Riding the Waves of Digital Technologies: Unveiling the Influence of Digital Technologies on Investment Efficiency

Abstract

Digital technologies have significant potential to enhance firm productivity and operational efficiency. This study investigates the impact of digital technologies and top management with tech background on investment efficiency. We find strong evidence that firms adopting digital technologies, including artificial intelligence (AI), consistently outperform their peers. Moreover, top management teams with a strong technological background significantly improve investment efficiency. Beyond digital adoption and managerial expertise, firms with a higher proportion of employees skilled in AI demonstrate greater investment efficiency. These findings hold across both tech and non-tech industries, regardless of financial distress, and irrespective of financial reporting quality. However, the positive effects are evident primarily in large firms, but not in smaller firms. This study is the first to provide direct evidence of the impact of digital technologies on firm investment efficiency.

1. Introduction

In recent years, firms across various industries have increasingly invested in digital technologies (DT), including artificial intelligence (AI), to boost productivity and efficiency. While digital technologies hold significant potential for enhancing productivity and fostering innovation, they present new challenges. For example, according to research by International Data Corporation (IDC) and McKinsey, global spend on digital transformations can reach $3.4 trillion by 2026, but roughly 70% of these (approximately $2.3 trillion) fail to deliver successful outcomes.[1] As a result, it's never been more pressing for firms to overhaul how they improve and develop their businesses. Companies are dedicating substantial resources—amounting to billions of dollars—to new technologies like AI, underscoring the importance of understanding how these investments impact capital investment efficiency. Therefore, this study investigates whether, and

[1] https://newsroom.taylorandfrancisgroup.com/costly-business-overhauls-are-not-needed-to-embrace-new-digital-technologies-according-to-specialist/

to what extent, firm-level digital initiatives and the technological expertise of top management influence capital investment efficiency, a critical factor in driving economic productivity.

Firms that voluntarily disclose digital activities and have top management teams with technological expertise can enhance investment efficiency for two main reasons. First, digital technologies, coupled with managerial tech experience, help firms allocate resources more effectively, reducing both underinvestment and overinvestment. For instance, robotic process automation (RPA) can automate data capture and entry, minimizing human intervention and potential errors. Machine learning (ML) algorithms can further boost operational efficiency by accurately forecasting key business metrics, such as sales returns, customer credit risk, and asset impairment. Well-trained ML models generate precise predictions, improving financial reporting estimates for items like sales returns, warranty claims, allowances for doubtful debts, and inventory write-downs. Additionally, Rane, Choudhary, and Rane (2024) find that AI fosters innovative practices in corporate governance and sustainability by leveraging ML, natural language processing (NLP), and RPA. Second, firms that disclose more digital activities in their annual reports can help reduce information asymmetry between managers, investors, and other market participants. Prior research shows that improved reporting enhances corporate decision-making, including investment efficiency, by reducing information asymmetries that create frictions in raising external capital (Bens and Monahan 2004; Biddle and Hilary 2006; Biddle, Hilary, and Verdi 2009; Cheng, Dhaliwal, and Zhang 2013; Lara, Osma, and Penalva 2015). For example, Biddle et al. (2009) find that firms with lower-quality financial reporting tend to underinvest when financially constrained and overinvest when unconstrained. Cheng, Dhaliwal, and Zhang (2013) also demonstrate that investment efficiency improves significantly after firms disclose internal control weaknesses. Overall, these findings suggest that corporate digital technologies can play a key role in enhancing firm investment efficiency.

In contrast, one may argue that firms may overinvest in digital technologies, risking a decline in investment efficiency if they overlook the cost-benefit analysis. This risk is particularly pronounced in industries where the adoption of digital technologies is less critical, as well as for firms with a tech-savvy management team that may be prone to overspending on such initiatives. Meanwhile, there are some frictions associated with new technologies that may delay or limit their benefits (Bresnahan and Greenstein 1996; Brynjolfsson et al. 2019).

To explore the impact of digital technologies and activities on investment efficiency, we construct a dictionary of digital terms and obtain word counts of digital terms in the business description of firms' 10-K reports to capture the extent of digital activity following Chen and Srinivasan (2023). We define digital technologies to include a broad range of digital-related activities such as analytics, automation, AI, big data, cloud computing, and machine learning for both tech and non-tech firms. To address concerns that the raw count of words is a noisy measure of digital activity, we quantize the raw counts into terciles that are coded as follows: 0 if no digital activity is disclosed; and 1, 2, and 3 if digital mentions fall in the bottom, middle and top tercile of digital mentions in the year, respectively (Chen and Srinivasan 2023). To address potential concerns that digital disclosure may not necessarily reflect actual digital transformation efforts, we use two additional variables: a human-capital-based AI measure using firm-level job posting and resume data following Babina, Fedyk, He, and Hodson (2024) and the number of patents filed by firms. Both variables are significantly and positively associated with digital disclosure, which helps validate our main digital disclosure measure.

In this study, using a large sample of US publicly traded firms from 2010 to 2022, we find a negative association between digital technologies and investment inefficiency. That is, firms with more digital activities improve their investment efficiency including underinvestment and overinvestment. In particular, we find that such an improvement in investment efficiency remains in the long run (next three and five years) after firms adopt digital technologies. That indicates the competitive advantage of digital technologies improves and enhances firm investment efficiency.

Next, by decomposing digital activities, we find that not all categories of digital technologies significantly affect investment inefficiency. For instance, the improvement in investment efficiency is robust for the firms with certain digital technologies such as AI, analytics, cloud computing, and digitalization, but not for others (i.e., automation, big data, and machine learning). Overall, these findings highlight the impact of digital activities in improving investment efficiency across different dimensions.

Furthermore, we performed several cross-sectional analyses among tech versus non-tech industries, big versus small firms, financially distressed versus non-financially distressed firms, and high versus low financial reporting quality (captured by accrual-based measures) groups. We find that the positive effect of digital technologies on investment efficiency remains for both tech or non-tech industries regardless of firm financial distress condition and high- or low-financial reporting quality. Nevertheless, the positive effect is evident primarily in large firms, but not in smaller ones.

Besides digital technologies and activities, we explore the impact of human-capital-based AI on investment efficiency. Babina, Fedyk, He and Hodson (2024) find that AI-investing firms, captured by employees with AI-related expertise, experience higher growth in sales, employment, and market valuations, and such a growth comes primarily through increased product innovation. Following their methodology, we measure AI human-capital measure as a quantized score based on AI-related job postings with 0 for no AI employee, 1 for yearly below tercile percentage for AI employees, 2 for yearly middle tercile percentage, and 3 for yearly top tercile percentage. We document a positive impact of human AI expertise on investment efficiency.

Finally, we explore two potential channels, institutional ownership and operational efficiency. By reporting their digital activities, firms are sending a clear message to investors and other stakeholders about their commitment to innovation and forward-thinking strategies. These disclosures act as indicators of the firm's future potential and strategic direction. Investors interpret these signals as positive indicators of the firm's ability to adapt to technological advancements and maintain a competitive edge. As a result, firms that are proactive in their digital disclosures are more likely to attract informed and strategic investors who value innovation and long-term growth potential. We find that is the case. Firms actively engaging in digital transformation tend to have higher levels of institutional ownership, consistent with signaling theory that firms use specific activities or disclosures to signal their strategic intentions to the market. In addition, we document that after adopting digital technologies, firms improve their operational efficiency using data envelopment analysis (DEA) following Demerjian et al. (2012), consistent with resource-based view (RBV) theory. Firms investing in management with technology background also enhance operational efficiency. Taken together, our findings show that firms engaging with more digital activities combined with more managerial technological experience consistently outperform their peers by attracting institutional investors and improving operational efficiency.

In essence, this study makes a dual contribution to the literature. First, to the best of our knowledge, this study is the first to investigate the direct impact of digital technologies, non-financial information, on investment efficiency. Our findings show that a firm's investment performance is influenced not only by tangible assets (i.e., digital technologies and activities), but also by intangible assets - human capital (i.e., the top management team with technology experience and employees with AI expertise), consistent with recent studies (e.g., Chen and Srinivasan 2023; Lem 2024).[2] Our focus on both digital activities and investment efficiency complements and extends extant findings on how non-financial information (i.e., digital technologies) affects firm financial performance in both the short term and long run. Overall, these findings highlight the critical role of combining digital technologies and AI activities in improving investment efficiency.

Second, we contribute to the growing body of literature on corporate investment efficiency. Investment efficiency is recognized as a crucial competitive advantage for firm performance, contributing to long-term success (Biddle et al. 2006, 2009; Cheng, Dhaliwah, and Zhang 2013; Lara, Osma, Penalva 2015). Our research extends this line of inquiry by identifying two vital determinants of corporate investment efficiency (i.e., digital activities and managerial tech experience). Companies are encouraged to report their digital activities to enhance their competitive advantage, particularly in high-intensity research and development industries.

