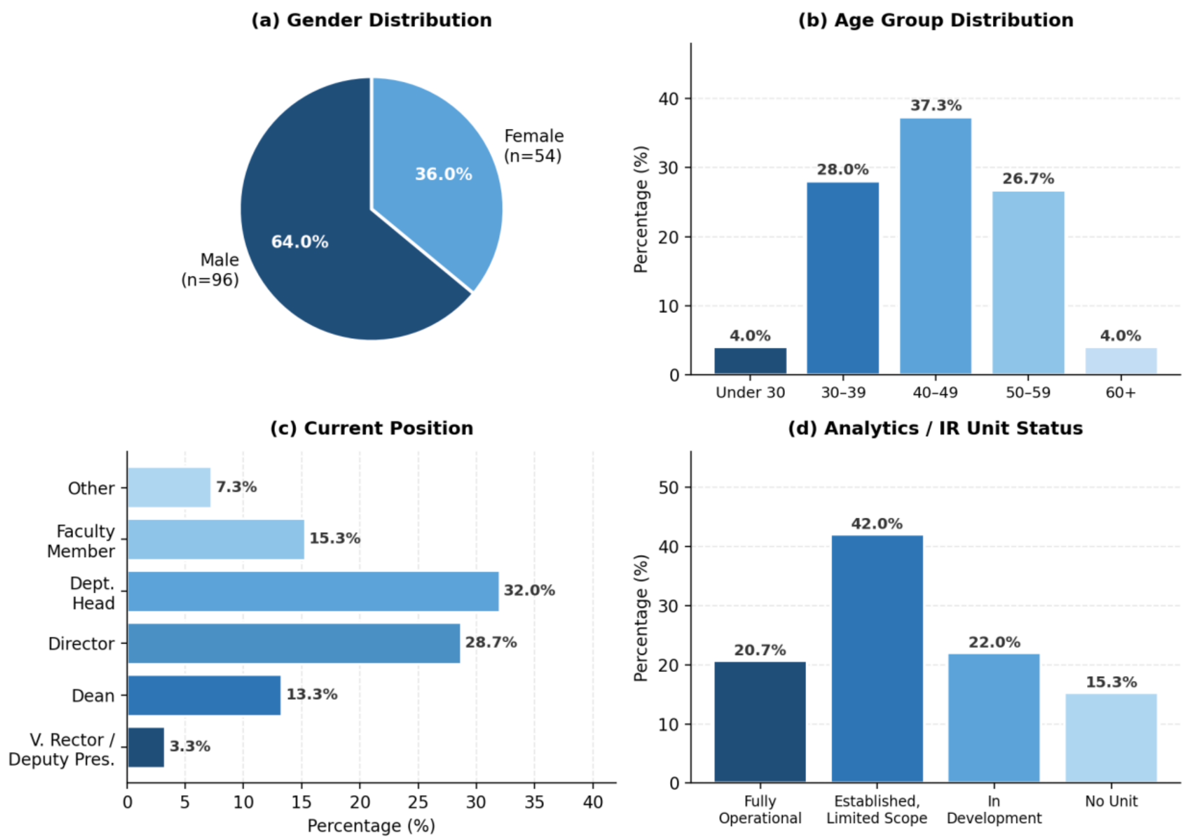

Figure 1. Sample Demographic Profile (N = 150)

Figure 1. Sample Demographic Profile (N = 150). Panel (a) gender; (b) age group; (c) current position; (d) analytics/IR unit status.

Common Method Bias Assessment

CMB was assessed using procedural controls (item separation, reverse-coding, respondent anonymity) and two statistical procedures (Podsakoff et al., 2003). Harman's single-factor test yielded 31.2% variance explained — well below the 50% threshold — and the unmeasured latent common method factor procedure produced negligible changes in path estimates ($\Delta\beta < 0.03$ for all paths). CMB does not constitute a significant threat to the validity of the findings.

Measurement Model Assessment

The measurement model was evaluated for indicator reliability, convergent validity, and discriminant validity in accordance with Section 3.5.2 criteria (Table 2; Figures 2 and 4).

Indicator Reliability and Internal Consistency

All 39 items achieved outer loadings ≥ 0.70 (range: $\lambda = 0.701$–0.882). Cronbach's alpha ($\alpha = 0.780$–0.876) and composite reliability (CR = 0.858–0.914) exceeded the CR ≥ 0.70 threshold (Hair et al., 2022), confirming adequate internal consistency across all dimensions.

