Machine Readership and Financial Reporting Decisions*

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Abstract

Machine learning and AI technologies can identify patterns related to financial misreporting that traditional methods may overlook. This study investigates whether increased machine readership of corporate financial statements influences managers' financial reporting decisions. We find that greater machine readership is associated with a significant reduction in financial misreporting, especially in complex, nonlinear, and high-dimensional patterns detectable by machine learning algorithms. In contrast, we observe no incremental disciplining effect on misreporting identifiable through traditional linear methods. This effect is stronger in contexts where machine learning provides detecting advantages, such as when financial statements are complex or when alternative data sources are available. Furthermore, our results indicate that machine readership enhances the overall quality of financial reporting rather than prompting managers to shift misreporting to areas less detectable by machines.

Keywords: Artificial Intelligence, Financial Reporting, Machine Learning, Earnings Management.

JEL Classification: G34, M41, M48

I. INTRODUCTION

In recent years, the adoption of artificial intelligence (AI) and machine learning technologies has surged among participants in the capital markets. According to a 2023 Market Makers survey, nine out of ten hedge fund traders are now using AI to boost portfolio returns (Yahoo Finance 2023). This technological integration extends beyond hedge funds, with financial analysts, auditors, and even regulators increasingly incorporating AI and machine learning into their practices. For instance, the Division of Economic and Risk Analysis at the Securities and Exchange Commission (SEC) has utilized data from regulatory filings of investment advisers to perform topic modeling and tonality analysis, identifying language that may warrant further investigation by enforcement agencies (Bauguess 2017).[1] Consequently, we are now in an era where corporate financial statements are predominantly read and analyzed by machines.

The growing reliance on machine-based analysis marks a significant shift in financial analysis (Allee et al. 2018; Mayew et al. 2020; Binz et al. 2022; Hunt et al. 2022; Chen et al. 2022; Coleman et al. 2022; Bochkay et al. 2023; Huang et al. 2023; Jones et al. 2023; Kim et al. 2023, 2024; Laporte 2024; Kim and Nikolaev 2024; Call et al. 2024). This development also underscores the need to consider how machine learning and AI can in turn change the preparation of financial statements. In response to this evolving landscape, this study examines how such increasing prevalence of machine readership of financial statements affects the quality of financial reporting.

Ex ante, it is uncertain how the emergence of machine readership can influence the quality of financial reporting. On one hand, machine readership may incentivize managers to adapt their

[1] Later in 2023, SEC Chair Gary Gensler told Senate lawmakers in a Senate oversight hearing that the SEC was using AI to monitor the financial sector for signs of fraud and manipulation. When asked how he envisioned the SEC using AI, Gensler responded: “So, we already do. In some market surveillance and enforcement actions. To look for patterns in the market. … It’s one of the reasons why we’ve asked Congress for greater funding this year, in 2024, to help build up our technology budget for the emerging technologies.” (Cointelegraph, 2023)

communications to appeal to machine trading algorithms. For instance, Cao et al. (2023) find that managers cater to machine readership by "positifying" qualitative language to create a more favorable impression on machine readers. On the other hand, managers may behave differently regarding quantitative disclosure, such as financial statements, as these are easier to verify compared to linguistic styles, which reduces the scope for managerial discretion. Therefore, it is worthwhile to explore whether machine readership could lead to catering or disciplining behaviors in the context of financial statements.

Machine readership can impose different incentives on managers in financial reporting decisions compared to traditional readers. This difference stems from two primary advantages of machines: processing high-dimensional data and formulating complex nonlinear models, which enhance their effectiveness in detecting financial irregularities. To better understand these advantages, consider a model with 20 input variables. While this number may not seem substantial, accounting for potential non-linear relationships would require 190 interaction terms, and a more comprehensive analysis incorporating triple interactions would demand another 1,140 terms. In a study examining significant predictors of cross-sectional stock returns, Yan and Zheng (2017) construct over 18,000 fundamental signals derived from 240 accounting variables from financial statements. Such volume poses significant challenges for traditional models, whereas machines inherently possess the capability to identify significant combinations within this intricate landscape. Therefore, we posit that machine learning algorithms can detect abnormal data patterns beyond the scope of traditional methods, and such enhanced detection capability will influence managers' incentives regarding financial reporting decisions.

From a managerial perspective, concealing misreporting from traditional readers may have been feasible, but the rise of machine readership has increased the capability of detection, making previously overlooked misreporting more visible. So, what types of suspicious transactions can machines detect but often elude traditional models? For instance, when a manager aims to boost earnings by reporting inflated sales, they could be undetected if they were able to offset the influence of sales by adjusting the values of other input variables to maintain the predicted values within the acceptable range from traditional models (Dechow, Sloan, and Sweeney 1995; Kothari, Leone, and Wasley 2005; Dechow et al. 2011). In contrast, machines take into consideration a wide range of functional forms with many potential interactions and alternative data sources to uncover irregularities, making it harder for managers to hide their opportunistic behaviors (See Section 2 for a concrete example that illustrates how machine readership could affect managers' financial reporting decisions). Furthermore, empirical evidence indicates that managers are often aware of the rise of machine readership, both directly and indirectly.[2] Collectively, the emergence of machine readership increases the likelihood of detecting managers' misreporting behaviors and thus shifts the equilibrium in managerial misreporting decision-making. Therefore, we anticipate that machine readership plays a disciplining role in managers' financial reporting decisions.

We study two types of misreporting patterns to document managers' reaction: *traditional methods (TM)-sensitive misreporting* and *machine-sensitive misreporting*. We define *TM-sensitive misreporting* as irregularities detectable by traditional methodologies such as logistic and linear regression models, and *machine-sensitive misreporting* as irregularities that are detectable by machine learning models but not traditional methodologies. In response to the increasing

[2] Managers can observe interest of machine-equipped investors in real time, both directly and indirectly. Directly, they can learn about investors' use of machine learning and AI techniques through investor conferences, private meetings, or public disclosures of these technologies in their investment analysis. Indirectly, managers can infer the adoption of machine learning and AI by investors based on changes in participation during conference calls (Cao et al. 2024), shifts toward more detailed and data-driven questions (Mercer 2024), rapid integration of new information into stock prices (Cao et al. 2023), and increased attention to non-traditional intangibles such as sentiment or economic beliefs (Retail Banker International, 2024).

prevalence of machine readership, we anticipate that managers will adjust their reporting practices, particularly focusing on patterns that are more likely to be detected by machines. Thus, we expect a negative correlation between machine readership and *machine-sensitive misreporting*. In the case of *TM-sensitive misreporting*, if machine learning has an additional advantage within the linear structure over traditional methods, it is plausible that managers also reduce *TM-sensitive misreporting* in response to the rise of machine readership. However, if traditional methods already possess a robust ability to detect misreporting patterns within linear models, the influence of machine readership might not be substantial. Thus, it is ex-ante unclear whether managers would adjust *TM-sensitive misreporting* along with the rise of machine readership.

We measure machine readership using the percentage of machine downloads of 10-K filings in the SEC Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system, following Lee et al. (2015) and Cao et al. (2023). A machine download is defined as a download request from an IP address that conducts daily downloads of more than 50 unique firms' filings from the SEC EDGAR system. By aggregating the number of download requests made by machines and scaling it against the total number of downloads, we obtain our measure of *Machine Downloads*. We use this measure as a proxy for machine readership of financial reports for several reasons. Firstly, machine requests are a prerequisite and necessary condition for machine reading activity. Secondly, given the substantial volume of machine downloads, it is highly improbable that humans alone could process all the files downloaded by machines. Moreover, Cao et al. (2023) find that machine downloads are associated with quicker and more profitable high-speed trades once a filing becomes publicly available. Given the brief window of time available to process copious amounts of information, it is unlikely that a human subsequently reads the filings downloaded by machine.[3]

[3] Machine readers are not limited to algorithmic traders; they also include investors employing trading styles other

Our measure of *machine-sensitive misreporting* is based on the *Restatement Risk* developed by Bertomeu et al. (2021), which employs gradient boosted regression tree methods and publicly available data to identify restatements. Given the widespread adoption of the machine learning techniques and the accessibility of the underlying input data, we can reasonably anticipate a strong correlation between our *machine-sensitive misreporting* measure and the actual outcomes observed by market participants utilizing similar methods to analyze financial statements. Notably, institutional investors, particularly hedge funds, often leverage proprietary information sources and advanced computational capabilities. Our *machine-sensitive misreporting* measure likely reflects the minimum level of irregularities detectable by these sophisticated entities.[4]