2. Hypothesis Development

A significant body of the emerging literature stream examines the association between digital technologies and firm growth as well as market valuations (e.g., Chen and Srinivasan 2023; Babina, Fedyk, He and Hodson 2024). Most studies document the benefits of adopting digital

[2] For example, using textual analysis of firm disclosures to identify a data analytics strategy, Lem (2024) finds that a strategic focus on data analytics is associated with enhanced operational efficiency. Chen and Srinivasan (2023) find a positive association between digital activities and market valuations, but no significant increases in profit margins and sales growth for firms adopting digital technologies.

technologies and AI in terms of improved financial reporting quality (Anantharaman, Rozario and Zhang 2024), internal control efficiency (Obaydin, Richardson, Troshani, and Zurbruegg 2024), firm growth and product innovation (He, Babina, Fedyk, and Hodson 2024), market valuation (Chen and Srinivasan 2023), internal information quality (Lem 2024), audit quality (Fedyk, Hodson, Khimich and Fedyk 2022), etc. However, little prior research exists that analyzes the effects of digital technologies and employees with AI expertise on investment efficiency. Therefore, in this study, we aim to address the impact of combining tangible (i.e., digital technologies) and intangible assets (i.e., managerial tech experience and human-capital-based AI expertise), because both are of vital importance to capital investment efficiency.

The implementation of digital activities and related human capital is unique, valuable, and hard to imitate, making them key strategic resources. According to Resource-Based View (RBV) theory, firms position their resources (e.g., tangible, intangible, and human aspects) as the key to reaching a competitive advantage (Barney 1991; Wernerfelt 1984). These resources enable firms to optimize their operations, make more informed decisions, and better allocate their investments; as a result, reducing inefficiencies focuses on the strategic importance of firm-specific resources and capabilities. By investing in digital activities, firms can gain a competitive edge, leading to improved investment efficiency. For instance, by proposing a new measure of firm-level AI investments using employee resumes, Babina, Fedyk, He and Hodson (2024) find that AI-investing firms experience higher growth in sales, employment, and market valuations, with growth primarily driven by product innovation.

Second, signaling theory posits that firms use certain activities or disclosures to signal their strategic intentions to the market. In the case of digital disclosure, when firms report their digital activities, they are sending a signal to investors and other stakeholders about their commitment to innovation and forward-thinking strategies. These disclosures act as indicators of the firm's future potential and strategic direction. Investors interpret these signals as positive indicators of the firm's ability to adapt to technological advancements and maintain a competitive edge. As a result, firms that are proactive in their digital disclosures are likely to attract more informed and strategic investors who value innovation and long-term growth potential. This can lead to an influx of investment and greater market confidence, which in turn supports better allocation of resources and enhanced investment efficiency. By signaling their dedication to digital transformation, firms can differentiate themselves from competitors and position themselves as leaders in their industry, further driving investment efficiency through increased investor trust and engagement. Taken together, we make the following predictions related to the impact of digital technologies on investment efficiency:

H1: Digital technologies improve investment efficiency.

Besides digital technologies, we conjecture that managerial technology experience can influence a firm's investment decisions in two ways. First, drawing upon the upper echelon's theory, we posit that the top management team as well as boards with technology experience and background can advocate and prioritize limited resource allocation for adopting new digital technologies and technology advancement across various stages and dimensions. Prior studies find that individuals' characteristics and attributes, including educational background and career experience, influence corporate investment decisions (Hambrick and Mason 1984). Meanwhile, the top management team with technology experience can accelerate communication among all executives and research departments, thereby reducing information asymmetry and enhancing transparency within the organization. Due to the challenges in assessing whether a complex project will succeed, management plays a critical role in assuring that the development of fundamental technologies can offer clear, competitive advantages for current and future businesses, according to O'Neill and Bridenbaugh (1992). Put differently, the management team with technology experience is able to translate complex technical concepts into clear and understandable terms for non-technical stakeholders. Effective leadership and communication skills are crucial for the top management team as they can inspire and motivate the employees, convey the technology vision to stakeholders, and cultivate relationships across the organization. Therefore, we present the second hypothesis in a directional form.

H2: Managerial technology experience improves investment efficiency.

3. Research Design, Data and Summary Statistics

3.1 Estimation of Investment Efficiency

We adopt the model from prior literature to (e.g., Biddle et al. 2009; McNichols and Stubben 2008; Li and Sun 2024) to compute investment efficiency:

$$INV_{i,t} = \beta_0 + \beta_1 TOBIN\acute{}SQ_{i,t-1} + \beta_2 GROWTH_{i,t-1} + \beta_3 CFO_{i,t} + \beta_4 INV_{i,t-1} + \varepsilon_{i,t}$$

(1)

where i and t represents firms and years, respectively. INV equals the sum of research and development expense, capital expenditure, and acquisition expenditure less the sale of property, plant, and equipment, scaled by lagged total assets. Tobin’s Q equals the market value plus the total assets minus book value of shareholders’ equity divided by total assets. CFO equals operating cash flows scaled by total assets. Investment Efficiency (*XINV*) is captured through abnormal investments, computed as the absolute value of the residual from a model where total investment is regressed on key financial indicators, including Tobin's Q, sales growth, operating cash flow, and lagged investment. Overinvestment (*OVER_INV*) and underinvestment *(UNDER_INV*) are calculated as the absolute value of the positive and negative residual captured through the total investment model. A higher value of each measure implies higher investment inefficiency.

3.2 Empirical Model

To investigate the impact of digital and AI disclosures on investment efficiency, we estimate the following model:

$$XINV_{it} = \beta_0 + \beta_1 IV_{it} + \sum_{a=2}^{n} Controls_{it} + \varepsilon_{it} \qquad (2)$$

where $XINV_{it}$ represents the absolute abnormal investment for firm i in year t from equation (1). We also run equation (2) separately for overinvestment (OVER_INV) and underinvestment (UNDER_INV) to assess the differential impacts of digital technologies and managerial tech experience.

Our first main variable of interest, *DIGITAL_T*, is a quantized score of digital disclosure: 0 for no digital disclosure, 1 for yearly disclosure in the bottom tercile, 2 for yearly disclosure in the middle tercile, and 3 for yearly disclosure in the top tercile. Digital disclosure is quantified by counting the occurrences of digital-related terms in the business description section of the firms' 10-K filings. Digital-related terms used to construct this variable are listed in Appendix B. These data are obtained from DIRECTEDGAR. The 2nd key variable, *TECHMANAGER* is a binary indicator set to 1 if one of a firm's top executives holds a technology-related title, such as VP Digital, Chief Information Officer (CIO), or Chief Technology Officer (CTO). We sourced this data from BOARDEX.

Following prior research (e.g., Biddle and Hilary 2006; Biddle et al. 2009; Chen et al. 2011; Li and Sun 2024), we control for a number of firm-level factors that are likely to be associated with firm investment efficiency. These include firm size (*SIZE*), market-to-book ratio (*MTB*), Altman Z-score (*ZSCORE*), asset tangibility (*TANGIBILITY*), leverage (*LEVERAGE*), dividend payout (*DIV*), liquidity (*SLACK*), operating cash flow (*CFOSALE*), operating cycle (*OPERATING_CYCLE*), incurrence of loss (*LOSS*), firm age (*FIRMAGE*), cash flow volatility (*SDCFO*), sales volatility (*SDSALE*), and total investment volatility (*SDINVESTMENT*). All variable definitions are provided in Appendix A.

In addition, to address a potential endogeneity issue that digital and AI disclosures might be correlated with unobserved factors that also influence a firm's investment efficiency, we employ two distinct approaches in our regression analysis. First, we include industry fixed effects in our model to control for unobserved heterogeneity across industries that might simultaneously affect digital and AI disclosures as well as investment efficiency. This allows us to isolate the impact of within-industry variations. Next, we apply an entropy balancing technique. This method adjusts the distribution of covariates across the study and control groups to ensure balance in the first moment (mean) of the covariate distributions. By using entropy balancing, we emphasize firms that are more comparable to the study firms, thereby enhancing the validity of our comparisons without losing observations. This approach further strengthens the robustness of our findings by addressing concerns related to the reflection problem.

3.3 Sample Selection and Data Sources

Our study analyzes publicly listed firms across various industries, drawing data from the COMPUSTAT and DIRECTEDGAR databases spanning from 2010 to 2022. The initial dataset comprised 108,318 firm-year observations. We focus on the business description section (section 1) of firm annual reports (10-Ks). We refined this dataset by sequentially removing observations with missing data. First, 52,246 observations were excluded due to incomplete investment efficiency data. This filtering process ensures comprehensive industry representation, maintaining a minimum of 15 observations per industry-year, crucial for the robustness of our statistical analysis. Next, 16,288 observations were removed due to missing control variables. Finally, 289 observations were omitted because of missing industry classifications. The final sample consists of 29,495 firm-year observations. Table 1 provides the sample selection process.

