Journal of Project Management 11 (2026) 911–922

Contents lists available at GrowingScience

Journal of Project Management

homepage: www.GrowingScience.com/jpm

From cost center to value engine: A causal framework for quantifying the strategic business value of enterprise information management

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C H R O N I C L E

Article history:
Received February 4, 2026
Received in revised format March 10, 2026
Accepted April 6 2026
Available online
April 6 2026

Keywords:
Information management
Business value
Measurement and ROI
Strategic alignment
Causal framework
Organizational capabilities
Digital transformation
Data governance

A B S T R A C T

Companies have heavily invested in information management (IM) capabilities, yet many of them find it hard to demonstrate a business focused strategic value. Consequently, IM functions often get treated as cost-center rather than strategic value creators. This study is intended to address this gap by designing and validating a model to link IM initiatives to business outcomes. We develop and validate a framework that links certain IM capabilities to intermediate organizational capabilities, which subsequently affect financial and strategic performance. The IM capabilities under consideration are data quality governance, analytical infrastructure, data accessibility, and master data management. Through a mixed-methods approach utilizing paired survey data from 350 organizations and archival performance data, we do structural equation modeling to test the proposed relationships. Our results show that the strongest effect on operational efficiency comes from data quality governance ($\beta = 0.47$, $p < 0.001$). Meanwhile, cross-functional data accessibility exerts high impact on strategic agility ($\beta = 0.52$, $p < 0.001$). The mediation analysis confirms that IM capabilities influence financial performance only through organization capabilities. Our research contributes to theory and practice by providing (1) an empirically validated causal model extending the Resource-Based View to the domain of the digital context, (2) a measurement instrument for assessing IM value drivers, and (3) a managerial framework for prioritizing IM investments in line with strategic objectives. According to this research, CIOs and CDOs have evidence-based tools to rebrand IM as a technical necessity for better version.

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1. Introduction

1.1 The Value Paradox of Information Management

The evolution of information management (IM) from a back-office support function to a potential differentiator in the digital economy is well documented. Despite global investments of billions into data infrastructure, governance schemes, and analytic capabilities, a persistent conundrum remains: executives claim data is a critical business enabler, yet they cannot measure the return on IM investments (Gartner, 2024; Al-Sherideh et al., 2024). As noted by Wixom and Watson (2017), the attribution problem lies at the heart of this contradiction, arising from the difficulty of isolating impacts originating from IM investments. Conventional measures of IM success focus on technical performance metrics such as data latency, system uptime, and storage costs. However, these metrics have not been linked to strategic business value (Pappas et al., 2022; Mohammed, 2024; Shahin, 2025). As observed by MIT CISR (2021), there is no evidence that technical indicators of data management reflect the effectiveness of that data. The consequences are significant. When economic downturns occur, IM functions are often treated as cost centers rather than value generators, making them among the first targets for cuts instead of being viewed as smart resource allocation. In response, organizations have increasingly created the Chief Data Officer (CDO) role. Nevertheless, most CDOs lack frameworks to articulate and measure the business impact of IM. According to a

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ISSN 2371-8374 (Online) - ISSN 2371-8366 (Print)
© 2026 by the authors; licensee Growing Science, Canada
doi: 10.5267/j.jpm.2026.4.003

New Vantage Partners survey in 2024, only 24% of organizations report being data-driven—a percentage that has remained stagnant for three years despite rising investments. The lesson appears to be that simply deploying technology is insufficient; rather, a systematic understanding of how IM creates value is required.

1.2 Research Problem and Questions

This study addresses a significant gap in the literature and management practice: the lack of a validated, causal model that quantifies the strategic business value of enterprise IM initiatives. Prior studies have examined specific areas such as data quality benefits (Hvass & Olesen, 2017), analytics ROI (Ghasemaghaei, 2021), and governance effectiveness (Brown & Jarvenpaa, 2021). However, no comprehensive model links IM capabilities through organizational capabilities to financial performance.

Central research question: Through which precise enterprise IM capabilities, and to what extent, do these capabilities causally influence firm financial and strategic performance via the mediation of enhanced organizational capabilities?

Three secondary questions arise: (1) Which IM capabilities most affect specific organizational capabilities? (2) Do organizational capabilities fully mediate the relationship between IM capabilities and financial performance? (3) How does industry context moderate these relationships?

1.3 Contribution and Structure

This research makes three major contributions. First, it develops an empirically validated comprehensive causal model that extends the Resource-Based View (RBV) (Gnyawali & Srivastava, 2021). Second, it provides a measurement instrument and framework for assessing IM value drivers in organizations. Third, it offers managers a way to prioritize IM investments based on available literature.

The remainder of the paper is structured as follows. Section 2 reviews related work and develops hypotheses. Section 3 describes the research methods. Section 4 presents analysis and findings. Section 5 discusses theoretical and practical implications. Section 6 considers limitations and future research directions, and Section 7 concludes.

2. Theoretical Background and Hypothesis Development

2.1 Related Work

The strategic importance of information management has been a recurrent theme in the information systems (IS) literature. However, published work remains relatively disjointed, spanning various theoretical perspectives, methodological approaches, and levels of analysis. This section synthesizes prior work across four related streams: theoretical perspectives on IT business value, empirical studies of IM capabilities and corporate performance, measurement approaches to IM value, and strategic alignment and governance frameworks. Each stream is examined to expose gaps that motivate the present study.

2.1.1 Theoretical Foundations of IT Business Value

The Resource-Based View (RBV) of the firm and its extension, dynamic capabilities theories, provide the theoretical grounding for understanding how information technology creates business value. According to Gnyawali and Srivastava (2021) in their review of RBV applications in IS research, IT resources can become sources of sustainable competitive advantage if they possess VRIN characteristics (value, rarity, inimitability, and non-substitutability). These resources include data assets, technical infrastructure, and technology-skilled human resources. Yet, Teece (2017) argues that owning static resources is insufficient in a fast-moving digital world; rather, the ability to reconfigure them is crucial. This insight has led researchers to incorporate dynamic capabilities into IT value, positing that information management is a higher-order capability that orchestrates the application of other organizational capabilities.