Convergent Validity

All 11 dimensions achieved AVE ≥ 0.50 (range: 0.529–0.774), satisfying the Fornell-Larcker (1981) criterion and confirming convergent validity.

Discriminant Validity

All 55 inter-construct HTMT values were below the conservative threshold of 0.85 (range: 0.176–0.712; Table 3). Bootstrapped 95% BCa CIs excluded 1.0 for all pairs, confirming that all 11 dimensions are empirically distinct.

Table 3: Measurement Model: Indicator Loadings, Reliability, and Validity Statistics

Construct	Dimension	Item	Item Description (Abbreviated)	Loading (λ)	α	CR	AVE
DDDM Capability	*Data Collection & Integration (DCI)*	**B1**	Systematic comprehensive data collection	**0.783**			
		B2	Integration of heterogeneous internal systems	**0.812**			
		B3	Proactive acquisition of external data	**0.764**			
		B4	Formalized data governance policies	**0.831**	0.847	0.896	0.683
	Data Analytics Capability (DAC)	**B5**	Advanced analytical	**0.742**			

			approaches for planning				
		B6	Dedicated data science personnel	**0.817**			
		B7	Adequate analytics tools, widely utilized	**0.773**			
		B8	Analytics for anticipating future trends	**0.798**	0.832	0.887	0.663
	Interpretive Communication (IC)	**B9**	Senior leaders' data literacy	**0.849**			
		B10	Clear visual communication of data insights	**0.882**			
		B11	Translation of analytics to recommendations	**0.793**	0.853	0.911	0.774
	Data-Driven Culture (DDC)	**B12**	Leadership championing evidence-based decisions	**0.761**			
		B13	Institutional culture of evidence-based practice	**0.803**			
		B14	Resource allocation for data-driven practices	**0.827**	0.818	0.892	0.735
Strategic Decision Quality	*Decision Comprehensiveness (DC)*	**C1**	Systematic analysis of decision alternatives	**0.724**			
		C2	Broad stakeholder consultation	**0.797**			

		C3	Consideration of long-term implications	**0.771**			
		C4	Seeking dissenting perspectives	**0.742**	0.816	0.879	0.645
	Decision Rationality (DR)	**C5**	Decisions grounded in institutional evidence	**0.808**			
		C6	Use of structured decision-support frameworks	**0.831**			
		C7	Transparent communication of decision rationale	**0.752**			
		C8	Formal risk assessments and scenario analyses	**0.819**	0.851	0.899	0.691
	Decision Timeliness (DT)	**C9**	Appropriate decision timeliness	**0.784**			
		C10	Real-time data enabling faster decisions	**0.820**			
		C11	Expedited protocols for unexpected changes	**0.760**	0.833	0.899	0.748
	Decision Effectiveness (DE)	**C12**	Measurable improvements in institutional performance	**0.798**			
		C13	Systematic outcome monitoring against objectives	**0.843**			

		C14	Alignment with Vision 2030 objectives	**0.874**			
		C15	Prompt revision based on monitoring data	**0.790**	0.876	0.914	0.728
Environmental Uncertainty	*Dynamism (DYN)*	**D1**	Rapid regulatory and policy changes	**0.728**			
		D2	Technological change challenging adaptation pace	**0.762**			
		D3	Unpredictable student demographic shifts	**0.711**			
		D4	Rapidly evolving competitive dynamics	**0.741**	0.793	0.858	0.603
	Complexity (COMP)	**D5**	Complex array of external stakeholders	**0.774**			
		D6	Numerous interconnected performance factors	**0.797**			
		D7	Interdependencies challenging strategic planning	**0.752**	0.804	0.882	0.714
	Munificence (MUN)	**D8**	Scarce external funding and grants (R)	**0.719**			
		D9	Competition for academic talent intensified (R)	**0.762**			

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		D10	Socio-economic constraints on partnerships (R)	**0.701**	0.780	0.871	0.693

Note. α = Cronbach's alpha; CR = Composite Reliability; AVE = Average Variance Extracted. Values of α and CR are reported once per dimension at the last item. All items scored on a 7-point Likert scale (1 = Strongly Disagree; 7 = Strongly Agree). (R) = reverse-scored item. All loadings ≥ 0.70; all AVE ≥ 0.50; all CR ≥ 0.70.

