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Digital Technology Disclosure and Firm Performance: Evidence from U.S. Financial Institutions

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Digital Technology Disclosure and Firm Performance: Evidence from U.S. Financial Institutions

Abstract

This study investigates the relationship between digital technology disclosure and firm performance among U.S. financial institutions. While digital transformation has accelerated across the financial services industry, limited evidence exists on whether disclosures related to specific digital technologies are associated with firms' operating and market performance. Using a panel of 5,172 firm year observations from 535 U.S. financial institutions over the period 2014–2025, this study develops a custom, empirically validated digital technology disclosure dictionary to measure disclosures relating to Artificial Intelligence (AI), Big Data Analytics, Cloud Computing, and Digital Transformation from SEC Form 10-K filings. The empirical analysis employs two way fixed effects panel regressions with a comprehensive set of robustness tests.

The results indicate substantial heterogeneity across digital technology categories. AI disclosure exhibits the most consistent positive association with operating performance, particularly transformed measures of net income, whereas its relationship with return on assets is less robust across model specifications. Big Data disclosure shows limited evidence of a positive association after controlling for extreme observations, while Digital Transformation disclosure demonstrates specification dependent results. Cloud Computing disclosure is not significantly associated with firm performance under any estimated specification. Furthermore, none of the four disclosure categories is significantly associated with the market based performance measure, Tobin's Q.

This study contributes to the literature by introducing a validated industry specific digital technology disclosure dictionary and by providing a technology disaggregated analysis of digital disclosure rather than treating digitalization as a single construct. The findings suggest that different digital technologies exhibit distinct relationships with firm performance, highlighting the importance of examining individual technology categories separately. The reported relationships should be interpreted as statistical associations rather than causal effects.

Keywords: Artificial Intelligence, Big Data Analytics, Cloud Computing, Digital Transformation, Digital Technology Disclosure, Financial Institutions, Textual Analysis, Firm Performance, Panel Data

JEL Classification: C23 , G21 , G32 , M41 , O33

1 Introduction

Digital technologies have become a fundamental driver of transformation in the financial services industry, reshaping business models, operational processes, risk management, and customer engagement. As financial institutions increasingly adopt technologies such as artificial intelligence (AI), big data analytics, cloud computing, and broader digital transformation initiatives, disclosures relating to these technologies have become more prominent in mandatory corporate reporting. In particular, SEC Form 10-K filings provide an important channel through which firms communicate their technological strategies, innovation activities, and future growth opportunities to investors and other stakeholders.

Despite the growing importance of digital technology disclosures, whether they are systematically associated with firm performance remains an open empirical question. Existing studies report mixed and often conflicting findings, with the direction and magnitude of the relationship varying across technologies, industries, countries, and research designs. Moreover, much of the current literature focuses on a single technology or employs aggregate measures of digitalization, implicitly assuming that different digital technologies generate similar economic outcomes. Such an approach may obscure important differences among technologies that vary substantially in maturity, strategic importance, and organizational application.

An additional challenge concerns the measurement of digital technologies. This study measures *digital technology disclosure* rather than technology adoption, investment, or organizational capability. Keyword frequencies extracted from SEC Form 10-K filings capture the extent to which firms discuss digital technologies in their annual reports but do not directly measure their implementation or effectiveness. Consequently, the disclosure measures should be interpreted as indicators of corporate communication rather than direct proxies for firms' technological capabilities.

To address these gaps, this study investigates the relationship between digital technology disclosure and firm performance using a panel of 5,172 firm year observations from 535 publicly listed U.S. financial institutions over the period 2014–2025. Four distinct technology categories are examined Artificial Intelligence, Big Data Analytics, Cloud Computing, and Digital Transformation allowing each technology to be evaluated separately rather than being combined into a single measure of digitalization.

This study makes five main contributions. First, it provides new evidence from U.S. financial institutions, extending a literature that has been dominated by studies from emerging and non U.S. markets. Second, it develops and empirically validates a financial industry specific digital technology disclosure dictionary designed for textual analysis of SEC Form 10-K filings. Third, it adopts a technology disaggregated framework that distinguishes among AI, Big Data Analytics, Cloud Computing, and Digital Transformation, enabling a more comprehensive assessment of their individual relationships with firm performance. Fourth, it evaluates both operating performance and market based measures of firm performance, providing a broader perspective on the economic implications of digital technology disclosure. Finally, the study performs extensive robustness analyses to assess the stability and reliability of the empirical findings across alternative model specifications.

The remainder of the paper is organized as follows. The next section reviews the relevant literature, develops the theoretical framework, and presents the research hypotheses. The subsequent sections describe the data, variable construction, disclosure dictionary, and empirical methodology, followed by the main results and robustness analyses. The paper concludes with a discussion of the findings, their implications, the study's limitations, and directions for future research.

2 Literature Review and Hypothesis Development

2.1 Digital Disclosure and Textual Analysis

Textual analysis has become an established approach for measuring firm level disclosure in accounting and finance research. By extracting information from corporate reports, researchers can construct quantitative measures of firms' strategic communication that complement traditional financial indicators. Because mandatory filings such as SEC Form 10-K reports contain detailed discussions of business strategy, technological developments, and risk factors, they have become an important source of data for examining corporate disclosure practices.

A key development in this literature was the work of Loughran and McDonald [1], who demonstrated that general purpose sentiment dictionaries frequently misclassify financial reporting language. Their findings highlighted the need for domain specific dictionaries tailored to the financial reporting environment and have since motivated numerous studies employing customized textual analysis approaches.

Recent research has extended textual analysis to digital technologies. Zheng et al. [2] developed a text based measure of cloud computing disclosure from SEC Form 10-K filings and reported a positive relationship between cloud adoption and subsequent operating performance, with the magnitude of the effect varying across competitive strategies. More recently, Song and Kim [3] examined AI related disclosures in annual reports. Their working paper provides evidence that AI disclosure intensity is positively associated with subsequent firm valuation, suggesting that AI related narratives disclosed in corporate reports contain economically relevant information.

Although textual analysis offers an objective and scalable method for measuring corporate disclosure, it also has important limitations. Keyword based measures capture the extent to which firms discuss particular technologies rather than their actual adoption, investment, or technological capability. Consequently, disclosure intensity should be interpreted as a measure of corporate communication rather than a direct indicator of technology implementation. Moreover, keyword based approaches remain sensitive to contextual issues, including generic boilerplate language, industry wide discussions, and references to competitors or regulatory developments. These limitations underline the importance of carefully developing and validating domain specific disclosure dictionaries before they are applied in empirical research.

Overall, the existing literature demonstrates the growing value of textual analysis for studying digital technology disclosure while also emphasizing the importance of context specific measurement. Building on these developments, the present study develops a financial industry specific digital technology disclosure dictionary designed

to capture disclosures relating to AI, Big Data Analytics, Cloud Computing, and Digital Transformation in SEC Form 10-K filings.

2.2 Artificial Intelligence and Firm Performance

The relationship between artificial intelligence (AI) and firm performance has attracted increasing attention in the finance and banking literature, yet the empirical evidence remains inconclusive. Existing studies report positive, negative, and insignificant effects, suggesting that the economic value of AI depends on institutional context, measurement approach, and the stage of technological adoption.

Several studies report beneficial effects of artificial intelligence on organizational performance. For example, Li [4] examined 430 Chinese commercial banks over the period 2007–2022 and found that AI adoption improves profitability by reducing operating costs, diversifying income sources, and promoting mobile banking development. These findings suggest that AI can strengthen operational efficiency and competitive advantage when effectively integrated into banking activities.

In contrast, other studies suggest that AI investments may generate short term financial costs before producing measurable economic benefits. Using patent based measures of AI innovation for 31 large U.S. commercial banks, Ni et al. [4] report that AI innovation is associated with improved asset quality but lower short term profitability, reflecting the substantial investment costs required to develop and implement AI technologies. Their findings are consistent with a "J-curve" pattern, whereby initial investments reduce financial performance before longer term benefits materialize.

Additional evidence indicates that the relationship between AI and firm performance may be sensitive to econometric specification and firm heterogeneity. Evidence from Algerian corporations suggests that positive associations observed in baseline models become statistically insignificant after controlling for unobserved firm characteristics, implying that part of the reported performance effect may reflect differences between firms rather than the direct impact of AI itself.

Overall, the existing literature provides no clear consensus regarding the performance implications of AI. Differences in country settings, industry characteristics, measures of AI, and empirical methodologies contribute to the inconsistent findings reported across studies. These mixed results highlight the need for further evidence using alternative measures of AI related corporate disclosure and different institutional settings, particularly within U.S. financial institutions.

2.3 Big Data and Firm Performance

Big Data Analytics Capability (BDAC) has become an important research area in the information systems, management, and finance literature. Rooted primarily in the Resource Based View (RBV) and Dynamic Capabilities Theory (DCT), BDAC is generally viewed as a strategic organizational capability that enables firms to create value by acquiring, integrating, and exploiting large volumes of data for decision making and innovation.

Empirical evidence generally supports a positive relationship between Big Data Analytics Capability (BDAC) and firm performance, although the underlying mechanisms differ across studies. Wamba et al. [5] proposed and empirically validated a hierarchical BDAC model, showing that BDAC enhances firm performance both directly and indirectly through process oriented dynamic capabilities. Their findings suggest that competitive advantage arises not only from access to data, but also from an organization's ability to transform data into actionable knowledge and improve organizational processes.

Evidence from broader empirical syntheses also indicates that the relationship between Big Data Analytics Capability (BDAC) and firm performance is context dependent. Using a meta analysis of 42 empirical studies, Ansari and Ghasemaghaei [6] found a significant positive average relationship between BDAC and firm performance. They further showed that the strength of this relationship is moderated by the type of performance measure and by country of origin, whereas respondent type does not have a significant moderating effect. These findings indicate that the business value of BDAC varies across different organizational and institutional contexts.

An important methodological distinction exists within this literature. Most previous studies measure big data capabilities directly through surveys, organizational assessments, or capability based constructs that capture firms' technological resources and analytical competencies. Comparatively little research has examined big data using textual disclosure measures derived from corporate reports. Consequently, it remains unclear whether firms' disclosure of big data activities conveys information comparable to direct measures of organizational capability. This distinction represents an important research gap and provides a strong motivation for examining Big Data disclosure using textual analysis of SEC Form 10-K filings.

2.4 Cloud Computing and Business Value

Cloud computing has become an important component of firms' digital infrastructure, enabling scalable computing capacity, data storage, software delivery, and greater organizational flexibility. From a business value perspective, cloud technologies may improve firm performance by reducing information technology infrastructure costs, increasing operational scalability, facilitating access to advanced digital services, and supporting the modernization of legacy systems. These potential benefits are particularly relevant to financial institutions, which depend heavily on information intensive processes and increasingly complex technological infrastructures.

Empirical evidence generally suggests a positive relationship between cloud computing and firm performance. Studies employing quasi experimental approaches, including difference in differences estimation combined with propensity score matching, report that cloud adoption is associated with improvements in both profitability and market value, although the magnitude of these effects varies across firm size and industry characteristics. Such findings indicate that the economic benefits of cloud computing may depend on firms' organizational characteristics and their ability to integrate cloud infrastructure effectively into existing operations.

Using a textual analysis approach based on SEC Form 10-K filings, Zheng et al. [2] developed a cloud computing disclosure measure and found that cloud adoption

is positively associated with subsequent operating performance. Their results further indicate that the performance benefits of cloud computing vary across firms' competitive strategies, suggesting that the value created by cloud technologies depends not only on adoption itself but also on how these technologies are integrated into firms' broader strategic and organizational capabilities.

Within financial services, cloud computing may be particularly important for modernizing legacy information systems, improving scalability, supporting data intensive applications, and reducing technology infrastructure costs. At the same time, the increasing diffusion of cloud services raises an important question regarding their ability to provide a sustained differentiating advantage. As cloud infrastructure becomes more widely available and standardized, its adoption may represent an operational necessity rather than a rare strategic resource. Consequently, the presence or intensity of cloud related disclosure may not necessarily translate into observable differences in firm performance.

Although existing evidence generally supports the business value of cloud computing, comparatively limited research has examined whether cloud related disclosure in mandatory corporate filings is systematically associated with the performance of U.S. financial institutions. This distinction between the economic value of cloud *adoption* and the informational content of cloud *disclosure* remains an important empirical question.

2.5 Digital Transformation and Organizational Performance

Digital transformation (DT) has emerged as a strategic priority for financial institutions seeking to improve operational efficiency, enhance customer experience, and strengthen long term competitiveness. By integrating digital technologies into business processes, organizations aim to redesign traditional operating models, develop new digital services, and improve organizational agility. Despite its strategic importance, the empirical evidence linking digital transformation to firm performance remains mixed.