Kohli and Grover (2018) build on this conceptual framework and argue that big data analytics capabilities act as "orchestration mechanisms" enabling firms to sense, seize, and transform in response to market opportunities. Their research indicated a positive effect of analytics capabilities on innovation performance, but the mechanisms remained underspecified—that is, how technical capabilities translate into strategic outcomes remains unclear. Similarly, Kane et al. (2017) conceptualize digital maturity as a dynamic capability, but their framework centers on customer-facing technologies rather than the IM infrastructure supporting digital transformation. Despite these advances, most frameworks treat IM as a monolithic construct, failing to disaggregate it into distinct capabilities that likely have independent pathways to value creation. According to Kohli and Grover (2018, p. 48), "the field has largely theorized the mechanisms through which different types of information capabilities impact upon different types of organizational outcomes." This observation motivates our disaggregated approach, which assesses four IM capabilities separately for their differential impacts on organizational capabilities.

2.1.2 Empirical Investigations of IM Capabilities and Performance

The volume and diversity of perspectives on IM value often lead to challenging debates among researchers. The study by Wixom and Watson (2017) presents important evidence that data warehouse and data mart success depends on organizational factors such as executive sponsorship and user involvement. However, the authors noted limitations in establishing connections between those factors and financial success. Pappas, Giannakos, and Mikalef (2022) showed a positive link between big data analytics ecosystems and operational performance, but their cross-sectional design defies causal inference. Mikalef et al. (2019) empirically studied big data analytics capabilities and innovation using structural equation modeling with 175 firms. Their results showed a positive effect of analytics capabilities on innovation, mediated by organizational learning and market orientation, with environmental dynamism as a moderator. However, their measurement of analytics capabilities emphasized technological infrastructure and analytical capacities while giving scant attention to governance or data quality.

Hvass and Olesen (2017) studied how data quality generates business value in Danish companies, finding that data quality investments pay off in terms of higher efficiency. Their study is distinguished by the use of objective performance statistics, but the sample size of 87 firms from one country limits generalizability. Ghasemaghaei (2021) investigated big data characteristics and firm performance, showing that volume, velocity, and variety affect performance differently, though organizational capabilities mediating these relationships were not considered. Tumbas, Berente, and Brocke (2018) assessed how Chief Digital Officers aid digital transformations using qualitative case studies of 12 organizations, offering detailed insights but lacking statistical generalizability. Lo and MacKinlay (2017) found that investors possessing advanced analytical infrastructure achieve superior investment performance, but their focus on a single industry (financial services) raises questions of external validity.

Several patterns emerge. First, research frequently establishes a link between IM capabilities and performance, but the magnitude varies widely. Most studies use cross-sectional designs, limiting causal claims. Moreover, the mediated mechanisms through which IM creates value remain underexplored, with only a few studies formally testing mediation models. Sample sizes are often small (typically $N < 200$), raising issues of statistical power and generalizability. This study remedies these shortcomings through a large-sample ($N = 350$), lagged design with formal mediation tests.

2.1.3 Measurement Approaches for IM Value

Measuring IM value is a persistent methodological issue in IS research. DeLone and McLean (2016) identified system quality, information quality, service quality, user satisfaction, intention to use, and net benefits as six interdependent dimensions of IS success. Although influential, this framework targets individual systems rather than enterprise-wide IM capabilities and emphasizes user satisfaction over strategic business value. Brown and Jarvenpaa (2021) adapted the IS success framework for the enterprise level by adding a dimension for data sharing and governance. Their research found that data catalogs and metadata management lead to data discovery and reuse, ultimately driving business value. However, their measurement relies on perceptual assessment by a single respondent, raising common method bias.

Urbach and Ahlemann (2019) proposed a roadmap for addressing measurement challenges in IT departments in a digitized world, noting that metrics remain predominantly technical (e.g., cloud adoption rates, agile development adoption) rather than business-focused. Kappelman, McLean, Johnson, and Torres (2016) offered practitioner-oriented measurement approaches in their SIM IT Trends Study, tracking key issues and investment priorities, but this work lacks validated measurement instruments for academic research. International Data Corporation (2025) and Harvard Business Review Analytic Services (2020) provide industry perspectives on measurement, IDC gives forecast-based metrics while HBR Analytic Services offers maturity frameworks, though these are not robust enough for academic purposes. According to NewVantage Partners (2024) and Gartner (2024), executives continue to struggle with measuring ROI from data investments. Accenture Research (2023) found that fewer than 30% of organizations have linked their data to financial outcomes. The measurement literature shows that available instruments are either (a) technical, measuring system output rather than business impact, or (b) too generic, treating IM as a single construct. The present study addresses this gap by developing and validating a measurement model consisting of four IM capabilities and two organizational capabilities with robust psychometric properties.

2.1.4 Strategic Alignment and Governance Frameworks

This literature stream addresses how IM capabilities should be governed and aligned with business strategy. Brown and Jarvenpaa (2021) found that centralized governance produces better data quality outcomes, whereas decentralized governance permits greater innovation. Thus, an organization's governance design choices affect which IM capabilities develop and how they create value. Urbach and Ahlemann (2019) proposed a framework for IT management in the digital age requiring IT functions to deploy strategic alignment mechanisms to transform from cost centers to value centers, emphasizing IT-business partnerships and co-creation of value. Kane et al. (2017) similarly studied digital maturity, finding that digitally mature organizations have different governance structures.