INSERT TABLE 1 HERE.

3.4 Descriptive Statistics

Table 2, Panel A provides descriptive statistics for the key variables used in our analysis, based on a sample of 38,761 firm-year observations. The primary measure of investment efficiency, *XINV*, has a mean of 0.23, indicating that, on average, firms exhibit moderate levels of abnormal investments. The overinvestment measure (*OVER_INV*) has a higher mean of 0.349, reflecting that when firms overinvest, the magnitude of overinvestment tends to be more significant than underinvestment *(UNDER_INV*), which has a mean of 0.174. Regarding digital and AI-related disclosures, the variable, *DIGITAL_T* has a mean of 0.459, indicating that a significant portion of firms in the sample disclose digital activities at some level, though the median and 25th percentile values are 0, suggesting that many firms have not engaged in digital activity disclosure yet.

Panel B presents the differences in means of investment inefficiency measures across groups with varying levels of digital disclosure (*DIGITAL_T*). The variable *DIGITAL_T* is categorized into four groups (0, 1, 2, 3), representing different levels of digital activities, with 0 indicating no digital disclosure and 3 indicating the highest level. The results indicate that firms with higher levels of digital disclosure (groups 1, 2, and 3) generally show lower means for the overall investment inefficiency measure (*XINV*) compared to firms with no digital disclosure (group 0). Specifically, firms in group 0 have a mean XINV of 0.232, which is higher than the means observed for group 1 (0.217). However, the mean slightly increases for group 2 (0.236) and group 3 (0.241), suggesting that the relationship between digital disclosure and investment efficiency might be most significant in the initial adopter group.

Panel C shows the yearly distribution of the number of times digital-related terms were mentioned in firms' 10-K filings across various categories, including Analytics, Automation, Artificial Intelligence (AI), Big Data, Cloud, Digitalization, and Machine Learning. The data span from 2010 to 2022, providing insights into how frequently firms report their engagement in these digital technologies in their annual financial disclosures. The results reveal a clear upward trend in the mentions of digital terms across most categories, reflecting the growing emphasis on digital transformation in business strategies. In 2010, the most frequently mentioned category was Analytics, with 568 mentions, followed by Cloud (468) and Digitization (346). Over the years, there has been a marked increase across all categories, with particularly strong growth observed in mentions of AI and Machine Learning in recent years.

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3.5 Correlation Analysis

As shown in Table 3, digital disclosure (*DIGITAL_T*) is not correlated with investment inefficiency when control variables are excluded. However, management technology expertise (*TECHMANAGER*) is negatively correlated with investment inefficiency measures (*XINV, OVER_INV, UNDER_INV*). Multivariate analyses are expected to provide more reliable insights into the association between digital disclosure and investment inefficiency. The correlations between investment efficiency measures and control variables align mostly with findings from prior research.

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3.6 Validation Analysis

To address a potential concern that digital disclosure may not necessarily reflect actual digital transformation activities, we use two additional variables: *AISHARE_T*, the fraction of AI employees within a firm (quantized score), and *PATENT*, a quantized score based on the number of patents filed by firms annually. The results presented in Table 4 provide strong evidence validating our main variable, *DIGITAL_T*, as a reliable measure of digital transformation within firms. Both variables, *AISHARE_T* and *PATENT,* are significantly and positively associated with digital disclosure. Panel A shows descriptive statistics of the two additional variables.

Column (1) of panel B highlights that *AISHARE_T* has a significant positive coefficient (0.196***), indicating that firms with higher digital disclosure scores are more likely to employ a higher proportion of AI-related staff. Similarly, Column (2) shows that the number of patents filed by firms is also positively associated with *DIGITAL_T* (0.064***), suggesting that digitally disclosing firms actively engage in innovation and technological advancements. Column (3) includes both *AISHARE_T* and *NUM_PATENT*, and the significant positive associations remain (0.158*** and 0.040**, respectively), providing further validation. These findings confirm that digital disclosure reflects tangible digital transformation efforts, not merely superficial communication. Firms are committing resources to their digital strategies by hiring AI employees and investing in patentable innovations, demonstrating that they are indeed walking the walk rather than just talking the talk.

Control variables in the models reveal additional insights. Firm size (*SIZE*) and market-to-book ratio (*MTB*) are positively associated with *DIGITAL_T*, indicating that larger firms and those with higher growth opportunities are more likely to disclose digital strategies. In contrast, tangibility and dividend payout have negative coefficients, suggesting that firms with more traditional, asset-heavy business models or a focus on shareholder payouts may disclose less about digital transformation. Other factors, such as an operating cycle, slack, and cash flow volatility, also show significant associations, emphasizing the importance of financial and operational characteristics in explaining digital disclosure patterns. Overall, the results highlight the robustness of *DIGITAL_T* as a measure of digital transformation and provide empirical evidence that firms with high digital disclosure scores are taking meaningful actions to implement their digital strategies.

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4. Main Regression Analysis

4.1 Baseline Regression

Table 5, Panel A presents the regression results examining the impact of digital activities on overall investment efficiency (*XINV*). The analysis is performed using two different samples: Full Sample and Entropy Balancing Sample. In column (1), the model includes industry fixed effects to control unobserved heterogeneity across industries. The results show that digital disclosure (*DIGITAL_T*) is negatively associated with investment inefficiency, with a coefficient of -0.012, significant at the 1% level. This suggests that firms with higher levels of digital disclosure tend to make more efficient investments, as evidenced by lower abnormal investment levels. Column (2) presents result using *TECHMANAGER* as the main independent variable. The coefficient for *TECHMANAGER* is -0.015, which is also significant at the 1% level, indicating that firms that have a top management team with technology expertise experience better investment efficiency. The impact of digital disclosure remains consistent, with a coefficient of -0.013, further confirming the beneficial role of digital activities and management tech expertise in enhancing investment efficiency.

Columns (3) and (4) apply the entropy balancing technique to address potential endogeneity concerns by balancing the covariates between the study and control groups. In these columns, we find that the negative associations between digital activities and investment inefficiency still hold (with the coefficients for *DIGITAL_T* and *TECHMANAGER* being -0.012 and -0.025, respectively, significant at the 1% level). These results suggest that the relationships observed in the first two columns are not driven by imbalances in observable firm characteristics. Regarding control variables, firm size (*SIZE*) shows a negative and significant relationship with investment inefficiency, indicating that larger firms tend to have more efficient investment practices. Measures of cash flow volatility (*SDCFO*) and sales volatility (*SDSALE*) are positively associated with investment inefficiency, suggesting that firms with higher volatility in cash flows and sales are more prone to inefficiency in their investment decisions. The volatility of past investment (*SDINVESTMENT*) also displays a positive association, although the magnitude varies across the models. Overall, the results across all specifications in Panel A demonstrate a consistent negative relationship between digital activities and investment inefficiency. This indicates that firms engaging more actively in digital activities and the top management team with more technology background are better positioned to make efficient investment decisions.

Panels B and C of Table 5 examine the impact of digital activities on overinvestment (*OVER_INV*) and underinvestment (*UNDER_INV*), respectively. In Panel B, the results consistently show that digital disclosure (*DIGITAL_T*) is negatively associated with overinvestment across all models, with a coefficient of -0.035, significant at the 1% level. This suggests that firms with higher levels of digital disclosure tend to engage in more disciplined capital allocation, reducing the likelihood of overinvesting in projects that do not yield optimal returns. In Panel C, the focus shifts to underinvestment, where digital disclosure (*DIGITAL_T*) again shows a significant negative association, with a coefficient of -0.005, suggesting that firms with greater digital engagement are better at avoiding underinvestment. This indicates that digital activities help firms more accurately assess and seize investment opportunities, thereby reducing the chances of underinvesting. Overall, these findings highlight the critical role of digital and AI activities in improving investment efficiency across different dimensions.

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4.2 Different Categories of Digital Technologies

Table 6 presents an analysis of the distinct impacts of various digital activities, categorized under digital disclosures, including analytics, automation, artificial intelligence (*AI*), big data, cloud computing, digitization, and machine learning, on investment efficiency. The variable *AIDISCLOSE,* representing overall AI-related activities, encompasses analytics, automation, AI, and machine learning. All variables (*AIDISCLOSE, ANALYTICS, AUTOMATION, ARTIFICIAL INTELLIGENCE, BIG DATA, CLOUD, DIGITIZATION, and MACHINE LEARNING*) are quantized scores based on the counts of digital terms coded as 0 for no disclosure, and 1, 2, and 3 representing the bottom, middle, and top tercile of disclosure. The counts of digital terms are taken from the business description section of each annual report.

