

The Effect of AI Adoption on Earnings Quality: Evidence from S&P 500 Technology FirmsAuthor: Julien Merheb¹*Affiliation:*

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Abstract:

This study examines whether the extent to which firms discuss Artificial Intelligence (AI) in their annual reports is associated with the quality of their reported earnings. Traditional financial reporting depends heavily on managerial judgment, while previous research has shown that the language used in corporate filings can contain information beyond the financial statements themselves (Loughran & McDonald, 2011). However, relatively little empirical research has directly examined whether AI-related disclosure is connected to earnings quality, particularly during the period following the rapid rise of generative AI. To investigate this relationship, I constructed a balanced panel of S&P 500 technology firms covering the study period. AI disclosure intensity was measured through keyword-frequency analysis of Form 10-K filings, while earnings quality was proxied by the absolute value of discretionary accruals estimated using the Modified Jones Model (Dechow et al., 1995). The analysis controls for firm size, leverage, profitability, growth, and year effects. The results indicate a statistically significant negative association between AI disclosure intensity and absolute discretionary accruals. Because lower absolute discretionary accruals are interpreted as higher earnings quality, the findings suggest that firms with more extensive AI-related disclosure tend to report higher-quality earnings. These results contribute to the growing literature on textual analysis of corporate disclosures and provide potentially useful information for investors, auditors, and regulators evaluating AI-related corporate communication.

Keywords:

Artificial Intelligence, Earnings Quality, Discretionary Accruals, Textual Analysis, Financial Reporting

Introduction:

Financial reporting has retained much of the same basic structure for decades. Companies close their books periodically, rely on managerial estimates, and undergo audits that generally examine transactions after they have been recorded. This approach was developed for a business environment that was slower and less digitally connected than the one companies operate in today. Transaction volumes have expanded, disclosure requirements have become more demanding, and the consequences of inaccurate financial reporting can be substantial.

At the same time, Artificial Intelligence has quickly become one of the most prominent themes in corporate communication. Beginning during the study period and accelerating considerably following the public release of ChatGPT, companies have increasingly discussed AI initiatives, machine-learning capabilities, automation, and algorithmic decision-making in their annual reports. For technology firms in particular, AI has moved beyond being a specialized research topic and has become an important part of corporate strategy and communication with investors, analysts, and other stakeholders.

This development raises an important question about the credibility of corporate reporting.

Earnings quality refers broadly to the extent to which reported earnings faithfully represent a firm's underlying economic performance rather than being substantially affected by managerial discretion or accounting distortions. When earnings quality is high, financial information can support more effective capital allocation. When it deteriorates, information asymmetry can increase, the cost of capital may rise, and confidence in financial reporting can weaken (Dechow & Dichev, 2002).

The combination of these two developments leads to the central question of this study:

Is the intensity of a firm's AI disclosure in its annual report associated with the quality of its reported earnings?

There are at least two possible explanations for such a relationship.

The first is the signaling channel. Firms that genuinely invest in AI may also have stronger technological infrastructure, internal controls, data systems, and reporting processes. Under this interpretation, greater AI disclosure could be associated with higher earnings quality.

The second is the impression-management channel. Firms could use AI-related terminology primarily to attract attention or create a technologically advanced image, even when their underlying fundamentals or reporting practices are weaker. In this case, extensive AI disclosure could be associated with lower earnings quality, consistent with the idea of "cheap talk" instead of revolutionizing audit practices (Sawaya et al., 2026).

Which of these explanations better describes the relationship is ultimately an empirical question.

Accordingly, this study has four main objectives:

- Measure AI disclosure intensity using keyword-frequency analysis of Form 10-K filings.
- Measure earnings quality using discretionary accruals estimated through the Modified Jones Model.
- Test the relationship between AI disclosure and earnings quality using regression analysis.
- Discuss the implications of the findings for investors, auditors, and regulators interpreting AI-related corporate disclosures.

Literature Review:

The determinants and measurement of earnings quality have been central topics in accounting research for several decades. One of the foundational contributions came from Jones (1991), who separated total accruals into discretionary and non-discretionary components. This approach provided researchers with a way to examine the portion of reported earnings that may be influenced by managerial discretion.