Our findings reveal negative correlations between *Machine Downloads* and all specifications of *machine-sensitive misreporting*. Specifically, a one-standard-deviation increase in *Machine Downloads* is associated with a 6 percent to 12 percent decrease in *machine-sensitive misreporting*, and a 2 percent decrease in the likelihood of being perceived as high restatement risk. We also use an alternative measure of machine readership *AI Ownership*, which captures a firm's cumulative ownership by investment companies that are equipped with artificial intelligence (AI) capabilities. *AI Ownership* is a more direct measure and can capture managers' awareness of machine readership more accurately. Results using *AI Ownership* also reveal a significant and negative correlation with *machine-sensitive misreporting*. Overall, our findings suggest that machine readership has a disciplining effect on managers and reflects an improvement in financial reporting quality in areas that are sensitive to machine learning.

than high-frequency trading. For example, several studies identify top machine downloaders as investors who focus on fundamental analysis or exchange-traded funds (ETFs) (Chen et al. 2020; Crane et al. 2022; Cao et al. 2023).

[4] We also use *Fraud Score*, a measure developed by Bao et al. (2020) using an ensemble learning method. The results are consistent with our main findings and are presented in Section 6.

Firms with higher reporting quality may attract more machine readers because their filings are easier for machines to analyze. To address this potential reverse-causality issue, we employ an instrumental variable approach, leveraging the ownership-weighted *AI Talent Supply* accessible to institutional investors. We calculate *AI Talent Supply* based on the local AI talent pools at the headquarters of institutional investors, scaled at the firm level according to institutional ownership (Jiang et al., 2021). *AI Talent Supply* is positively correlated with *Machine Downloads*, as a significant proportion of machine downloads from the SEC EDGAR system are conducted by institutional investors (Crane, Crotty, and Umar 2022; Cao et al. 2023). Furthermore, the exclusion restriction is satisfied because the AI talent supply available to institutional investors is unlikely to influence companies' financial reporting decisions directly. Using a two-stage least squares regression analysis, we find consistent evidence of a negative correlation between machine readership and machine-sensitive misreporting.

We expect the disciplining effect of machine readership to be more pronounced in areas where AI and machine learning techniques provide substantial advantages. Therefore, we focus on two of AI and machine learning's key attributes: the ability to handle more complex information structures and the capacity to incorporate a greater variety of information sources. To explore the first attribute, we examine the context of financial statement complexity, which reflects both business and reporting intricacy (Guay et al. 2016). We find that the negative association between machine readership and machine-sensitive misreporting is stronger when financial statements are more complex, consistent with our hypothesis that complex statements increase information processing costs for readers. Next, to explore AI and machine learning's ability to incorporate diverse information sources, we consider the introduction of satellite coverage for major retailers. Prior research indicates that investors integrate alternative data sets into their investment decisions

(Zhu 2019; Kang et al. 2021; Katona et al. 2022). Consistent with our expectations, we find that firms covered by satellite data experience a reduction in machine-sensitive misreporting following the initiation of satellite data coverage.

For the *TM-sensitive misreporting* measures, we use traditional metrics for the likelihood of financial misreporting: *F-score* (Dechow et al. 2011) and discretionary accrual measures (Dechow, Sloan, and Sweeney 1995; Kothari, Leone, and Wasley 2005). Unlike its observed effect on machine-sensitive misreporting, we do not find significant correlations between any machine readership and *TM-sensitive misreporting* measures. This result suggests that machine readership does not influence financial misreporting trends detectable by traditional methods. Instead, it highlights the strength of machine learning and AI technologies in identifying complex, non-linear, and high-dimensional patterns. These findings align with Kelly and Xiu (2023), emphasizing the ability of machine learning and AI to incorporate a greater number of predictors and utilize rich nonlinear models.

The results above indicate that the disciplining effect of machine readership on managers' misreporting decisions is primarily concentrated on misreporting patterns susceptible to detection through machine learning techniques. However, it remains uncertain whether this effect translates into an overall improvement in investors' welfare. To address this concern, we examine the relation between machine readership and actual misstatements. Our result reveals a negative correlation between machine readership and the likelihood of misstatements. This finding suggests that managers are unlikely to shift the *machine-sensitive misreporting* to areas that can elude machine readership, but rather, managers exhibit an overall reduction in misreporting behavior. In conclusion, the adoption of machine effectively disciplines managers by reducing overall misreporting, especially *machine-sensitive misreporting*, and such reduction enhances the overall welfare of financial reporting users.

We conduct cross-sectional analyses to further validate these findings. Specifically, we expect firms to be more sensitive to the rise of machine readership when misreporting costs are higher. Prior research shows that restatements by industry peers can lead investors to scrutinize other firms in the same sector (Gleason et al. 2008). Consistent with this spillover effect, we find a stronger negative correlation between machine readership and *machine-sensitive misreporting* for firms exposed to restating peers. Additionally, as technology firms face higher litigation risks (Kasznik and Lev 1995; Ajinkya, Bhojraj, and Sengupta 2005), we observe a more pronounced negative relationship between machine readership and *machine-sensitive misreporting* in the technology sector.

Our study contributes to the existing literature in three ways. Firstly, this paper, by highlighting the impact of machine readership, adds to an emerging literature exploring the influence of new technology adoption on firm behaviors (Zhu 2019; Cao et al. 2023; Abis and Veldkamp 2024; Charoenwong et al. 2024; Christensen et al. 2024). Specifically, Cao et al. (2023) find that firms cater to increased machine readership by adjusting qualitative language and acoustic style to appear more favorable to machines, suggesting that new technology can encourage opportunistic managerial behaviors. In contrast, our paper demonstrates that in the context of quantitative reporting, where managerial discretion is more constrained, machine readership disciplines managers' financial reporting decisions. This contrast underscores our paper's contribution to the literature, highlighting the need for further exploration of the nuanced effects of machine readership on managerial behavior and financial reporting. In addition, our paper builds on Zhu (2019), which explores the corporate governance implications of big data. We extend this work by providing evidence that new technologies, along with new data, can also serve as effective tools for auditing and detecting financial accounting fraud (Cao et al. 2015; Teoh 2018; Frankel et al. 2022; Campbell and Shang 2022; Huang et al. 2024).

Second, we provide novel insights into managerial incentives under the rise machine readership, documenting a strategic shift in managerial behavior. Specifically, managers respond strategically to machine readership by reducing forms of misreporting particularly detectable by machine learning algorithms, but not those detectable by traditional methods. Our findings suggest that the emergence of machine readership introduces a new dimension to managerial considerations, as managers must now anticipate detection by algorithms designed to identify subtle patterns. Thus, certain misreporting practices become riskier and less viable, prompting managers to alter their disclosure strategies. Overall, our study highlights that machine-driven financial statement analysis reshapes managerial incentives, affecting both the content and quality of financial disclosures.

Our study also contributes to the literature on information acquisition by highlighting the distinctive role of robotic (machine-based) readership relative to traditional readership. Prior studies predominantly use non-robotic EDGAR downloads as proxies for fundamental investors' information acquisition (Ahmed et al. 2020; Lee and Watts 2021). For example, Ahmed et al. (2020) find that higher non-robotic EDGAR search volumes, a proxy for fundamental investors' information acquisition, reduce managers' incentives to misreport. In contrast, we document that machine readership constitutes a separate and increasingly influential channel of information processing. Our findings suggest that machine downloads can discipline managers' opportunistic behaviors, offering initial evidence for the distinct role robotic downloads may play in information acquisition compared to non-robotic downloads.