Evidence on the relationship between digital transformation and firm performance remains mixed. Several studies report positive effects. For example, He et al. [7] examined 39 listed Chinese commercial banks over the period 2012–2021 and found that digital transformation significantly improves operational performance. Their results indicate that this relationship is primarily driven by higher asset operation efficiency, with the magnitude of the effect varying according to bank ownership and geographic location. These findings suggest that digital transformation can strengthen organizational capabilities and improve financial performance under favorable organizational conditions.

However, other studies report less favorable outcomes. Zhang [2] examined 116 Chinese commercial banks during 2011–2023 and found that digital transformation is associated with lower return on assets (ROA) and net interest margins (NIM). The study suggests that substantial investments in digital technologies, implementation costs, and organizational restructuring may outweigh short term operational benefits during the early stages of transformation. Similar evidence is reported in the Vietnamese banking sector. Nguyen et al. [8] found that digital transformation, measured

using an information and communication technology (ICT) index, is negatively associated with subsequent financial performance. The authors attribute this relationship to high implementation costs, organizational adjustments, and the delayed realization of benefits from digital transformation initiatives.

Overall, the existing evidence indicates that the relationship between digital transformation and firm performance is not yet conclusive. While some studies document positive performance effects [7], others report negative associations [2, 8]. These mixed findings suggest that the financial consequences of digital transformation depend on organizational capabilities, implementation strategy, institutional context, and the maturity of digital initiatives, consistent with the Resource Based View and Dynamic Capabilities Theory [9, 10].

These contrasting findings indicate that the relationship between digital transformation and firm performance is highly dependent on institutional context, measurement approach, and the stage of digital maturity. Differences in country settings, regulatory environments, organizational capabilities, and empirical methodologies contribute to the inconsistent evidence reported in the literature.

Although digital transformation has become an increasingly important research topic, relatively few studies have examined digital transformation disclosure using textual analysis of mandatory corporate filings. Most existing research focuses on measures of technology adoption, investment, or organizational capability rather than disclosure itself. Consequently, whether digital transformation disclosure conveys economically meaningful information for investors and is systematically associated with firm performance remains an open empirical question, particularly within the context of U.S. financial institutions.

2.6 Theoretical Framework

This study is grounded in three complementary theoretical perspectives: the Resource Based View (RBV), Dynamic Capabilities Theory (DCT), and Signaling Theory. Together, these frameworks explain how digital technologies may create competitive advantage, how firms transform technological resources into organizational capabilities, and how technology related disclosures communicate information to external stakeholders.

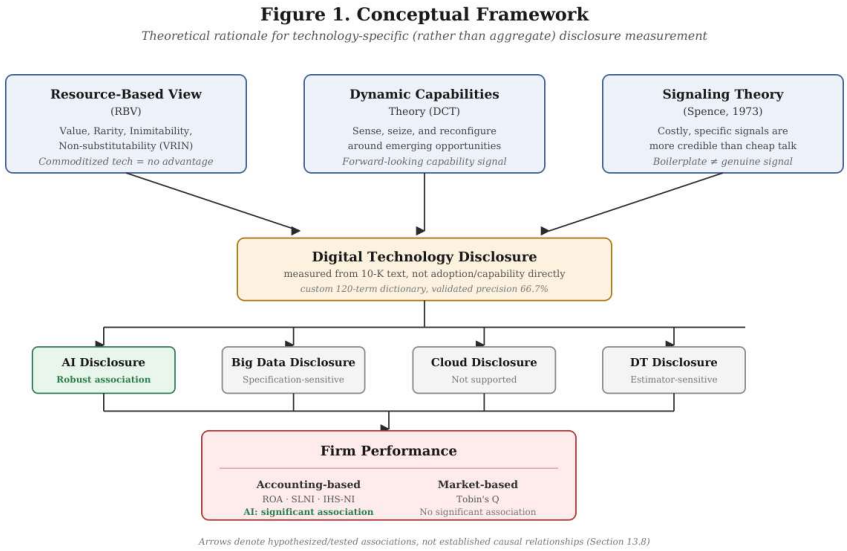


Fig. 1 Conceptual Framework linking RBV, Dynamic Capabilities Theory, and Signaling Theory to Digital Technology Disclosure and Firm Performance

Resource Based View (RBV); The Resource Based View proposed by Barney [9] argues that sustainable competitive advantage arises from resources that are valuable, rare, imperfectly imitable, and non substitutable (VRIN). From this perspective, digital technologies can become strategic resources when they enable firms to improve operational efficiency, innovation, or customer value in ways that competitors cannot easily replicate. However, the extent to which a particular technology satisfies the VRIN criteria depends on its degree of diffusion and the firm's ability to deploy it effectively. Consequently, different digital technologies may have different implications for firm performance rather than generating a uniform digitalization effect.

Dynamic Capabilities Theory (DCT); Dynamic Capabilities Theory extends the RBV by emphasizing firms' ability to integrate, build, and reconfigure internal and external resources in response to rapidly changing business environments [10]. Rather than focusing solely on the possession of technological resources, DCT highlights the organizational processes through which firms sense new opportunities, seize them through strategic investment, and continuously transform their resource base. Within the context of digital technologies, this perspective suggests that competitive advantage depends not only on technology adoption but also on firms' capability to integrate and exploit digital resources effectively. Previous research on Big Data Analytics Capability has frequently adopted this theoretical perspective, emphasizing that organizational capabilities mediate the relationship between digital technologies and firm performance.

Signaling Theory. Signaling Theory provides a complementary perspective by explaining how firms communicate private information to investors and other stakeholders. Spence [11] argues that signals are informative only when they are sufficiently

costly or difficult for lower quality firms to imitate. Extending this framework to organizational settings, Connelly et al. [12] propose that corporate disclosures reduce information asymmetry by conveying credible information about firms' underlying resources, capabilities, and strategic intentions. Within the context of digital technology disclosure, annual reports represent an important communication channel through which firms signal their technological priorities and innovation activities. Accordingly, disclosures related to Artificial Intelligence (AI), Big Data, Cloud Computing, and Digital Transformation may provide investors with information about firms' digital capabilities and strategic direction. However, the credibility and informational value of these disclosures are unlikely to be uniform across technologies. More specific and difficult to imitate disclosures may constitute stronger signals than broad or generic technology statements, suggesting that different categories of digital technology disclosure may vary in their ability to explain differences in firm performance.

Taken together, RBV, DCT, and Signaling Theory provide a coherent theoretical foundation for examining the relationship between digital technology disclosure and firm performance. RBV explains why digital technologies may constitute strategic resources, DCT highlights the organizational capabilities required to translate technological resources into superior performance, and Signaling Theory explains how disclosures relating to these technologies may reduce information asymmetry and influence stakeholders' assessments of firm value. These complementary perspectives provide the theoretical basis for the hypotheses developed in the following subsection.

Synthesis: Heterogeneous Evidence Across Technologies, Contexts, and Methodologies

The literature reviewed above provides no clear consensus regarding the relationship between digital technologies and firm performance. Across the four technology categories, empirical findings vary considerably depending on the technology examined, the institutional setting, the measurement approach, and the empirical methodology employed. Studies on artificial intelligence report positive, negative, and statistically insignificant effects, while research on digital transformation similarly presents conflicting evidence across countries and industries. In contrast, the literature on Big Data Analytics and Cloud Computing generally reports positive performance effects, although these studies predominantly measure organizational capabilities or technology adoption rather than corporate disclosure.

These differences highlight two important gaps in the existing literature. First, digital technologies should not be viewed as a homogeneous construct, as each technology differs in its maturity, strategic role, and potential contribution to firm performance. Second, relatively little evidence is available on whether technology related disclosures contained in mandatory corporate reports provide economically meaningful information beyond direct measures of technology adoption or organizational capability.

Taken together, the existing evidence suggests that the relationship between digital technology disclosure and firm performance is likely to be heterogeneous rather

than uniform across technology categories. Consequently, this study examines Artificial Intelligence, Big Data Analytics, Cloud Computing, and Digital Transformation separately instead of combining them into a single measure of digitalization. This technology specific approach enables a more comprehensive assessment of whether different forms of digital technology disclosure are associated with firm performance.

2.7 Hypothesis Development

Drawing on the Resource Based View, Dynamic Capabilities Theory, and Signaling Theory, together with the mixed empirical evidence reviewed above, this study examines whether digital technology disclosure is associated with firm performance. Rather than treating digitalization as a single construct, the analysis distinguishes among four technology categories Artificial Intelligence, Big Data Analytics, Cloud Computing, and Digital Transformation to determine whether each exhibits a different relationship with firm performance. In addition, two composite measures are considered to capture the overall intensity and breadth of firms' digital technology disclosure.

- **H1.** Artificial Intelligence (AI) Disclosure is positively associated with firm performance.
- **H2.** Big Data Analytics (BD) Disclosure is positively associated with firm performance.
- **H3.** Cloud Computing Disclosure is positively associated with firm performance.
- **H4.** Digital Transformation (DT) Disclosure is positively associated with firm performance.
- **H5.** Composite Digital Technology Disclosure is positively associated with firm performance.
- **H6.** Technology Breadth is positively associated with firm performance.

3 Research Methodology

3.1 Data Sources

This study examines the relationship between digital technology disclosure and firm performance among publicly listed U.S. financial institutions over the period 2014–2025. The empirical dataset was constructed by integrating textual disclosure data, firm level financial information, and market data obtained from publicly available sources.

The primary source of textual data is the U.S. Securities and Exchange Commission (SEC) Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. Annual reports filed on Form 10-K were collected for all firms included in the sample, resulting in an initial dataset of 5,516 filing level observations obtained from twelve source files. Form 10-K filings were selected because they provide standardized and comprehensive disclosures regarding firms' operations, strategic initiatives, risk factors, and technology related activities, making them particularly suitable for textual analysis.

Firm level financial information was retrieved from the SEC Company Facts API, which provides standardized Extensible Business Reporting Language (XBRL) financial statement data reported by SEC registrants. The database was used to obtain the

financial variables required to construct the dependent variables and firm level controls, including total assets, total liabilities, net income, cash and cash equivalents, and common shares outstanding.

To construct the market based performance measure, historical year end share prices were obtained from Yahoo Finance. These data were matched to firms' fiscal year end reporting dates and used to calculate market value of equity and Tobin's Q.

Combining SEC EDGAR filings, SEC Company Facts, and Yahoo Finance produced a comprehensive firm year panel containing both textual disclosure measures and financial information. The integration of these complementary data sources enables the simultaneous examination of firms' digital technology disclosures, operating performance, and market valuation within a consistent empirical framework.

3.2 Text Preprocessing

The raw SEC Form 10-K filings were preprocessed before constructing the digital technology disclosure measures to ensure consistency, eliminate duplicate observations, and remove extraction artefacts that could bias the textual analysis. The preprocessing procedure was applied sequentially to the initial corpus of 5,516 filing level observations.

The preprocessing consisted of six filtering steps:

1. Only annual reports filed as Form `10-K` were retained, excluding amendments and other filing types.
2. Observations were required to satisfy `filing_match_status = MATCHED`, ensuring that each filing was correctly linked to the corresponding firm and fiscal year.
3. Only filings successfully downloaded with an HTTP 200 response were retained.
4. Duplicate filing URLs were removed.
5. Duplicate firm year observations, identified by identical combinations of Central Index Key (CIK) and fiscal year, were removed by retaining the filing containing the most complete textual content.
6. Filings containing fewer than 1,000 characters were excluded because they did not provide sufficient narrative information for reliable textual analysis.

After applying these procedures, the final textual corpus comprised 5,494 Form 10-K filings representing 539 publicly listed U.S. financial institutions.

An additional preprocessing step addressed the presence of Inline XBRL taxonomy information embedded within many SEC filings. Preliminary inspection revealed that approximately 60% of the filings (3,309 of 5,494) contained extensive blocks of machine readable Inline XBRL tags preceding the narrative content. These metadata are generated automatically during the SEC reporting process and substantially increase document length without contributing meaningful textual information. If left untreated, they would artificially inflate document length and distort keyword frequency measures.

To remove this artefact, the beginning of each filing was identified using the first occurrence of the phrase "Securities and Exchange Commission." A whitespace tolerant matching procedure was adopted to accommodate minor formatting inconsistencies introduced during automated text extraction, including merged or irregularly

spaced words. All content preceding this anchor was removed, leaving only the substantive narrative disclosure contained in the filing. Manual verification confirmed that this procedure successfully cleaned all 5,494 filings, including reports with minor variations in cover page formatting.

Because several technology related abbreviations are potentially ambiguous, a parallel version of each filing preserving the original capitalization was retained throughout the preprocessing stage. This case preserved corpus enabled case sensitive matching for selected acronyms, while all remaining dictionary terms were matched using case insensitive expressions. Preserving capitalization improves the accuracy of acronym identification by distinguishing genuine technology related abbreviations from unrelated lowercase words or abbreviations with alternative meanings.

3.3 Digital Technology Disclosure Dictionary

3.3.1 Dictionary Development

To measure firms' digital technology disclosure, a custom dictionary was developed specifically for the U.S. financial services industry. The dictionary was designed to identify technology related disclosures within SEC Form 10-K filings by systematically matching predefined keywords associated with four major categories of digital technologies: Artificial Intelligence (AI), Big Data Analytics (BD), Cloud Computing, and Digital Transformation (DT).