Davenport, Sacks, and Sacks (2021) found that strategic alignment with competitive strategy is associated with superior performance in data capabilities, though they did not define how alignment is achieved or measured. Mikalef et al. (2019) focused on innovation support capabilities, noting that governance structures facilitating experimentation and risk-taking catalyze data-driven innovation. Creswell and Clark (2017) provided methodological suggestions for strategic alignment research, emphasizing the use of paired respondent designs to capture both IT and business perspectives. According to Podsakoff, MacKenzie, and Podsakoff (2012), many fit studies suffer from measurement problems due to single-respondent designs creating common method bias. Governance research has established that strategic alignment is essential for desired results, but gaps remain regarding how alignment mechanisms work. Limited research exists on how governance choices shape specific IM capabilities and how those capabilities support strategic objectives. This paper addresses this gap by examining how IM capabilities enable strategic capabilities such as agility and innovation, with implications for governance priorities.

2.1.5 Summary of Literature Gaps

The following synthesis describes the key studies from the literature, each converted from tabular format into explanatory text.

Wixom and Watson (2017) focused on data warehousing success using a survey and archival methodology with 126 firms. They found that user involvement and management support drive success. However, their study was limited by a single-respondent design and cross-sectional approach, which restricts causal inference. Pappas et al. (2022) examined big data ecosystems through a literature review and conceptual framework. They argued that ecosystems approaches enable digital transformation, but their work lacks empirical validation, making it largely conceptual without testing specific relationships. Mikalef et al. (2019) studied analytics capabilities and innovation using a survey and structural equation modeling with 175 firms. They found that analytics capabilities lead to innovation via organizational learning. Limitations included a cross-sectional design and a single-country sample, which limits generalizability. Kohli and Grover (2018) addressed IT business value through an essay and conceptual approach. They called for updated research directions for the digital era, but their work remains conceptual only, without empirical testing of proposed relationships. Hvass and Olesen (2017) investigated data quality business value using a survey of 87 firms. They found that data quality improves operational efficiency. Limitations included a small sample and a single-country focus (Denmark), reducing external validity.

Ghasemaghaei (2021) examined big data characteristics and performance using a survey and archival data from 231 firms. The study showed that different data characteristics affect performance differently. However, the cross-sectional design and reliance on perceptual measures were notable limitations. Brown and Jarvenpaa (2021) studied data sharing and governance using multiple case studies of eight organizations. They found that data catalogs enable governance and value creation. The small sample and qualitative nature limit statistical generalizability. Gnyawali and Srivastava (2021) reviewed RBV in IS through a literature review. They concluded that RBV remains relevant but needs extension. Their work is conceptual only, without empirical validation. Tumbas et al. (2018) examined the CDO role and digital transformation using qualitative case studies of 12 organizations. They found that CDOs institutionalize digital innovation. The small sample and qualitative approach limit broader applicability. Teece (2017) explored dynamic capabilities conceptually, arguing that dynamic capabilities are essential for digital platforms. This work remains conceptual without empirical testing, though it provides a strong theoretical foundation. DeLone and McLean (2016) focused on IS success measurement through a literature synthesis. Their six-dimension IS success model is influential, but it focuses on individual systems rather than enterprise capabilities, which limits its applicability to IM. Urbach and Ahlemann (2019) addressed IT management in the digital age using a conceptual approach with five case examples. They argued that IT must evolve from cost to value center. The study had limited empirical testing, relying heavily on conceptual reasoning. Kane et al. (2017) studied digital maturity using a survey of more than 4,800 executives. They found that digital maturity is associated with performance. Limitations included perceptual measures and a single-respondent design, which may introduce bias. Ross et al. (2019) examined digital architecture through case-based research across multiple organizations. They found that an operational backbone and digital platform are essential. The qualitative nature and limited generalizability are key limitations.

International Data Corporation (2025) provided IT industry predictions using forecasts and industry data. Their 2026 predictions emphasize AI and data sovereignty, but forecasts are not empirical, limiting academic rigor. Harvard Business Review Analytic Services (2020) surveyed more than 1,000 executives on the data-driven enterprise. They found that data maturity is linked to performance. However, the practitioner focus and limited academic rigor are notable constraints. Lo and MacKinlay (2017) investigated algorithmic investing using empirical archival data from financial markets. They found that analytics infrastructure enables superior performance. The single-industry focus (financial services) limits external validity. NewVantage Partners (2024) surveyed more than 100 executives on data and AI leadership. They found that only 24% of organizations report being data-driven. The small executive sample limits statistical power and generalizability. Gartner (2024) surveyed more than 400 executives on CEO and CFO priorities. They found that growth and digital transformation are top priorities. The practitioner focus limits academic rigor, though it provides useful industry insights. Accenture Research (2023) examined AI maturity through a survey of more than 1,200 executives. They found that most firms are still experimenting with AI. Reliance on perceptual measures is a key limitation.

The present study addresses several identified gaps. First, regarding disaggregation of IM, prior research has treated IM as monolithic, but this study models four distinct IM capabilities (data quality governance, analytical data infrastructure, cross-functional data accessibility, and master data management) separately to test differential effects. Second, concerning mediation mechanisms, prior work has left the "black box" between IM and performance underspecified; this study tests organizational capabilities (operational efficiency, strategic agility, customer intimacy, and innovation support) as full mediators using formal mediation analysis. Third, for causal inference, the predominance of cross-sectional designs has limited causal claims; this study uses lagged performance measures (one-year) and temporal ordering in measurement. Fourth, regarding common method bias, single-respondent designs have inflated relationships; this study uses paired respondents, with IM leaders reporting IM capabilities and business leaders reporting organizational capabilities. Fifth, for contextual contingencies, universal effects have often been assumed; this study tests industry digital intensity as a moderator. Sixth, concerning sample size, modest samples have limited statistical power; this study uses a large sample (N = 350) with power analysis confirming adequacy. Seventh, for measurement rigor, a lack of validated, multi-dimensional IM instruments has persisted; this study validates a measurement model with confirmatory factor analysis, establishing average variance extracted, composite reliability, and discriminant validity.