II. BACKGROUND

2.1 Information acquisition from SEC-filings

Over the past decade, researchers have examined the retrieval of EDGAR data to better understand how capital market participants use corporate financial statements. Studies by Drake et al. (2015, 2016, 2017) and Loughran and McDonald (2017) explore the determinants and map out usage of the EDGAR database. Building on these studies, researchers focus on how to identify EDGAR users by unmasking the Internet Protocol (IP) addresses that accessed filings. Bozanic et al. (2017) identify acquisitions of financial reports by the Internal Revenue Service (IRS), while Li et al. (2023) study the Federal Reserve's usage of accounting reports. Gibbons, Iliev, and Kalodimos (2021) study analysts' information acquisition through EDGAR, and Bernard, Blackburne, and Thornock (2020) and Cao et al. (2021) identify accessions of corporate financial reports by industry peers. Additional research has focused on how investors use EDGAR information, for example, via the association between EDGAR usage and institutional investors' profitability (Drake et al. 2020; Chen et al. 2020; Crane et al. 2022) and geographical location (Dyer 2021; Chen 2022). Other researchers have examined specific filings or specific sections, including Form 8-Ks (Iliev et al. 2021; Ben-Rephael et al. 2022), exhibits in Form 10-K (Cheng et al. 2024), and infographics (Christensen et al. 2024).

Studies initially focus on human investors' information acquisition using non-robotic EDGAR downloads (Lee and Watts 2021). Cao et al. (2023) is the first to examine the impact of machine readership by identifying machine downloads through IP addresses that conduct large-batch daily downloads of SEC filings. They trace these downloads to the identities of downloaders to help validate that the measure indeed represents likely precursors for machine processing, and they find that the top 20 downloaders are either prominent quantitative hedge funds, such as

Renaissance Technologies and Two Sigma Investments, or brokers and investment banks with significant asset management operations, such as JPMorgan Chase and Morgan Stanley. Using this validated measure, they document that firms with greater machine readership prepare filings better suited to machine processing and strategically avoid linguistic tones perceived negatively by algorithms.

2.2 Financial Reporting Quality

Measuring the quality of firms' financial reporting is challenging, though many studies use accounting-based measures, particularly accrual-based earnings management proxies (see, e.g., Dechow et al. (2010) for a review). Jones (1991) proposed that the nondiscretionary portion of accruals is correlated with changes in revenue and gross property, plant, and equipment (PPE), with the residual part of total accruals serving as a proxy for earnings management. Dechow et al. (1995) refined this model by limiting revenue to cash revenue, while Kothari et al. (2005) introduced a performance-matching procedure to address misspecification concerns. Dechow et al. (2011) expanded on these approaches by analyzing characteristics of misstating firms and developed the *F-score*, a predictive measure.

Recent studies have applied machine learning methods to further improve prediction power. Using Ensemble learning to predict Accounting and Auditing Enforcement Releases (AAERs), Bao et al. (2020) introduced a model that outperforms the *F-score* in Dechow et al. (2011) and the model by Cecchini et al. (2010). Similarly, Bertomeu et al. (2021) apply gradient boosted regression tree (GBRT) to predict misstatements, also outperforming the logit models in Dechow et al. (2011).

Figure 1. A simplified example on machine-sensitive misreporting

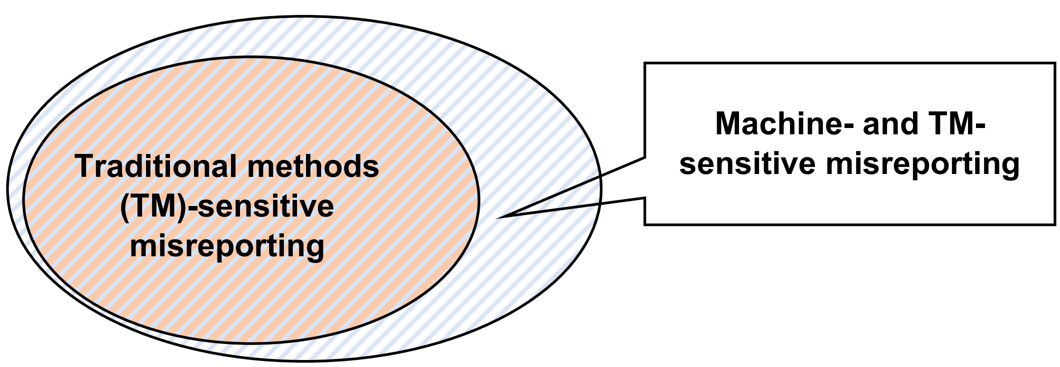
Panel A. Misreporting undetected by traditional models (Dechow et al., 2011)

$$
\begin{aligned}
F\text{-score} = & -7.893 + 0.790 \times (rsst\_acc) + 2.518 \times (ch\_rec) \\
& + 1.191 \times (ch\_inv + 0.78(\frac{0.932}{1.191})) + 1.979 \times (soft\_assets) + 0.171 \times (ch\_cs) \\
& + (-0.932) \times (ch\_roa + 1) + 1.029 \times (issue)
\end{aligned}
$$

Panel B. Misreporting now detected by machine learning methods

$$
\begin{aligned}
\text{Predicted Value} = & -7.893 + 0.790 \times (rsst\_acc) + 2.518 \times (ch\_rec) \\
& + 1.191 \times (ch\_inv + 0.78(\frac{0.932}{1.191})) + 1.979 \times (soft\_assets) + 0.171 \times (ch\_cs) \\
& + (-0.932) \times (ch\_roa + 1) + 1.029 \times (issue) \\
& \underbrace{+\beta_1 \times \frac{ch\_roa + 1}{ch\_inv + 0.78} + \beta_2 \times \frac{rsst\_acc}{ch\_roa + 1} + \beta_3 \times ch\_rec \times (ch\_inv + 0.78)}_{\text{Possible interaction terms that trigger machine alerts}} + \ldots
\end{aligned}
$$

Panel C. Relation between Machine-sensitive misreporting and TM-sensitive misreporting



2.3. An example of machine detection of financial misreporting

To gain a clearer understanding of how machine learning methods can detect misreporting patterns more effectively than traditional approaches, let's explore a derived example based on variables from prior research (Dechow et al. 2011; Bao et al. 2020; Bertomeu et al. 2021). Imagine a firm trying to boost its Return on Assets (ROA) by one unit without triggering suspicion. In the pre-machine learning and AI era, the manager could do so by simultaneously increasing reported inventory by 0.78 unit (0.932/1.191), as calculated through the ratios of their coefficients in the model of Dechow et al. (2011) (refer to Panel A in Figure 1). Importantly, this opportunistic behavior would not alter the predicted value of *F-score* in the model.

However, when investors adopt AI and machine learning methods, these approaches also consider the relationships between variables, including how changes in ROA and inventory interact. In this context, the previous distortion becomes highly likely to trigger alerts from machine learning algorithms. This is because the ratio of *Change in ROA/Change in inventory* no longer remains unchanged; it shifts from Original *Change in ROA*/*Change in inventory* to *(Change in ROA +1)/(Change in inventory +0.78).* In Panel B of Figure 1, the last line illustrates some potential interactions based on existing input variables. When machine learning models incorporate these interactions, the predicted values no longer align with those before the manipulation.

III. DATA AND MEASURE

We construct our sample by intersecting several datasets. We first obtain the SEC filings download records from the SEC Edgar system, which starts in 2003 and paused in 2017.[5] The EDGAR Log File Data Sets provide information on all records of requests and downloads of SEC filings, including IP address, date, time, CIK, and accession number associated with a given document request. We then merge the information with EDGAR index files to narrow down to visits to Form 10-K filings. Next, we obtain machine-sensitive misreporting measures from

[5] The SEC filings download records are available again from 2020. However, we restrict our main sample period till 2016, since the machine-sensitive misreporting measures is available up to 2019.

Bertomeu et al. (2021), and AI-equipped investors data from Cao et al. (2023).[6] Last, we obtain firm-level characteristics from Compustat, analyst followings from I/B/E/S, and institutional investors from Thomson Reuters.

Our sample comprises all publicly listed companies in the United States, spanning from 2004 to 2016. Table 1 outlines the sample selection procedures. Our primary sample includes 4,403 unique firms and 33,709 firm-year observations. To mitigate the bias of outliers, we winsorize all continuous variables at 1 percent and 99 percent. Table 2 presents the summary statistics on outcome, and control variables.