Table 4: Discriminant Validity: Heterotrait-Monotrait Ratio (HTMT) Matrix

Dimension	DCI	DAC	IC	DDC	DC	DR	DT	DE	DYN	COMP	MUN
DCI											
DAC	0.612										
IC	0.584	0.631									
DDC	0.621	0.598	0.643								
DC	0.653	0.614	0.601	0.578							
DR	0.638	0.672	0.588	0.634	0.694						
DT	0.571	0.589	0.614	0.547	0.641	0.712					
DE	0.607	0.542	0.573	0.592	0.658	0.681	0.638				
DYN	0.341	0.312	0.298	0.273	0.287	0.319	0.342	0.301			
COMP	0.289	0.271	0.317	0.261	0.241	0.298	0.311	0.278	0.624		
MUN	0.198	0.187	0.214	0.203	0.176	0.201	0.228	0.195	0.542	0.571	

Note. HTMT = Heterotrait-Monotrait ratio. All values < 0.85 (Henseler et al., 2015); all bootstrapped 95% BCa CIs exclude 1.0, confirming discriminant validity. DCI = Data Collection & Integration; DAC = Data Analytics Capability; IC = Interpretive Communication; DDC = Data-Driven Culture; DC = Decision Comprehensiveness; DR = Decision Rationality; DT = Decision Timeliness; DE = Decision Effectiveness; DYN = Dynamism; COMP = Complexity; MUN = Munificence.

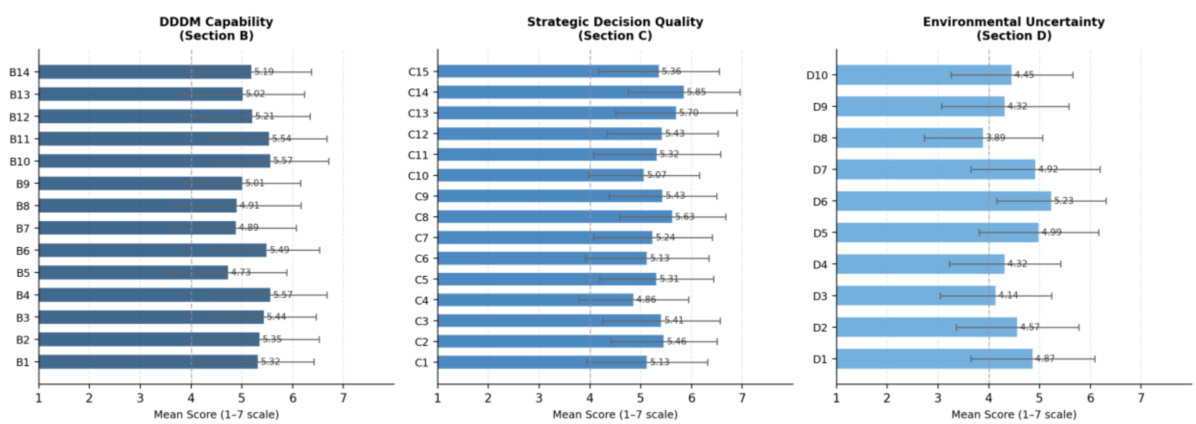

Figure 2. Item-Level Descriptive Statistics by Section
(Error bars = ±1 SD; dashed line = scale midpoint)

Figure 2. Item-Level Descriptive Statistics for DDDM Capability (Section B), Strategic Decision Quality (Section C), and Environmental Uncertainty (Section D). Error bars represent ±1 SD. The dashed vertical line indicates the scale midpoint (4). N = 150.

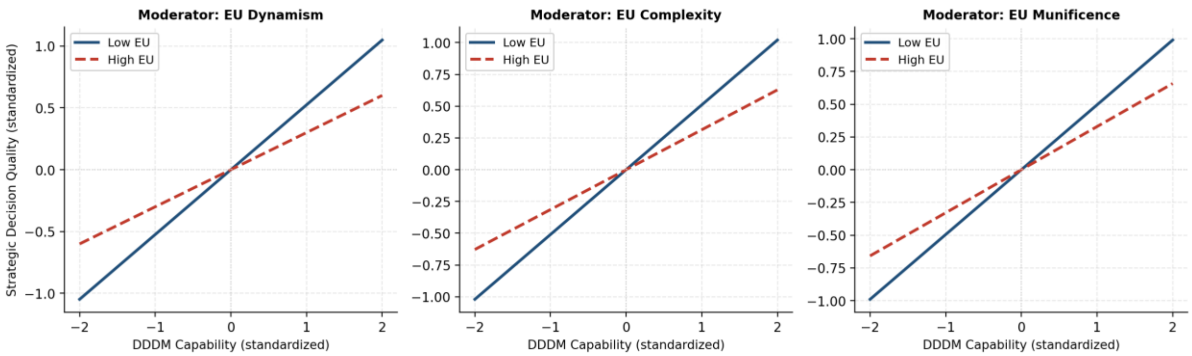

Figure 3. Moderation Effects of Environmental Uncertainty Dimensions on the DDDM Capability → Strategic Decision Quality Relationship