The final dictionary contains 120 technology related terms, comprising 29 Artificial Intelligence terms, 27 Big Data Analytics terms, 33 Cloud Computing terms, and 31 Digital Transformation terms. The classification follows the conceptual distinction between strategic digital technologies, represented by Artificial Intelligence and Big Data Analytics, and enabling digital technologies, represented by Cloud Computing and Digital Transformation.

Rather than adopting an existing dictionary, a new domain specific lexicon was developed for two principal reasons. First, all keywords were implemented using explicit word boundary matching to minimize false positive matches arising from partial words. Second, the dictionary incorporates terminology commonly used within the financial services industry but largely absent from general purpose technology dictionaries. Examples include digital banking, mobile banking, online banking, robo advisory, algorithmic trading, robotic process automation (RPA), open banking, and Banking as a Service (BaaS).

Because several technology abbreviations are inherently ambiguous, nine acronyms (AI, LLM, NLP, SaaS, PaaS, IaaS, RPA, API, and BaaS) were matched using case sensitive regular expressions applied to the case preserved corpus described in the previous subsection. All remaining keywords were matched using case insensitive expressions to maximize coverage while maintaining matching accuracy.

3.3.2 Dictionary Validation

The reliability of the dictionary was evaluated through a multi stage manual validation procedure designed to assess the precision of the keyword matching process.

The objective of the validation was to determine the proportion of identified keyword matches that represented genuine disclosures of the reporting firm's own digital technology activities.

The initial validation stage focused on the generic keyword "fintech." Manual examination of eight representative filings revealed that the majority of occurrences referred to competitors or industry developments rather than the reporting firm's own technological activities. To improve measurement precision, the keyword was removed from the dictionary and replaced with the more specific expressions "fintech partnership(s)" and "Banking as a Service (BaaS)," which more accurately capture firm specific digital initiatives.

Following this refinement, a broader validation exercise was conducted using a stratified sample of 72 keyword matches. The validation sample was evenly distributed across the four technology categories, with 18 observations drawn from each category. The sample included high and low frequency keywords, firms from different financial subsectors, and observations spanning the entire sample period (2014–2025), thereby ensuring broad representation of disclosure contexts.

Each sampled keyword match was manually classified as either a true positive or a false positive according to whether it referred to the reporting firm's own digital technology activities. False positive classifications included references to competitors, industry wide developments, regulatory discussions, cybersecurity threats, accounting standard boilerplate, acronym ambiguity, or descriptions of executives' previous experience at other organizations.

The validation focused on dictionary precision rather than recall. Precision measures the proportion of identified keyword matches that correctly represent firm specific technology disclosure, whereas recall measures the proportion of all genuine disclosures identified by the dictionary. Estimating recall would require a comprehensive manual review of the complete filing corpus and was therefore beyond the scope of the present study.

Table 1 Validation Results of the Digital Technology Disclosure Dictionary

Category	Sampled	True Positives	False Positives	Precision
Artificial Intelligence	18	10	8	55.6%
Big Data Analytics	18	14	4	77.8%
Cloud Computing	18	14	4	77.8%
Digital Transformation	18	10	8	55.6%
Overall	**72**	**48**	**24**	**66.7%**

Source: Authors' manual validation of the custom digital technology disclosure dictionary using sampled SEC Form 10-K filings.
Note: Precision is calculated as the proportion of sampled keyword matches that correctly identify firm specific digital technology disclosure.

The validation process identified several recurring sources of false positive matches. These included references to regulatory initiatives involving digital technologies,

descriptions of cybercriminal activities related to artificial intelligence, accounting standard boilerplate associated with cloud computing, acronym ambiguity (particularly the use of "RPA" to denote Risk Participation Agreements), and references to technology related experience acquired by executives before joining the reporting firm. Identifying these patterns enabled refinement of the disclosure dictionary and improved the accuracy and reliability of the resulting disclosure measures.

To assess coding consistency, a second independent reviewer evaluated a stratified subsample of 20 observations using the same coding protocol. The reviewers agreed on 19 of the 20 observations, corresponding to an agreement rate of 95.0% and a Cohen's kappa coefficient of 0.90 [13]. According to the benchmark proposed by Landis and Koch [14], this level of agreement represents almost perfect intercoder reliability, providing strong evidence of coding consistency.

Overall, the validation results indicate that the proposed disclosure dictionary provides a reliable and transparent approach for measuring digital technology disclosure in SEC Form 10-K filings. Although some measurement error is unavoidable in dictionary based textual analysis, the validation procedure substantially increases confidence in the resulting disclosure measures and supports their use in the subsequent empirical analysis [1].

3.4 Disclosure Measures

The validated digital technology disclosure dictionary was applied to each preprocessed Form 10-K filing to identify technology related keywords. For every annual report, raw keyword frequencies were computed separately for the four technology categories: Artificial Intelligence (AI), Big Data Analytics (BD), Cloud Computing, and Digital Transformation (DT).

Because SEC filings differ substantially in length, raw keyword counts are not directly comparable across firms or years. To account for these differences, all disclosure measures were normalized by the total number of words contained in each filing and expressed as keyword occurrences per 1,000 words. This normalization reduces the influence of document length and facilitates meaningful comparisons across firms and reporting periods.

The following disclosure measures were constructed:

- **Category Disclosure (AI, BD, Cloud, and DT)** was calculated as the number of keywords identified within each technology category divided by the total number of words in the filing and multiplied by 1,000:

$$\text{Category Disclosure} = \frac{\text{Raw Category Keyword Count}}{\text{Total Word Count}} \times 1000$$

  This measure represents the intensity of disclosure for each individual technology category.
- **Composite Digital Technology Disclosure (DTD)** was calculated as the sum of the four category specific disclosure measures:

$$\text{Composite DTD} = \text{AI} + \text{BD} + \text{Cloud} + \text{DT}$$

This variable captures the overall intensity of digital technology disclosure within a firm's annual report.

- **Technology Breadth** was measured as the number of technology categories for which at least one keyword was identified:

$$\text{Technology Breadth} = \sum_{k=1}^{4} I(\text{Category}_k > 0)$$

where $I(\cdot)$ is an indicator function equal to one if at least one keyword from a given technology category is disclosed and zero otherwise. Consequently, Technology Breadth ranges from 0 to 4 and captures the diversity of firms' technology disclosure independently of disclosure intensity.

Together, these measures capture two complementary dimensions of digital technology disclosure. The category specific measures and Composite DTD reflect the intensity of firms' technology related communication, whereas Technology Breadth measures the diversity of technologies disclosed within each annual report. Considering both dimensions provides a more comprehensive assessment of firms' digital disclosure strategies than relying on a single aggregate measure.

3.5 Financial Data

Firm level financial information was obtained from the SEC Company Facts API, which provides standardized financial statement data reported by SEC registrants using the Extensible Business Reporting Language (XBRL) format. The database was used to retrieve the financial variables required to construct the dependent variables and control variables employed in the empirical analysis, including Total Assets, Total Liabilities, Net Income, Cash and Cash Equivalents, and Common Shares Outstanding.

Primary XBRL concept tags were used whenever available. To maximize data completeness and ensure consistency across firms, documented fallback taxonomy elements were employed for companies using alternative reporting practices. In particular, `CashAndDueFromBanks` was used as an alternative measure for cash reported by banking institutions, while `dei:EntityCommonStockSharesOutstanding` was used as a fallback source for common shares outstanding when standard reporting elements were unavailable.

Matching financial information to the textual dataset required special attention because XBRL data frequently contain multiple observations for the same fiscal year. These duplicate records arise because previously reported values are often restated or included as comparative figures in subsequent filings. Consequently, matching observations solely on reporting dates would lead to incomplete or incorrect firm year assignments.

To address this issue, financial observations were matched primarily using the fiscal year identifier (`fy`) reported in the XBRL data, ensuring that each observation corresponded to the appropriate reporting year. A hierarchical matching strategy was then implemented to maximize data completeness:

1. Exact match between fiscal year and reporting date.

2. Nearest reporting date within the same fiscal year (maximum 30 day difference).
3. Nearest available reporting date within a 15 day window when no same year observation was available.

This matching strategy substantially improved the completeness of the financial dataset while preserving consistent firm year assignments and avoiding the missing value problems commonly associated with date only matching.

The matching procedure achieved very high coverage for the principal financial variables. Total Assets were successfully matched for 99.8% of observations, followed by Total Liabilities (98.3%) and Net Income (96.7%). Coverage was lower for Cash and Cash Equivalents (79.0%) and Common Shares Outstanding (72.4%), reflecting differences in firms' XBRL reporting practices rather than limitations of the matching procedure.

The resulting financial dataset provides a comprehensive and standardized panel of firm level financial information that forms the basis for constructing the performance measures and control variables used in the empirical analysis.

3.6 Variable Construction

The empirical analysis employs four measures of firm performance as dependent variables, six technology disclosure measures as the principal explanatory variables, and three firm level control variables. The definitions and mathematical formulations of all variables are presented below.

3.6.1 Dependent Variables

Firm performance is evaluated using both operating performance and market based measures in order to capture different dimensions of corporate performance. Operating performance measures reflect realized financial outcomes reported in firms' financial statements, whereas the market based measure incorporates investors' expectations regarding future performance.

Return on Assets (ROA)

Return on Assets (ROA) measures operating profitability relative to the firm's asset base and is calculated as:

$$\text{ROA}_{i,t} = \frac{\text{Net Income}_{i,t}}{\text{Total Assets}_{i,t}}$$

ROA is one of the most widely used indicators of financial performance in banking and corporate finance research because it measures the efficiency with which firms generate earnings from their total assets.

Signed Log Net Income (SLNI)

Because a substantial number of firm year observations report negative net income, a conventional logarithmic transformation would require excluding loss making firms from the analysis. To avoid this sample reduction, Signed Log Net Income (SLNI) is calculated as:

$$\text{SLNI}_{i,t} = \text{sign}\left(\text{NI}_{i,t}\right) \times \ln\left(1 + |\text{NI}_{i,t}|\right)$$

This transformation preserves the direction of profits and losses while reducing the influence of extreme observations.

Inverse Hyperbolic Sine Net Income (IHS-NI)

As an alternative transformation, the inverse hyperbolic sine of net income was also employed:

$$\text{IHS-NI}_{i,t} = \text{asinh}\left(\text{NI}_{i,t}\right)$$

Unlike the natural logarithm, the inverse hyperbolic sine transformation is defined for zero and negative values while exhibiting logarithm like behaviour for large observations. Using both SLNI and IHS-NI provides robustness against the choice of transformation for skewed income distributions.

Tobin's Q

Market based performance is measured using Tobin's Q:

$$\text{Tobin}'\text{s Q}_{i,t} = \frac{\text{Market Value of Equity}_{i,t} + \text{Total Liabilities}_{i,t}}{\text{Total Assets}_{i,t}}$$

where the market value of equity is calculated as

$$\text{Market Value of Equity}_{i,t} = \text{Common Shares Outstanding}_{i,t} \times \text{Year-end Share Price}_{i,t}$$

Historical year end share prices were obtained from Yahoo Finance and matched to firms' fiscal year end reporting dates. A valid market price was identified for 97.3% of observations within a 10 day matching window, with a median matching gap of zero days.

During data validation, a small number of implausible share prices were identified, including observations exceeding USD 15 million per share. These values reflect known anomalies in historical price data for a limited number of thinly traded securities rather than matching errors. Consequently, prices exceeding USD 2,000 per share were treated as missing values. This procedure affected only 29 observations (0.6% of all non missing prices).

Following data cleaning, valid Tobin's Q values were obtained for 3,598 firm year observations. Most missing observations resulted from unavailable XBRL data on common shares outstanding rather than missing market prices, indicating that the reduction in sample size is primarily attributable to differences in firms' financial reporting practices rather than limitations of the market data collection procedure.

3.6.2 Independent Variables

The principal explanatory variables capture firms' digital technology disclosure derived from the textual analysis of SEC Form 10-K filings. Six disclosure measures are employed to examine both technology specific and overall digital technology disclosure.

The first four variables measure disclosure intensity for the individual technology categories:

- Artificial Intelligence (AI) Disclosure;
- Big Data Analytics (BD) Disclosure;
- Cloud Computing Disclosure; and
- Digital Transformation (DT) Disclosure.

Each measure represents the frequency of technology specific keywords normalized by the total number of words in the corresponding annual report and expressed as keyword occurrences per 1,000 words.

Two additional variables capture broader dimensions of firms' digital technology disclosure. Composite Digital Technology Disclosure (DTD) measures the overall intensity of technology related disclosure by combining the four category specific measures into a single indicator. Technology Breadth measures the diversity of disclosure by counting the number of technology categories represented within each annual report, irrespective of disclosure intensity. Whereas Composite DTD captures how extensively firms discuss digital technologies, Technology Breadth reflects the range of technologies disclosed.

