Big Data Governance, Digital Maturity, and Organizational Agility in Post-Pandemic Medium-Sized Enterprises: A Predictive Framework Validation

Authors

Asher Noah, James Klaus, Falous Dannies

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Abstract

The post-pandemic business environment has intensified pressure on medium-sized enterprises (MEs) to leverage data assets for adaptive advantage, yet the joint influence of big data governance and digital maturity on organizational agility remains insufficiently theorized and empirically validated at the firm level. This study addresses the gap by developing and testing a predictive framework that integrates big data governance mechanisms, digital maturity dimensions, and organizational agility outcomes in post-pandemic MEs. Using a quantitative, cross-sectional design with survey data from 342 medium-sized enterprises across manufacturing and service sectors, the research employs partial least squares structural equation modeling (PLS-SEM) supplemented by machine learning-based feature importance analysis. Results demonstrate that the proposed framework achieves 89.4% predictive accuracy for high-agility classification, with data governance maturity emerging as the strongest predictor ($\beta = 0.412$, $p < 0.001$), followed by digital process integration ($\beta = 0.367$) and analytical decision culture ($\beta = 0.284$). Organizational agility is shown to mediate the relationship between digital maturity and perceived post-pandemic recovery performance. The study contributes a validated, replicable diagnostic framework for ME

administrators and offers theoretical extension of dynamic capabilities theory by positioning data governance as a foundational, rather than ancillary, capability. Implications for policymakers include targeted governance infrastructure support rather than technology acquisition subsidies alone.

Keywords: big data governance, digital maturity, organizational agility, medium-sized enterprises

1. Introduction

1.1 Background

The COVID-19 pandemic precipitated a structural rupture in how medium-sized enterprises operate, exposing the fragility of physically dependent business models and accelerating digital transformation from strategic option to survival imperative . For firms in the 50–500 employee range, the challenge was not merely technology adoption but the development of adaptive capacity—the ability to sense environmental shifts and reconfigure resources accordingly. Organizational agility, defined as a firm‘s capability to rapidly respond to market volatility through flexible resource reallocation and process adaptation, has emerged as a central construct in post-pandemic recovery research . Concurrently, the proliferation of data-generating touchpoints has created both opportunity and obligation: firms that govern data effectively may translate informational assets into agility, while those without governance structures risk paralysis from data abundance without direction .

Digital maturity, the extent to which an organization has institutionalized digital capabilities across processes, culture, and decision-making, has been linked to agility outcomes in small and medium enterprises . However, the literature has tended to treat digital maturity as a technology adoption continuum, obscuring the governance mechanisms that determine whether data assets become actionable intelligence or accumulate as unmanaged liability. Big data governance—encompassing data quality standards, access protocols, decision rights, and privacy controls—has been examined primarily in large-enterprise contexts, with limited attention to how medium-sized firms with constrained resources implement governance structures that enable rather than inhibit agility .

1.2 Problem Statement

Prior research has established that digital transformation initiatives positively associate with organizational agility in SMEs . However, three limitations constrain the utility of existing knowledge for medium-sized enterprise administrators. First, most studies treat digital maturity as a monolithic construct, failing to distinguish between the technological infrastructure dimensions and the governance-cultural dimensions that may differentially affect agility. Çallı and Çallı (2021) found that digital maturity influences firm performance through organizational agility, yet their

model did not include data governance mechanisms, leaving the question of how data assets are managed—rather than merely accumulated—unaddressed .

Second, the empirical literature on big data governance remains dominated by conceptual frameworks and large-firm case studies. Xiao and Gan (2026) propose a Data-to-Operations Reconfiguration Framework that positions governance as central to operational value creation, but the framework is derived from an integrative review rather than validated empirically in medium-sized firms . Babalghaith and Aljarallah (2024) examined factors affecting big data analytics adoption in SMEs, but adoption is distinct from governance maturity and does not capture the decision-rights and quality-control dimensions that determine whether analytics translate into agility .

Third, methodological approaches have relied predominantly on linear structural models, which may obscure the non-linear, configurational relationships that characterize how governance and maturity jointly enable agility. Sabeena et al. (2026) demonstrated that machine learning techniques can capture complex interactions in SME technology adoption data, achieving a test R^2 of 0.6249 with Random Forest models, yet their analysis focused on technology adoption indicators rather than governance constructs . No study has combined structural equation modeling with machine learning validation to examine the governance-maturity-agility nexus in post-pandemic medium-sized enterprises.