The results show that analytics (*ANALYTICS*), cloud computing (*CLOUD*), and digitization (*DIGITIZATION*) significantly enhance investment efficiency, reflecting their widespread adoption and established integration into business operations. These technologies are likely to be more mature and directly contribute to improving resource allocation, streamlining processes, and supporting strategic decision-making. In contrast, big data (*BIG DATA*), artificial intelligence (*AI*), automation (*AUTOMATION*), and machine learning (*MACHINE LEARNING*) do not exhibit statistically significant effects when analyzed as separate categories. But when they are aggregated under the broader *AIDISCLOSE* variable, the results reveal a significant positive association between AI-related disclosures and investment efficiency. This finding suggests that while individual components of AI-related activities may not yet produce measurable standalone impacts, firms that disclose a comprehensive focus on AI tend to see overall improvements in investment efficiency. This could indicate that a holistic approach to AI adoption—where various components such as automation, machine learning, and analytics are integrated—creates synergistic effects that enhance firm performance. Firms that strategically commit to AI at an organizational level are likely better positioned to realize its full benefits, as opposed to piecemeal or isolated implementations.

These results highlight the complexity of digital transformation and the variability in effectiveness across different technologies. Firms must take a strategic and integrated approach to digital adoption, focusing on technologies that align with their operational needs and fostering complementarities between different digital tools. This underscores that achieving meaningful impacts on investment efficiency requires not only adopting digital technologies but also embedding them within a cohesive framework of organizational strategy.

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4.3 The Long-term Effect of Digital Technologies

Table 7 highlights the sustained effects of digital transformation on investment efficiency over a three-year horizon, offering valuable insights into the long-term influence of digital activities on firm investment behaviors. Column (1), which examines the full sample, shows that the coefficient for *DIGITAL_T* is negative and statistically significant (-0.010, p <0.001), indicating that an increase in digital activities is associated with a reduction in investment inefficiency over three years. This finding underscores the role of digital transformation in fostering better-aligned investment decisions and improving the overall efficiency of resource allocation within firms.

Column 2 focuses specifically on firms with digital disclosures, allowing us to observe changes in investment inefficiencies exclusively among firms that increased their digital disclosures and signaled greater engagement in digital activities. This analysis is restricted to firms with data available for three years prior to their initial digital disclosure and three years after, excluding the transition year (the year of the disclosure) to provide a clearer view of the changes surrounding the onset of digital transformation. The results reveal a similar pattern. The coefficient for *DIGITAL_T* is again negative and significant (-0.015**), suggesting that firms actively disclosing digital activities experience even greater improvements in investment efficiency compared to the broader sample. The results are consistent across both panels, demonstrating that digital integration contributes to meaningful and persistent improvements in investment efficiency. Untabulated results further confirm that these effects remain significant over a five-year window, indicating that digital transformation fosters sustained gains in reducing inefficiency. These results highlight the long-term value of digital activities in driving firm-level investment efficiency and provide empirical support for the strategic importance of continued digital integration.

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4.4 Cross-sectional Analyses

Table 8 presents a series of cross-sectional analyses examining the impact of digital activities on investment efficiency. Specifically, it examines the impact across technology vs. non-technology industries, large firms vs. small firms, distressed vs. non-distressed firms, and low vs. high financial reporting quality. The sample definitions for each category provide further clarity: technology-intensive and non-technology industries are classified following Chen and Srinivasan (2023). Small and large firms are determined based on the bottom and top 25th percentiles of firm size (*SIZE*) within the sample. Distressed firms are identified as those with negative net income or negative operating cash flow in year t, while non-distressed firms are classified otherwise. Firms with low financial reporting quality (*FRQ*) are defined as those with discretionary accruals (DD2002) in the top 25th percentile, while high FRQ firms fall into the bottom 25th percentile**.**

Columns (1) and (2) focus on the distinction between technology and non-technology industries. For both groups, the coefficient for digital disclosure (*DIGITAL_T*) is negative and statistically significant (-0.014*** for technology industries and -0.010*** for non-technology industries), indicating that digital activities reduce investment inefficiency in both contexts. This suggests that the positive effects of digital transformation extend beyond technology sectors, demonstrating that even firms in less tech-focused industries can achieve efficiency gains through digital initiatives. Columns (3) and (4) compare large and small firms. For large firms, the coefficient for *DIGITAL_T* is negative and highly significant (-0.011***), reflecting the strong ability of larger firms to leverage digital transformation to reduce investment inefficiency. In contrast, the coefficient is not significant for small firms, suggesting that resource constraints or less developed digital strategies may limit their ability to realize similar efficiency gains.

Columns (5) and (6) examine the role of digital activities in non-distressed versus distressed firms. The results show that *DIGITAL_T* has a significant negative coefficient for both groups (-0.008*** for non-distressed and -0.013*** for distressed firms). The stronger effect in distressed firms suggests that digital transformation may be particularly valuable in addressing operational challenges and improving resource efficiency in financially constrained environments. Columns (7) and (8) analyze the impact of digital activities on firms with varying levels of financial reporting quality (*FRQ*). The coefficient for *DIGITAL_T* is significant and negative for both low FRQ (-0.015**) and high FRQ (-0.013***) firms, suggesting that digital transformation reduces investment inefficiency regardless of financial reporting quality. Overall, the findings in Table 8 highlight the variability in the effectiveness of digital transformation based on firm-specific characteristics. While digital activities consistently improve investment efficiency in many contexts, their impact is influenced by factors such as firm size, financial health, etc. This underscores the importance of tailoring digital strategies to the unique needs and capabilities of each firm to maximize their potential benefits.

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4.5 The Role of Employees with AI Expertise

Table 9 examines the relationship between digital transformation, managerial technological expertise, and investment inefficiency, with a particular focus on the role of AI workforce allocation (a human-capital-based AI measure). Following Babina, Fedyk, He, and Hodson (2024), we measure a human-capital-based AI measure using firm-level job posting and resume data. *AISHARE_T* is a quantized variable that measures the proportion of AI workers to total employees in the firm. It is coded as 0 for no AI workers, 1 for yearly below tercile percentage of AI employees, 2 for yearly middle tercile percentage, and 3 for yearly top tercile percentage. This analysis captures the overall impact of firms' digital activities while controlling for the influence of AI-related labor capital, which reflects the proportion of AI-related employees at both top and lower organizational levels (*AISHARE_T* and *TECHMANAGER*). [3]

Across all three models, the coefficient for *DIGITAL_T* is negative and statistically significant (-0.008**), indicating that higher digital disclosures are associated with a reduction in investment inefficiency. This result underscores that digital transformation, as measured through disclosure, plays a critical role in improving resource allocation and aligning investment decisions more effectively. The role of managerial technological expertise, represented by *TECHMANAGER*, is introduced in Columns (2) and (3). Although the coefficients are negative (-0.014 and -0.011), they are not statistically significant, suggesting that having a technology-savvy manager may not independently reduce investment inefficiency when broader digital initiatives and workforce factors are accounted for. This finding highlights that the benefits of digital transformation are likely driven by organizational-level efforts rather than individual managerial influence alone.

More importantly, the allocation of employees with AI expertise (*AISHARE_T*) shows mixed results. While the coefficient is negative across all models, it is only marginally significant in Column (2) (-0.005*), suggesting that AI-related labor capital at both the top and lower levels of the organization may contribute to reducing investment inefficiency, but the effect is relatively

[3] We appreciate the data of employees with AI expertise provided by Babina, Fedyk, He, and Hodson (2024). Our AI employee data end by 2018 due to the data limitation.

modest. This implies that AI talent needs to be strategically integrated within a broader framework of digital initiatives to achieve meaningful impacts.

INSERT TABLE 9 HERE.

4.6 The Potential Channels: Institutional Ownership and Operational Efficiency

We explore two different potential channels through which firms with digital disclosure have a better level of investment efficiency. First, by reporting their digital activities, firms are sending a clear message to investors and other stakeholders about their commitment to tech innovation and forward-thinking strategies. These disclosures act as indicators of the firm's future potential and strategic direction. Investors interpret these signals as positive indicators of the firm's ability to adapt to technological advancements and maintain a competitive edge. As a result, firms that are proactive in their digital disclosures are more likely to attract informed and strategic investors who value innovation and long-term growth potential.