Dechow, Sloan, and Sweeney (1995) subsequently developed the Modified Jones Model, which became one of the most widely used approaches for estimating discretionary accruals. Dechow and Dichev (2002) later emphasized the importance of accrual estimation errors in evaluating earnings quality, arguing that smaller estimation errors are generally associated with higher-quality earnings. Beneish (1999) offered another perspective through the M-Score, which uses financial ratios to identify potential earnings manipulation.

A separate body of research has focused on the language contained in corporate disclosures. Loughran and McDonald (2011) showed that the tone and wording of Form 10-K filings can contain information beyond the numerical financial statements and can help explain firm-level outcomes. Later studies expanded this approach through methods such as keyword-frequency analysis, readability measures, and topic modeling.

This study builds on that textual-analysis literature by focusing specifically on AI-related language.

More recent research has examined the rapid growth of AI-related disclosure in corporate filings and in analyzing investor sentiments ((Khalife et al., 2025). The increase in AI references has been particularly visible among technology firms, while researchers have also investigated whether AI disclosure is associated with firm value, innovation, and other corporate outcomes. At the same time, concerns have emerged around "AI washing," where companies may make broader AI-related claims than their actual technological capabilities justify.

Despite this growing interest, the relationship between AI disclosure and financial reporting quality remains relatively underexplored. Existing research often examines AI, automation, disclosure, competitive intelligence (Subrahmanyam & Saber, 2027) or earnings quality as separate areas of interest, or focus less on traditional investments and more on Cryptocurrency and newer assets (Beainy & Kamel, 2026). Fewer studies directly connect AI-related disclosure with the quality of reported earnings, instead the focus of the current literature is on earnings themselves and investment opportunities (Athari et al., 2025).

Agency theory provides a useful theoretical foundation for examining this relationship. Jensen and Meckling (1976) explain how information asymmetry between principals and agents can create agency costs and opportunities for managerial behavior that does not necessarily align with the interests of shareholders. Financial reporting is one of the main mechanisms available for reducing this information gap, which can have a positive effect on uncertainty and risk (Subrahmanyam & Beainy, 2027).

From this perspective, AI disclosure could provide a credible signal of stronger internal systems and organizational capabilities. Alternatively, it could become another form of impression management if firms use AI-related language primarily to influence stakeholder perceptions instead of increasing performance (Khalife et al., 2024).

This study therefore addresses a relatively specific gap by directly examining the relationship between AI disclosure intensity and earnings quality using publicly available corporate data.

Methodology:

This study uses a quantitative longitudinal panel design covering S&P 500 technology firms during the study period. A panel approach makes it possible to examine differences across firms while also accounting for changes over time. This is particularly useful when studying corporate disclosure because AI-related communication has changed considerably over the sample period. The sample consists of S&P 500 companies belonging to the Information Technology and Communication Services GICS sectors that remained continuously listed during the study period and had complete Form 10-K filings available.

The resulting dataset is a balanced panel of firm-year observations.

The sample includes:

Apple, Microsoft, NVIDIA, Alphabet, Meta, Intel, AMD, Salesforce, Adobe, Oracle, Qualcomm, Broadcom, Cisco, Texas Instruments, Micron, Applied Materials, ServiceNow, Palo Alto Networks, Intuit, Automatic Data Processing, Motorola Solutions, Corning, Amphenol, Fortinet, KLA Corporation, Lam Research, Synopsys, Cadence Design Systems, Analog Devices, and NXP Semiconductors.

Two primary data sources were used. AI keyword counts were obtained from Form 10-K filings available through SEC EDGAR. Financial data, including total assets, net income, cash flow from operations, revenue, receivables, property, plant and equipment, total debt, market capitalization, and book value, were collected from StockAnalysis.com.

Dependent Variable: Earnings Quality

Earnings quality (EQ) is measured using the absolute value of discretionary accruals estimated with the Modified Jones Model.

The model is expressed as:

$$TA_{it} / A_{it-1} = \alpha_1(1 / A_{it-1}) + \alpha_2(\Delta REV_{it} - \Delta REC_{it}) / A_{it-1} + \alpha_3(PPE_{it} / A_{it-1}) + \varepsilon_{it}$$

Here, total accruals are calculated as net income minus cash flow from operations. Lagged total assets are used to scale the variables, while changes in revenue and receivables and gross property, plant, and equipment are included in the model.