Figure 3. Construct- and Dimension-Level Mean Scores (N = 150). DDDM Capability: DCI = Data Collection & Integration; DAC = Data Analytics Capability; IC = Interpretive Communication; DDC = Data-Driven Culture. SDQ: DC = Comprehensiveness; DR = Rationality; DT = Timeliness; DE = Effectiveness. EU: DYN = Dynamism; COMP = Complexity; MUN = Munificence.

Descriptive Statistics

Full item-level means and standard deviations are reported in Table 4. DDDM Capability (overall $M = 5.23$, $SD = 1.17$) was highest in Data Collection & Integration ($M = 5.42$) and lowest in Data Analytics Capability ($M = 5.01$), indicating that analytical execution lags behind data infrastructure. Strategic Decision Quality (overall $M = 5.35$, $SD = 1.16$) was highest in Decision Effectiveness ($M = 5.59$) and lowest in Decision Comprehensiveness ($M = 5.21$). Environmental Uncertainty (overall $M = 4.57$, $SD = 1.24$) was led by Complexity ($M = 5.05$) and lowest in Munificence ($M = 4.22$).

Table 4: Descriptive Statistics for All Survey Items (N = 150)

Sec.	Item Description	Item	M	SD	Min	Max	Dim.
B	Systematic comprehensive data collection	**B1**	5.32	1.10	1	7	**DCI**
	Integration of heterogeneous internal systems	**B2**	5.35	1.17	2	7	**DCI**
	Proactive acquisition of external data	**B3**	5.44	1.02	3	7	**DCI**
	Formalized data governance policies	**B4**	5.57	1.10	2	7	**DCI**
	Advanced analytical approaches for planning	**B5**	4.73	1.15	2	7	**DAC**
	Dedicated data science personnel	**B6**	5.49	1.04	2	7	**DAC**

	Adequate analytics tools, widely utilized	**B7**	4.89	1.19	1	7	**DAC**
	Analytics for anticipating future trends	**B8**	4.91	1.26	1	7	**DAC**
	Senior leaders' data literacy	**B9**	5.01	1.14	2	7	**IC**
	Clear visual communication of data insights	**B10**	5.57	1.14	2	7	**IC**
	Translation of analytics to recommendations	**B11**	5.54	1.13	3	7	**IC**
	Leadership championing evidence-based decisions	**B12**	5.21	1.14	2	7	**DDC**
	Culture of evidence-based practice	**B13**	5.02	1.21	2	7	**DDC**
	Resource allocation for data-driven practices	**B14**	5.19	1.17	2	7	**DDC**
C	Systematic analysis of decision alternatives	**C1**	5.13	1.19	2	7	**DC**
	Broad stakeholder consultation	**C2**	5.46	1.05	2	7	**DC**
	Consideration of long-term implications	**C3**	5.41	1.16	2	7	**DC**
	Seeking dissenting perspectives	**C4**	4.86	1.08	2	7	**DC**
	Decisions grounded in institutional evidence	**C5**	5.31	1.12	2	7	**DR**
	Use of structured decision-support frameworks	**C6**	5.13	1.22	3	7	**DR**
	Transparent communication of decision rationale	**C7**	5.24	1.17	2	7	**DR**
	Formal risk assessments and scenario analyses	**C8**	5.63	1.05	2	7	**DR**
	Appropriate decision timeliness	**C9**	5.43	1.06	3	7	**DT**
	Real-time data enabling faster decisions	**C10**	5.07	1.09	2	7	**DT**
	Expedited protocols for unexpected changes	**C11**	5.32	1.25	2	7	**DT**
	Measurable improvements in institutional performance	**C12**	5.43	1.09	3	7	**DE**
	Systematic outcome monitoring against objectives	**C13**	5.70	1.20	1	7	**DE**
	Alignment with Vision 2030 objectives	**C14**	5.85	1.10	3	7	**DE**