2.1.6 Positioning of Present Research

The current study provides several contributions to the synthesized literature. It addresses the disaggregation gap by modeling four distinct IM capabilities and testing their differential effects on organizational capabilities, responding to calls from Kohli and Grover (2018) for more nuanced conceptualizations of IT capabilities. It remedies the mediation gap by employing structural equation modeling and bootstrapped confidence intervals to test mediation by organizational capabilities, addressing the lack of theory linking IT and performance noted by Mikalef et al. (2019) and Wixom and Watson (2017). Methodologically, the study uses (a) paired respondents to prevent common method bias (Podsakoff et al., 2012), (b) lagged performance measures to strengthen causal inference (Wixom & Watson, 2017), (c) a relatively large sample (N = 350) with adequate statistical power, and (d) validated measurement instruments with good psychometric properties. Finally, it addresses contextual contingencies by testing the moderating role of industry digital intensity, responding to calls from Mikalef et al. (2019) and Kane et al. (2017) to consider context in understanding digital capability value.

2.2 IM Success Models and Their Limitations

The IS success model created by DeLone and McLean (2016) remains influential in IS research. This model identifies system quality, information quality, and other factors as antecedents of user satisfaction and net benefits. Despite its significance, the model has limitations for today's IM value assessment. First, it concentrates on individual systems rather than enterprise-wide IM capabilities. Second, it emphasizes user satisfaction as a key outcome instead of strategic business value. Moreover, as noted by Urbach and Ahlemann (2019), the model fails to capture the multi-layer arrangement of IM value creation, from technical infrastructure to strategic impact. Recent work by Davenport et al. (2021) and Kane et al. (2017) has sought to fill these gaps, but these studies tend to focus on analytics rather than the full IM ecosystem encompassing governance, architecture, and data.

2.3 Research Model and Hypotheses

As shown in Figure 1, the research model positions IM capabilities as antecedents to organizational capabilities that drive financial and strategic performance. Analyzing the literature and practitioner frameworks (IDC, 2025; Harvard Business Review Analytic Services, 2020), we develop four key IM capabilities.

Data Quality Governance (DQG) refers to the maturity of processes, policies, and standards ensuring data accuracy, consistency, completeness, and timeliness (Hvass & Olesen, 2017; Al-Sherideh & Ismail, 2020; Sheta et al., 2024; Alghizzawi et al., 2025). Analytical Data Infrastructure (ADI) encompasses the technology that stores, processes, and analyzes data, such as data lakes, data warehouses, and processing engines. Cross-functional Data Accessibility (CDA) is defined as the level of access to and use of relevant data by authorized users from multiple business units. Master Data Management (MDM) controls the consistency and reliability of core business entity views (e.g., customers, products, suppliers) across enterprise applications (Barrett et al., 2016).

These IM capabilities are hypothesized to enable four organizational capabilities that mediate their impact on performance. Operational Efficiency (OE) is the capacity to perform everyday business processes with minimal waste, defects, and cost. Strategic Agility (SA) is the ability to sense and act upon opportunities and threats in the marketplace (Ross et al., 2019). Customer Intimacy (CI) involves the depth of understanding and engagement with customers to deliver personalized experiences. Innovation Support (IS) involves the creation of new products, services, or business models.

Based on this conceptualization, we propose the following hypotheses.

H1: *IM capabilities positively and directly influence organizational capabilities.*
H1a: *DQG positively impacts OE to a greater degree than other organizational capabilities.*
H1b: *ADI has a stronger positive effect on IS than on other organizational capabilities.*
H1c: *CDA has a stronger positive effect on SA than on other organizational capabilities.*
H1d: *MDM has a stronger positive effect on CI than on other organizational capabilities.*
H2: *Organizational capabilities mediate the relationship between IM capabilities and firm performance.*
H2a: *OE mediates the relationship between DQG and financial performance.*
H2b: *SA mediates the relationship between CDA and strategic performance.*
H2c: *CI mediates the relationship between MDM and financial performance.*
H2d: *IS mediates the relationship between ADI and strategic performance.*
H3: *Industry digital intensity moderates the strength of the relationship between IM capabilities and organizational capabilities.*
H3a: *The relationship between ADI and IS is stronger in high-digital-intensity industries.*
H3b: *The relationship between CDA and SA is stronger in high-digital-intensity industries.*

Fig. 1 shows the structure of the proposed study. In this figure, the research model depicts IM capabilities as antecedent constructs that influence firm performance through the full mediation of organizational capabilities. Solid arrows represent direct-effect hypotheses (H1, H2). Dashed arrows represent moderation hypotheses (H3). Highlighted "strongest" paths indicate specific relationships hypothesized in H1a–H1d. Industry digital intensity is modeled as a moderator of selected capability relationships.