3.6.3 Control Variables

Three firm level control variables are included to account for differences in firm characteristics that may influence financial performance independently of digital technology disclosure.

Firm Size is measured as the natural logarithm of total assets:

$$\text{Firm Size}_{i,t} = \ln\left(\text{Total Assets}_{i,t}\right)$$

Firm size controls for differences in organizational scale, which may affect both firms' disclosure behaviour and financial performance.

Leverage is calculated as:

$$\text{Leverage}_{i,t} = \frac{\text{Total Liabilities}_{i,t}}{\text{Total Assets}_{i,t}}$$

Leverage captures firms' capital structure and financial risk, both of which are well established determinants of corporate performance.

Cash Ratio is measured as:

$$\text{Cash Ratio}_{i,t} = \frac{\text{Cash and Cash Equivalents}_{i,t}}{\text{Total Assets}_{i,t}}$$

The Cash Ratio controls for firms' liquidity position and financial flexibility, which may influence both investment decisions and operating performance.

3.6.4 Data Treatment

Prior to estimating the regression models, all continuous variables were winsorized at the 1st and 99th percentiles to reduce the influence of extreme observations while

preserving the full analytical sample. Winsorization was applied to the four technology specific disclosure measures, Composite Digital Technology Disclosure, ROA, Signed Log Net Income, IHS Net Income, Tobin's Q, Firm Size, Leverage, and Cash Ratio.

Descriptive statistics are reported using the original non winsorized data to accurately characterize the distribution of the sample. In contrast, the regression models are estimated using the winsorized variables in order to limit the influence of extreme observations on the coefficient estimates.

The decision to adopt winsorization as the primary specification was motivated by the presence of genuine, but highly influential, outliers identified during the data validation process. These observations primarily reflected a small number of thinly traded firms and institutions with exceptionally small asset bases rather than data errors. Winsorization provides a robust approach to mitigating the influence of such observations without reducing the analytical sample through additional exclusions.

To evaluate the sensitivity of the findings, all baseline regressions were also estimated using the original non winsorized data. Comparing the two sets of results enables an assessment of whether the estimated relationships are robust to the treatment of extreme observations.

3.7 Sample Selection

The final analytical sample was constructed through a sequential screening procedure designed to improve data quality and ensure comparability across firms. The screening criteria were applied after completing the text preprocessing and integrating the textual and financial datasets.

The initial merged dataset contained 5,494 firm year observations. Preliminary diagnostics identified a small number of shell and micro cap entities with exceptionally low asset values and extreme financial ratios. Manual verification confirmed that these observations were not data matching errors. To exclude firms that were not economically comparable with the broader population of U.S. financial institutions, a minimum total assets threshold of USD 10 million was applied. This objective size based criterion avoids excluding observations directly on the basis of the dependent variables.

Observations with missing Total Assets or Total Liabilities were subsequently removed because these variables are required to construct the principal financial measures and control variables. Firm year observations with missing Net Income were then excluded because they do not permit the calculation of ROA, SLNI, or IHS-NI.

After applying these screening criteria, the final analytical sample comprised 5,172 firm year observations representing 535 publicly listed U.S. financial institutions over the period 2014–2025.

Variables required only for specific model specifications were not imposed as selection criteria for the main sample. In particular, Cash Ratio and Common Shares Outstanding were retained only where available and used in the specifications requiring liquidity controls or Tobin's Q. This approach avoids unnecessarily excluding observations from models that do not require these variables.

Following sample selection, the distributions of the financial variables became substantially more stable. The standard deviation of ROA declined from 0.679 to

Table 2 Definition of Variables

Variable	Definition	Source
Dependent Variables		
ROA	Net Income / Total Assets	SEC Company Facts (XBRL)
SLNI	$\text{sign}(NI) \times \ln(1 + \lvert NI \rvert)$	SEC Company Facts (XBRL)
IHS-NI	$\text{asinh}(NI)$	SEC Company Facts (XBRL)
Tobin's Q	(MVE + Total Liabilities)/Total Assets	SEC Company Facts (XBRL); Yahoo Finance
Independent Variables		
AI Disclosure	AI keywords per 1,000 words	SEC Form 10-K
BD Disclosure	BD keywords per 1,000 words	SEC Form 10-K
Cloud Disclosure	Cloud keywords per 1,000 words	SEC Form 10-K
DT Disclosure	DT keywords per 1,000 words	SEC Form 10-K
Composite DTD	AI + BD + Cloud + DT	Authors' calculation
Technology Breadth	Number of disclosed categories (0–4)	Authors' calculation
Control Variables		
Firm Size	ln(Total Assets)	SEC Company Facts (XBRL)
Leverage	Total Liabilities / Total Assets	SEC Company Facts (XBRL)
Cash Ratio	Cash and Cash Equivalents / Total Assets	SEC Company Facts (XBRL)

Source: Authors' compilation based on SEC EDGAR Form 10-K filings, SEC Company Facts (XBRL), and Yahoo Finance.

0.164, while the maximum leverage ratio declined from 438 to 2.108. Remaining genuine extreme observations were addressed through winsorization at the 1st and 99th percentiles rather than through further sample exclusion.

4 Empirical Results

4.1 Descriptive Statistics

Descriptive statistics provide an overview of the distributional characteristics of the study variables and offer preliminary evidence regarding the disclosure behavior and financial performance of the sampled firms.

The four technology specific disclosure measures exhibit substantial heterogeneity across firm year observations. Artificial Intelligence, Big Data Analytics, and Cloud

Table 3 Sample Selection Process

Sample Selection Step	Observations Remaining	Observations Removed
Initial merged dataset	5,494	–
Total Assets $\geq$ USD 10 million	5,411	83
Non missing Total Assets and Total Liabilities	5,345	66
Non missing Net Income	5,172	173

Source: Authors' compilation based on SEC EDGAR Form 10-K filings and SEC Company Facts (XBRL) data. *Note:* The exclusion criteria were applied sequentially. The final analytical sample consists of 5,172 firm year observations representing 535 U.S. financial institutions over the period 2014–2025.

Computing disclosures all have median values of zero, whereas Digital Transformation Disclosure has a small positive median value. Across all disclosure measures, the mean exceeds the median, indicating positively skewed distributions in which relatively few firms disclose digital technologies extensively while the majority report limited or no technology related information.

Technology Breadth has a mean value of 1.574, suggesting that the average firm discloses information relating to approximately one or two of the four technology categories. This finding indicates considerable variation in firms' digital technology communication strategies.

The operating performance measures also display substantial dispersion across firms. Return on Assets exhibits a mean of 0.5% and a median of 1.1%, while both transformed net income measures demonstrate wide distributions reflecting the diversity of financial performance within the U.S. financial services industry. Tobin's Q displays the greatest variability among the performance measures, which is expected given its dependence on market valuations.

Firm Size, Leverage, and Cash Ratio are broadly consistent with the characteristics of publicly listed financial institutions. Although several variables exhibit extreme values, these observations represent genuine firm characteristics rather than data errors and were therefore addressed through winsorization in the regression analysis rather than through additional sample exclusion.

5 Descriptive Statistics and Correlation

The descriptive statistics indicate substantial heterogeneity in digital technology disclosure across the sample. AI, Big Data, and Cloud Disclosure have median values of zero, while Digital Transformation Disclosure has a small positive median, indicating that many firms report little or no technology related disclosure in a given fiscal year. Across all disclosure measures, the mean exceeds the median and the distributions exhibit pronounced right skewness, suggesting that relatively high disclosure levels are concentrated among a limited number of firms. Technology Breadth has a mean of 1.574, indicating that the average firm discloses approximately one to two of the four

Table 4 Descriptive Statistics

Variable	N	Mean	SD	Min	Median	Max
AI Disclosure	5,172	0.061	0.206	0.000	0.000	3.403
BD Disclosure	5,172	0.012	0.056	0.000	0.000	2.246
Cloud Disclosure	5,172	0.018	0.057	0.000	0.000	1.018
DT Disclosure	5,172	0.047	0.132	0.000	0.020	4.515
Composite DTD	5,172	0.138	0.291	0.000	0.054	4.648
Technology Breadth	5,172	1.574	1.162	0	1	4
ROA	5,172	0.005	0.164	-5.687	0.011	1.159
SLNI	5,172	14.653	11.035	-23.851	17.902	25.290
IHS-NI	5,172	15.203	11.450	-24.544	18.595	25.983
Tobin's Q	3,598	2.122	14.236	0.172	1.023	623.934
Firm Size (ln Assets)	5,172	22.412	1.983	16.120	22.296	28.396
Leverage	5,172	0.793	0.206	0.000	0.877	2.108
Cash Ratio	4,067	0.077	0.103	0.000	0.041	0.996

Source: Authors' calculations based on SEC EDGAR Form 10-K filings, SEC Company Facts (XBRL), and Yahoo Finance.
Note: Statistics are reported for the original (non winsorized) variables. The analytical sample comprises 5,172 firm year observations unless otherwise indicated. Continuous variables were winsorized at the 1st and 99th percentiles before estimating the baseline regression models.

technology categories, while 1,005 firm year observations report no disclosure across any of the four categories.

The financial variables also display considerable cross sectional variation. ROA, SLNI, IHS-NI, and Leverage exhibit distributions characterized by moderate central tendencies together with a limited number of extreme observations. These extreme values are primarily associated with relatively small firms included in the analytical sample after applying the minimum asset threshold. To reduce the influence of such observations without excluding valid firm year records, continuous variables were winsorized at the 1st and 99th percentiles prior to the baseline regression analysis.

Among the dependent variables, Tobin's Q exhibits the greatest dispersion, with a maximum value substantially exceeding its median, reflecting the higher variability typically associated with market based valuation measures. The smaller number of observations available for Tobin's Q (3,598 compared with 5,172 for the operating performance variables) reflects data availability rather than additional sample selection criteria.

5.1 Regression Diagnostics

Potential multicollinearity was evaluated using Variance Inflation Factors (VIFs). Because Composite Digital Technology Disclosure (DTD) is constructed as the sum of the four technology specific disclosure measures, separate diagnostics were performed for the technology specific and composite model specifications. Estimating a single model including both the composite measure and its individual components would

Table 5 Pearson Correlation Matrix

	AI	BD	Cloud	DT	Firm Size	Leverage	Cash Ratio
AI Disclosure	1.000	0.313	0.312	0.188	0.038	-0.129	0.113
BD Disclosure	0.313	1.000	0.441	0.068	0.034	-0.197	0.205
Cloud Disclosure	0.312	0.441	1.000	0.172	0.005	-0.233	0.232
DT Disclosure	0.188	0.068	0.172	1.000	0.016	0.108	0.025
Firm Size	0.038	0.034	0.005	0.016	1.000	0.348	-0.349
Leverage	-0.129	-0.197	-0.233	0.108	0.348	1.000	-0.468
Cash Ratio	0.113	0.205	0.232	0.025	-0.349	-0.468	1.000

footnotetext *Source:* Authors' calculations.
Note: Pearson correlation coefficients are reported for the winsorized variables. The correlation matrix is based on 4,067 complete firm year observations after excluding observations with missing values for Cash Ratio.

generate mechanical multicollinearity by construction rather than provide a meaningful diagnostic. Both specifications were estimated using the same complete case sample of 4,067 firm year observations.

Table 6 Model A — Technology Specific Model (AI, BD, Cloud, DT entered simultaneously)

Variable	VIF	Tolerance (1/VIF)
AI Disclosure	1.192	0.839
Big Data Disclosure	1.328	0.753
Cloud Disclosure	1.376	0.727
Digital Transformation Disclosure	1.088	0.919
Firm Size (ln Total Assets)	1.237	0.808
Leverage (Total Liabilities / Total Assets)	1.446	0.692
Cash Ratio (Cash / Total Assets)	1.405	0.712
Mean VIF	**1.296**	—
Maximum VIF	**1.446**	—

All variance inflation factor (VIF) values are well below the commonly accepted thresholds of 5 and 10, while all tolerance values exceed the recommended minimum value of 0.20, indicating that multicollinearity is not a concern in either regression specification [**?**]. Although the composite disclosure model exhibits slightly higher VIF values than the technology-specific model, this outcome is expected because Composite Digital Technology Disclosure and Technology Breadth are derived from related disclosure measures. Nevertheless, the observed values remain well within acceptable limits, supporting the inclusion of all explanatory variables in the regression analysis.