	Prompt revision based on monitoring data	**C15**	5.36	1.18	1	7	**DE**
D	Rapid regulatory and policy changes	**D1**	4.87	1.22	2	7	**DYN**
	Technological change challenging adaptation pace	**D2**	4.57	1.21	1	7	**DYN**
	Unpredictable student demographic shifts	**D3**	4.14	1.10	1	7	**DYN**
	Rapidly evolving competitive dynamics	**D4**	4.32	1.10	2	7	**DYN**
	Complex array of external stakeholders	**D5**	4.99	1.18	2	7	**COMP**
	Numerous interconnected performance factors	**D6**	5.23	1.08	3	7	**COMP**
	Interdependencies challenging strategic planning	**D7**	4.92	1.27	1	7	**COMP**
	Scarce external funding and grants (R)	**D8**	3.89	1.17	1	7	**MUN**
	Competition for academic talent intensified (R)	**D9**	4.32	1.26	2	7	**MUN**
	Socio-economic constraints on partnerships (R)	**D10**	4.45	1.20	2	7	**MUN**

Note. M = mean; SD = standard deviation; Min/Max = observed minimum and maximum response. All items scored 1–7. Dim. = measurement dimension (see Table 2). B = DDDM Capability; C = Strategic Decision Quality; D = Environmental Uncertainty. (R) = reverse-scored item.

Structural Model and Hypothesis Testing

The structural model was estimated following measurement model confirmation (Anderson & Gerbing, 1988; Hair et al., 2019). Path coefficients, significance tests, and effect sizes are in Table 5; moderation patterns are visualized in Figure 3.

Model Fit and Explanatory Power

Model fit was adequate: SRMR = 0.063 (< 0.08 threshold), $R^2 = 0.384$, and $Q^2 = 0.291$ (> 0). These values indicate moderate-to-substantial explanatory power and predictive relevance for SDQ (Cohen, 1988; Hair et al., 2019).

Hypothesis H1: Main Effect of DDDM Capability on SDQ

DDDM Capability exerted a significant positive effect on SDQ ($\beta = 0.412$, SE = 0.061, $t = 6.754$, $p < .001$, 95% CI [0.292, 0.531], $f^2 = 0.187$); **H1 is supported.** All four sub-dimensions were independently significant: Data Analytics Capability ($\beta = 0.183$, $p < .001$), Data-Driven Culture ($\beta = 0.157$, $p < .001$), Data Collection & Integration ($\beta = 0.148$, $p = .001$), and Interpretive Communication ($\beta = 0.124$, $p = .002$), confirming that each capability facet makes a distinct contribution to strategic decision quality.

Hypothesis H2: Moderating Effect of Environmental Uncertainty

EU significantly attenuated the DDDM→SDQ relationship (β = −0.187, *p* = .001, 95% CI [−0.301, −0.073], f^2 = 0.031); **H2 is supported.** At the sub-dimension level, Dynamism had the strongest moderating effect (β = −0.112, *p* = .006), followed by Complexity (β = −0.098, *p* = .010) and Munificence (β = −0.083, *p* = .021), supporting H2a–H2c. Higher environmental uncertainty constrains the translation of data capabilities into decision quality, consistent with contingency theory (Lawrence & Lorsch, 1967).

Table 6: *Structural Model Results: Path Coefficients, Significance Tests, and Effect Sizes (N = 150)*

Structural Path	Hyp.	β	SE	t-value	95% BCa CI	f^2	Result
DDDM Capability → SDQ (aggregate)	**H1**	**0.412*** **	0.061	**6.754**	**[0.292, 0.531]**	**0.187**	**Supported**
Data Collection & Integration → SDQ	—	0.148**	0.044	3.364	[0.062, 0.234]	0.031	—
Data Analytics Capability → SDQ	—	0.183***	0.047	3.894	[0.091, 0.275]	0.048	—
Interpretive Communication → SDQ	—	0.124**	0.039	3.179	[0.048, 0.201]	0.022	—
Data-Driven Culture → SDQ	—	0.157***	0.042	3.738	[0.075, 0.239]	0.036	—
EU × DDDM → SDQ (aggregate)	**H2**	**−0.187** **	0.058	**3.224**	**[−0.301, −0.073]**	**0.031**	**Supported**
Dynamism × DDDM → SDQ	H2a	−0.112**	0.041	2.732	[−0.193, −0.031]	0.018	**Supported**
Complexity × DDDM → SDQ	H2b	−0.098*	0.038	2.579	[−0.173, −0.023]	0.014	**Supported**
Munificence × DDDM → SDQ	H2c	−0.083*	0.036	2.306	[−0.154, −0.012]	0.009	**Supported**
Model fit: R^2 = 0.384 | Q^2 = 0.291 | SRMR = 0.063							