3.1 Machine Readership

Our main measure of machine readership is the expected percentage of downloads of the companies' SEC filings that are conducted by machines, termed as *Machine Downloads*. It measures the expected frequency of machine downloads of a firm's Form 10-K. Despite the availability of various data sources, the SEC EDGAR website remains the most authoritative source for company filings to be publicly released and machine download friendly. Following Cao et al. (2023), we first retrieve all downloads of companies' Form 10-Ks by linking the EDGAR Log File Data Sets and EDGAR index files using accession number. We exclude requests landed on index pages since they are not related to actual downloads. Next, we aggregate all the IP addresses in the EDGAR index files, and identify an IP address as a *machine reader* if such IP address downloads more than 50 unique firms' filings from the SEC EDGAR system, following the definition in Lee et al. (2015). We also include download requests attributed to web crawlers in the SEC Log File Data as machine-initiated requests. Given that the majority of download

[6] We thank authors of Bertomeu et al. (2021) for making machine learning predicted restatement risk measures available online; we thank authors of Cao et al. (2023) for providing AI-ownership dataset.

requests occur within seven days of a filing becoming available on EDGAR, we aggregate the number of download requests made by machine readers for each 10-K filing over the seven-day period after it appears on EDGAR. We define *Machine Downloads* as the ratio of the number of download requests made by machine readers of the Form 10-K in the last fiscal year scaled by the number of total downloads of the same form. We also control for total download volumes and define *Total Downloads* as the natural logarithm of the total download requests of the Form 10-K in the last fiscal year.

Our analysis using machine downloads inherently assumes that firms were aware of the extent of expected machine readership, even though the SEC log files were first made publicly available in 2015, with retrospective data from 2003. We make this assumption because we believe machine downloads closely reflect actual, observable machine readership, and prior study has validated the effectiveness of machine downloads. [7] To further address this potential concern of such assumption, we employ an alternative measure, *AI Ownership*, which directly assesses the proportion of firm shares held by investment firms with AI capabilities. *AI Ownership* is defined as the percentage of shares outstanding held by investment companies with AI capabilities. Following Abis and Veldkamp (2024), we consider an investment company to have AI capabilities if it has posted AI-related job openings within the past five years. [8] *AI Ownership* represents aggregate ownership measured at the firm level from the quarter preceding the firm's most recent

[7] To establish the effectiveness of machine downloads as a proxy for the presence of machine readership, Cao et al.(2023) conduct two validity tests. In their first test, they match the IP addresses with the highest volumes of machine downloads to the universe of investors who submit 13F filings. They find that half of the top twenty machine downloaders are prominent quantitative hedge funds, and brokers and investment banks with significant asset management divisions. In the second test, they manually identify hedge funds that have adopted AI strategies and find a significant association between firms' AI hedge fund ownership and their *Machine Downloads*. Both tests provide compelling evidence supporting the validity of *Machine Downloads* as a measure for machine readership.

[8] We extend our gratitude to the authors of Cao et al. (2023) for providing the dataset on *AI Ownership* at the firm level.

Form 10-K filing. The sample for *AI Ownership* is available for the period from 2011 to 2019, as job posting data is only available from 2010 onward.

3.2 Financial Reporting Quality

Our main proxy for *machine-sensitive misreporting* is *Restatement_Risk*, a measure from Bertomeu et al. (2021), which applies the gradient boosted regression tree (GBRT) method to predict firm's material misstatements. Bertomeu et al. (2021) utilize over a hundred variables organized into five categories: financial, audit, credit ratings, opinion divergence, and corporate governance, and predict a probability of misreporting ranging from zero to one. We use the measure from Bertomeu et al. (2021) because it is created using state-of-the-art machine learning technique.[9] However, it should be noted that this measure relies on publicly available information, while institutional investors, particularly hedge funds, often have access to proprietary information and advanced computing capabilities. Therefore, the measure in our study likely represents the minimum level of irregularities detectable by these entities.

Figure 2 shows the distribution of *Restatement_Risk*. Since *Restatement_Risk* is a probability measure that has a heavy right tail, most observations are concentrated in the area where *Restatement_Risk* is less than 0.1. To capture the significance of *Restatement_Risk*, we follow the spirit of Dechow et al. (2011) and create a binary measure, *I_Risk*. *I_Risk* is an indicator that equals one when the misstatement probability is above the annual cutoff with a Type I error of five percent, and zero otherwise.[10] This classification indicates that the non-misstating

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[9] We also use the *Fraud Score* measure developed Bao et al. (2020), which relies solely on information from firms' financial statements as input and applies an ensemble learning method to detect accounting fraud. The results are consistent with our main findings and presented in Section 6.

[10] Type I error is calculated as the number of observations where predicted misstatement equals to one and observed misstatement equals to zero scaled by the number of observations where observed misstatement is zero. Since the incidence of restatement has decreased over the year, the *I_Risk* measure is also decreasing by year. We create the 5% cutoff by year to overcome the year trend, with the average values of all the cutoff for 5% being 0.15.

observations are correctly identified at 95 percent. Figure 3 shows a comparison between the indicator *I_Risk* and data on actual misstatement cases. Among the whole sample, 21 percent of the observations where *I_Risk* = 1 are actual misstatements.

We employ multiple measures to capture *TM-sensitive misreporting*, including *F-score, MJones,* and *PM-Jones*. The *F-score*, developed by Dechow et al. (2011), assesses the likelihood of financial misconduct and is used to predict material misstatements. *MJones* is an absolute value of the discretionary accruals calculated using the modified Jones model (Dechow, Sloan, and Sweeney 1995). Lastly, *PM-Jones* is based on the performance-matched discretionary accruals measure developed by Kothari et al. (2005), which adjusts for firm performance to improve the accuracy of detecting earnings management.

Lastly, we explore the effect of machine readership on the actual material misstatement. We define *Restate* as an indicator variable equal to one if the firm issues a restatement via the SEC Form 8-K Item 4.02, and zero otherwise. Our analysis focuses on non-reliance restatements, which indicate material accounting misstatements that compromise the reliability of prior or current financial statements. We exclude nonmaterial errors, such as out-of-period adjustments, as well as revision restatements related to voluntary or mandatory changes in accounting standards.

3.3 Other Variables

We include a set of firm-level control variables that are correlated with business aspects and financial reporting decisions, following the literature on financial misreporting (Jia et al. 2014; Samuels et al. 2021). In particular, we control for the following variables: Return on Assets (*ROA*), Market-to-Book ratio (*MTB*), *Size*, *Leverage*, *Sales growth*, research and development expenses

(*RD*), *Loss*, *Analysts Following*, *Institutional Ownership*, and *Big4*. See Appendix A for detailed variable definitions.

Table 2 presents descriptive statistics for the variables used in the regression. The mean of *Machine Downloads* is 70 percent, with a standard deviation of 0.18. The average proportion of machine downloads in our sample rose from 48 percent in 2004 to 92 percent in 2016, with the standard deviation decreasing from 0.16 to 0.06, indicating greater consistency across firms.[11] The annual growth in machine downloads ranged from 32 percent to 125 percent, reflecting year-to-year variations and a growing reliance on automated processing, particularly post-2010. *Restatement_Risk* has a mean of 0.07 and the mean of *I_Risk* is 0.08. The mean of *Sales Growth* is 13 percent, and the mean of *Leverage* is approximately 21 percent. In addition, 34 percent of the firm-year observations experience negative net income (*Loss*). The means of *Sales Growth*, *Leverage*, and *Loss* of the Compustat universe are 9 percent, 25 percent, and 38 percent, respectively. Overall, our sample is comparable to the Compustat universe.

In the subsample using *AI Ownership* as the measure of machine readership, the mean of *AI Ownership* is 0.10 (standard deviation of 0.11), indicating that, on average, 10 percent of firms' shares outstanding are owned by shareholders from AI-equipped investment companies. Due to the limited availability of *AI Ownership* data, this subsample consists of 9,681 observations. *Restatement_Risk* in this subsample has a mean of 0.06 and the mean of *I_Risk* is 0.07, both slightly smaller than the main sample but not statistically different. Most firm characteristics are

[11] Figure 1 of Cao et al. (2023) highlights the significant increase in aggregate machine downloads as a proportion of total downloads over the sample period. Specifically, machine downloads for 10-K filings surged from 38 percent in 2004 to a peak of 83 percent in 2015, before slightly declining to 80 percent in 2016. The decrease in 2016 is temporary, as the upward trend continues during the first half of 2017 (Cao et al. 2023). This is not shown in the figure because the SEC log information is only partially available for 2017, covering only the first half of the year.

comparable to the main sample, while *Leverage* is larger, with a mean 0.48 vs. 0.21 in the main sample.