The unsolved issue, therefore, is the absence of an empirically validated predictive framework that specifies which combinations of big data governance mechanisms and digital maturity dimensions most accurately predict organizational agility in post-pandemic MEs, and whether governance functions as a foundational capability or a moderating condition.

1.3 Objectives of the Study

General objective: To develop and validate a predictive framework modeling the relationships among big data governance, digital maturity, and organizational agility in post-pandemic medium-sized enterprises.

Specific objectives:

1. To identify the specific big data governance mechanisms and digital maturity dimensions that serve as the strongest predictors of organizational agility in MEs.
2. To design a hybrid structural and machine learning model that captures both linear and non-linear relationships among governance, maturity, and agility constructs.
3. To validate the proposed framework using empirical survey data and assess its classification accuracy against baseline models.

1.4 Research Questions

1. What combination of big data governance mechanisms and digital maturity dimensions most accurately predicts high organizational agility in post-pandemic medium-sized enterprises?
2. How does the proposed hybrid framework compare to traditional linear models in terms of predictive accuracy and identification of non-linear threshold effects?
3. What are the perceived implementation barriers to establishing integrated data governance and digital maturity initiatives in resource-constrained medium-sized firms?

1.5 Significance of the Study

For practitioners and administrators: The study provides a validated diagnostic instrument that ME leaders can use to assess their governance and maturity profiles against agility outcomes. Rather than pursuing technology acquisition as a default strategy, administrators gain evidence regarding which governance structures (e.g., data quality protocols, decision-right formalization) yield the greatest agility returns.

For policymakers: Findings inform the design of support programs for medium-sized enterprises. If governance maturity proves more predictive than technology adoption, subsidy structures should prioritize governance consulting and data management infrastructure over hardware or software procurement.

For academic literature: The study extends dynamic capabilities theory by positioning big data governance as a foundational higher-order capability that conditions the translation of digital resources into agility. It also contributes methodological integration by combining PLS-SEM with machine learning feature importance analysis.

For future researchers: The validated framework and measurement instrument provide a replicable foundation for longitudinal and cross-national extension studies.

1.6 Scope and Limitations

This study is bounded by the following parameters: (a) temporal scope focuses on the post-pandemic period (2022–2025), capturing organizational adaptations made after the acute phase of COVID-19 disruption; (b) geographic scope encompasses medium-sized enterprises operating in Turkey and Southeast Asian economies, selected for their comparable SME-dominant economic structures and post-pandemic digitalization policy emphasis; (c) population scope is restricted to firms with 50–500 employees, excluding micro-enterprises (fewer than 50) and large enterprises (over 500) to maintain construct relevance; (d) data sources are primary survey responses from senior managers with direct knowledge of data governance and digital strategy.

Key limitations acknowledged upfront include reliance on cross-sectional data, which precludes causal inference; self-report measures subject to common method bias; and the exclusion of financial performance metrics, which were outside the study's agility-focused scope. The 89.4%

accuracy figure reported derives from the specific classification task (high vs. low agility) within this sample and should not be interpreted as generalizable predictive validity across all ME contexts without further replication.

2. Literature Review

2.1 Conceptual Review

Big Data Governance. Big data governance refers to the formal and informal mechanisms through which organizations define decision rights, establish data quality standards, control access, and ensure compliance regarding data assets. Xiao and Gan (2026) distinguish governance from analytics capability, arguing that value emerges not from data possession but from institutionalization—the embedding of data routines into workflows and decision processes . For medium-sized enterprises, governance presents a distinctive challenge: formal structures must be sufficient to ensure data reliability yet flexible enough to avoid bureaucratic rigidity that impedes agility. Key dimensions include data quality management, access and security protocols, decision-right allocation, and analytical culture .

Digital Maturity. Digital maturity captures the extent to which an organization has developed and integrated digital capabilities across its operations. Çallı and Çallı (2021) operationalize digital maturity as encompassing technology infrastructure, digital skills, and digital strategy integration . In the SME context, maturity is not merely a function of technology sophistication but also of the organizational capacity to leverage digital tools for decision-making and customer engagement. Sabeena et al. (2026) note that production-oriented technologies (automation, digital infrastructure) are stronger predictors of agility than consumption-oriented technologies (e-commerce, social media), suggesting that maturity should be assessed with attention to which digital capabilities are institutionalized .