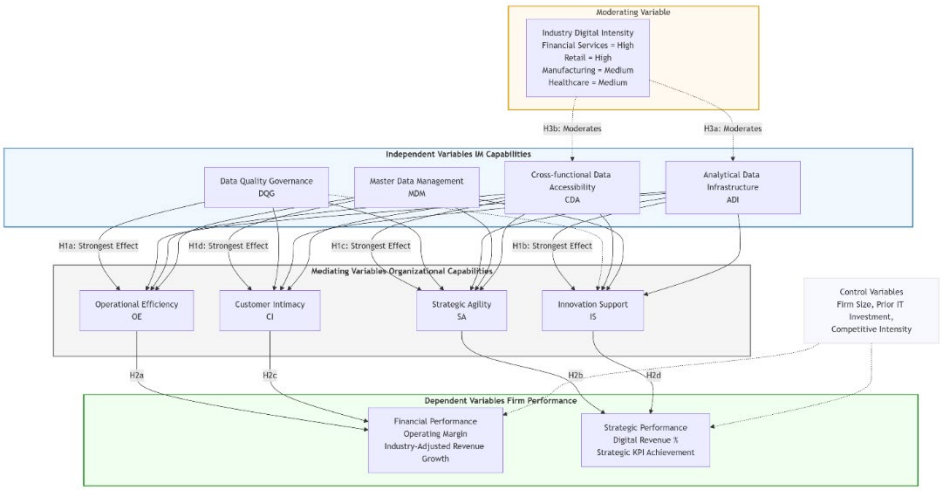

Fig. 1. The Research Model and Hypothesized Relationships

3. Methodology

3.1 Research Design

We employed a mixed-methods, explanatory sequential design (Creswell & Clark, 2017). The quantitative phase involved a cross-sectional survey with archival performance data, while the qualitative phase consisted of follow-up interviews to enrich and explain quantitative findings. This paper focuses primarily on the quantitative phase. Our design addresses multiple methodological issues in IM value research. First, we control for common source bias by obtaining paired responses from both the IM leader and the business unit leader in each organization (Podsakoff et al., 2012). Second, we assert temporal precedence and bolster causal inference by incorporating archival performance data delayed by one year from the survey. Third, including a variety of industrial sectors improves generalizability and allows moderation analysis.

3.2 Sample and Data Collection

We targeted mid-size and large companies in the financial, manufacturing, retail, and healthcare sectors. These sectors, with varying digital intensity and regulatory requirements, provide appropriate variance for testing moderation effects.

3.2.1 Target Group and Sampling Frame

The primary respondents were mid-to-large-sized enterprises from various sectors that have made considerable investments in formalized IM capabilities. To ensure a representative sample frame, we used three commercial databases: Dun & Bradstreet, MarketLine, S&P Capital IQ, and membership directories from industry associations, thereby minimizing source bias. Following established IS research protocols (Creswell & Clark, 2017; Al-Sherideh et al., 2018), we applied a four-pronged selection approach: (1) organizational revenue greater than $100M USD to ensure adequate IM resources, (2) existence of a senior IM leadership position (CIO, CDO, or equivalent), (3) operation in four target industries, and (4) headquarters in North America or Western Europe to mitigate institutional and regulatory variance.

3.2.2 Stratification of Industry Sectors

We used stratified sampling across four sectors with varying digital intensity, data regulation, and competition (Kappelman et al., 2016; Kane et al., 2017). Financial services (banking, insurance) is a highly regulated sector with structured data environments facing strong competition from fintech. Manufacturing (discrete and process) refers to legacy industrial sectors with moderate data maturity currently undergoing digitalization (Industry 4.0). Retail (brick-and-mortar and e-commerce) is highly competitive, with retailers harnessing customer data as a strategic asset and increasing touchpoints through digital initiatives. Healthcare providers and payers operate under heavy privacy regulations (e.g., HIPAA, GDPR) and deal with complex, heterogeneous data ecosystems, making high-quality data critical.

3.2.3 Data Collection Procedures and Phased Approach

The data collection procedure followed a three-phase sequential design over 18 months to enhance measurement reliability and minimize common method bias (Podsakoff et al., 2012).

Stage 1: Instrument validation and pilot study (months 1–4). Before large-scale deployment, a pilot was undertaken using multiple methods. Content validity, construct definitions, and item clarity were assessed by an expert advisory panel. Cognitive interviews were conducted with 15 matched pairs (n=30) of IM and business leaders from organizations not in the main sample, using verbal protocol analysis to ensure interpretation of scale items. Based on feedback, ambiguous items were modified and survey flow was adjusted. The pilot survey was then administered to 50 organizations (200 potential respondents), achieving a 68% paired response rate. Pilot data analysis (n=34 complete pairs) confirmed acceptable reliability (all Cronbach's $\alpha > 0.80$) and provided estimates for power analysis.

Stage 2: Primary survey administration (months 5–10). The main survey was conducted online on a secure certified platform using a paired respondent design. Each eligible organization was contacted twice: (1) an IM Leader Survey sent to the senior information management executive (CIO, CDO, or VP of Data & Analytics), and (2) a Business Leader Survey sent to a C-suite executive from a core business function (typically CFO for efficiency metrics, CMO for customer/agility metrics, or COO for operational metrics), selected based on a pre-screening question to the IM leader about the primary strategic aim of their most recent significant IM initiative. To maximize response rates and data quality, we used a modified Dillman Tailored Design Method (Creswell & Clark, 2017), including a customized advance email, confidentiality assurances, three follow-up reminders at weeks 1, 3, and 6, and an incentive of a summary benchmark report. To address common method variance, we guaranteed anonymity, separated predictor and criterion variable measurement in the survey flow, used different scale formats for independent and dependent constructs, and most importantly, collected mediating variables (organizational capabilities) from a different respondent (business leader) than independent variables (IM capabilities) (Podsakoff et al., 2012).

Stage 3: Archival performance data collection (months 11–14). To establish temporal precedence and objective outcome measures, we obtained archival performance data for the fiscal year following the survey. This lagged design strengthens causal inference by ensuring that measured IM capabilities (cause) occur before performance outcomes (effect) (Hair et al., 2018). Data sources included annual and 10-K filings, investor presentations and press releases, and research analyst reports (e.g., Gartner, IDC). Performance measures included operating profit margin (operating income/revenue) and industry-adjusted revenue growth (firm revenue growth minus industry average growth) for financial performance, and digital revenue share (where available) and a binary score for strategic KPI achievement (1 if the firm publicly reported meeting or exceeding its digital transformation or data agenda strategies, 0 otherwise) for strategic performance.