The empirical analysis employs two way fixed effects panel regression models with firm and year fixed effects. Firm fixed effects control for unobserved time invariant firm characteristics that may influence both digital technology disclosure and firm performance, whereas year fixed effects account for macroeconomic conditions and industry wide shocks common to all firms during each year. Standard errors are clustered at

Table 7 Model B — Composite DTD Model (the Composite DTD measure and Technology Breadth entered together, in place of the four individual category measures)

Variable	VIF	Tolerance (1/VIF)
Composite Digital Technology Disclosure (DTD)	1.606	0.623
Technology Breadth	1.742	0.574
Firm Size (ln Total Assets)	1.373	0.728
Leverage (Total Liabilities / Total Assets)	1.370	0.730
Cash Ratio (Cash / Total Assets)	1.387	0.721
Mean VIF	**1.496**	—
Maximum VIF	**1.742**	—

the firm level to account for heteroskedasticity and serial correlation within firms over time, following the recommendations of Petersen [15]. Firm clustered standard errors constitute the primary estimation approach adopted in this study. To further assess the robustness of the statistical inference, the preferred combined specification is also estimated using Driscoll Kraay standard errors, which are robust to heteroskedasticity, serial correlation, and cross sectional dependence [16].

6 Baseline Regression Results, Return on Assets (ROA)

Table 8 Baseline Two Way Fixed Effects Regression Results: Return on Assets (ROA)

	Model 1 (AI)	Model 2 (BD)	Model 3 (Cloud)	Model 4 (DT)	Model 5 (Comp.)	Model 6 (Breadth)	Model 7 (Combined)
AI Disclosure	0.0374**						0.0384**
	(0.0153)						(0.0156)
	[0.0074, 0.0675]						[0.0078, 0.0689]
Big Data Disclosure		0.0260					0.0046
		(0.0682)					(0.0719)
		[-0.1077, 0.1597]					[-0.1365, 0.1456]
Cloud Disclosure			0.0092				-0.0068
			(0.0479)				(0.0463)
			[-0.0848, 0.1032]				[-0.0976, 0.0841]
DT Disclosure				-0.0519			-0.0557
				(0.0360)			(0.0360)
				[-0.1224, 0.0186]			[-0.1262, 0.0149]
Composite DTD					0.0237**		
					(0.0115)		
					[0.0011, 0.0462]		
Technology Breadth						-0.0005	
						(0.0015)	
						[-0.0034, 0.0023]	
Firm Size	0.0114**	0.0116**	0.0116**	0.0116**	0.0115**	0.0116**	0.0114**
	(0.0054)	(0.0054)	(0.0055)	(0.0054)	(0.0054)	(0.0054)	(0.0055)
Leverage	-0.1070***	-0.1092***	-0.1095***	-0.1088***	-0.1084***	-0.1096***	-0.1062***
	(0.0315)	(0.0317)	(0.0317)	(0.0318)	(0.0315)	(0.0317)	(0.0315)
Cash Ratio	0.0450	0.0427	0.0431	0.0419	0.0433	0.0427	0.0437
	(0.0477)	(0.0474)	(0.0477)	(0.0474)	(0.0469)	(0.0476)	(0.0479)
Observations	4,067	4,067	4,067	4,067	4,067	4,067	4,067
Firms	511	511	511	511	511	511	511
Within R^2	0.0412	0.0417	0.0419	0.0453	0.0406	0.0427	0.0460
Adj. Within R^2	0.0403	0.0408	0.0410	0.0443	0.0397	0.0417	0.0443
F (robust, clustered)	5.7453	4.1786	4.2404	5.3456	4.7780	4.2607	3.8747
F p-value (robust)	0.0001	0.0022	0.0020	0.0003	0.0008	0.0019	0.0003
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Authors' calculations.
Note: The dependent variable is Return on Assets (ROA). All models include firm and year fixed effects, and standard errors are clustered at the firm level. Continuous explanatory variables were winsorized at the 1st and 99th percentiles prior to estimation, whereas Technology Breadth was not winsorized because it is a discrete count variable. Coefficients are reported with firm clustered standard errors in parentheses. The estimation sample comprises 4,067 firm year observations from 511 firms over the period 2014–2025. The robust (firm clustered) F statistic is reported for each model. Statistical significance is denoted by *** ($p < 0.01$), ** ($p < 0.05$), and * ($p < 0.10$).

The control variables display stable signs and levels of statistical significance across all seven specifications. Firm Size is positively associated with ROA, with coefficients ranging from approximately 0.011 to 0.012 and remaining statistically significant at the 5% level. Leverage is consistently negative and statistically significant at the 1% level, with coefficients ranging from approximately -0.110 to -0.106. Cash Ratio is positive but statistically insignificant in every specification. The poolability tests are also highly significant across all models, supporting the use of firm and year fixed effects rather than pooled ordinary least squares.

Among the four technology specific disclosure measures, only AI Disclosure exhibits a positive and statistically significant association with ROA. Its coefficient increases slightly from 0.0374 in the individual specification to 0.0384 when all four technology categories are included simultaneously, while remaining statistically significant at the 5% level. The stability of the coefficient indicates that the positive association between AI Disclosure and ROA is not explained by the simultaneous disclosure of Big Data, Cloud Computing, or Digital Transformation.

Big Data Disclosure remains positive but statistically insignificant in both the individual and combined specifications. Cloud Disclosure also remains insignificant, with its coefficient changing from a small positive value in the individual specification to a small negative value in the combined model. Digital Transformation Disclosure is negative in both specifications but does not reach conventional levels of statistical significance. Accordingly, the estimates provide no evidence of an independent association between these three disclosure categories and ROA.

The combined specification is treated as the preferred technology specific model because it estimates the association of each disclosure category while holding the remaining technology measures constant. The individual specifications remain informative for comparison, but the combined model provides the more appropriate basis for evaluating the independent association of each technology category with firm performance.

Composite Digital Technology Disclosure is positively and statistically significantly associated with ROA. Because the composite measure is constructed as the sum of AI, Big Data, Cloud Computing, and Digital Transformation Disclosure, it is estimated separately from its underlying components to avoid mechanical multicollinearity. By contrast, Technology Breadth is statistically insignificant, indicating that the number of technology categories disclosed is not independently associated with ROA. Taken together, these findings suggest that the intensity of technology related disclosure is more informative than the breadth of technology topics discussed.

The estimated associations are also economically meaningful. A one standard deviation increase in winsorized AI Disclosure ($SD = 0.142$) corresponds to an increase in ROA of approximately 0.0055 in the combined specification:

$$0.0384 \times 0.142 = 0.00545.$$

This magnitude is equivalent to approximately 55 basis points. Similarly, a one standard deviation increase in Composite DTD ($SD = 0.211$) corresponds to an increase in ROA of approximately 0.0050:

$$0.0237 \times 0.211 = 0.00500.$$

This is equivalent to approximately 50 basis points. Relative to the dispersion of ROA, the estimated magnitudes represent approximately 8% and 7% of its standard deviation, respectively. Because the sample mean of ROA is close to zero, the coefficients are interpreted in basis points and relative to the distribution of ROA rather than as percentages of the mean. These estimates describe conditional associations and should not be interpreted as causal effects.

7 Robustness Analysis Using Alternative Performance Measures

To examine whether the baseline findings are sensitive to the choice of performance measure, the analysis was repeated using Signed Log Net Income (SLNI), Inverse Hyperbolic Sine Net Income (IHS-NI), and Tobin's Q as alternative dependent variables. SLNI and IHS-NI provide complementary operating performance measures that accommodate both positive and negative net income while reducing the influence of extreme observations. Tobin's Q represents a market based measure of firm value and enables an assessment of whether digital technology disclosure is reflected in investors' valuation of firms.

The same seven model specifications employed in the baseline analysis were estimated for each alternative dependent variable. All models include firm and year fixed effects, firm clustered standard errors, and the same control variables used in the baseline ROA models. Confidence intervals and additional regression diagnostics are reported in the Appendix.

Table 9 Panel A — DV: SLNI

Model	Variable	Coefficient	Clustered SE
1 (AI)	AI Disclosure	6.6537***	(2.3504)
2 (BD)	Big Data Disclosure	19.6536	(13.2967)
3 (Cloud)	Cloud Disclosure	7.3112	(7.7307)
4 (DT)	Digital Transformation Disclosure	-5.7240	(5.2249)
5 (Composite)	Composite DTD	3.8836**	(1.9363)
6 (Breadth)	Technology Breadth	0.4722	(0.2981)
7 (Combined)	AI Disclosure	6.4253***	(2.4096)
7 (Combined)	Big Data Disclosure	14.8019	(13.9221)
7 (Combined)	Cloud Disclosure	2.8987	(8.0520)
7 (Combined)	Digital Transformation Disclosure	-6.6604	(5.1673)

N = 4,067; Firms = 511; Firm FE = Yes; Year FE = Yes; Clustered SE = Firm; Within R^2 ranges 0.0041–0.0091; Adj. Within R^2 ranges 0.0031–0.0074 across models (see Appendix A for per model detail and robust F statistics).

Table 10 Panel B — DV: IHS-NI

Model	Variable	Coefficient	Clustered SE
1 (AI)	AI Disclosure	6.9138***	(2.4427)
2 (BD)	Big Data Disclosure	20.4584	(13.8000)
3 (Cloud)	Cloud Disclosure	7.6175	(8.0393)
4 (DT)	Digital Transformation Disclosure	-5.9279	(5.4247)
5 (Composite)	Composite DTD	4.0357**	(2.0120)
6 (Breadth)	Technology Breadth	0.4919	(0.3094)
7 (Combined)	AI Disclosure	6.6751***	(2.5038)
7 (Combined)	Big Data Disclosure	15.4127	(14.4536)
7 (Combined)	Cloud Disclosure	3.0279	(8.3711)
7 (Combined)	Digital Transformation Disclosure	-6.9018	(5.3650)

N = 4,067; Firms = 511; Firm FE = Yes; Year FE = Yes; Clustered SE = Firm; Within R^2 ranges 0.0040–0.0089; Adj. Within R^2 ranges 0.0030–0.0072 (see Appendix A).

Table 11 Panel C — DV: Tobin's Q

Model	Variable	Coefficient	Clustered SE
1 (AI)	AI Disclosure	-0.7650	(0.9377)
2 (BD)	Big Data Disclosure	0.2283	(5.3583)
3 (Cloud)	Cloud Disclosure	-2.6799	(2.8621)
4 (DT)	Digital Transformation Disclosure	1.1082	(0.9278)
5 (Composite)	Composite DTD	-0.4786	(0.7249)
6 (Breadth)	Technology Breadth	-0.0304	(0.0646)
7 (Combined)	AI Disclosure	-0.7142	(0.9501)
7 (Combined)	Big Data Disclosure	1.6287	(5.4158)
7 (Combined)	Cloud Disclosure	-2.6450	(2.6732)
7 (Combined)	Digital Transformation Disclosure	1.2450	(0.9402)

N = 2,767; Firms = 388 (smaller sample due to limited market-value/shares-outstanding data). Within R^2 ranges 0.0372–0.0440; Adj. Within R^2 ranges 0.0358–0.0416 (see Appendix A). Significance: ***p<0.01, **p<0.05, *p<0.10.

The results obtained using SLNI and IHS-NI are highly consistent with the baseline ROA estimates. AI Disclosure remains positive and statistically significant in both the individual and combined specifications, indicating that the positive association between AI related disclosure and firm performance is robust to alternative operating performance measures. Composite Digital Technology Disclosure also remains positively associated with both transformed net income measures, whereas Technology Breadth does not exhibit a statistically significant relationship.

In contrast, Big Data, Cloud Computing, and Digital Transformation Disclosure remain statistically insignificant across both operating performance measures. The consistency of these findings across ROA, SLNI, and IHS-NI suggests that the observed association between AI Disclosure and firm performance is not driven by the particular scaling or transformation of the dependent variable.

The market based analysis provides a different picture. None of the technology specific disclosure measures, the composite disclosure measure, or Technology Breadth exhibits a statistically significant association with Tobin's Q. Consequently, the positive association identified for AI Disclosure appears to be limited to operating performance measures and is not reflected in firms' market valuation within the available sample. Because the Tobin's Q analysis is estimated using fewer firm year observations than the operating performance models, these findings should be interpreted with appropriate caution.

Overall, the robustness analysis confirms the stability of the principal findings. AI Disclosure consistently exhibits a positive association with operating performance across all three measures, whereas Big Data, Cloud Computing, and Digital Transformation Disclosure remain statistically insignificant. Composite Digital Technology Disclosure is positively associated with operating performance, while Technology Breadth does not demonstrate an independent relationship with firm performance. Collectively, these results indicate that the baseline findings are robust to alternative operating performance measures but do not extend to the market based valuation measure.

8 Discussion

8.1 Artificial Intelligence

AI Disclosure is the only technology specific disclosure measure that exhibits a consistent positive association with operating performance across the baseline and robustness analyses. This finding suggests that AI related disclosure captures economically meaningful differences among firms that are not observed for the other digital technology categories.

The positive association is consistent with the Resource Based View, which argues that competitive advantage arises from valuable and difficult to imitate organizational resources [9]. AI applications in financial institutions, such as fraud detection, credit risk assessment, and algorithmic decision making, are more likely to represent firm specific capabilities than standardized digital infrastructure. From a Dynamic Capabilities perspective, AI Disclosure may also reflect firms' ability to develop, integrate, and reconfigure technological resources in response to changing market conditions [10]. In addition, Signaling Theory suggests that detailed AI related disclosure can communicate information about firms' technological capabilities to external stakeholders, thereby distinguishing organizations with more advanced digital initiatives from their competitors [11, 12]. These theoretical perspectives should be viewed as complementary explanations rather than directly tested mechanisms.