The residual represents discretionary accruals. Earnings quality is then measured as the absolute value of this residual:

$$EQ = |\varepsilon|$$

Under this measure, larger absolute discretionary accruals indicate lower earnings quality.

Independent Variable: AI Disclosure Intensity

AI disclosure intensity is measured using the frequency of AI-related keywords in each Form 10-K filing, scaled by filing length:

$$AI_{it} = (\text{Number of AI-related keywords in } 10\text{-K}_{it} / \text{Total words in } 10\text{-K}_{it}) \times 1,000$$

The keyword set includes terms related to artificial intelligence, machine learning, deep learning, neural networks, AI, algorithms, automation, generative AI, and large language models.

Scaling the measure by filing length helps account for differences in the overall size of annual reports across firms and years.

Control Variables:

The regression includes several control variables based on previous literature:

- Firm size (SIZE): natural logarithm of total assets.
- Leverage (LEV): total debt divided by total assets.
- Profitability (ROA): net income divided by total assets.

- Growth (MTB): market value divided by book value of equity.
- Year effects: included to account for changes that affect firms across the same year.

Empirical Model

The primary regression model is:

$$EQ_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 SIZE_{it} + \beta_3 LEV_{it} + \beta_4 ROA_{it} + \beta_5 MTB_{it} + \sum \gamma_t YEAR_t + \varepsilon_{it}$$

The null hypothesis states that there is no relationship between AI disclosure intensity and earnings quality, while the alternative hypothesis states that a relationship exists.

The regression was estimated using Ordinary Least Squares with robust standard errors in Excel's Data Analysis ToolPak. A fixed-effects specification was also used as a robustness check.

AI tools, including ChatGPT and Claude, were used as complementary tools for keyword-extraction assistance, formula development, literature synthesis, and editing. All AI-generated outputs were checked against primary sources. No AI tool was used to fabricate data or research results.

Results:

The descriptive statistics indicate substantial variation in both AI disclosure and earnings-quality measures across the sample. AI disclosure intensity varies considerably between firms and across years, while the distribution of absolute discretionary accruals is broadly consistent with the type of measures commonly used in earnings-quality research.

The complete numerical results are organized in the accompanying Excel workbook.

Descriptive Statistics:

The descriptive statistics provide the initial picture of the dataset. AI disclosure intensity has a positive average and considerable dispersion, indicating that firms differ meaningfully in the extent to which they discuss AI in their annual reports.

Absolute discretionary accruals also vary across observations, suggesting differences in reported earnings quality within the sample.

Correlation Analysis

The correlation matrix shows a negative association between AI disclosure intensity and absolute discretionary accruals. This preliminary relationship is statistically significant at the conventional level reported in the study.

Firm size and profitability also show negative correlations with absolute discretionary accruals. These relationships are broadly consistent with previous research suggesting that larger and more profitable firms may exhibit higher earnings quality.

Correlation results should, however, be interpreted as associations rather than evidence of causality.

Regression Results

The regression analysis provides further evidence of a negative relationship between AI disclosure intensity and absolute discretionary accruals.

The estimated coefficient for AI disclosure is negative and statistically significant. In practical terms, an increase in AI disclosure intensity is associated with a decrease in absolute discretionary accruals. Because lower absolute discretionary accruals correspond to higher earnings quality under the study's measurement approach, the result is consistent with the signaling hypothesis.

Firm size and profitability also have statistically significant negative coefficients, while leverage has a positive coefficient. The positive relationship between leverage and absolute discretionary

accruals is consistent with arguments in prior literature concerning financial pressure and debt-related incentives.

The regression explains a meaningful portion of the variation in the dependent variable, although a substantial share remains unexplained. This is not unexpected in a study examining a complex concept such as earnings quality through a disclosure-based measure.

All numerical coefficients, significance levels, and model statistics are presented in the Excel workbook accompanying this article.

AI Disclosure Over Time:

The annual pattern is particularly interesting. AI-related disclosure remained relatively stable during the earlier part of the study period before increasing sharply in the years following the emergence of generative AI.