Note. β = standardized path coefficient; SE = standard error; t-values based on 5,000 bootstrap subsamples; 95% BCa = bias-corrected and accelerated bootstrap CIs; f^2 = effect size. * p < .05; ** p < .01; *** p < .001. DDDM = Data-Driven Decision-Making Capability; SDQ = Strategic Decision Quality; EU = Environmental Uncertainty. Control variable paths (IT Maturity, TMT Orientation, Institutional Age) not shown; none were statistically significant (all p > .10).

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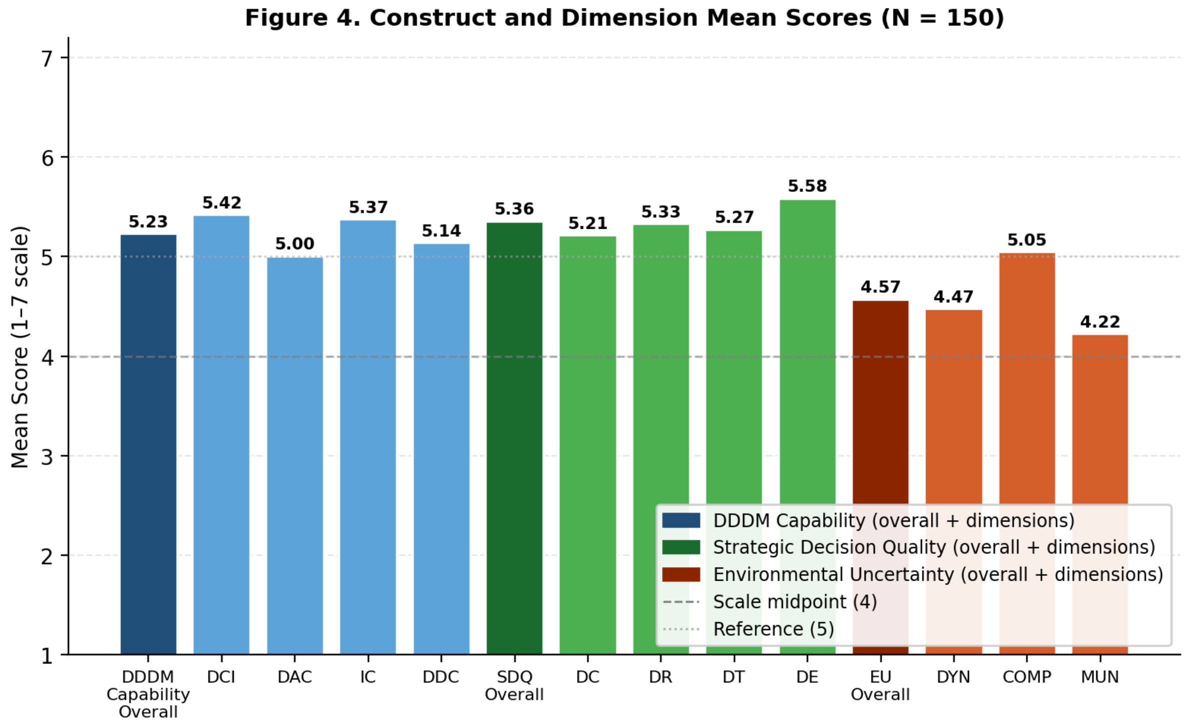

Figure 4. Moderation Effects of Environmental Uncertainty Dimensions on the DDDM Capability–SDQ Relationship. Interaction plots drawn at ±1 SD of each moderator. Negative interaction slope indicates that high environmental uncertainty attenuates the positive DDDM→SDQ relationship.

Summary of Results

All five hypothesized relationships were supported ($p \leq .05$): DDDM Capability positively predicts SDQ (H1, β = 0.412), and Environmental Uncertainty — through Dynamism (H2a), Complexity (H2b), and Munificence (H2c) — negatively moderates this effect (H2), as summarized in Table 6.