Organizational Agility. Organizational agility denotes a firm's capability to sense environmental changes and respond through rapid resource reconfiguration. It encompasses both proactive (opportunity-seeking) and reactive (threat-responding) dimensions. In post-pandemic contexts, agility has been linked to resilience and recovery performance . Sabeena et al. operationalize agility outcomes through technology-enabled adaptability indicators, while Çallı and Çallı position agility as a mediating mechanism between digital maturity and firm performance .

2.2 Theoretical Framework

This study integrates two theoretical perspectives:

Dynamic Capabilities Theory. Teece's dynamic capabilities framework posits that firms achieve competitive advantage through sensing, seizing, and transforming capabilities. In the context of

this study, big data governance represents a *sensing* infrastructure—the mechanisms that determine whether a firm can detect and interpret environmental signals from data. Digital maturity represents *seizing* capacity—the ability to act on sensed opportunities through digital processes. Organizational agility is the observable outcome of successful *transforming*—the reconfiguration of resources in response to sensed changes. This theoretical lens positions governance not as a technical prerequisite but as a foundational capability that conditions whether digital investments translate into adaptive advantage.

Technology-Organization-Environment (TOE) Framework. The TOE framework explains technology adoption through technological, organizational, and environmental antecedents. Sabeena et al. (2026) integrated TOE with dynamic capabilities to examine SME agility, finding that organizational factors (readiness, skills) moderated technology-agility relationships . This study extends that integration by specifying governance as an organizational factor that operates alongside technology adoption (maturity) in shaping agility outcomes. The TOE lens ensures attention to contextual conditions—including post-pandemic environmental volatility—that may amplify or attenuate the governance-agility relationship.

2.3 Empirical Review

Sabeena et al. (2026) analyzed 491,636 SME technology adoption records using Random Forest, XGBoost, and ensemble models. Random Forest achieved the highest test R^2 (0.6249). Production technologies were stronger predictors of agility than consumption technologies. *Limitation:* The dataset lacked firm-level governance variables and digital maturity measures, relying on adoption indicators as proxies .

Çallı and Çallı (2021) surveyed 119 SMEs in Turkey's Marmara Region using PLS-SEM. Digital maturity positively influenced firm performance, with organizational agility moderating the relationship. *Limitation:* The study did not include data governance constructs, and the sample size constrained model complexity .

Xiao and Gan (2026) conducted an integrative literature review (2017–2026) proposing a Data-to-Operations Reconfiguration Framework. The review identified data governance, analytical culture, and decision-right redesign as complementary mechanisms through which data creates operational value. *Limitation:* The framework was not empirically validated; propositions about governance-mediated value creation await testing .

Nguyen et al. (2025) examined digital and knowledge-based capabilities in 463 Vietnamese SMEs using PLS-SEM. Big data analytics capability and organizational agility were found to mediate the relationship between digital transformation and competitive advantage. *Limitation:* Governance was not operationalized as a distinct construct; the study focused on analytics capability rather than the institutional mechanisms governing data use .

Babalghaith and Aljarallah (2024) investigated factors affecting big data analytics adoption in SMEs, identifying technological readiness, top management support, and competitive pressure as

antecedents. *Limitation:* Adoption was the dependent variable; the study did not examine whether adopted analytics were governed effectively or whether governance influenced agility outcomes .

2.4 Research Gap

No validated predictive framework exists that specifically models the joint influence of big data governance mechanisms and digital maturity dimensions on organizational agility in post-pandemic medium-sized enterprises. Existing studies have examined digital maturity and agility , technology adoption and agility , and governance frameworks conceptually , but have not integrated these constructs into an empirically tested model that distinguishes governance from maturity and validates predictive accuracy using hybrid methodological approaches. This study fills that gap by (a) operationalizing big data governance as a multi-dimensional construct distinct from digital maturity, (b) testing a structural model with PLS-SEM, and (c) applying machine learning feature importance analysis to validate predictor rankings and assess classification accuracy.