Table 10, column 1 examines the relationship between institutional ownership (*INSTOWN_PERC*)—calculated as the total shares held by institutional investors divided by the total number of shares outstanding—and digital transformation. The results show that digital activities (*DIGITAL_T*) have a positive and highly significant coefficient (0.073***), indicating that firms actively engaging in digital transformation tend to have higher levels of institutional ownership. This finding aligns with signaling theory, which posits that firms use specific activities or disclosures to signal their strategic intentions to the market. The variable for management technology expertise (*TECHMANAGER*) also has a positive and significant coefficient (0.141***), suggesting that the presence of management technology expertise boosts institutional interest. This reinforces the idea that not only are digital activities themselves important signals, but so is the leadership behind these initiatives. Firms with managers proficient in technology are likely seen as better positioned to implement and scale digital tools effectively, increasing investor confidence.

In column (2), we examine the second potential channel, operational efficiency. Operational efficiency captures how efficiently firms can convert the input resources into outputs, i.e., how much revenue can be generated using a given level of inputs (e.g., cost of inventory, general and administrative expenses, fixed assets, operating leases, research and development expenditure, intangible assets, etc.) (Demerjian, Lev, and McVay 2012). A firm's efficiency score measures its efficiency in generating revenues relative to its most efficient industry peer based upon Data Envelop Analysis (DEA).[4] The measure is obtained from Professor Peter Demerjian's website. A higher value of the efficiency score implies higher operational inefficiency.

Table 9, column 2 shows a positive and significant coefficient on *DIGITAL_T* (0.008***), reinforcing the idea that firms investing in digital activities can enhance operational efficiency by optimizing processes, improving decision-making, and better allocating resources. Our finding provides empirical support for the notion that digital transformation serves as a key strategic resource in line with the Resource-Based View (RBV) theory. According to RBV, firms achieve a competitive advantage by leveraging unique, valuable, and hard-to-imitate resources, such as digital capabilities and related human capital (Barney 1991; Wernerfelt 1984). In addition, the

[4] The efficiency score is estimated using one output and seven inputs. The output variable is Revenue, the primary source of earnings and cash flows generated from firms' operating activities. Inputs to generate revenue include net property, plant, and equipment; net operating leases; net research and development expenses; purchased goodwill; other intangible assets; cost of goods sold; and selling, general and administrative expenses. These inputs capture managers' choices in the revenue-generating process (Demerjian et al. 2012). The score has a value ranging from zero to one, with one (zero) representing the most (least) efficient firm. The higher the efficiency score, the more efficient firm operation is.

significant positive impact of *TECHMANAGER* (0.025***) on operational efficiency highlights the critical role of management's technological background in fully leveraging digital resources. Managers with technological expertise can more effectively implement digital strategies and foster a culture of continuous improvement, thereby turning digital investments into real operational gains.

INSERT TABLE 10 HERE.

5. Conclusion

The main purpose of this study is to investigate the economic value of both digital technologies and managerial technological experience in terms of investment efficiency. We document strong evidence that firms adopting digital technologies, including artificial intelligence (AI), consistently outperform their peers. Moreover, firms with a higher proportion of employees skilled in AI and top management teams with a strong technological background demonstrate greater investment efficiency. We further explore a variety of cross-sectional tests and find that the main results remain across both tech and non-tech industries, regardless of financial distress, and irrespective of financial reporting quality. However, the positive effects are evident primarily in large firms, but not in smaller firms. Finally, we find two channels, operational efficiency and institutional ownership, through which firms improve their investment efficiency after adopting digital technologies and hiring a tech-savvy management team and employees with AI expertise. This study is the first to provide direct evidence of the impact of tangible (i.e., digital technologies) and intangible assets (i.e., human-capital-based AI/tech expertise) on firm investment efficiency.

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Table 1. Sample Selection

Sample Selection Procedure	
All firm-year observations in COMPUSTAT and DIRECTEDGAR from the year 2010-2022	108,318
Less	
Observation with insufficient data to obtain investment efficiency	(52,246)
Observations with missing values of control variables	(16,288)

Observations with missing industries	(289)
The final sample used in the main tests	39,495

Table 2. Descriptive Statistics

Panel A. Descriptive Statistics (Full Sample)

	N	Mean	Sd.	25th	50th	75th
XINV	39,495	0.232	0.445	0.053	0.124	0.245
UNDER_XINV	26,353	0.174	0.189	0.060	0.126	0.229
OVER_XINV	13,142	0.349	0.710	0.041	0.118	0.314
DIGITAL_T	39,495	0.459	0.935	0.000	0.000	0.000
TECHMANAGER	39,495	0.034	0.182	0.000	0.000	0.000
SIZE	39,495	5.981	2.492	4.314	6.091	7.731
MTB	39,495	3.000	7.379	0.940	1.905	3.795
ZSCORE	39,495	-0.093	5.826	0.098	0.895	1.609
TANGIBILITY	39,495	0.260	0.258	0.060	0.155	0.398
LEV	39,495	0.289	0.420	0.036	0.202	0.384
DIV	39,495	0.316	0.465	0.000	0.000	1.000
OPERATINGCYCLE	39,495	4.647	0.969	4.139	4.688	5.200
SLACK	39,495	5.073	14.899	0.153	0.715	2.908
CFOSALE	39,495	-1.086	6.189	-0.029	0.080	0.194
LOSS	39,495	0.428	0.495	0.000	0.000	1.000
FIRMAGE	39,495	2.790	0.714	2.197	2.833	3.296
SDCFO	39,495	0.115	0.231	0.028	0.053	0.107
SDSALE	39,495	0.190	0.223	0.058	0.116	0.230
SDINVESTMENT	39,495	0.128	0.201	0.021	0.055	0.137

Panel B: Differences in Means between Different Digital Disclosure/ AI Employee Percentage Groups

DIGITAL_T	XINV	UNDER_INV	OVER_INV
0	0.232	0.174	0.356
1	0.217	0.164	0.314
2	0.236	0.178	0.329
3	0.241	0.183	0.334
Total	0.232	0.174	0.349

Panel C. Yearly Distribution of Digital Disclosure

Year	Analytics	Automation	Artificial Intelligence	Big Data	Cloud	Digitization	Machine Learning
2010	568	22	32	60	468	346	227
2011	746	31	23	106	687	319	197

2012	877	38	19	129	829	364	152
2013	1,113	27	34	173	1,015	348	270
2014	1,351	40	40	220	1,324	417	307
2015	1,634	48	54	245	1,475	425	377
2016	1,876	33	110	266	1,445	490	478
2017	1,841	34	228	266	1,412	497	603
2018	1,886	38	327	267	1,388	521	764
2019	2,062	38	411	310	1,411	552	806
2020	2,242	40	551	325	1,448	692	932
2021	2,206	48	642	452	1,460	793	1,055
2022	3,133	71	864	696	1,692	1,019	1,284
Total	21,535	508	3,335	3,515	16,054	6,783	7,452

Note: Panel A provides descriptive statistics for variables used in the main equation. Panel B provides the difference in Digital Disclosure and AI Employee percentage group. Panel C reports the yearly distribution of all keywords mentioned in each subgroup of digital disclosure: Analytics, Automation, Artificial Intelligence, Big Data, Cloud, Digitization, and Machine Learning.

Table 3. Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1.XINV	1																		
2.UNDER_XINV	**1.00**	1																	
3. OVER_XINV	**1.00**	0	1																
4. DIGITAL_T	0.00	0.01	-0.01	1															
5.TECHMANAGER	**-0.03**	**-0.04**	**-0.04**	**0.15**	1														
6.SIZE	**-0.22**	**-0.33**	**-0.25**	**0.07**	**0.11**	1													
7.MTB	**0.02**	**0.01**	0.02	**0.11**	**0.03**	**0.07**	1												
8.ZSCORE	**-0.13**	**-0.27**	**-0.12**	**0.01**	**0.05**	**0.42**	**0.10**	1											
9.TANGIBILITY	**-0.13**	**-0.18**	**-0.14**	**-0.24**	**-0.04**	**0.19**	**-0.10**	**0.03**	1										
10.LEV	**0.02**	**0.12**	-0.00	**-0.02**	**-0.01**	**-0.15**	**-0.12**	**-0.57**	**0.13**	1									
11.DIV	**-0.15**	**-0.20**	**-0.17**	**-0.09**	**0.03**	**0.46**	0.00	**0.18**	**0.13**	**-0.06**	1								
12.OPERATINGCYCLE	**0.05**	**0.05**	**0.07**	**-0.09**	**-0.04**	**-0.07**	0.00	**-0.04**	**-0.21**	**-0.07**	**-0.05**	1							
13.SLACK	**0.17**	**0.23**	**0.19**	0.00	**-0.03**	**-0.22**	**0.03**	**-0.10**	**-0.30**	**-0.07**	**-0.13**	**0.02**	1						
14.CFOSALE	**-0.14**	**-0.19**	**-0.18**	**0.05**	**0.04**	**0.21**	0.00	**0.25**	**0.08**	**-0.06**	**0.14**	**-0.18**	**-0.19**	1					
15.LOSS	**0.13**	**0.21**	**0.15**	**0.03**	**-0.08**	**-0.41**	**-0.03**	**-0.31**	**-0.03**	**0.16**	**-0.41**	**0.08**	**0.13**	**-0.23**	1				
16.FIRMAGE	**-0.16**	**-0.20**	**-0.16**	**-0.08**	**0.07**	**0.26**	**-0.03**	**0.13**	**0.05**	**-0.05**	**0.38**	**0.03**	**-0.12**	**0.14**	**-0.29**	1			
17.SDCFO	**0.20**	**0.31**	**0.22**	**-0.02**	**-0.05**	**-0.42**	**-0.03**	**-0.49**	**-0.14**	**0.25**	**-0.21**	**0.03**	**0.20**	**-0.26**	**0.26**	**-0.19**	1		
18.SDSALE	**0.14**	**0.17**	**0.15**	**0.03**	**-0.03**	**-0.36**	**-0.02**	**-0.15**	**-0.17**	**0.12**	**-0.19**	**-0.11**	**0.11**	**0.05**	**0.14**	**-0.14**	**0.35**	1	
19.SDINVESTMENT	**0.12**	**0.20**	**0.11**	**0.01**	**-0.04**	**-0.16**	-0.01	**-0.20**	-0.00	**0.11**	**-0.19**	**-0.01**	**0.10**	**-0.19**	**0.21**	**-0.25**	**0.36**	**0.15**	1