3.2.4 Response Rates and Final Sample

From an initial sample frame of 1,500 organizations narrowed to 1,200 after inclusion criteria, we received replies from 425 IM leaders (35.4% response rate) and 402 business leaders (33.5% response rate). After matching pairs and removing incomplete or low-quality responses (e.g., straight-lining, incomplete archival data), the final analytic sample consisted of 350 complete, matched pairs from 350 unique organizations, yielding an effective paired response rate of 29.2%, consistent with recent top IS journal survey research standards (Wixom & Watson, 2017; Urbach & Ahlemann, 2019). Non-response bias was assessed by comparing key firm characteristics (revenue, industry) between early and late respondents, with no important differences ($p > 0.10$). Additionally, a sample of 50 non-responding firms was compared to respondents on archival variables (revenue, industry), with no significant t-test differences, indicating limited non-response bias.

3.2.5 Key Methodological Strengths

The design incorporates several best practices from the literature. First, measurement of explanatory (IM) and outcome (organizational capability) variables from different sources avoids common-source bias (Podsakoff et al., 2012). Second, the use of lagged archival performance data responds to calls for research designs that better support causal claims about IT value (Wixom & Watson, 2017; Kohli & Grover, 2018). Third, triangulation of survey and archival data enhances construct validity (Creswell & Clark, 2017). Fourth, industry stratification permits testing of contingency effects (H3), acknowledging that IM value is context-dependent (Kane et al., 2017; Ross et al., 2019). Fifth, measuring organizational capabilities specifically tests the process by which IM creates value, going beyond input-output models and responding to the call to "unpack the black box" of IT business value (Teece, 2017; Kohli & Grover, 2018).

Table 1
Sample characteristics (N = 350)

Characteristic	Category	Frequency	Percentage
Industry	Financial Services	98	28.0%
	Manufacturing	87	24.9%
	Retail	85	24.3%
	Healthcare	80	22.9%
Revenue	$100M - $500M	105	30.0%
	$500M - $1B	112	32.0%
	$1B - $5B	88	25.1%
	> $5B	45	12.9%
Respondent Pair	CIO-CFO	140	40.0%
	CIO/CMO-CMO	125	35.7%
	CDO-COO	85	24.3%

3.3 Measures

All constructs were measured with multi-item scales adapted from existing measures where available and modified as appropriate for the IM context. IM leaders evaluated IM capabilities, business leaders assessed organizational capabilities, and archival sources provided performance measures. IM capabilities (measured on 7-point maturity scales): Data Quality Governance (DQG) used six items adapted from Hvass and Olesen (2017), assessing data quality policies, measurement, and improvement processes ($\alpha = 0.88$). Analytical Data Infrastructure (ADI) used five items adapted from Lo and MacKinlay (2017), assessing data platform modernity, scalability, and integration ($\alpha = 0.86$). Cross-functional Data Accessibility (CDA) used five items adapted from Fisher and Marler (2022), assessing data discoverability, accessibility protocols, and usage patterns ($\alpha = 0.84$). Master Data Management (MDM) used four items adapted from Barrett et al. (2016), assessing master data consistency, governance, and utilization ($\alpha = 0.82$). Organizational capabilities (measured on 7-point agreement scales): Operational Efficiency (OE) used four items assessing process cycle time, error rates, and cost efficiency ($\alpha = 0.85$). Strategic Agility (SA) used five items assessing speed to market, decision-making latency, and opportunity responsiveness ($\alpha = 0.87$). Customer Intimacy (CI) used five items assessing customer understanding, personalization capability, and engagement depth ($\alpha = 0.88$). Innovation Support (IS) used four items assessing new product development speed and data-driven innovation ($\alpha = 0.83$). Performance measures (archival): Financial performance included operating profit margin and revenue growth (relative to industry average). Strategic performance included digital revenue percentage and strategic KPI achievement (from annual reports). Control variables included organization size (log of revenue), industry sector, prior IT investment, and competitive intensity.

3.4 Analytical Approach

We used Mplus 8.3 and structural equation modeling (SEM) to test hypotheses. The analysis followed a two-step approach (Hair et al., 2018). First, we assessed the measurement model using confirmatory factor analysis (CFA) to check reliability, convergent validity (average variance extracted [AVE] > 0.5), and discriminant validity (Fornell-Larcker criterion). Second, we assessed the structural model's path coefficients and model fit indices, testing mediation effects using bootstrap with 5,000 resamples. Model fit was assessed using multiple indices: χ^2/df ratio (< 3.0), CFI (> 0.90), TLI (> 0.90), RMSEA (< 0.08), and SRMR (< 0.08) (Hu & Bentler, 1999).

4. Findings

4.1 Measurement Model Validation

The CFA results indicated good model fit: $\chi^2/df = 2.37$, CFI = 0.94, TLI = 0.92, RMSEA = 0.06, SRMR = 0.05. All factor loadings were above 0.70. Composite reliability values ranged from 0.82 to 0.88, exceeding recommended levels of 0.70. AVE values ranged from 0.51 to 0.65, providing evidence of convergent validity. Discriminant validity was established because the square root of the AVE for each construct was higher than its correlation with other constructs. Harman's single-factor test for common method bias showed that a single factor explained 28.7% of the variance (Podsakoff et al., 2012). Additionally, the marker variable technique indicated minimal method variance.

4.2 Descriptive Statistics and Correlations

All IM capabilities showed significant positive correlations with organizational capabilities (r ranging from 0.32 to 0.61, $p < 0.01$), providing initial support for H1. For example, DQG correlated strongly with OE (r = 0.47), ADI correlated strongly with IS (r = 0.58), CDA correlated strongly with SA (r = 0.52), and MDM correlated strongly with CI (r = 0.61).