IV. THE IMPACT OF MACHINE READERSHIP ON FINANCIAL REPORTING QUALITY

4.1 Machine Readership and Machine-sensitive Misreporting

To assess the effect of machine readership on financial reporting decisions, we consider the following model specification:

$$\textit{machine-sensitive misreporting}_{i,t} = \alpha_t + \alpha_i + \beta\ \textit{Machine Downloads}_{i,t} + \textit{Controls}_{i,t} \quad (1)$$

where i represents the firm (or industry) index, and t represents the year index. α_i and α_t denote firm and year fixed effects, respectively, to control for firm-specific idiosyncratic misreporting patterns and time-series shocks. The dependent variable, *machine-sensitive misreporting*, is measured by *Restatement_Risk* and *I_Risk*. *Restatement_Risk* captures the continuous degree of restatement risk as identified by machine analysis, while *I_Risk* represents the likelihood of being classified as high-risk by machine algorithms.

We include control variables based on prior research on financial misreporting, namely *Total Downloads*, *ROA*, *MTB*, *Size*, *Leverage*, *Sales Growth*, *R&D*, *Loss*, *Analyst Following*, *Institutional Ownership*, and *Big4*. Specifically, *Analyst Following* and *Institutional Ownership* are included to account for the monitoring effects of external stakeholders. We hypothesize a negative relationship between *Machine Downloads* and *machine-sensitive misreporting*, suggesting that increased machine readership may discourage misreporting behaviors. Thus, we expect the coefficient β to be negative. To address potential correlations within firms over time, we cluster standard errors at the firm level.

Table 3, Panel A presents our results. Across all specifications, the coefficients of *Machine Downloads* are negative and significant. Columns (1) and (2) provide OLS regression results examining the relation between *Machine Downloads* and *Restatement_Risk*, controlling only for industry-year and firm-year fixed effects. Columns (3) and (4) report regression results that also include additional control variables. The coefficients do not change significantly when control variables are included, indicating that other firm characteristics have minimal confounding effects. The coefficients for *Machine Downloads* in columns (3) and (4) are −0.056 and −0.027, respectively. With the standard deviations of *Machine Downloads* and *Restatement_Risk* being 0.18 and 0.09 respectively (see Panel B, Table 2), the third and fourth columns show that a one-standard-deviation increase in *Machine Downloads* is associated with a 6 percent to 12 percent standard-deviation decrease in *Restatement Risk*. Considering that the mean *Restatement_Risk* is 0.07, this corresponds to a decrease from 0.07 to approximately 0.062 – 0.066.

Given the left-skewed distribution of *Restatement_Risk*, a 6 percent to 12 percent reduction may have a limited impact for firms with low initial risk but could be substantial for those with high initial risk. To further examine this relationship, we use an indicator variable, *I_Risk*, which equals one when the misstatement probability is above the annual cutoff with a Type I error of 5 percent. Column (5) displays the logistic regression results, which are consistent with prior findings. The coefficient on *Machine Downloads* in the logistic regression model of *I_Risk* is −1.778, which translates to an odds ratio of 0.169. This coefficient implies that a one-standard-deviation increase in *Machine Downloads* is associated with a 2 percent ($0.18 \times -0.10 = -0.02$) decrease in the likelihood of being perceived as high risk by a machine reader. Consistent with our hypothesis, all estimated coefficients of *Machine Downloads* are negative and significant at the 1 percent confidence level.

We also find that *Leverage*, *Sales Growth*, and *Loss* are positively associated with financial misreporting, while *Size* and *R&D* are negatively associated, consistent with our prior expectation. Overall, the empirical evidence on the relationship between *Machine Downloads* and *machine-sensitive misreporting* suggests that machine readership has an economically significant and negative impact on machine-detectable financial misreporting patterns.

Our second measure of machine readership is *AI Ownership*. While the measure *Machine Downloads* relies on the assumption that users who download SEC filings with automated tools will also employ machine learning to analyze them, *AI Ownership* captures the percentage of institutional investors utilizing AI, as indicated by their demand for AI-related talent. The *AI Ownership* variable is available from 2011 to 2019.

We use the following model specification to examine the effect of *AI Ownership* on *machine-sensitive misreporting*:

$$\textit{machine-sensitive misreporting}_{i,t} = \alpha_t + \alpha_i + \beta\, \textit{AI Ownership}_{i,t} + \textit{Controls}_{i,t} \qquad (2)$$

where i represents the firm (or industry) index, and t represents the year index. α_i and α_t denote firm and year fixed effects, respectively, to control firm-specific idiosyncratic misreporting patterns and time-series shocks. *Controls* include *ROA*, *Market-to-Book*, *Size*, *Leverage*, *Sales growth*, *RD*, *Loss*, *Analysts following*, *Institutional ownership*, and *Big4*. We expect a negative correlation (β) between *AI Ownership* and *machine-sensitive misreporting*. Standard errors are clustered at the firm level to account for potential within-firm correlations over time.

Panel B in Table 3 presents the results with *AI Ownership* as a proxy for machine readership. Across all specifications, *AI Ownership* exhibits a significantly negative correlation to *machine-*

sensitive misreporting, measured by *Restatement_Risk* and *I_Risk*. With the standard deviations of *AI Ownership* and *Restatement_Risk* being 0.11 and 0.06, respectively (see Panel B, Table 2), the third and fourth columns show that a one-standard-deviation increase in *AI Ownership* is associated with a 4 percent to 7 percent standard deviation decrease in *Restatement_Risk*. To further calibrate the effect in a firm fixed-effect context, a one-standard-deviation increase in within-firm variation of *AI Ownership* is associated with a 0.07-standard-deviation decrease in within-firm variation of *Restatement_Risk*. The effects are stronger with control variables, indicating that other firm characteristics have little confounding effect. Column (5) displays the results using logistic regression of *I_Risk*. The coefficient of *AI Ownership* is -1.251, indicating that a one-standard deviation increase in *AI Ownership* changes the probability of being in the top 5th percentile of *Restatement_Risk* by approximately one percent ($0.11 \times -0.082 = -0.01$). Overall, the results confirm with the previous results that machine readership is negatively correlated with *machine-sensitive misreporting*.

4.2 Instrument Variable for Machine Readership

It is possible that higher financial reporting quality attracts more machine readers, raising concerns about endogeneity. To address this issue, we explore a potential instrument variable for machine readership: the ownership-weighted AI talent supply available to institutional investors. This serves as a suitable instrument variable for several reasons. First, institutional investors are the main sources of machine readers of financial reports,[12] and there has been a recent trend in the finance industry emphasizing the recruitment of talent with expertise in information technology and data analytics (Abis and Veldkamp 2024). In addition, the local talent supply with machine learning and AI experience can influence investors' decision of whether or not a given to adopt AI

[12] See Table 2 in Cao et al. (2023) for the top machine download investors.

and machine learning techniques (Babina et al. 2024; Hunt et al. 2024). Lastly, the AI talent supply for institutional investors is unlikely to be correlated with firms' financial reporting decisions, as institutional investors' headquarters were likely to be established before the rise of AI and machine learning trends.

Our instrument, *AI Talent Supply*, is calculated based on the size of the AI-related employment pool near the headquarters of a firm's investors, and thus is positively associated with *Machine Downloads*. Following Jiang et al. (2021) and Cao et al. (2023), we first obtain the number of people between 18 and 64 with undergraduate and/or graduate degrees in information technology in each state from 2011 to 2016 and calculate the talent supply using state-year population data from the Integrated Public Use Microdata Series (IPUMS) survey. Next, we match the headquarters states of the firm's institutional investors and thereby obtain the investor-state-level AI talent supply. Finally, we take the average of the talent supply, weighted by the firm's level of institutional ownership, and create the local AI Talent Supply at the firm level.