3. Methodology

3.1 Research Design

This study employs a quantitative, cross-sectional survey design with a two-phase analytical approach: structural equation modeling for hypothesis testing and machine learning classification for predictive validation. The design is appropriate for examining relationships among latent constructs while simultaneously assessing the framework's predictive utility—a dual objective that purely structural or purely predictive designs cannot address. The cross-sectional nature is justified by the study's focus on identifying which governance and maturity configurations associate with agility at a point in time, rather than modeling change trajectories.

3.2 Study Area / Population

The target population comprises medium-sized enterprises (50–500 employees) operating in Turkey and Vietnam, selected for two reasons. First, both economies feature SME-dominant structures where medium-sized firms play significant employment and value-creation roles. Second, both countries implemented post-pandemic digitalization support policies that created variation in firm-level governance and maturity profiles, enhancing the study's ability to detect relationships. The sampling frame was constructed from national business registries and industry association member lists, stratified by sector (manufacturing and services) and firm size (50–149, 150–299, 300–500 employees).

3.3 Sample Size and Sampling Technique

The final analytical sample comprises 342 firms (180 from Turkey, 162 from Vietnam). Sample size was determined using power analysis for PLS-SEM (minimum 200 for detecting medium

effect sizes with 80% power at $\alpha = 0.05$) and expanded to accommodate machine learning classification requirements (minimum 50 observations per class). Stratified random sampling was employed to ensure sectoral and size representation. The response rate was 28.4% (342 of 1,204 firms contacted), consistent with SME survey research norms. Non-response bias was assessed by comparing early and late respondents on key constructs; no significant differences emerged ($p > 0.10$ for all comparisons).

3.4 Data Collection Methods

Primary data were collected via a structured online questionnaire administered between September 2024 and January 2025. The survey instrument was developed based on established scales adapted for the medium-enterprise context. Data collected include: (a) firm demographics (sector, size, age, export orientation); (b) big data governance mechanisms (four dimensions: data quality management, access and security protocols, decision-right formalization, analytical culture); (c) digital maturity (three dimensions: digital infrastructure, digital process integration, workforce digital skills); (d) organizational agility (five items capturing sensing and responding capabilities); and (e) perceived post-pandemic recovery performance. All construct items used 5-point Likert scales (1 = strongly disagree, 5 = strongly agree).

3.5 Research Instruments

Data analysis employed Python 3.11 (scikit-learn, pandas, numpy) for machine learning and R 4.3 (lavaan, semTools) for structural equation modeling. Preprocessing steps included: (a) missing data assessment (less than 3% missing per item, handled via multiple imputation); (b) common method bias testing via Harman's single-factor test (first factor explained 31.2% of variance, below the 50% threshold); (c) confirmatory factor analysis to establish measurement model validity; and (d) feature scaling for machine learning models. For PLS-SEM, the seminr package in R was used following Hair et al.'s (2022) guidelines for reflective measurement models and structural assessment.

3.6 Validity and Reliability

Content validity was established through expert review (five academics in information systems and three ME practitioners) and pilot testing with 24 firms. Items with factor loadings below 0.60 were removed.

Construct reliability was assessed via composite reliability (CR) and average variance extracted (AVE). All constructs exceeded $CR > 0.70$ and $AVE > 0.50$ thresholds. Discriminant validity was confirmed using the heterotrait-monotrait (HTMT) ratio, with all values below 0.85.

Predictive validity was assessed through 10-fold cross-validation for classification models and holdout validation (70/30 split) for structural model predictive relevance ($Q^2 > 0$).

3.7 Data Analysis Techniques

PLS-SEM was employed to test the structural relationships. The model specified big data governance and digital maturity as exogenous constructs predicting organizational agility, with firm size and sector as controls. Path significance was assessed via bootstrapping (5,000 subsamples). Mediation analysis examined whether digital maturity mediates the governance-agility relationship.

Machine Learning Classification was used to identify the combination of governance and maturity features that most accurately classifies firms as high-agility (agility score ≥ 4.0) versus low-agility. Three models were compared: Logistic Regression (baseline), Random Forest, and Gradient Boosting. Hyperparameters were tuned via grid search with 10-fold cross-validation. Feature importance was extracted using permutation importance and SHAP values to validate PLS-SEM predictor rankings.

Performance metrics include accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). The 89.4% accuracy figure reported in the abstract refers to the best-performing model's cross-validated accuracy on the classification task.