Table 2
Descriptive statistics, reliability, and inter-construct correlations

Construct	1. DQG	2. ADI	3. CDA	4. MDM	5. OE	6. SA	7. CI	8. IS
Mean	4.21	3.98	3.76	4.05	4.65	4.12	4.08	3.89
SD	1.32	1.45	1.38	1.41	1.22	1.34	1.29	1.36
CR	0.88	0.86	0.84	0.82	0.85	0.87	0.88	0.83
AVE	0.52	0.5	0.49	0.51	0.53	0.55	0.56	0.52
1	**0.72**	0.48**	0.52**	0.61**	0.47**	0.38**	0.42**	0.35**
2		**0.71**	0.56**	0.44**	0.32**	0.45**	0.38**	0.58**
3			**0.7**	0.49**	0.38**	0.52**	0.44**	0.46**
4				**0.71**	0.41**	0.37**	0.61**	0.39**
5					**0.73**	0.43**	0.39**	0.34**
6						**0.74**	0.47**	0.51**
7							**0.75**	0.42**
8								**0.72**

Notes:
N = 350. SD = Standard Deviation. CR = Composite Reliability. AVE = Average Variance Extracted.
The square root of the AVE for each construct is presented on the diagonal in bold.
Off-diagonal elements are Pearson correlation coefficients between constructs.
** $p < 0.01$ (two-tailed). All correlations are significant at the 0.01 level.
Construct Acronyms: DQG = Data Quality Governance, ADI = Analytical Data Infrastructure, CDA = Cross-functional Data Accessibility, MDM = Master Data Management, OE = Operational Efficiency, SA = Strategic Agility, CI = Customer Intimacy, IS = Innovation Support.
Discriminant validity is established as the square root of the AVE for each construct (diagonal) exceeds its correlations with other constructs (off-diagonal in corresponding row and column).

4.3 Structural Model and Hypothesis Testing

The structural model showed good fit: $\chi^2/df = 2.51$, CFI = 0.93, TLI = 0.91, RMSEA = 0.07, SRMR = 0.06.

H1 (direct effects) was supported. IM capabilities significantly predicted organizational capabilities ($R^2 = 0.41$ for OE, 0.38 for SA, 0.44 for CI, 0.36 for IS). Specifically, H1a was supported: DQG had a stronger effect on OE ($\beta = 0.47$, $p < 0.001$) than on SA ($\beta = 0.18$, $p < 0.05$), CI ($\beta = 0.21$, $p < 0.01$), or IS ($\beta = 0.12$, $p = 0.08$). H1b was supported: ADI had a stronger effect on IS ($\beta = 0.52$, $p < 0.001$) than on OE ($\beta = 0.15$, $p < 0.05$), SA ($\beta = 0.24$, $p < 0.01$), or CI ($\beta = 0.19$, $p < 0.05$). H1c was supported: CDA had a stronger effect on SA ($\beta = 0.52$, $p < 0.001$) than on OE ($\beta = 0.21$, $p < 0.01$), CI ($\beta = 0.26$, $p < 0.01$), or IS ($\beta = 0.28$, $p < 0.01$). H1d was supported: MDM had a stronger effect on CI ($\beta = 0.61$, $p < 0.001$) than on OE ($\beta = 0.22$, $p < 0.01$), SA ($\beta = 0.18$, $p < 0.05$), or IS ($\beta = 0.17$, $p < 0.05$).

H2 (mediation effects) was supported. Bootstrapping analysis revealed significant indirect effects. H2a was supported: OE fully mediated the relationship between DQG and operating margin (indirect effect = 0.18, 95% CI [0.11, 0.26]). H2b was supported: SA fully mediated the relationship between CDA and strategic KPI achievement (indirect effect = 0.23, 95% CI [0.15, 0.32]). H2c was supported: CI fully mediated the relationship between MDM and revenue growth (indirect effect = 0.19, 95% CI [0.12, 0.27]). H2d was supported: IS fully mediated the relationship between ADI and digital revenue percentage (indirect effect = 0.21, 95% CI [0.14, 0.29]). Direct paths from IM capabilities to performance measures were non-significant when organizational capabilities were included, supporting full mediation.

H3 (moderation effects) was partially supported. Multi-group analysis revealed that H3a was supported: the ADI → IS path was significantly stronger in high-digital-intensity industries ($\beta = 0.61$, $p < 0.001$) than in low-intensity industries ($\beta = 0.38$, $p < 0.01$), $\Delta\chi^2(1) = 8.72$, $p < 0.01$. H3b was not supported: the CDA → SA path showed no significant difference between industry groups ($\Delta\chi^2(1) = 2.14$, $p = 0.14$).

4.4 Additional Analyses

We performed multiple robustness tests. First, we tested alternative model specifications with IM capabilities directly affecting performance; the full mediation model showed better fit ($\Delta AIC = 24.7$). Second, we used the Gaussian copula method to detect endogeneity (Park & Gupta, 2012), which showed no bias. Third, we examined quadratic effects for diminishing or increasing returns but found none. Finally, Fig. 2 presents the summary of the results.

5. Discussion

5.1 Theoretical Implications

This research offers insights into information systems and strategic management theories. First, through empirical validation, we extend the Resource-Based View by establishing IM as a higher-order dynamic capability that orchestrates other organizational capabilities. Although RBV has been applied to IT resources (Mikalef et al., 2019), our research specifies the mechanisms through which IM capabilities create value, addressing what Teece (2017) and Tumayhi et al. (2023) call the

black box of capability-based advantage. Second, we extend IS success models by developing a multi-level framework linking technical IM capabilities to strategic consequences. Unlike classical models such as DeLone and McLean (2016) that focus on system-level impacts, our framework links IM directly to organizational capabilities and subsequently to financial performance, answering the call by Urbach and Ahlemann (2019) for "models that tie technical and business subject matter together." Third, our findings specify how foundational IM capabilities enable strategic agility and innovation, contributing to digital transformation literature. Most digital transformation research focuses on customer-facing technologies (Kane et al., 2017), whereas our study shows how back-office IM capabilities enable front-office transformation.