We employ a two-stage least-squares regression to conduct the analysis. In the first stage, we use an OLS model to estimate the correlation between *AI Talent Supply* and *Machine Downloads*, expecting a positive relationship between the instrumental variable and machine readership. The results, reported in column (1) of Table 4, indicate that *AI Talent Supply* is positively and significantly associated with *Machine Downloads*. In the second stage, we regress the fitted value from the first stage, denoted as *Instrumented Machine Downloads,* on *machine-sensitive misreporting* measures. Columns (2) and (3) of Table 4 present the results of this analysis, showing that *Instrumented Machine Downloads* is negatively and significantly associated with *machine-sensitive misreporting* measures. This finding is consistent with the results in Table 3 and suggests that firms with higher machine readership have a lower risk of misstatement. Notably, the coefficients on *Instrumented Machine Downloads* are larger in magnitude than those in the main test (Panel A Table 3), which is consistent with the survey results documented by Jiang (2017). In evaluating the results shown in Table 4, our primary focus is on the statistical significance of the instrument rather than the economic magnitude of the coefficients. These findings support our hypothesis that machine readership has a disciplining effect on financial reporting decisions.

4.3 Machine Readership and TM-sensitive Misreporting

We hypothesize that the strength of machine readership is in discovering non-linear and high-dimensional patterns, and for those misreporting patterns that can be detected by traditional methods, the effect of machine readership is unclear. If traditional methods are strong enough to detect linear misreporting patterns, machine readership should have no incremental effect on traditional-method-detectable misreporting patterns. However, if machine learning techniques are more capable in detecting linear misreporting patterns than traditional methods, and thus effectively deter managers from conducting misreporting, we will find a significant relation between machine readership and *TM-sensitive misreporting*. Therefore, we use the following model specification to test the effect of *Machine Readership* on *TM-sensitive misreporting*:

$$\textit{TM-sensitive misreporting}_{i,t} = \alpha_t + \alpha_i + \beta \textit{ Machine Readership}_{i,t} + \textit{Controls}_{i,t} \tag{3}$$

where i is the firm (or industry) index, and t is the year index. α_i and α_t denote firm and year fixed effects to control for firm fixed idiosyncratic misreporting patterns and time-series shocks. We use the following measures to proxy for *TM-sensitive misreporting*: (1) the absolute value of discretionary accruals measure from modified Jones model (*MJones*), (2) discretionary accruals measure (*PM-Jones*) from the performance-matched model by Kothari et al. (2005), and (3) *F-score,* the likelihood of financial misconduct developed by Dechow et al. (2011) to predict material misstatements. *Machine Readership* includes both *Machine Download* and *AI Ownership*. *Controls* include *ROA*, *Market-to-Book*, *Size*, *Leverage*, *Sales growth*, *RD*, *Loss*, *Analysts Following*, *Institutional Ownership*, and *Big4*. We cluster standard errors at the firm level to account for potential correlations within firms over time.

Table 5 presents the results of *Machine Readership* and *TM-sensitive misreporting*. We do not find any statistical significance on the coefficients of the three measures of *TM-sensitive misreporting*, indicating that machine readership does not have significant association with misreporting patterns that can be detected by traditional methods. The insignificance of machine readership coefficients confirms our hypothesis. Prior to the introduction of machine readership, traditional methods for identifying misreporting were effective in identifying certain abnormal patterns in accounting variables using linear or logistic models. Hence, the adoption of machine readership, along with its underlying AI and machine learning technologies, has not significantly impacted investors' ability to detect such irregularities. As a result, we do not observe a significant correlation between machine readership and *TM-sensitive misreporting* in Table 5. We suspect that machine readership has improved the detection of irregular patterns in more complex structures, such as from interactions among accounting and non-accounting variables. Consequently, in response to increased and still increasing machine readership, managers have altered the aspects of financial reporting irregularities that are only detectable by machines. The results from Table 3 and Table 5 collectively indicate managers' selective adjustments to their financial reporting in response to the unique capabilities of machine readers.

4.4 Machine Readership and Actual Restatement Incidence

Our next objective is to explore whether machine readership can contribute to an overall improvement in the quality of financial reporting. This inquiry is motivated by our earlier findings, which suggest that machine readership plays a disciplining role by restricting managers from engaging in machine-detectable misreporting, while having no effect on misreporting detectable through traditional methods. This raises an important question: Do managers genuinely limit their discretionary reporting behavior, or do they adapt by concealing misreporting in ways that even machine readers cannot detect?

To address this question, we examine the correlation between machine readership and actual restatements using the following model specification:

$$Restate_{i,t} = \alpha_t + \alpha_i + \beta\ Machine\ Readership_{i,t} + Controls_{i,t} \tag{4}$$

where i represents the firm (or industry) index, and t is the year index. α_i and α_t denote firm and year fixed effects, respectively, to control for firm-specific idiosyncratic misreporting patterns and time-series shocks. *Restate* is an indicator variable that equals to one if a firm filed a restatement through Form 8−K Item 4.02, and zero otherwise. Table 6 presents our results. Column (1) and (3) display the results of a linear probability model after controlling firm and year fixed effects. Columns (2) and (4) present the results from a logistic regression model with industry and year fixed effects. We observe negative and statistically significant coefficients in column (1) through (3). Specifically, in the linear probability model in column (1), a one-standard-deviation increase in *Machine Downloads* is associated with a 1 percent decrease in the likelihood of actual restatement. Given that the average likelihood of actual restatement in our sample is 0.08 (or 8 percent), this represents about an 11 percent relative decrease in the probability of actual restatement, suggesting the effect of *Machine Downloads* is economically meaningful.

The results presented in the previous three tables suggest that machine readership positively influences the overall quality of financial reporting, as indicated by its negative association with *machine-sensitive misreporting*, no significant effect with *TM-sensitive misreporting*, and an overall reduced likelihood of misstatements. This improvement in reporting quality is primarily observed in the context of *machine-sensitive misreporting*.

V. ADDITIONAL ANALYSES

We conduct several additional analyses to further explore the disciplining effect of machine readership on managers' financial reporting behavior. First, we explore settings wherein machine learning techniques can plausibly offer substantial advantages over traditional methods, particularly through their ability to process complex information structures and their capacity for incorporating diverse information sources. To assess these advantages, we perform two targeted analyses. Next, we examine how the effect of machine readership varies with the costs of misreporting.

5.1 Advantages of Machines - Complex Information Structures

One distinct advantage of machine learning is its capacity to process information in complex structures. We explore this capability by examining variations in firms' financial statement complexity. Such complexity arises from both the intricacies of a firm's business transactions as well as the complications associated with reporting standards, and literature has shown that firms with high financial statement complexity are associated with high likelihood of internal control weaknesses and misstatement risk (Hoitash and Hoitash, 2018; Chychyla et al., 2019).

To capture this complexity, we utilize the length of a firm's 10-K report, calculated as the natural logarithm of the word count, following Guay et al. (2016) and Chakraborty et al. (2022). They find a positive relation between voluntary disclosure and financial statement complexity, measured by both the length and readability of a firm's 10-K. We adopt the length of the firm's 10-K as our measure of financial statement complexity. To incorporate this complexity measure into our analysis, we create an indicator variable named *FS Complexity*. This variable takes a value of one if the length of the firm's Form 10-K exceeds the sample average, and zero otherwise. We include an interaction term between *FS Complexity* and *Machine Downloads*, which allows us to examine whether machine readership can mitigate information processing frictions caused by financial statement complexity. If machine readership is effective in reducing these frictions, we expect the coefficient of the interaction term to be negative.

Table 7 presents the results. In columns (1) and (2), the coefficients on *Machine Downloads* are negative and significant, ranging from -0.010 to -0.036, aligning with our main findings. Similarly, the coefficients of *FS Complexity* are positive and significant, ranging from 0.035 to 0.038, consistent with the expectation that firms with more complex financial statements are more likely to engage in misreporting. Importantly, as hypothesized, the coefficients on the interaction term between *Machine Downloads* and *FS Complexity* are significantly negative, ranging from -0.033 to -0.035, indicating that the disciplining effect of machine readership is stronger among firms that produce more complex financial statements. This evidence implies that the influence of machine readership on reporting quality is more pronounced among firms with greater financial statement complexity.