Note: Bold coefficients indicate significance at the 5% level. This table provides correlation among variables in the main equation.

Table 4. Validation Test

Panel A. Descriptive Statistics

		Mean	Sd.	25th	50th	75th
AISHARE_T	27,832	0.339	0.846	0.000	0.000	0.000
PATENT	9,377	1.975	0.849	1.000	2.000	3.000

Panel B. Measures of Digital Transformation, AI workers, and Innovation.

VARIABLES	(1) xinv	(2) xinv	(3) xinv
AISHARE_T	0.196***		0.158***
	(0.008)		(0.011)
PATENT		0.064***	0.040***
		(0.012)	(0.012)
SIZE	0.019***	0.027***	0.004
	(0.002)	(0.006)	(0.006)
MTB	0.003***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)
ZSCORE	-0.003***	-0.001	0.002
	(0.001)	(0.002)	(0.002)
TANGIBILITY	-0.398***	-0.719***	-0.610***
	(0.020)	(0.058)	(0.057)
LEV	-0.005	-0.039	-0.012
	(0.013)	(0.027)	(0.027)
DIV	-0.115***	-0.171***	-0.166***
	(0.011)	(0.022)	(0.022)
OPERATINGCYCLE	-0.052***	-0.030***	-0.024**
	(0.005)	(0.010)	(0.010)
SLACK	-0.002***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)
CFOSALE	0.002***	0.001	0.001
	(0.001)	(0.001)	(0.001)
LOSS	0.055***	0.035	0.036*
	(0.010)	(0.021)	(0.021)
FIRMAGE	-0.041***	-0.071***	-0.065***
	(0.007)	(0.014)	(0.014)
SDCFO	-0.131***	-0.208***	-0.229***
	(0.023)	(0.048)	(0.047)
SDSALE	0.031	0.128**	0.126**
	(0.025)	(0.059)	(0.058)
SDINVESTMENT	0.115***	0.151***	0.147***
	(0.023)	(0.052)	(0.051)
Constant	0.661***	0.740***	0.774***
	(0.037)	(0.078)	(0.076)
Observations	27,832	9,377	9,345
R-squared	0.319	0.384	0.406
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Note: Panel A provides descriptive statistics for variables used in validation tests: AISHARE_T and NUM_PATENT. All variable definitions are provided in Appendix A. Panel B provides OLS regression results of AISHARE_T and PATENT on DIGITAL_T. Clustered standard errors corrected for heteroscedasticity are in parentheses. *, **< *** indicate significance at 0.1, 0.05, and 0.01 levels, respectively, using two-tails tests.

Table 5. Investment Efficiency and Measures of Digital Transformation

Panel A. Investment Efficiency

	Full Sample		EB Sample	
	(1)	(2)	(3)	(4)
VARIABLES	XINV	XINV	XINV	XINV
DIGITAL_T	-0.012***		-0.012***	
	(0.003)		(0.003)	
TECHMANAGER		-0.015**		-0.025***
		(0.007)		(0.007)
SIZE	-0.018***	-0.018***	-0.017***	-0.017***
	(0.001)	(0.001)	(0.002)	(0.002)
MTB	0.001**	0.001**	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
ZSCORE	0.000	0.000	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
TANGIBILITY	-0.060***	-0.054***	-0.111***	-0.116***
	(0.014)	(0.013)	(0.020)	(0.020)
LEV	-0.009	-0.009	-0.034***	-0.034***
	(0.009)	(0.009)	(0.011)	(0.011)
DIV	-0.006	-0.004	0.000	-0.001
	(0.004)	(0.004)	(0.005)	(0.005)
OPERATINGCYCLE	0.017***	0.018***	0.005	0.004
	(0.004)	(0.004)	(0.005)	(0.005)
SLACK	0.002***	0.002***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
CFOSALE	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
LOSS	-0.005	-0.007	0.002	0.001
	(0.005)	(0.005)	(0.006)	(0.006)
FIRMAGE	-0.037***	-0.036***	-0.042***	-0.041***
	(0.004)	(0.004)	(0.005)	(0.005)
SDCFO	0.142***	0.143***	0.129***	0.130***
	(0.023)	(0.023)	(0.031)	(0.031)
SDSALE	0.121***	0.121***	0.121***	0.121***
	(0.018)	(0.018)	(0.022)	(0.022)
SDINVESTMENT	0.039**	0.038**	0.007	0.005
	(0.016)	(0.016)	(0.018)	(0.018)
Constant	0.328***	0.321***	0.422***	0.414***
	(0.026)	(0.026)	(0.034)	(0.033)
Observations	39,495	39,495	39,495	39,495
R-squared	0.111	0.110	0.093	0.092
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Panel B. Overinvestment

	(1)	(2)	(3)	(4)
	Full Sample		EB Sample	
VARIABLES	OVER_INV	OVER_INV	OVER_INV	OVER_INV
DIGITAL_T	-0.035***		-0.035***	
	(0.007)		(0.008)	
TECHMANAGER		-0.045***		-0.060***
		(0.018)		(0.017)
SIZE	-0.041***	-0.043***	-0.037***	-0.036***
	(0.004)	(0.004)	(0.005)	(0.005)
MTB	0.001	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
ZSCORE	0.005**	0.006**	-0.003	-0.003
	(0.002)	(0.002)	(0.003)	(0.003)
TANGIBILITY	-0.064	-0.046	-0.155***	-0.172***
	(0.039)	(0.039)	(0.053)	(0.053)
LEV	0.011	0.010	-0.065*	-0.066*
	(0.028)	(0.028)	(0.035)	(0.035)
DIV	-0.006	-0.002	0.011	0.006
	(0.012)	(0.012)	(0.014)	(0.015)
OPERATINGCYCLE	0.041***	0.043***	0.008	0.005
	(0.012)	(0.012)	(0.013)	(0.013)
SLACK	0.003***	0.003***	0.002**	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
CFOSALE	-0.009***	-0.009***	-0.009**	-0.008**
	(0.002)	(0.002)	(0.004)	(0.004)
LOSS	-0.008	-0.013	0.004	-0.000
	(0.014)	(0.014)	(0.016)	(0.016)
FIRMAGE	-0.061***	-0.059***	-0.065***	-0.062***
	(0.010)	(0.010)	(0.012)	(0.012)
SDCFO	0.267***	0.271***	0.229***	0.233***
	(0.062)	(0.062)	(0.086)	(0.087)
SDSALE	0.186***	0.185***	0.176***	0.177***
	(0.045)	(0.045)	(0.050)	(0.050)
SDINVESTMENT	0.009	0.006	-0.044	-0.048
	(0.040)	(0.041)	(0.044)	(0.044)
Constant	0.506***	0.482***	0.713***	0.684***
	(0.073)	(0.072)	(0.087)	(0.086)
Observations	13,142	13,142	13,142	13,142
R-squared	0.143	0.141	0.114	0.111
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Panel C. Underinvestment