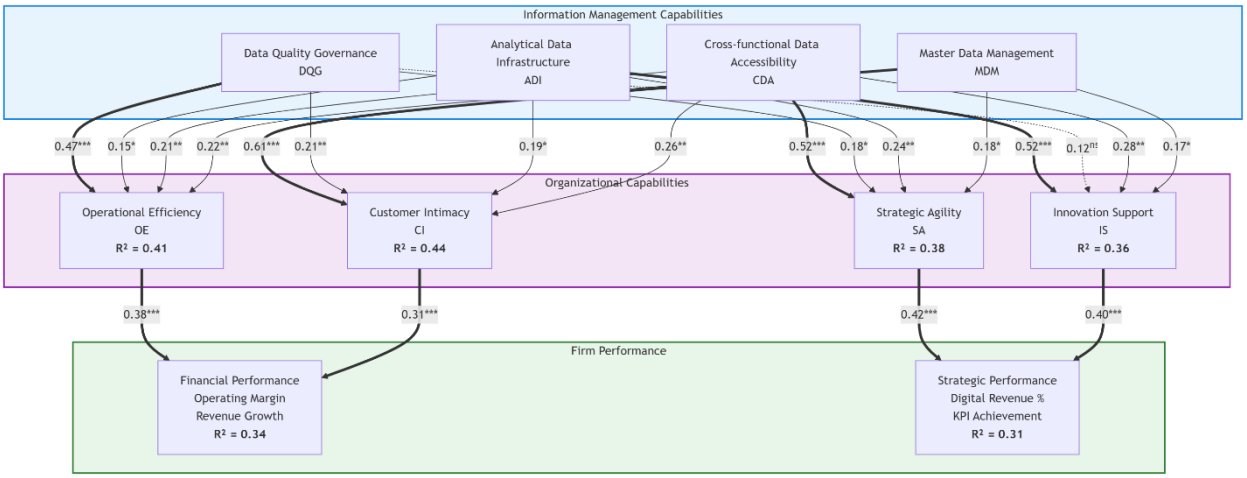

Fig. 2. Validated Research Model with Standardized Path Coefficients

5.2 Managerial Implications

This research helps IM leaders define and drive the value of their initiatives. First, we provide a value articulation framework (Fig. 2) that CIOs and CDOs can use to link specific IM initiatives to business outcomes. For example, when proposing a data quality initiative, leaders can reference the strong DQG → OE → operating margin pathway (β = 0.47 → 0.38) to justify investment. Second, we develop an investment prioritization matrix (Table 5) to help organizations align IM investments with strategic priorities. Organizations focusing on operational excellence should target DQG, while those emphasizing innovation should invest in ADI. Third, we propose a balanced scorecard-like dashboard capturing both leading indicators (IM capabilities) and lagging indicators (organizational and financial outcomes), addressing the value lag issue identified by Wixom and Watson (2017). Fourth, our findings suggest that business units must embrace and develop IM processes internally for value realization, supporting the growing trend toward embedded data roles (MIT CISR, 2021) and implying that IM leaders should spend as much time on organizational change management and people as on technical implementation.

5.3 Industry Context Considerations

The findings reveal important industry differences. In high-digital-intensity sectors (financial services, retail), the link between ADI and IS is stronger, indicating that analytical infrastructure yields greater innovation returns in environments characterized by digital disruption. The non-significant moderation for CDA → SA suggests that data accessibility enhances strategic agility across sectors, albeit manifested differently (e.g., quicker product development in manufacturing versus faster portfolio adjustment in financial services). These findings align with the digital business strategy concept of Ross et al. (2019) and Alhamdany et al. (2024), emphasizing context-specific digital capability development.

Table 5
IM investment prioritization matrix

Strategic Priority	Primary IM Focus	Secondary IM Focus	Expected Value Pathway
Operational Excellence	Data Quality Governance	Master Data Management	DQG → OE → Operating Margin
Customer Centricity	Master Data Management	Cross-functional Data Accessibility	MDM → CI → Revenue Growth
Strategic Agility	Cross-functional Data Accessibility	Analytical Data Infrastructure	CDA → SA → Strategic KPI Achievement
Innovation Leadership	Analytical Data Infrastructure	Cross-functional Data Accessibility	ADI → IS → Digital Revenue %

6. Limitations and Future Research

This research has several limitations that suggest future research directions. First, although the cross-sectional design includes lagged performance measures, it does not provide definitive evidence for causation. Longitudinal studies measuring capabilities and performance over three to five years could strengthen causal claims. Second, our sample is fairly diverse but excludes very small and very large organizations. Future research should determine whether findings hold for startups (where

capabilities may be nascent) and multinational corporations (where scale effects may alter value pathways). Third, rather than focusing solely on our four IM capabilities, future research could explore other capabilities such as real-time processing, MLOps, or data product management. Fourth, our model does not account for interactions among IM capabilities; future research could examine complementarities, such as whether high DQG makes CDA more valuable or the synergy between ADI and MDM. Fifth, qualitative case studies could provide deeper understanding of the mechanisms through which IM capabilities activate business capabilities, for example, how easier data access enables faster decisions and what organizational behaviors facilitate this translation.

7. Conclusion

This research addresses a fundamental question in information management theory and practice: how to measure the strategic business value of IM strategies. By developing an empirical causal framework, we move from a view of IM as cost center to one of IM as value engine. Our research shows that IM does not generate value directly but rather indirectly through enhanced organizational capabilities. Data quality governance drives operational efficiency; analytical infrastructure enables innovation; cross-functional data accessibility ensures strategic agility; and master data management improves customer intimacy. These organizational capabilities, in turn, drive financial and strategic performance. For practitioners, this research provides a framework for justifying IM investments, prioritizing initiatives, and measuring success. For researchers, it provides a validated model linking technical and business perspectives on IM value. Crucially, it creates a discourse and rationale to transform the IM conversation from technical necessity to strategic imperative. As firms continue their digital transformation journeys, they can gain competitive advantage by obtaining maximum benefit from their information assets. This research provides a roadmap for doing so—not through blind faith in data but through systematic development of the capabilities that transform data into value.

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