The empirical findings are broadly consistent with studies reporting positive associations between artificial intelligence (AI) adoption and firm performance [4], although they differ from evidence suggesting that AI innovation may involve substantial implementation costs and weaker short term profitability despite improvements in asset quality [17]. They also contrast with studies reporting insignificant relationships after controlling for firm heterogeneity. These differences may reflect variations in how AI is

measured across studies. Whereas previous research has primarily examined AI adoption, investment, or patent activity, the present study focuses on AI related disclosure in annual reports as an indicator of firms' strategic emphasis on AI. Furthermore, the analysis is based on publicly listed U.S. financial institutions operating in a mature regulatory and technological environment, which differs from the institutional settings examined in much of the existing literature. Consequently, differences in measurement approaches, sample composition, and institutional context may contribute to the variation in empirical findings reported across studies.

8.2 Big Data

Unlike AI Disclosure, Big Data Disclosure does not exhibit a statistically significant association with firm performance in either the baseline or robustness analyses. This finding differs from much of the Big Data Analytics Capability (BDAC) literature, which generally reports positive effects of big data capabilities on organizational performance [5, 6].

A plausible explanation lies in the distinction between *capability* and *disclosure*. Most BDAC studies measure firms' technological capabilities directly through survey based assessments of data infrastructure, analytical skills, and managerial competencies. By contrast, the present study captures the extent to which firms disclose big data initiatives in their annual reports. Disclosure intensity may therefore reflect communication practices rather than the actual development or effective utilization of big data capabilities. Consequently, the absence of a significant relationship should not be interpreted as evidence that big data lacks economic value, but rather that disclosure alone does not provide a sufficiently strong indicator of underlying capability or performance.

8.3 Cloud Computing

Cloud Computing Disclosure does not exhibit a statistically significant association with firm performance in either the baseline or robustness analyses. This finding differs from previous studies reporting positive effects of cloud adoption on organizational performance [2].

One possible explanation is provided by the Resource Based View. While cloud computing may improve operational efficiency, scalability, and cost management, these benefits do not necessarily translate into differences in firm performance once cloud infrastructure becomes widely adopted within the industry. In such circumstances, cloud computing may represent a necessary operational capability rather than a distinctive strategic resource capable of generating sustained competitive advantage. Consequently, although cloud technology remains economically valuable, variation in cloud related disclosure may no longer differentiate higher performing firms from their peers.

Another explanation relates to the measurement approach adopted in this study. The analysis captures the extent of cloud related disclosure in annual reports rather than firms' actual investment in, or utilization of, cloud technologies. As a result, disclosure intensity may not accurately reflect the scale or effectiveness of cloud

implementation, which may contribute to the absence of a statistically significant relationship with firm performance.

8.4 Digital Transformation

Digital Transformation Disclosure does not exhibit a robust association with firm performance across the estimated specifications. Although the estimated coefficients are consistently negative for the operating performance measures, they do not reach conventional levels of statistical significance in the baseline models. These findings suggest that the relationship between digital transformation disclosure and firm performance is weaker and less stable than that observed for AI Disclosure.

The results are broadly consistent with the mixed empirical evidence reported in the literature, where studies have documented both positive and negative associations between digital transformation and firm performance. One possible explanation is that digital transformation represents a broad organizational process encompassing multiple technologies, strategic initiatives, and operational changes. Consequently, disclosure intensity may capture firms at different stages of their digital transformation journey, reducing its ability to serve as a consistent indicator of realized performance.

The findings therefore suggest that digital transformation disclosure alone does not provide a sufficiently robust measure for explaining differences in firm performance among U.S. financial institutions. Future research may benefit from combining disclosure based measures with direct indicators of digital transformation investment, implementation, or organizational capability to better capture the economic effects of digital transformation.

8.5 Operating Performance vs. Market Valuation

An important finding of this study is the difference between operating performance and market based performance measures. AI Disclosure exhibits a positive and statistically significant association with ROA, SLNI, and IHS-NI, whereas none of the digital technology disclosure measures is significantly associated with Tobin's Q. This divergence suggests that the relationship between digital technology disclosure and firm performance depends on the performance metric employed.

One possible explanation is that operating performance measures capture realized outcomes, whereas Tobin's Q reflects investors' expectations regarding firms' future growth opportunities. Consequently, technology related disclosure may be more closely associated with current operating performance than with market valuation. At the same time, market prices are influenced by a broad range of firm specific and macroeconomic factors that extend beyond the information contained in annual reports, potentially weakening the observable relationship between technology disclosure and Tobin's Q.

The absence of statistically significant market based results should be interpreted with appropriate caution. The Tobin's Q models are estimated using a smaller sample because of data availability, which reduces statistical precision relative to the operating performance models. In addition, Tobin's Q is inherently more volatile than operating performance measures, making the detection of statistically significant associations

more challenging. Future research employing market based methodologies, such as event studies or long horizon stock return analyses, may provide further evidence on whether investors incorporate digital technology disclosure into firm valuation.

8.6 Practical Implications

The findings have several practical implications. First, AI related disclosure appears to provide more informative signals about firms' operating performance than broader digital technology disclosures, suggesting that financial institutions should emphasize specific and substantive discussions of AI initiatives rather than relying on generic descriptions of digital transformation. Second, the divergence between the operating performance and market based results indicates that technology disclosure should be interpreted together with firms' underlying financial performance rather than in isolation. Finally, the results highlight the importance of consistent and transparent technology disclosure practices, which can improve the usefulness of annual reports for investors, regulators, and other stakeholders.

8.7 Relevance to the U.S. Financial Services Industry

The findings should be interpreted within the institutional context of publicly listed U.S. financial institutions. Unlike many previous studies conducted in emerging markets or using survey based measures of digital capabilities, this study examines technology disclosure in SEC Form 10-K filings. Consequently, the results reflect the information that firms voluntarily communicate to investors and other stakeholders within a highly regulated disclosure environment.

The evidence indicates that AI Disclosure provides more informative signals of firm performance than the remaining technology categories in the U.S. financial services sector. This finding suggests that, within this institutional setting, AI related disclosure captures greater variation in firms' technological capabilities or strategic priorities than broader disclosures relating to Big Data, Cloud Computing, or Digital Transformation.

The results should not be generalized automatically to other industries or countries. The adoption, maturity, and strategic importance of digital technologies vary across institutional and competitive environments, and technologies that do not exhibit significant associations in the present study may play a more prominent role in other sectors. Future research should examine whether the observed relationships remain consistent across industries, countries, and regulatory settings.

8.8 Interpretation of the Findings

The findings should be interpreted as statistical associations rather than causal relationships. Although the empirical models control for unobserved firm heterogeneity through firm and year fixed effects and include a comprehensive set of firm level control variables, the research design does not establish causality. It remains possible that firms with stronger financial performance are more likely to invest in digital technologies and disclose these initiatives, or that unobserved time varying factors jointly

influence both technology disclosure and firm performance. Consequently, the estimated coefficients should be interpreted as conditional associations rather than causal effects.

The estimated magnitudes nevertheless indicate that the observed relationships are economically meaningful. A one standard deviation increase in AI Disclosure is associated with an increase of approximately 55 basis points in ROA, while a one standard deviation increase in Composite Digital Technology Disclosure corresponds to an increase of approximately 50 basis points. These magnitudes represent meaningful differences relative to the distribution of ROA within the sample, suggesting that the statistical associations identified in the analysis are also economically relevant.

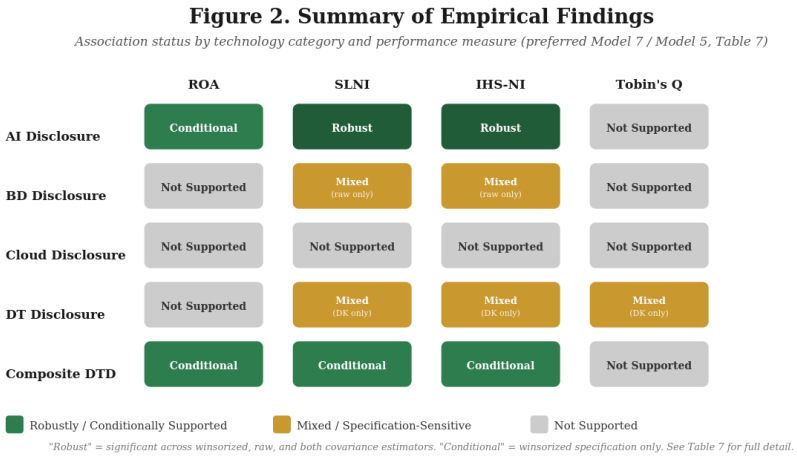


Fig. 2 Graphical summary of empirical findings by technology category and performance measure

Table 12 Hypothesis Summary. Status categories: **Robustly Supported** (significant and consistent across the winsorized primary specification, the raw data comparison, and both covariance estimators tested); **Conditionally Supported** (significant in the primary winsorized specification only); **Mixed/Specification Sensitive** (significance depends on the covariance estimator or winsorization treatment); **Not Supported** (not significant under any specification tested).

Hypothesis	ROA	SLNI	IHS-NI	Tobin's Q
H1: AI Disclosure	Conditional	**Robust**	**Robust**	Not Supported
H2: Big Data Disclosure	Not Supported	Mixed (raw only)	Mixed (raw only)	Not Supported
H3: Cloud Disclosure	Not Supported	Not Supported	Not Supported	Not Supported
H4: DT Disclosure	Not Supported	Mixed (DK only)	Mixed (DK only)	Mixed (DK only)
H5: Composite DTD	Conditional	Conditional	Conditional	Not Supported
H6: Technology Breadth	Not Supported	Not Supported	Not Supported	Not Supported

Note on H5: leave one component out re estimation (excluding each of AI, BD, Cloud, and DT from the composite in turn) confirms that AI Disclosure is the component driving the Composite DTD result: excluding AI collapses the composite to non significance in ROA (p=0.334), SLNI (p=0.899), and IHS-NI (p=0.895), while excluding any other single component leaves the composite significant, in most cases more so than the full four component composite (e.g., excluding DT: ROA p=0.018, SLNI p=0.002, IHS-NI p=0.002). This was formally tested, not merely inferred from AI's individually stronger pattern.

9 Panel Diagnostics

To assess the suitability of the panel regression models, four diagnostic tests were performed using the preferred combined specification (Model 7) for each dependent variable. These diagnostics evaluate the appropriateness of the fixed effects specification, the presence of heteroskedasticity, serial correlation, and cross sectional dependence. Together, they provide the statistical basis for the estimation strategy adopted in this study.

The Hausman test was employed to compare the fixed effects and random effects estimators. Following the standard econometric procedure, the test was estimated using conventional covariance matrices because the classical Hausman statistic is derived under this assumption. The regression models reported throughout the study, however, use firm clustered standard errors to provide inference that is robust to heteroskedasticity and within firm serial correlation. Consequently, the covariance estimator used for the Hausman test does not affect the reported regression coefficients or their statistical significance.

Table 13 Panel Diagnostic Tests

Diagnostic Test	**ROA**	**SLNI**	**IHS-NI**	**Tobin's Q**
Hausman	55.46	76.95	77.11	84.09
	($p < 0.001$)	($p < 0.001$)	($p < 0.001$)	($p < 0.001$)
Wooldridge	$t = 5.69$	$t = 8.71$	$t = 8.74$	$t = 6.09$
	($p < 0.001$)	($p < 0.001$)	($p < 0.001$)	($p < 0.001$)
Modified Wald	28,896	5,852	5,834	34,510
	($p < 0.001$)	($p < 0.001$)	($p < 0.001$)	($p < 0.001$)
Pesaran CD	96.79	309.12	312.11	125.83
	($p < 0.001$)	($p < 0.001$)	($p < 0.001$)	($p < 0.001$)
Observations	4,067	4,067	4,067	2,767

Source: Authors' calculations.
Note: Hausman tests support the fixed effects specification for all dependent variables. Wooldridge, Modified Wald, and Pesaran CD tests indicate the presence of serial correlation, heteroskedasticity, and cross sectional dependence, respectively. The Tobin's Q models use fewer observations because market value data were unavailable for a subset of firms.

All four tests reject their null hypothesis at $p<0.001$ for every dependent variable, and together they justify rather than merely assume the modeling choices made throughout this paper:

- **Hausman:** the null of RE consistency is rejected in every model, supporting the fixed effects specification used throughout over random effects, rather than establishing fixed effects as unconditionally "correct."
- **Wooldridge and Modified Wald:** both serial correlation and cross firm heteroskedasticity are strongly present in every model, which is precisely the justification for clustering standard errors by firm rather than using classical, non robust standard errors.
- **Pesaran CD:** cross sectional dependence is also strongly present in every model. This is a materially important finding, because firm clustered standard errors correct for correlation *within* a firm over time but do **not** correct for correlation *across* firms at a given point in time. This motivates re estimating the preferred models with Driscoll Kraay standard errors.