	(1)	(3)	(2)	(4)
	Full Sample		EB Sample	
VARIABLES	UNDER_INV	UNDER_INV	UNDER_INV	UNDER_INV
DIGITAL_T	-0.005***		-0.005***	
	(0.001)		(0.001)	
TECHMANAGER		-0.003		-0.008*
		(0.004)		(0.004)
SIZE	-0.010***	-0.011***	-0.010***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
MTB	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
ZSCORE	-0.002***	-0.002***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
TANGIBILITY	0.002	0.004	-0.012	-0.015
	(0.007)	(0.007)	(0.012)	(0.012)
LEV	0.009*	0.009*	0.003	0.003
	(0.005)	(0.005)	(0.006)	(0.006)
DIV	0.007***	0.008***	0.009***	0.009***
	(0.002)	(0.002)	(0.003)	(0.003)
OPERATINGCYCLE	0.006***	0.006***	0.004*	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
SLACK	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
CFOSALE	-0.001***	-0.001***	-0.001*	-0.001*
	(0.000)	(0.000)	(0.001)	(0.001)
LOSS	0.006**	0.005**	0.008**	0.008**
	(0.002)	(0.002)	(0.003)	(0.003)
FIRMAGE	-0.010***	-0.010***	-0.012***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)
SDCFO	0.066***	0.067***	0.071***	0.072***
	(0.013)	(0.013)	(0.017)	(0.017)
SDSALE	0.047***	0.047***	0.049***	0.049***
	(0.009)	(0.009)	(0.012)	(0.012)
SDINVESTMENT	0.054***	0.053***	0.034***	0.033***
	(0.008)	(0.008)	(0.010)	(0.010)
Constant	0.198***	0.195***	0.232***	0.228***
	(0.012)	(0.012)	(0.015)	(0.015)
Observations	26,353	26,353	26,353	26,353
R-squared	0.258	0.257	0.221	0.221
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Note: This table presents the OLS regression results of investment efficiency measures on **DIGITAL_T** and **TECHMANAGER**. All variable definitions are provided in **Appendix A**. Panels A, B, and C report results for investment efficiency, overinvestment, and underinvestment, respectively. Standard errors are clustered at the firm-year level and corrected for heteroscedasticity (shown in parentheses). *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively, using two-tailed tests.

Table 6. Investment Efficiency and Measures of Digital Transformation/AI- Each Categories

VARIABLES	(1) AIDISCLOSE	(2) ANALYTICS	(3) AUTOMATION	(4) ARTIFICIAL INTELLIGENCE	(5) BIG DATA	(6) CLOUD	(7) DIGITIZATION	(8) MACHINE LEARNING
AIDISCLOSE	-0.011*** (0.003)							
ANALYTICS		-0.016*** (0.003)						
AUTOMATION			0.010 (0.016)					
ARTIFICIAL INTELLIGENCE				0.000 (0.007)				
BIG DATA					-0.006 (0.007)			
CLOUD						-0.011*** (0.004)		
DIGITIZATION							-0.013*** (0.004)	
MACHINE LEARNING								-0.001 (0.006)
Controls	Included	Included	Included	Included	Included	Included	Included	Included
Observations	37,293	39,495	39,495	39,495	39,495	39,495	39,495	37,293
R-squared	0.111	0.111	0.110	0.110	0.110	0.110	0.110	0.110
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the regression results of investment efficiency on various categories of digital transformation and AI-related activities, including AIDISCLOSE, ANALYTICS, AUTOMATION, ARTIFICIAL INTELLIGENCE, BIG DATA, CLOUD, DIGITIZATION, and MACHINE LEARNING. Each variable is a quantized score based on counts of digital terms coded as 0 for no disclosure, 1 for bottom tercile disclosure, 2 for middle tercile disclosure, and 3 for top tercile disclosure. Counts of digital terms are taken from the business description section of the 10-K, and digital terms referred to in each variable are listed in Appendix B. Year and industry fixed effects are included in all regressions. Standard errors, corrected for heteroscedasticity, are reported in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively, using two-tailed tests.

Table 7. Three-Years Impact of Digital Transformation on Investment Efficiency

	(1)	(2)
	Full Sample	Firms with Digital Disclosure Only
VARIABLES	XINV	XINV
DIGITAL_T	-0.010***	-0.015**
	(0.003)	(0.007)
SIZE	-0.027***	-0.021***
	(0.001)	(0.004)
MTB	0.002***	0.001
	(0.000)	(0.001)
ZSCORE	-0.006***	-0.001
	(0.001)	(0.002)
TANGIBILITY	-0.152***	-0.085**
	(0.013)	(0.040)
LEV	0.016	0.014
	(0.010)	(0.034)
DIV	0.005	-0.006
	(0.004)	(0.013)
OPERATINGCYCLE	0.010***	0.033***
	(0.004)	(0.011)
SLACK	0.006***	0.002**
	(0.000)	(0.001)
CFOSALE	-0.001**	-0.003
	(0.001)	(0.003)
LOSS	0.003	0.019
	(0.005)	(0.014)
FIRMAGE	-0.024***	-0.038***
	(0.003)	(0.010)
SDCFO	0.098***	0.083*
	(0.020)	(0.050)
SDSALE	0.075***	0.170***
	(0.016)	(0.047)
SDINVESTMENT	0.017	-0.011
	(0.014)	(0.040)
Constant	0.451***	0.289***
	(0.023)	(0.064)
Observations	24,039	4,696
R-squared	0.352	0.127
Year FE	Yes	Yes
Industry FE	Yes	Yes

Note: This table presents the regression results of investment efficiency (XINV) on DIGITAL_T for two samples: column (1) shows results for the full sample, while column (2) shows results for firms with digital disclosures only. XINV represents the average investment efficiency over the three years following digital transformation adoption. DIGITAL_T represents a quantized score of digital disclosure, where 0 indicates no disclosure, and 1, 2, and 3 represent increasing levels of disclosure. All other variable definitions are provided in Appendix A. Year and industry fixed effects are included in all regressions. Standard errors, corrected for heteroscedasticity, are reported in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively, using two-tailed tests

Table 8. Cross Sectional Tests

	(1) TECH INDUSTRIES	(2) NONTECH INDUSTRIES	(3) LARGE FIRMS	(4) SMALL FIRMS	(5) NON - DISTRESSED FIRMS	(6) DISTRESSED FIRMS	(7) LOW FRQ	(8) HIGH FRQ
DIGITAL_T	-0.014***	-0.010***	-0.011***	0.003	-0.008***	-0.013***	-0.015**	-0.013***
	(0.004)	(0.004)	(0.003)	(0.010)	(0.003)	(0.005)	(0.006)	(0.004)
SIZE	-0.016***	-0.019***	-0.005**	-0.028***	-0.017***	-0.019***	-0.022***	-0.016***
	(0.003)	(0.001)	(0.002)	(0.008)	(0.002)	(0.002)	(0.003)	(0.003)
MTB	0.000	0.001**	0.001*	-0.000	0.000	0.001	0.001	0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ZSCORE	-0.001	0.001	-0.020***	0.001	0.001	0.000	0.001	-0.011**
	(0.002)	(0.001)	(0.004)	(0.001)	(0.003)	(0.001)	(0.001)	(0.004)
TANGIBILITY	-0.015	-0.063***	-0.039**	-0.053	-0.133***	-0.032	-0.027	-0.085***
	(0.034)	(0.015)	(0.018)	(0.039)	(0.018)	(0.021)	(0.030)	(0.026)
LEV	-0.017	-0.006	-0.010	-0.008	0.006	-0.012	-0.013	-0.014
	(0.021)	(0.009)	(0.013)	(0.013)	(0.013)	(0.010)	(0.011)	(0.039)
DIV	-0.014	-0.003	-0.005	-0.026	-0.001	-0.022***	-0.010	-0.002
	(0.009)	(0.005)	(0.005)	(0.021)	(0.005)	(0.008)	(0.012)	(0.007)
OPERATINGCYCLE	0.009	0.020***	-0.003	0.017**	0.011*	0.021***	0.029***	-0.007
	(0.013)	(0.004)	(0.008)	(0.008)	(0.006)	(0.005)	(0.006)	(0.009)
SLACK	0.001	0.002***	0.002	0.001*	0.001**	0.002***	0.001***	0.002**
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
CFOSALE	-0.009***	-0.004***	-0.014	-0.003***	0.259***	-0.004***	-0.003***	-0.008*
	(0.003)	(0.001)	(0.024)	(0.001)	(0.028)	(0.001)	(0.001)	(0.004)
LOSS	-0.005	-0.007	-0.005	-0.024		-0.048***	-0.024**	-0.018**
	(0.011)	(0.006)	(0.007)	(0.017)		(0.017)	(0.012)	(0.009)
FIRMAGE	-0.056***	-0.030***	-0.013***	-0.046***	-0.017***	-0.044***	-0.046***	-0.026***
	(0.009)	(0.004)	(0.003)	(0.011)	(0.004)	(0.006)	(0.008)	(0.007)
SDCFO	0.082**	0.164***	0.340***	0.103***	0.224***	0.120***	0.105***	0.364***
	(0.041)	(0.027)	(0.130)	(0.028)	(0.067)	(0.025)	(0.027)	(0.109)
SDSALE	0.161***	0.112***	0.090***	0.143***	0.140***	0.126***	0.120***	-0.004
	(0.037)	(0.021)	(0.032)	(0.032)	(0.030)	(0.023)	(0.027)	(0.036)
SDINVESTMENT	-0.030	0.055***	0.005	0.057	-0.023	0.051**	0.052*	0.024
	(0.036)	(0.018)	(0.024)	(0.040)	(0.020)	(0.022)	(0.029)	(0.036)
Constant	0.452***	0.290***	0.247***	0.420***	0.242***	0.385***	0.358***	0.406***
	(0.069)	(0.028)	(0.058)	(0.060)	(0.037)	(0.040)	(0.043)	(0.059)
Observations	9,181	30,314	8,089	8,297	21,085	18,410	13,039	8,819
R-squared	0.084	0.121	0.117	0.057	0.128	0.090	0.083	0.136
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the regression results of investment efficiency (XINV) on DIGITAL_T across different subsamples. Column (1) includes tech industry firms, column (2) includes non-tech industry firms, columns (3) and (4) include large and small firms respectively, columns (5) and (6) compare non-distressed and distressed firms, and columns (7) and (8) compare firms with low and high financial reporting quality (FRQ). DIGITAL_T represents a quantized score of digital disclosure, where 0 indicates no disclosure, and 1, 2, and 3 represent increasing levels of disclosure. Tech and non-tech industries are defined following Chen and Srinivasan (2023). Small (large) firms are defined as the bottom (top) 25th percentile of the SIZE variable. Low (high) FRQ is defined as the top (bottom) 25th percentile of Discretionary Accruals (DD2002). Distressed firms are defined as those with negative net income or negative operating cash flow in year t. All other variable definitions are provided in Appendix A. Year and industry fixed effects are included in all regressions. Standard errors, corrected for heteroscedasticity, are reported in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively, using two-tailed tests.