5.2 Advantages of Machines - Alternative Data Coverage

Another advantage of machine learning and AI techniques is the ability to incorporate and process vast amounts of data. To further strengthen our analysis of machine readership, we conduct an event study to explore this capability. One valuable type of data frequently utilized by investors is consumer footprints, such as satellite images of retail parking lots. Due to the sheer volume of satellite images, this type of information has to be processed by machine learning models before it can be effectively used to inform investment decisions. Prior studies have found that this type of data provides incremental information to capital market participants (Zhu 2019; Kang et al. 2021; Katona et al. 2022). We build on the setting from Katona et al. (2022), which examines the staggered introduction of satellite image coverage and conduct a difference-in-differences test of *machine-sensitive misreporting*.[13] We define indicator variables named *Alt_Data_Covered* and *Post Coverage*. *Alt_Data_Covered* takes a value of one if a firm is covered by satellite images, and zero otherwise, following Katona et al. (2022). *Post Coverage* takes a value of one after the initiation of satellite coverage, and zero otherwise. We hypothesize that the availability of satellite image coverage provides machine readers with a broader pool of information to incorporate into their analyses, increasing the likelihood of detecting patterns and anomalies that may indicate potential misreporting. As a result, firms are less likely to engage in misreporting behavior due to the enhanced detection capabilities of machine readers.

Table 8 presents the results. The negative coefficient, reported as -0.009 in column (4), of the interaction terms between treatment firms (*Alt_Data_Covered*) and the post-coverage period (*Post_Coverage*) indicates that the presence of alternative data is linked to a reduced likelihood of restatements. This result suggests that the availability of alternative data serves as a mitigating factor in restatement risk. Moreover, even when accounting for alternative data coverage, the

[13] We thank Katona et al. (2022) for sharing the list of treatment and control firms.

coefficients on *Machine Downloads* remain significantly negative, ranging from -0.027 to -0.056, implying the presence of disciplining effect of machine readership even after controlling for alternative data.

5.3 Potential Costs of Misreporting

We next explore whether firms respond differently to the adoption of machine readership when they are more sensitive to the cost of detection. We utilize two scenarios: firms with a peer firm that recently issued a restatement and firms in high-litigation industries.

5.3.1 Peer Restatements

Prior study has documented a spillover effect of scrutiny caused by peer firm restatements (Gleason et al. 2008). We examine whether the association between machine readership and financial reporting quality is stronger for firms whose peers recently issued restatements. To test this prediction, we define *Peer Restate* as an indicator variable equal to one for firms with restating peers in the same year, and zero otherwise, following Gleason et al. (2008). We conduct an OLS regression analysis of the main model with an interaction term of *Machine Downloads* × *Peer Restate*.

Table 9 reports the results. In columns (1) and (2), the coefficients on *Machine Downloads* are negative, ranging from -0.003 to -0.019. Importantly, the coefficients on the interaction between *Machine Downloads* and *Peer Restate* are significantly negative, ranging from -0.034 to -0.050, indicating that the disciplinary effect of machine readers is stronger among firms exposed to a spillover effect from a restating peer than firms without. The effect is also economically significant. For example, in column (1), the effect of machine readership on *Restatement Risk* is 13 percent higher for firms with a restating peer. We also find that *Peer Restate* is positively correlated with *machine-sensitive misreporting*, consistent with evidence in prior research that firms with restating peers are subject to higher scrutiny by capital market participants as well as regulators. Overall, these results provide evidence that when firms are subjected to greater scrutiny for potential misstatements, they react more strongly to machine readership and experience a stronger disciplining effect in the context of *machine-sensitive misreporting*.

5.3.2 Litigation Costs

Firms in the high-technology industry face higher cost of misreporting, as they are exposed to an above-average risk of shareholder lawsuits, resulting in large price fluctuations and potential losses to investors (Kasznik and Lev 1995). Thus, we expect that machine readership has a stronger effect on the financial reporting decisions among firms in the high-technology industry. Following Kasznik and Lev (1995) and Ajinkya et al. (2005), we define *Litigate* as an indicator variable with a value of one if the firm is in the following industries: biotechnology (SIC codes 2833 − 2836), R&D services (8731 − 8734), programming (7371 − 7379), computers (3570 − 3577), or electronics (3600 − 3674), and zero otherwise. We partition the sample based on the values of *Litigate* and reconduct the main analysis on *machine-sensitive misreporting* as in Section 4.1.

The results are reported in Table 10. Consistent with our previous findings, the coefficients on *Machine Downloads* are significantly negative, ranging from -0.017 to -0.044, and the coefficients on *Litigate* are significantly positive, ranging from 0.038 to 0.039, in columns (1) and (2). The coefficients of *Machine Downloads* × *Litigate* is significantly negative, -0.045 and -0.041 respectively, consistent with our hypothesis that firms facing higher litigation costs respond more strongly to machine readership and reduce their *machine sensitive misreporting* to a greater degree.

VI. ROBUSTNESS TESTS

6.1 Alternative Measure for Machine Readership

In the main analysis, we focus on a seven-day window to aggregate machine-generated and total download requests for each filing in EDGAR, as the majority of requests occur within the first seven days of a filing being made accessible (Cao et al. 2023). To assess the robustness of our results, we extend this period to fourteen days (thirty days) to verify whether the aggregation method influences our results. Specifically, we define *Machine Downloads_14D* and *Machine Downloads_30D* in the same manner as the original *Machine Downloads* variable, but aggregate requests within fourteen and thirty days, respectively. We expect the results from these extended windows to align with those from our main analysis.

Panel A of Table 11 presents the results. Consistent with our prediction, the coefficients of *Machine Downloads_14D* and *Machine Downloads_30D* in both the OLS and logistic regression models are both significantly negative. Moreover, the magnitudes of the coefficients are very similar to those reported in the main analysis (Panel A, Table 3). These results provide robust evidence of the disciplining effect of machine readership on firms' financial reporting decisions.

6.2 Alternative Measure for Machine-sensitive Misreporting

Our measure of *machine-sensitive misreporting* measure is based on the method developed by Bertomeu et al. (2021) to predict accounting misstatements. In a recent paper, Bao et al. (2020) also develop a similar measure using a machine learning approach. They employ an ensemble learning method and raw accounting numbers from the ratios used in Dechow et al. (2011) as input to predict material accounting misstatements disclosed in the SEC's Accounting and Auditing Enforcement Releases (AAERs). Following Bao et al. (2020), we construct a variable called *Fraud*

Score and explore the relation between machine readership and *Fraud Score*. The results, reported in Panel B of Table 11, are consistent with our main findings, indicating that machine readership is negatively related to machine-sensitive misreporting.

VII. CONCLUSION

Recent advancements in AI and machine learning have garnered significant attention among scholars and practitioners. In this study, we explore the relation between the adoption of new technologies by financial statement users and firms' decisions pertaining to financial reporting. Our findings suggest that higher machine readership is associated with a reduction in overall misreporting, particularly for patterns that are sensitive to machine analysis. This suggests that the adoption of AI and machine learning technologies exerts a disciplining effect on managerial reporting behavior.

This study is also the first to provide empirical evidence on how the adoption of AI and machine learning affects financial statement preparation — an underexplored yet essential topic in financial accounting. Our findings contribute to the understanding of the broader implications of AI adoption in financial markets, demonstrating its potential to enhance transparency and accountability. Future research can build upon our findings by examining other dimensions of AI adoption and investigating the various mechanisms through which AI influences managerial decision-making and financial reporting quality.

We acknowledge certain limitations in our analysis, particularly regarding the potential noise and Type II errors inherent in measures of *TM-sensitive misreporting* (Leone 2022). To address these limitations, we recommend future studies consider employing more refined misreporting measures, incorporating clear identification strategies, or leveraging advanced machine learning approaches. Such efforts could enhance the precision of findings and contribute to the growing body of literature on the intersection of AI and financial reporting.

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Figure 2: Distribution of Machine-sensitive Misreporting (*Restatement_Risk*)

This figure plots the distribution of *Restatement_Risk* measure provided by Bertomeu et al. (2021). Following the method outlined by Dechow et al. (2011), we create an indicator variable of *I*_Risk, which takes a value of one when *Restatement_Risk* = 0.157, using a cutoff of Type I error to be five percent. The red vertical dash line indicates that if an indicator variable for misstatement takes value of 1 for area above the line, the Type 1 error for such indicator variable is five percent.