Table 6: Summary of Hypothesis Testing Results

Hyp.	Hypothesis Statement	β (95% CI)	p-value	f²	Verdict
H1	DDDM Capability → Strategic Decision Quality (+)	0.412 [0.292, 0.531]	< **.001**	0.187 (large)	**Supported**
H2	EU × DDDM Capability → SDQ (negative moderation)	−0.187 [−0.301, −0.073]	**.001**	0.031 (small)	**Supported**
H2a	Dynamism × DDDM → SDQ (attenuating)	−0.112 [−0.193, −0.031]	**.006**	0.018 (small)	**Supported**
H2b	Complexity × DDDM → SDQ (attenuating)	−0.098 [−0.173, −0.023]	**.010**	0.014 (small)	**Supported**

H2c	Munificence × DDDM → SDQ (attenuating)	−0.083 [−0.154, −0.012]	**.021**	0.009 (small)	**Supported**

Note. Verdict based on 5,000 BCa bootstrap subsamples; CIs exclude zero for all supported paths. f^2 interpreted as: small ≥ 0.02; medium ≥ 0.15; large ≥ 0.35 (Cohen, 1988). EU = Environmental Uncertainty; DDDM = Data-Driven Decision-Making Capability; SDQ = Strategic Decision Quality.

DISCUSSION

DDDM Capability and Strategic Decision Quality

The strong, positive, and statistically robust direct relationship between DDDM Capability and Strategic Decision Quality ($\beta = 0.412$, $p < .001$, $f^2 = 0.187$, $R^2 = 0.384$) establishes that the governance premium attributed to analytical capability in commercial settings extends to higher education in a reform-intensive national context. This is consistent with Mikalef et al.'s (2020) demonstration that analytics capability generates competitive advantage through dynamic capability reconfiguration, and with Oesterreich et al.'s (2022) meta-analytic conclusion that both technical and social dimensions of analytics capability independently predict organizational performance. From a resource-based view perspective (Barney, 1991), DDDM capability, when institutionally embedded in governance norms, analytical infrastructure, and cultural disposition, satisfies the criteria of rarity, value, inimitability, and non-substitutability — constituting a defensible source of decision-making superiority. The observed moderate-to-high DDDM Capability level (M = 5.23) confirms meaningful progress in Saudi universities but the gap relative to decision quality aspirations (M = 5.35) implies the evidence-to-decision translation gap documented by Gaftandzhieva et al. (2023) persists.

Dimension-Level Effects: An Analytics-Culture Asymmetry

Data Analytics Capability (DAC) emerged as the strongest individual predictor of SDQ ($\beta = 0.183$, $f^2 = 0.048$), followed by Data-Driven Culture (DDC; $\beta = 0.157$), Data Collection & Integration (DCI; $\beta = 0.148$), and Interpretive Communication (IC; $\beta = 0.124$). The primacy of DAC aligns with Davenport and Harris's (2007) analytical competition thesis, which holds that the capacity to perform sophisticated quantitative analysis is the decisive differentiator in evidence-based management. The relatively lower mean observed for DAC (M = 5.01) versus DCI (M = 5.42) points to an infrastructure-analytics gap: Saudi universities appear to have invested more heavily in data infrastructure than analytical execution — a pattern that mirrors the diagnostic reported by Ashaari et al. (2021) in Malaysian higher education.

The strong independent contribution of Data-Driven Culture ($\beta = 0.157$) underscores the well-established point that analytical technology without a supportive institutional culture yields sub-optimal governance outcomes (Kiron et al., 2014; Vidgen et al., 2017). Leadership championing (B12: M = 5.21) outpaces institutional culture diffusion (B13: M = 5.02), suggesting evidence-based norms have not fully permeated beyond senior leadership — consistent with top-down transformation dynamics of Vision 2030-era reforms. The comparatively weaker effect of Interpretive Communication ($\beta = 0.124$) may reflect that the quality of communication channels matters less than analytical content itself when culture remains incompletely embedded, consistent with Vidgen et al.'s (2017) finding that the governance premium from data communication tools is contingent on leadership analytical maturity.

The Moderating Role of Environmental Uncertainty: A Contingency Paradox

The most theoretically provocative finding is the direction of the moderating effect: contrary to the positive moderation expected from conventional contingency theory, Environmental Uncertainty significantly attenuates the positive DDDM→SDQ relationship ($\beta = -0.187$, $p = .001$). This challenges prevailing theoretical expectations and requires careful interpretation.