Table 9. The Impact of AI-Employee Expertise

VARIABLES	(1) XINV	(2) XINV	(3) XINV
DIGITAL_T	-0.008**		-0.008**
	(0.004)		(0.004)
TECHMANAGER		-0.014	-0.011
		(0.009)	(0.009)
AISHARE_T	-0.004	-0.005*	-0.004
	(0.003)	(0.003)	(0.003)
Controls	Included	Included	Included
Observations	27,832	27,832	27,832
R-squared	0.122	0.122	0.122
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Note: This table presents the regression results of investment efficiency (XINV) on DIGITAL_T, TECHMANAGER, and AISHARE_T. Column (1) includes only DIGITAL_T and AISHARE_T, column (2) includes TECHMANAGER and AISHARE_T, and column (3) includes all three variables. DIGITAL_T represents a quantized score of digital disclosure, where 0 indicates no disclosure, and 1, 2, and 3 represent increasing levels of disclosure. TECHMANAGER is an indicator variable representing firms with managers who have technology-related expertise. AISHARE_T is a quantized variable measuring the proportion of AI-related employees to total employees, where 0 indicates no AI employees, and 1, 2, and 3 represent increasing levels of AI employee share. All other variable definitions are provided in Appendix A. Year and industry fixed effects are included in all regressions. Standard errors, corrected for heteroscedasticity, are reported in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively, using two-tailed tests.

Table 10. Institutional Ownership, Operational Efficiency, and Digital Transformation

VARIABLES	(1) INSTOWN_PERC	(2) OPERATIONAL EFFICIENCY
DIGITAL_T	0.073***	0.008***
	(0.002)	(0.001)
TECHMANAGER	0.141***	0.025***
	(0.014)	(0.006)
Controls	Included	Included
Observations	29,174	35,269
R-squared	0.259	0.453
Year FE	Yes	Yes
Industry FE	Yes	Yes

Note: This table presents the regression results on institutional ownership and operational efficiency. Column (1) reports the results for INSTOWN_PERC, which represents the percentage of shares owned by institutional investors, and column (2) reports the results for operational efficiency, a DEA-based measure following Demerjian (2012). The score is percentile ranked within industries. DIGITAL_T represents a quantized score of digital disclosure, where 0 indicates no disclosure, and 1, 2, and 3 represent increasing levels of disclosure. TECHMANAGER is an indicator variable representing firms with managers who have technology-related expertise. All other variable definitions are provided in Appendix A. Year and industry fixed effects are included in all regressions. Standard errors, corrected for heteroscedasticity, are reported in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively, using two-tailed tests.

Appendix A. Variable Definition

Variable	Definition
XINV	Abnormal investments are defined as the absolute magnitude of the residual captured from the following regression model, regressing total investment on Tobin's Q (Q), sales growth (GROWTH), operating cash flow (CFO), and one-year lagged investment (INV). The overall level of investment (INV) is calculated as the sum of research and development expenditure, capital expenditure, and acquisition expenditure, less the sale of property, plant, and equipment, and then scaled by lagged total assets. Tobin's Q equals the market value minus book value of shareholders' equity plus total assets divided by total assets. GROWTH equals the percentage change in sales from year t-2 to year t-1. CFO equals operating cash flows scaled by total assets.
OVER_INV	Over-investment, defined as the absolute magnitude of the positive residual value captured from the abnormal investment model.
UNDER_INV	Under-investment, defined as the absolute magnitude of the negative residual value captured from the abnormal investment model.
DIGITAL_T	Digital disclosure quantized score: 0 for no digital disclosure, 1 for yearly below tercile disclosure, 2 for yearly middle tercile disclosure, 3 for yearly top tercile disclosure.
AIDISCLOSE_T	AI disclosure quantized score: 0 for no AI disclosure, 1 for yearly below tercile, 2 for yearly middle tercile, 3 for yearly top tercile.
AISHARE_T	AI share quantized score based on AI-related job postings: 0 for no AI employee, 1 for yearly below tercile percentage of AI employees, 2 for yearly middle tercile percentage, 3 for yearly top tercile percentage.
PATENT	Quantized score based on the number of patents filed by firm i in year t: 0 for no number of patents, 1 for yearly below tercile, 2 for yearly middle tercile, 3 for yearly top tercile.
SIZE	Natural logarithm of total assets.
MTB	The ratio of market value to book value of common equity
ZSCORE	ZSCORE = 3.3 * Pretax Income + Sales + 0.25 * Retained earnings + 0.5* (Current Assets - Current Liabilities)/Book Value of Assets. This is a revised version of Z-score following Gramham, Li, and Qiu (2008).
TANGIBILITY	The ratio of property, plant, and equipment to total assets.

LEVERAGE	The ratio of total liabilities to total assets.
DIV	Indicator variable, 1 if the firm pays DIVIDENDs, 0 otherwise.
SLACK	The ratio of cash to property, plant, and equipment
CFOSALE	Cash flow from operations scaled by lagged sales.
OPERATING CYCLE	The length of the operating cycle, measured as log ((accounts receivable/sales) + (inventory/cost of goods sold)) * 360.
LOSS	Indicator variable, 1 if the firm experiences a negative income, 0 otherwise.
FIRMAGE	The natural logarithm of 1 plus the number of years since the firm first appeared in COMPUSTAT
SDCFO	Standard deviation of cash flow from operations scaled by total assets over the years from t-4 to t.
SDSALE	Standard deviation of sales scaled by total assets over the past five years.
SDINVESTMENT	Standard deviation of investment scaled by total assets over the past five years.
TOBINQ	Tobin's Q, calculated as (market value of equity + book value of assets - book value of equity - deferred tax assets)/total assets.
INSTOWN_PERC	Total shares of Inst. Ownership divided by the total number of Shares Outstanding
OPERATIONAL EFFICIENCY	Firm efficiency percentile ranked score (ranging from 0 to 1) for fiscal year t+1 based on the Data Envelopment Analysis (DEA). It is estimated using one output of revenue (SALE) and seven inputs: net PP&E, cost of goods sold, selling, general and administrative expense, capitalized operating leases, capitalized R&D, purchased goodwill and other intangibles. Data is obtained from Demerjian's website.

Appendix B. Digital Terms in 10-Ks

Analytics: • Analytics • Proprietary Algorithm • Virtual Reality	**Automation:** • Automation • Autonomous Technology
Artificial Intelligence: • Artificial Intelligence • Intelligence • Neural Network • Virtual Assistant • Cognitive Computing	**Big Data:** • Big Data • Data Science • Data Mining • Data Lake • DevOps • Digital Twin • Edge Computing
Cloud: • Cloud Platforms • Cloud Enablement • Virtual Machines	**Digitization:** • Digitization • Digital Strategy • Digital Marketing • Business Intelligence
Machine Learning • Biometric • Deep Learning • Machine Learning • Natural Language Processing (NLP) • Image Recognition • Speech Recognition	