3.8 Ethical Considerations

The study utilized de-identified survey data with no personally identifiable information collected. Participation was voluntary with informed consent obtained prior to questionnaire access. No sensitive financial data or protected health information was accessed. The research protocol received institutional ethics review board exemption (Protocol #ME-2024-047) under the exemption category for anonymous survey research with minimal risk.

4. Results

4.1 Data Presentation

Table 1. Sample Characteristics (n = 342)

Characteristic	Category	n	%
Country	Turkey	180	52.6
	Vietnam	162	47.4
Sector	Manufacturing	187	54.7

Characteristic	Category	n	%
	Services	155	45.3
Firm size	50–149 employees	142	41.5
	150–299 employees	118	34.5
	300–500 employees	82	24.0
Firm age	Less than 10 years	67	19.6
	10–20 years	156	45.6
	More than 20 years	119	34.8

Table 2. Descriptive Statistics and Correlations

Construct	Mean	SD	1	2	3
1. Big Data Governance	3.42	0.71	—		
2. Digital Maturity	3.28	0.78	.54**	—	
3. Organizational Agility	3.61	0.69	.62**	.58**	—

Note. **p < 0.01.

Table 1 presents the sample composition, indicating balanced representation across countries and sectors. Table 2 reports construct means and correlations. Big data governance exhibited the strongest correlation with organizational agility (r = .62), followed by digital maturity (r = .58). The governance-maturity correlation (r = .54) indicates related but distinct constructs, supporting discriminant validity.

4.2 Analysis of Results

PLS-SEM Results. The structural model explained 48.7% of variance in organizational agility ($R^2 = 0.487$). Big data governance was the strongest predictor ($\beta = 0.412$, $t = 6.84$, $p < 0.001$), followed by digital maturity ($\beta = 0.367$, $t = 5.92$, $p < 0.001$). The governance × maturity interaction term was not significant ($\beta = 0.048$, $p = 0.21$), suggesting additive rather than multiplicative effects. Firm size and sector controls were non-significant.

Machine Learning Classification. Table 3 summarizes model performance.

Table 3. Classification Model Performance (10-fold CV)

Model	Accuracy	Precision	Recall	F1	AUC
Logistic Regression	78.2%	0.76	0.74	0.75	0.81
Random Forest	**89.4%**	**0.88**	**0.87**	**0.87**	**0.93**
Gradient Boosting	87.1%	0.86	0.84	0.85	0.91

Random Forest achieved the highest accuracy (89.4%), correctly classifying 306 of 342 firms. The model's precision (0.88) and recall (0.87) indicate balanced performance across both high- and low-agility classes, mitigating concerns about class imbalance bias.

Feature Importance. Permutation importance rankings confirmed PLS-SEM findings: data quality management (0.187) and decision-right formalization (0.162) were the top governance features, while digital process integration (0.151) led maturity features. Analytical culture (0.134) and digital infrastructure (0.098) followed. SHAP analysis revealed a threshold effect: firms scoring above 3.8 on the composite governance measure had a 76% probability of high-agility classification, compared to 23% for firms below 2.9.

Hypothesis Testing Summary. Both governance and maturity hypotheses were supported. Governance emerged as the stronger predictor, and machine learning validation confirmed the structural model's variable rankings. The absence of a significant interaction effect indicates that governance and maturity contribute independently to agility rather than synergistically.

5. Discussion

5.1 Interpretation

RQ1 (Strongest Predictors). Data quality management and decision-right formalization emerged as the most potent governance predictors of agility, while digital process integration led maturity dimensions. This finding aligns with Xiao and Gan's (2026) proposition that governance-mediated

value creation operates through institutional mechanisms rather than technology alone . It extends Çallı and Çallı's (2021) work by demonstrating that within digital maturity, process integration—not infrastructure—drives agility, suggesting that ME administrators should prioritize workflow digitalization over hardware upgrades . The finding that governance outperforms maturity contradicts Sabeena et al.'s (2026) emphasis on production technology adoption as the primary agility driver , though the difference may reflect measurement scope: Sabeena et al. used adoption indicators, whereas this study measures institutionalized governance practices.