This change suggests that the informational content of AI disclosure may not be constant over time. As AI has become increasingly important to corporate strategy, references to AI in annual reports have also become much more common.

The study's second figure illustrates the relationship between AI disclosure intensity and earnings quality, with the fitted line showing a downward relationship between AI disclosure and absolute discretionary accruals.

Discussion and Conclusion:

This study examined whether the extent of AI disclosure in Form 10-K filings is associated with earnings quality among S&P 500 technology firms.

The empirical results show a statistically significant negative relationship between AI disclosure intensity and absolute discretionary accruals. Since lower absolute discretionary accruals are interpreted as higher earnings quality, the findings are consistent with the view that firms discussing AI more extensively tend to report higher-quality earnings.

The results therefore provide greater support for the signaling explanation than for the impression-management explanation within the context of this sample.

One possible interpretation is that companies making substantial investments in AI may also have stronger technological infrastructure, internal systems, governance practices, and reporting processes. Another possibility is that the observed relationship is partly driven by broader characteristics of large, technologically advanced firms rather than AI disclosure itself.

The magnitude of the estimated relationship is economically meaningful but relatively modest. A one-standard-deviation increase in AI disclosure intensity is associated with a reduction in absolute discretionary accruals that represents a noticeable proportion of the sample's average EQ measure. The time pattern is also important. AI disclosure increased substantially after the emergence of generative AI, suggesting that the meaning of AI-related language in corporate filings may evolve as the technology becomes more established. In earlier years, mentioning AI may have represented a relatively specialized technological initiative. In later years, the same terminology may represent a much broader part of corporate strategy.

For investors, the findings suggest that AI disclosure intensity could potentially be considered alongside traditional financial indicators when evaluating the quality of corporate reporting, particularly among technology companies where AI is strategically important.

For regulators, the findings raise questions about how AI-related corporate statements should be communicated and monitored as AI becomes increasingly prominent in financial disclosures and

transparency becomes increasingly important (Saber & Sassine, 2022). If AI-related disclosure is to provide useful information to investors, its credibility and consistency will remain important. For auditors, the findings may also be relevant when considering how technological capabilities, internal systems, and corporate reporting practices interact. However, the results should not be interpreted as evidence that extensive AI disclosure automatically means lower audit risk or higher reporting quality for an individual company.

Several limitations should be recognized.

First, the sample is limited to S&P 500 technology firms. Consequently, the findings may not apply to smaller companies, firms in other industries, or companies operating in other countries.

Second, the keyword-based measure captures the frequency of AI-related terms but does not measure the depth or substance of those discussions. A company mentioning AI repeatedly does not necessarily have greater AI capabilities than another company that discusses AI less frequently. Third, discretionary accruals represent only one dimension of earnings quality. Other measures, such as financial restatements, accrual quality measures, or analyst forecast errors, could produce different results.

Fourth, the study cannot completely eliminate concerns about endogeneity. For example, companies with stronger earnings quality may also have greater resources to invest in AI. In that case, the relationship would not necessarily mean that AI disclosure itself improves reporting quality.

Finally, the study period includes the COVID-19 disruption, which may have affected corporate operations, financial reporting, and disclosure practices in ways that are difficult to isolate completely.

Future research could address these limitations by expanding the sample to additional industries and international markets, using natural-language-processing techniques and embeddings to measure the substance of AI disclosures, examining quarterly Form 10-Q filings, and testing whether audit quality or analyst coverage changes the relationship.

Cross-country studies could also provide useful evidence by comparing firms operating under different regulatory and accounting environments, including IFRS and US GAAP, additionally, the impact of AI on green investments and sustainability-oriented equity indices would have positive externalities on both the society and the environment (Kaspard et al., 2026).

Overall, this study provides an initial empirical examination of the relationship between AI-related corporate disclosure and earnings quality. The results suggest that AI disclosure contains information associated with reporting quality, but they should be interpreted as evidence of an association rather than proof of a causal relationship.

The more important question for future research may therefore be not simply whether AI disclosure is informative, but under which governance, reporting, and institutional conditions that information remains credible over time.

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