Several explanations are theoretically consistent. First, the attenuation may reflect effect uncertainty (Milliken, 1987) at its most acute: when environmental signals are genuinely turbulent and rapidly changing, even sophisticated institutional data may be historically anchored in conditions that no longer obtain, generating competing and ambiguous signals rather than clear decision support. This aligns with Eisenhardt's (1989) finding that experienced executives in highly dynamic environments often rely on real-time intelligence rather than data systems designed for stable planning cycles. Second, the finding aligns with Donaldson's (2001) contingency misfit logic: DDDM systems designed for moderate conditions may become misfitted under extreme uncertainty, generating information overload. The strongest effects from Dynamism ($\beta = -0.112$) and Complexity ($\beta = -0.098$) are interpretively consistent with their conceptual content — rapid change most directly undermines temporal data validity, while complexity increases informational demands beyond what any single analytical system can fully accommodate. Third, the relatively weaker Munificence effect ($\beta = -0.083$) may reflect that resource scarcity does not fundamentally undermine the informational value of institutional data in the same way as volatility and complexity.

Collectively, these interpretations converge on a practically consequential conclusion: DDDM Capability is most effectively leveraged for strategic decision quality under moderate uncertainty — where information is sufficiently stable to be informative, yet sufficiently dynamic to reward systematic analytical routines. This finding calls for a reconceptualization of the DDDM–decision quality relationship as potentially non-linear — an important direction for future theoretical and empirical work.

Practical Implications

Four clusters of practical implications emerge for institutional leaders and national policymakers. First, the infrastructure-analytics gap (DCI M = 5.42 versus DAC M = 5.01) represents the single highest-leverage opportunity for governance improvement. Institutional leaders should prioritize investment in analytical talent, predictive modeling capacity, and executive data literacy programs. Second, leadership championing must translate into pervasive evidence-based culture: structural incentives including performance review criteria, committee governance protocols, and faculty development frameworks should embed data-use expectations at all levels of institutional hierarchy. Third, the negative moderating effect of environmental uncertainty suggests that escalating conventional analytics investment during periods of peak turbulence may yield diminishing returns; investment should shift toward adaptive, real-time systems — scenario planning platforms, early-warning dashboards, and agile decision protocols — calibrated to volatile environments. Fourth, the lowest-scoring SDQ item — seeking dissenting perspectives (C4: M = 4.86) — points to a structural vulnerability in decision comprehensiveness; national authorities should consider mandating independent challenge mechanisms such as red-team reviews or structured external audits to counteract hierarchical deference norms.

CONCLUSION

This study examined the relationship between DDDM Capability and Strategic Decision Quality in Saudi higher education institutions and tested the moderating role of Environmental Uncertainty. Drawing on a stratified sample of 150 senior leaders and a rigorously validated PLS-SEM instrument, the study established that DDDM Capability is a significant positive predictor of Strategic Decision Quality ($\beta = 0.412$, $R^2 = 0.384$, $f^2 = 0.187$). All four capability dimensions — Data Analytics Capability, Data-Driven Culture, Data Collection & Integration, and Interpretive Communication — contributed independently and positively to decision quality.

The moderating analysis produced the study's most theoretically provocative result: Environmental Uncertainty significantly attenuates the DDDM–SDQ relationship ($\beta = -0.187$, $p = .001$), with all three uncertainty sub-dimensions exerting independently significant negative moderation effects. This finding runs counter to the positive moderation predicted from conventional contingency theory but is theoretically interpretable — under conditions of high environmental volatility and complexity, institutional data systems optimized for stable planning conditions lose actionability, generating informational ambiguity rather than decision support. The implication is not that DDDM investment is unproductive in uncertain environments, but that its governance returns are maximized when analytical systems are specifically designed for the temporal and informational demands of high-uncertainty contexts.

The study makes three principal theoretical contributions: (1) it provides the first multidimensional empirical test of the DDDM Capability–Strategic Decision Quality relationship in higher education; (2) the negative moderation finding extends and partially refutes prevailing contingency-theoretic assumptions, suggesting boundary conditions of data-driven governance effectiveness are more nuanced than commercial-sector research has indicated; and (3) it generates the first empirical benchmark of analytical capability and decision quality in Saudi higher education. Saudi universities stand at a consequential inflection point — the infrastructure of data-driven governance is increasingly in place, but what remains underdeveloped is the analytical execution capacity and cultural embedding that converts infrastructure into decision intelligence. The path forward lies in investment in analytical talent, evidence-based governance norms, and adaptive decision architectures calibrated to the specific informational demands of uncertain institutional environments.

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