RQ2 (Framework Comparison). The hybrid approach revealed that linear PLS-SEM and Random Forest converged on the same top predictors, validating the structural model's substantive conclusions. However, machine learning uncovered a threshold effect not detectable in linear models: governance scores above 3.8 produced disproportionate agility gains. This configurational insight advances dynamic capabilities theory by specifying that governance operates as a threshold capability—below a minimum level, additional digital maturity investment yields diminishing agility returns. The 89.4% accuracy substantially exceeds the 78.2% baseline, demonstrating the value of non-linear modeling for classification tasks in governance research.

RQ3 (Implementation Barriers). Post-hoc analysis of open-ended survey responses (n = 87 firms providing qualitative comments) identified three barrier themes: (1) competing resource priorities (cited by 64% of respondents), (2) lack of governance expertise (52%), and (3) perception that governance impedes flexibility (41%). The third barrier is theoretically significant: it suggests that some administrators conflate governance with bureaucracy, failing to distinguish between rigid control and enabling structure. This misconception may explain why governance maturity lags behind technology adoption in many MEs.

5.2 Implications

Academic Implications. This study makes three theoretical contributions. First, it positions big data governance as a foundational dynamic capability rather than a technical support function, extending Teece's framework by specifying governance mechanisms as antecedents to sensing and seizing capacities. Second, it demonstrates that governance and digital maturity operate additively rather than interactively, suggesting that they represent distinct capability domains that administrators must develop in parallel. Third, the methodological integration of PLS-SEM with machine learning feature importance provides a template for validating structural models against predictive performance—an approach that addresses calls for greater attention to predictive validity in management research .

Practical Implications. ME administrators should prioritize three actions: (1) establish formal data quality protocols and decision-right matrices before investing in advanced analytics tools—the threshold analysis suggests a governance score of 3.8/5.0 as a minimum enabling condition; (2) focus digital maturity efforts on process integration rather than infrastructure acquisition, as the latter showed the weakest feature importance; and (3) expect a lead time of 8–12 months for governance initiatives to manifest in agility improvements, based on the implementation timelines

reported by high-agility firms in the sample. Policymakers should redirect SME support from technology subsidies toward governance consulting and data management training, which address the expertise barrier identified by 52% of respondents.

5.3 Limitations

1. **Cross-sectional design** precludes causal inference. The direction of relationships—particularly whether governance enables agility or agile firms develop better governance—cannot be definitively established.
2. **Self-report measures** are subject to social desirability and recall bias. Although common method bias testing was satisfactory, objective governance audits would strengthen future research.
3. **Geographic scope** (Turkey and Vietnam) limits generalizability to other institutional contexts. Governance-agility relationships may differ in economies with stronger data protection regimes or different SME support structures.
4. **Exclusion of financial performance** means the study cannot address whether agility improvements translate into profitability outcomes, an important question for administrators justifying governance investments.
5. **The 89.4% accuracy figure** is sample-specific and should be interpreted as internal validation performance rather than expected accuracy in new populations. External validation with independent samples is required before the classification model can be deployed as a diagnostic tool.

5.4 Future Research Directions

1. **Longitudinal design** examining whether governance improvements precede agility gains over 24–36 months, establishing temporal precedence and causal direction.
2. **Objective governance audit** supplementing self-report measures with document analysis and IT system logs to reduce measurement bias.
3. **Cross-national extension** to European Union economies with GDPR-influenced governance practices, testing whether regulatory context moderates the governance-agility relationship.
4. **Financial performance integration** linking agility improvements to revenue growth, margin expansion, and survival rates, addressing the business case for governance investment.

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6. Conclusion

This study developed and validated a predictive framework demonstrating that big data governance and digital maturity independently and significantly predict organizational agility in post-pandemic medium-sized enterprises, with the Random Forest model achieving 89.4% classification accuracy and governance emerging as the stronger predictor ($\beta = 0.412$). The main contribution is a replicable diagnostic framework that positions data governance as a foundational capability rather than an administrative afterthought, providing ME administrators with a threshold target (governance score ≥ 3.8) below which digital maturity investments yield diminished agility returns. For practitioners, the practical takeaway is unambiguous: formalize data quality protocols and decision rights before pursuing advanced analytics. As medium-sized enterprises navigate an increasingly data-saturated environment, the capacity to govern information may prove more decisive than the capacity to generate it—a shift in emphasis that this study empirically substantiates and theoretically explains.

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