10 Driscoll Kraay Robustness

The panel diagnostic tests indicate the presence of serial correlation, heteroskedasticity, and cross sectional dependence. Although the baseline models employ firm clustered standard errors, these do not account for cross sectional dependence across firms. Therefore, the preferred **combined technology specific specification**, which includes AI Disclosure, Big Data Disclosure, Cloud Disclosure, and Digital Transformation Disclosure simultaneously, was re estimated using Driscoll Kraay standard errors. This estimator provides inference that is robust to heteroskedasticity, serial correlation, and cross sectional dependence. The regression coefficients remain unchanged because only the covariance estimator differs; consequently, any differences between the two approaches arise solely from the estimated standard errors and corresponding significance levels.

Table 14 Robustness Analysis Using Alternative Covariance Estimators

DV	Variable	Coef.	Clustered SE	Clust. p	DK SE	DK p	Inference Stability
ROA	AI Disclosure	0.038	0.016**	0.014	0.012***	0.002	Robust (sig., both)
ROA	Big Data Disclosure	0.005	0.072	0.950	0.046	0.922	Robust (n.s., both)
ROA	Cloud Disclosure	-0.007	0.046	0.884	0.049	0.891	Robust (n.s., both)
ROA	DT Disclosure	-0.056	0.036	0.122	0.039	0.150	Robust (n.s., both)
SLNI	AI Disclosure	6.425	2.410***	0.008	1.381***	<0.001	Robust (sig., both)
SLNI	Big Data Disclosure	14.802	13.922	0.288	11.757	0.208	Robust (n.s., both)
SLNI	Cloud Disclosure	2.899	8.052	0.719	2.739	0.290	Robust (n.s., both)
SLNI	DT Disclosure	-6.660	5.167	0.198	3.392**	0.050	**Sensitive** (n.s.→sig.)
IHS-NI	AI Disclosure	6.675	2.504***	0.008	1.437***	<0.001	Robust (sig., both)
IHS-NI	Big Data Disclosure	15.413	14.454	0.286	12.181	0.206	Robust (n.s., both)
IHS-NI	Cloud Disclosure	3.028	8.371	0.718	2.830	0.285	Robust (n.s., both)
IHS-NI	DT Disclosure	-6.902	5.365	0.198	3.517**	0.050	**Sensitive** (n.s.→sig.)
Tobin's Q	AI Disclosure	-0.714	0.950	0.452	0.542	0.188	Robust (n.s., both)
Tobin's Q	Big Data Disclosure	1.629	5.416	0.764	3.056	0.594	Robust (n.s., both)
Tobin's Q	Cloud Disclosure	-2.645	2.673	0.323	2.134	0.215	Robust (n.s., both)
Tobin's Q	DT Disclosure	1.245	0.940	0.186	0.530**	0.019	**Sensitive** (n.s.→sig.)

Significance: ***p<0.01, **p<0.05, *p<0.10. Coefficients are identical across both covariance estimators by construction — only the standard error, and therefore statistical significance, can differ. Driscoll Kraay standard errors (Driscoll and Kraay, 1998) are a nonparametric covariance estimator for panel data that remains consistent under heteroskedasticity, serial correlation of unknown form, and cross sectional dependence. Bartlett kernel, package default bandwidth.

The results demonstrate that the principal findings remain largely robust to the alternative covariance estimator. AI Disclosure continues to exhibit a positive and statistically significant association with ROA, SLNI, and IHS-NI under both firm clustered and Driscoll Kraay standard errors, providing additional support for the robustness of the baseline results.

Big Data Disclosure and Cloud Computing Disclosure remain statistically insignificant across all dependent variables regardless of the covariance estimator employed, indicating that their estimated relationships with firm performance are not sensitive to the method used for statistical inference.

Digital Transformation Disclosure exhibits greater sensitivity to the choice of covariance estimator. Although it is not statistically significant under firm clustered standard errors, it becomes significant in several specifications when Driscoll Kraay standard errors are applied. Because these significant results are not consistently observed across all performance measures and the estimated coefficients differ in direction between the operating performance and market based models, they should be interpreted with caution.

Overall, the robustness analysis supports the stability of the study's principal conclusions. AI Disclosure consistently demonstrates the strongest and most robust association with operating performance, whereas the remaining technology disclosure measures exhibit either weak or estimator sensitive relationships.

11 Raw versus Winsorized Robustness Comparison

To evaluate the sensitivity of the baseline findings to the treatment of extreme observations, the preferred combined technology specific specification was re estimated using the original (non winsorized) variables. Both specifications employ the same estimation approach, including firm and year fixed effects, firm clustered standard errors, and identical estimation samples. Consequently, the comparison isolates the effect of winsorization on the estimated coefficients and their statistical significance.

Table 15 Preferred Model 7, Raw (Non Winsorized) vs. Winsorized Specification

DV	Variable	Raw Coef (SE)	Raw Sig.	Wins. Coef (SE)	Stability
ROA	AI Disclosure	0.033 (0.024)	n.s.	0.038** (0.016)	**SENSITIVE**
ROA	Big Data Disclosure	0.068 (0.042)	n.s.	0.005 (0.072)	Robust
ROA	Cloud Disclosure	0.188 (0.196)	n.s.	-0.007 (0.046)	Robust
ROA	DT Disclosure	-0.033 (0.024)	n.s.	-0.056 (0.036)	Robust
SLNI	AI Disclosure	5.087*** (1.971)	***	6.425*** (2.410)	Robust
SLNI	Big Data Disclosure	17.249*** (2.774)	***	14.802 (13.922)	**SENSITIVE**
SLNI	Cloud Disclosure	-0.557 (6.969)	n.s.	2.899 (8.052)	Robust
SLNI	DT Disclosure	-3.846 (3.611)	n.s.	-6.660 (5.167)	Robust
IHS-NI	AI Disclosure	5.284*** (2.047)	***	6.675*** (2.504)	Robust
IHS-NI	Big Data Disclosure	17.906*** (2.882)	***	15.413 (14.454)	**SENSITIVE**
IHS-NI	Cloud Disclosure	-0.588 (7.235)	n.s.	3.028 (8.371)	Robust
IHS-NI	DT Disclosure	-3.994 (3.744)	n.s.	-6.902 (5.365)	Robust
Tobin's Q	AI Disclosure	-8.743 (7.023)	n.s.	-0.714 (0.950)	Robust
Tobin's Q	Big Data Disclosure	-11.554 (15.297)	n.s.	1.629 (5.416)	Robust
Tobin's Q	Cloud Disclosure	11.010 (14.857)	n.s.	-2.645 (2.673)	Robust
Tobin's Q	DT Disclosure	1.942 (2.461)	n.s.	1.245 (0.940)	Robust

Significance: ***p<0.01, **p<0.05, *p<0.10, n.s. = not significant at p<0.10. N = 4,067 (ROA/SLNI/IHS-NI) or 2,767 (Tobin's Q) in both specifications.

The comparison indicates that most of the study's findings are robust to the treatment of extreme observations, although two notable differences emerge.

First, AI Disclosure remains positively associated with operating performance. For ROA, the estimated coefficient changes only marginally from 0.033 in the raw specification to 0.038 after winsorization, although statistical significance is achieved only in the winsorized model (SE = 0.016, $p = 0.014$). In contrast, the association with the transformed net income measures is highly stable. For SLNI, the coefficient increases from 5.087 ($p < 0.01$) in the raw specification to 6.425 ($p < 0.01$) after winsorization, while for IHS-NI it changes from 5.284 ($p < 0.01$) to 6.675 ($p < 0.01$). These results indicate that the positive association between AI Disclosure and operating performance is not driven by the treatment of extreme observations.

Second, Big Data Disclosure exhibits the greatest sensitivity to winsorization. In the raw specification, the estimated coefficients are 17.249 for SLNI and 17.906 for IHS-NI, both statistically significant at the 1% level. After winsorization, the coefficients decrease to 14.802 and 15.413, respectively, and neither remains statistically

significant. This pattern suggests that the apparent association between Big Data Disclosure and operating performance is influenced by a relatively small number of extreme observations.

Cloud Computing Disclosure and Digital Transformation Disclosure remain statistically insignificant across both the raw and winsorized specifications for the operating performance measures. Similarly, none of the technology disclosure measures exhibits a statistically significant association with Tobin's Q under either specification.

Overall, the comparison supports the robustness of the study's principal findings. AI Disclosure consistently exhibits a positive association with SLNI and IHS-NI under both specifications, whereas its association with ROA is sensitive to the treatment of extreme observations. Likewise, the positive association between Big Data Disclosure and the transformed net income measures is not robust to winsorization. These results indicate that the strongest and most stable empirical evidence concerns the relationship between AI Disclosure and operating performance.

12 Implications

12.1 Theoretical Implications

This study contributes to the literature on digital technology disclosure by providing empirical evidence on the heterogeneous relationships between different technology disclosure categories and firm performance. Rather than treating digital technology as a single construct, the findings demonstrate that Artificial Intelligence, Big Data, Cloud Computing, and Digital Transformation differ in their associations with operating and market based performance measures.

From the perspective of the Resource Based View (RBV), the results are consistent with the proposition that not all digital technologies contribute equally to competitive advantage. AI Disclosure is the only technology specific measure that exhibits a consistent positive association with operating performance, suggesting that AI related capabilities may represent a more strategically valuable organizational resource than broader digital technology initiatives. In contrast, the absence of significant associations for Cloud Computing and Digital Transformation Disclosure indicates that the performance implications of digital technologies may depend on their strategic role and organizational implementation rather than on their mere disclosure.

The findings also contribute to the Dynamic Capabilities literature by highlighting the distinction between technology disclosure and technological capability. While previous studies commonly examine firms' digital capabilities through survey based or organizational measures, the present study demonstrates that disclosure intensity does not necessarily reflect the underlying capability to develop and exploit digital technologies. This distinction is particularly evident for Big Data Disclosure, which does not exhibit the positive association with firm performance frequently reported in the Big Data Analytics Capability literature.

Finally, the study extends Signaling Theory by showing that the informational value of technology disclosure depends on the quality and specificity of the disclosed information. The dictionary development and validation process demonstrated that

not all technology related terms convey equally informative signals. Generic technology language may provide limited information about firms' underlying capabilities, whereas more specific AI related disclosure appears to offer a stronger indication of firms' technological development and strategic orientation. These findings emphasize the importance of carefully constructing disclosure measures when applying text based methods to examine corporate technology strategies.

12.2 Managerial and Practitioner Implications

The findings provide several practical implications for managers, investors, and other stakeholders involved in the U.S. financial services industry.

For managers and executives, the results suggest that AI related initiatives are more closely associated with firm performance than broader digital technology disclosures. Consequently, annual reports may be more informative when they describe specific AI applications, such as fraud detection, credit risk assessment, customer service automation, or algorithmic decision making, rather than relying primarily on broad references to digital transformation or technological innovation. More specific disclosure can improve stakeholders' understanding of firms' strategic technology priorities and organizational capabilities.

For investors and financial analysts, the results indicate that technology disclosures should not be interpreted uniformly. AI Disclosure consistently exhibits positive associations with operating performance measures, whereas Big Data, Cloud Computing, and Digital Transformation Disclosure do not demonstrate comparable relationships. These findings suggest that technology specific disclosures may provide more useful information than aggregate statements regarding digital transformation. At the same time, the absence of significant associations with Tobin's Q indicates that technology disclosure alone should not be viewed as a reliable indicator of market valuation.

The findings are also relevant for regulators and standard setters concerned with the quality and comparability of corporate technology disclosure. The results highlight the importance of clear, specific, and consistent disclosure practices, particularly for emerging technologies such as artificial intelligence. More standardized reporting of technology related initiatives could improve the usefulness of annual reports for investors and facilitate future research based on textual disclosure measures.

12.3 Policy and Regulatory Implications

The findings also have implications for regulators and standard setters responsible for corporate disclosure practices and financial reporting infrastructure.

First, the study highlights the importance of improving the quality and consistency of technology related disclosures in corporate annual reports. More standardized reporting of digital technologies, particularly emerging technologies such as artificial intelligence, would improve the comparability of disclosures across firms and facilitate more reliable assessments by investors, regulators, and researchers.

Second, the data collection process identified practical limitations in the current SEC reporting infrastructure. The extraction of narrative information from Inline

XBRL filings remains challenging because machine readable tags are frequently embedded within narrative text, increasing the complexity of automated text analysis. Improving the consistency and readability of structured filings would enhance the reliability of disclosure based research and support the broader use of natural language processing techniques in financial analysis.

Finally, incomplete XBRL coverage for certain financial variables, particularly Shares Outstanding, reduced the number of observations available for the market based analyses. Expanding the completeness and consistency of structured financial reporting would improve data availability for researchers, regulators, and market participants and facilitate more comprehensive empirical analyses of corporate disclosure and firm performance.

12.4 Implications for Researchers

The findings provide several methodological implications for future research on digital technology disclosure and firm performance. First, the results demonstrate the importance of examining individual technology categories separately rather than treating digital technology as a single aggregate construct. The heterogeneous findings across AI, Big Data, Cloud Computing, and Digital Transformation indicate that aggregation may conceal meaningful differences in the relationships between specific technologies and firm performance.

Second, the study highlights the importance of rigorous validation when constructing text based disclosure measures. Dictionary based approaches should be systematically evaluated to ensure that the selected terms accurately capture the intended technological concepts and minimize false positive keyword matches. Careful dictionary development improves the reliability and validity of textual disclosure measures and strengthens the robustness of empirical findings.

Third, the differing results obtained from operating performance and market based performance measures demonstrate the value of employing multiple indicators of firm performance. Operating performance measures capture realized financial results, whereas market based measures reflect investors' expectations and valuation. Considering both perspectives provides a more comprehensive assessment of the economic implications of digital technology disclosure.

Finally, the results suggest that future studies should further investigate the relationship between technology disclosure, technology adoption, and organizational capabilities. Integrating text based disclosure measures with direct indicators of technology investment, implementation, or digital capability may provide a more complete understanding of how digital technologies influence firm performance.

13 Limitations

Several limitations should be considered when interpreting the findings of this study.

First, the empirical models identify statistical associations rather than causal relationships. Although firm and year fixed effects reduce concerns related to unobserved heterogeneity, reverse causality and omitted time varying factors cannot be completely excluded.

Second, some findings are sensitive to model specification. AI Disclosure exhibits a robust positive association with SLNI and IHS-NI across all robustness analyses, whereas its association with ROA is significant only after winsorization. Similarly, Big Data Disclosure is statistically significant for SLNI (coefficient = 17.249, $p < 0.01$) and IHS-NI (coefficient = 17.906, $p < 0.01$) in the raw specification, but becomes insignificant after winsorization. Digital Transformation Disclosure also shows estimator sensitivity, becoming significant under Driscoll Kraay standard errors while remaining insignificant under firm clustered standard errors. These findings indicate that the evidence for AI Disclosure is considerably more robust than for the remaining technology categories.

Third, the market based analysis relies on a smaller sample than the operating performance models. The Tobin's Q regressions include 2,767 firm year observations from 388 firms, compared with 4,067 observations from 511 firms for the operating performance measures. This reduction is primarily attributable to incomplete SEC XBRL reporting of Shares Outstanding, which limits the statistical power of the market based analysis.

Fourth, the study employs a dictionary based measure of digital technology disclosure. Although the dictionary was carefully developed and validated, keyword frequency captures firms' disclosure behavior rather than their actual technology adoption or investment. Consequently, disclosure intensity may not fully reflect firms' underlying technological capabilities.

Fifth, the analysis focuses exclusively on publicly listed U.S. financial institutions during 2014–2025. Therefore, the findings should not be generalized automatically to other industries, countries, or regulatory environments.

Sixth, the measurement of Big Data and Cloud Computing may underestimate firms' actual technological capabilities. Nearly half of the firms with repeated observations (255 of 521 firms, or 49%) exhibit no within firm variation in Big Data Disclosure, compared with only 13% for AI Disclosure, 32% for Cloud Computing Disclosure, and 14% for Digital Transformation Disclosure. Because fixed effects estimation relies exclusively on within firm variation, this limited variation likely contributes to the instability of the Big Data estimates across alternative specifications.

Seventh, the primary regression sample is reduced by missing values for Cash Ratio. The preferred specification includes 4,067 observations instead of the complete panel of 5,172 observations. Re estimating the preferred model without Cash Ratio increases the sample to 5,172 observations and yields consistent results for AI Disclosure (ROA = 0.031, $p = 0.021$; SLNI = 6.791, $p = 0.001$; IHS-NI = 7.058, $p = 0.001$), providing additional evidence that the main conclusions are not driven by sample selection.

Finally, although several additional robustness analyses including alternative covariance estimators, bandwidth sensitivity, matching procedures, and Tobin's Q construction support the stability of the principal findings, future research could further strengthen the evidence by employing alternative measures of digital technology adoption, extending the analysis to other industries and countries, and using research designs that allow stronger causal inference.

14 Conclusion

This study examined the relationship between digital technology disclosure and firm performance using a panel of 535 publicly listed U.S. financial institutions over the period 2014–2025. Unlike previous studies that frequently employ a single digitalization or ICT measure, this research distinguished four technology categories Artificial Intelligence (AI), Big Data, Cloud Computing, and Digital Transformation and measured each separately using a validated dictionary based textual analysis of SEC Form 10-K filings. Firm performance was evaluated using three operating performance measures (ROA, SLNI, and IHS-NI) together with the market based measure Tobin's Q.

The empirical findings demonstrate substantial heterogeneity across digital technology categories. AI Disclosure consistently exhibits the strongest association with operating performance. The positive relationship remains statistically significant for both SLNI and IHS-NI across the baseline models, alternative covariance estimators, and raw versus winsorized specifications, indicating that this finding is highly robust. For ROA, the estimated coefficient remains positive (0.033 in the raw specification and 0.038 after winsorization), although statistical significance is observed only in the winsorized specification. In contrast, Big Data Disclosure shows statistically significant coefficients for SLNI (17.249) and IHS-NI (17.906) only in the raw specification, with these relationships disappearing after winsorization. Cloud Computing Disclosure remains statistically insignificant across all specifications, while Digital Transformation Disclosure exhibits sensitivity to the choice of covariance estimator. None of the four technology disclosure measures demonstrates a statistically significant association with Tobin's Q.

The study makes several contributions to the literature. First, it demonstrates that disaggregating digital technology disclosure provides substantially richer evidence than treating digitalization as a single construct. The results show that the observed relationship between digital technology disclosure and firm performance is driven primarily by AI Disclosure rather than uniformly across all technology categories. Second, the study develops and validates a comprehensive dictionary based framework containing 120 technology related terms specifically designed for U.S. financial institutions. Third, by comparing operating performance and market based performance measures, the analysis reveals that technology disclosure is more strongly associated with realized financial performance than with market valuation. Finally, the extensive robustness analyses strengthen confidence in the principal findings by demonstrating that the AI related results remain stable across alternative model specifications and estimation approaches.

The findings also provide practical implications for managers, investors, regulators, and researchers. For corporate managers, the results suggest that specific AI related disclosure conveys more informative signals than broad references to digital transformation. For investors, the evidence indicates that different technology disclosures should not be interpreted uniformly, as AI Disclosure appears to contain more economically relevant information than the remaining technology categories. For regulators, the study highlights opportunities to improve the consistency and completeness of technology related disclosures and structured financial reporting. For researchers, the

findings emphasize the importance of disaggregating digital technology measures, validating text based dictionaries, and combining disclosure based measures with direct indicators of technology adoption and organizational capability.

Several limitations should be acknowledged. The analysis identifies statistical associations rather than causal relationships, the market based models rely on a smaller estimation sample because of incomplete Shares Outstanding data, and dictionary based disclosure measures capture firms' reporting behavior rather than their actual technology adoption. Future research could address these limitations by extending the analysis to other industries and countries, integrating disclosure measures with direct indicators of technology investment and capability, and applying causal research designs to further examine the relationship between digital technology disclosure and firm performance.

List of Abbreviations

AI Artificial Intelligence
BD Big Data
BDAC Big Data Analytics Capability
DCT Dynamic Capabilities Theory
DK Driscoll Kraay
DTD Digital Technology Disclosure
DT Digital Transformation
FE Fixed Effects
IHS-NI Inverse Hyperbolic Sine Net Income
RBV Resource Based View
ROA Return on Assets
SEC U.S. Securities and Exchange Commission
SIC Standard Industrial Classification
SLNI Signed Log Net Income
VIF Variance Inflation Factor
VRIN Valuable, Rare, Inimitable, and Non substitutable
XBRL eXtensible Business Reporting Language

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Appendix A Additional Regression Results

This appendix reports supplementary regression results supporting the main empirical analysis. Specifically, the tables present the 95% confidence intervals, sample size, number of firms, within R^2, adjusted within R^2, robust F statistics, and corresponding p-values for each model specification. These additional results complement the baseline and robustness analyses presented in the main text and provide complete estimation details for transparency and reproducibility

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Table A1 Panel A — DV: SLNI

Model	Variable	95% CI	N	Firms	Within R^2	Adj. Within R^2	F (robust)	F p-value
1 (AI)	AI Disclosure	[2.0454, 11.2620]	4,067	511	0.0073	0.0064	3.716	0.0050
2 (BD)	Big Data Disclosure	[-6.4163, 45.7235]	4,067	511	0.0060	0.0051	2.615	0.0335
3 (Cloud)	Cloud Disclosure	[-7.8458, 22.4683]	4,067	511	0.0060	0.0050	2.270	0.0594
4 (DT)	DT Disclosure	[-15.9680, 4.5201]	4,067	511	0.0070	0.0060	2.393	0.0485
5 (Composite)	Composite DTD	[0.0872, 7.6800]	4,067	511	0.0063	0.0053	3.302	0.0104
6 (Breadth)	Technology Breadth	[-0.1123, 1.0566]	4,067	511	0.0041	0.0031	2.695	0.0293
7 (Combined)	AI Disclosure	[1.7010, 11.1495]	4,067	511	0.0091	0.0074	2.846	0.0058
7 (Combined)	Big Data Disclosure	[-12.4942, 42.0980]	4,067	511	0.0091	0.0074	2.846	0.0058
7 (Combined)	Cloud Disclosure	[-12.8883, 18.6858]	4,067	511	0.0091	0.0074	2.846	0.0058
7 (Combined)	DT Disclosure	[-16.7915, 3.4708]	4,067	511	0.0091	0.0074	2.846	0.0058

Table A2 Panel B — DV: IHS-NI

Model	Variable	95% CI	N	Firms	Within R^2	Adj. Within R^2	F (robust)	F p-value
1 (AI)	AI Disclosure	[2.1244, 11.7031]	4,067	511	0.0071	0.0062	3.708	0.0051
2 (BD)	Big Data Disclosure	[-6.5984, 47.5152]	4,067	511	0.0059	0.0049	2.616	0.0335
3 (Cloud)	Cloud Disclosure	[-8.1447, 23.3797]	4,067	511	0.0059	0.0049	2.267	0.0597
4 (DT)	DT Disclosure	[-16.5636, 4.7079]	4,067	511	0.0069	0.0059	2.382	0.0494
5 (Composite)	Composite DTD	[0.0909, 7.9805]	4,067	511	0.0061	0.0051	3.297	0.0105
6 (Breadth)	Technology Breadth	[-0.1146, 1.0985]	4,067	511	0.0040	0.0030	2.697	0.0292
7 (Combined)	AI Disclosure	[1.7661, 11.5841]	4,067	511	0.0089	0.0072	2.842	0.0059
7 (Combined)	Big Data Disclosure	[-12.9255, 43.7508]	4,067	511	0.0089	0.0072	2.842	0.0059
7 (Combined)	Cloud Disclosure	[-13.3847, 19.4405]	4,067	511	0.0089	0.0072	2.842	0.0059
7 (Combined)	DT Disclosure	[-17.4207, 3.6171]	4,067	511	0.0089	0.0072	2.842	0.0059

Table A3 Panel C — DV: Tobin's Q

Model	Variable	95% CI	N	Firms	Within R^2	Adj. Within R^2	F (robust)	F p-value
1 (AI)	AI Disclosure	[-2.6038, 1.0738]	2,767	388	0.0392	0.0379	2.075	0.0815
2 (BD)	Big Data Disclosure	[-10.2792, 10.7358]	2,767	388	0.0373	0.0360	1.428	0.2223
3 (Cloud)	Cloud Disclosure	[-8.2924, 2.9325]	2,767	388	0.0394	0.0380	1.707	0.1456
4 (DT)	DT Disclosure	[-0.7112, 2.9277]	2,767	388	0.0388	0.0374	2.227	0.0638
5 (Composite)	Composite DTD	[-1.9001, 0.9429]	2,767	388	0.0386	0.0372	1.893	0.1090
6 (Breadth)	Technology Breadth	[-0.1571, 0.0963]	2,767	388	0.0372	0.0358	1.451	0.2148
7 (Combined)	AI Disclosure	[-2.5774, 1.1490]	2,767	388	0.0440	0.0416	1.672	0.1112
7 (Combined)	Big Data Disclosure	[-8.9915, 12.2489]	2,767	388	0.0440	0.0416	1.672	0.1112
7 (Combined)	Cloud Disclosure	[-7.8870, 2.5970]	2,767	388	0.0440	0.0416	1.672	0.1112
7 (Combined)	DT Disclosure	[-0.5986, 3.0887]	2,767	388	0.0440	0.0416	1.672	0.1112