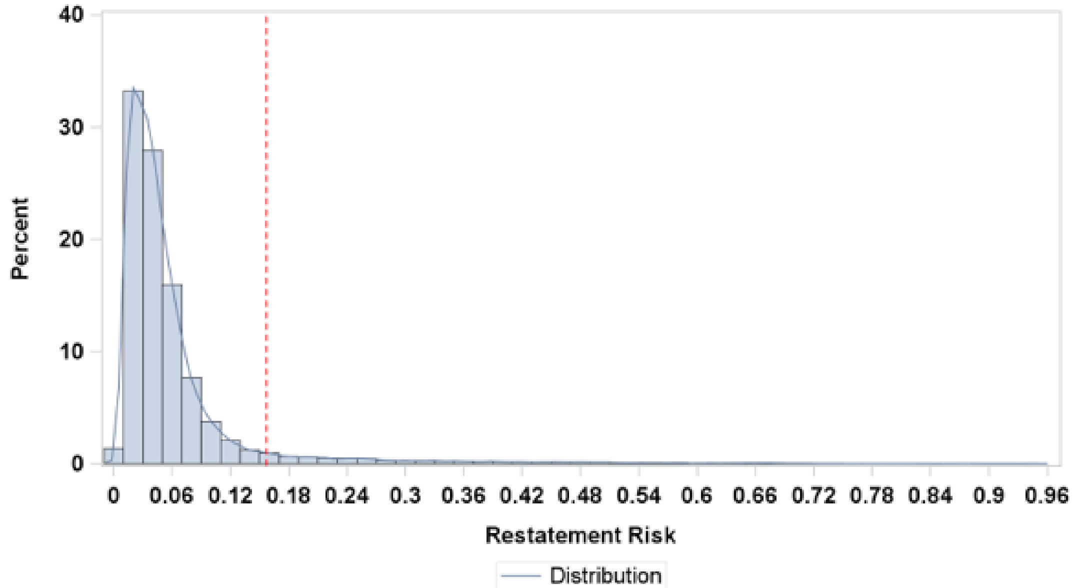

Figure 3: Validation of *I_Risk* using actual restatement

This figure displays an evaluation of *I_Risk* and the actual misstatement. *I_Risk* is an indicator variable equals one when *Restatement Risk* is greater than the cutoff values where the Type 1 error rate is at 5%. Cutoff value is calculated annually.

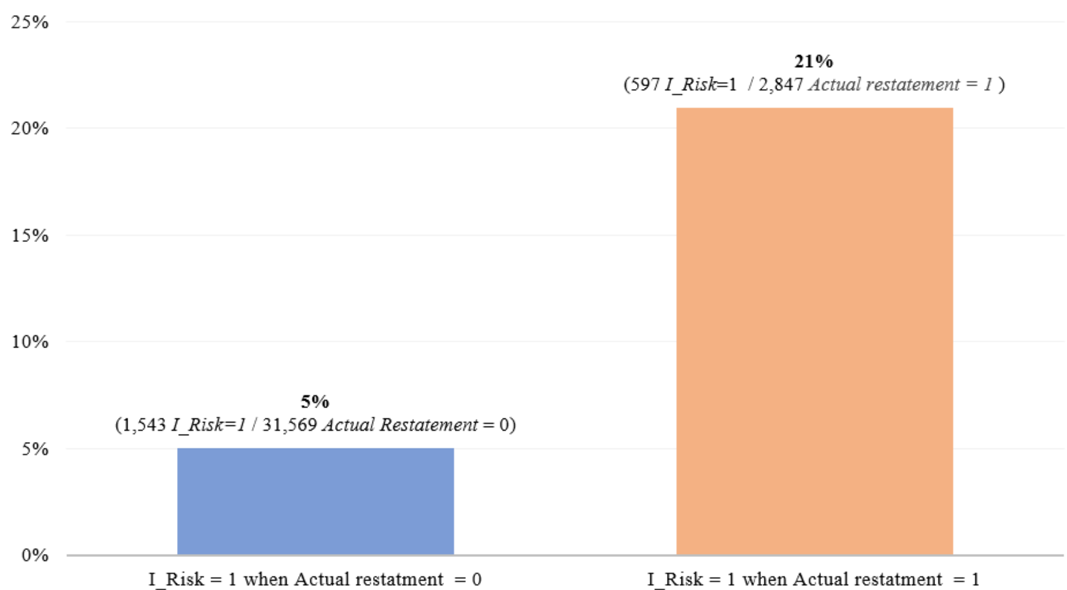

Table 1: Sample Selection

Panel A. Primary Sample	
	Firm-years
Firm-years from universe of Compustat (with non-missing total assets) (fiscal years 2004 - 2016)	117,670
Observations in finance and regulated industries, or listed in non-major exchange	(43,825)
Observations with missing control variables (from Compustat, CRSP, I/B/E/S, and Thomson Reuter Ownership database)	(35,019)
Observations with missing machine downloads information and restatement risk	(5,117)
Total Observations	33,709

Panel B. AI-ownership Sample	
	Firm-years
Firm-years from universe of Compustat (with non-missing total assets) (fiscal years 2011 - 2019)	77,543
Observations in finance and regulated industries, or listed in non-major exchange	(41,194)
Observations with missing control variables (from Compustat, CRSP, I/B/E/S and Thomson Reuter Ownership database)	(21,159)
Observations with missing AI Ownership information	(5,509)
Total Observations	9,681

Table 2. Descriptive Statistics

This table presents descriptive statistics for the variables used in our analysis. The sample is 33,709 firm-year observations and covers firms over 2004 – 2016 with non-missing financial data from Compustat, CRSP, Thomson/Refinitiv Institutional (13f) Holdings, I/B/E/S, IPUMS, and BurningGlass. Variable definitions are listed in Appendix A.

Variable	N	Std Dev	mean	p25	Median	p75
Actual Restatement	33,709	0.28	0.08	0	0	0
AI Talent Supply	13,651	0.02	0.10	0.10	0.11	0.12
Alt_Data_Covered	33,709	0.12	0.01	0	0	0
Analysts Following	33,709	1.00	1.64	0.69	1.79	2.40
Big4	33,709	0.43	0.75	1	1	1
I_Risk	33,709	0.24	0.06	0	0	0
Institutional Ownership	33,709	0.34	0.59	0.30	0.69	0.88
Leverage	33,709	0.20	0.21	0.01	0.17	0.33
Litigate	33,709	0.44	0.26	0	0	1
Loss	33,709	0.47	0.34	0	0	1
Machine Downloads	33,709	0.18	0.70	0.57	0.72	0.85
MTB	33,709	2.43	2.86	1.23	2.09	3.61
Peer Restatement	33,709	0.45	0.71	0	1	1
Post_Coverage	33,709	0.42	0.23	0	0	0
RD	33,709	2.38	0.44	0	0.00	0.09
Restatement_Risk	33,709	0.09	0.07	0.03	0.05	0.07
ROA	33,709	0.16	-0.01	-0.04	0.04	0.09
Sales Growth	33,709	0.44	0.13	-0.03	0.07	0.19
Size	33,709	1.92	6.32	4.90	6.32	7.72
Total Downloads	33,709	1.56	5.21	3.92	5.03	6.63

Panel B. AI_Ownership

Variable	N	Std Dev	mean	p25	Median	p75
AI_Ownership	9,681	0.11	0.10	0.01	0.06	0.16
Analysts Following	9,681	0.98	1.70	1.1	1.8	2.5
Big4	9,681	0.45	0.72	0	1	1
I_Risk	9,681	0.26	0.07	0	0	0
Institutional Ownership	9,681	0.31	0.62	0.37	0.72	0.88
Leverage	9,681	0.26	0.48	0.28	0.47	0.65
Loss	9,681	0.47	0.32	0	0	1
MTB	9,681	1.60	2.30	1.3	1.8	2.7
Restatement_Risk	9,681	0.06	0.05	0.02	0.04	0.06
ROA	9,681	0.20	0	-0.04	0.04	0.09
Sales Growth	9,681	0.48	0.18	0	0.07	0.18
Size	9,681	2.20	6.70	5.1	6.7	8.2

Table 3: Machine readership and Machine-sensitive Misreporting

This table reports the relation between *Machine Downloads* and machine-sensitive misreporting measures: (1) *Restatement_Risk* and (2) *I_Risk*. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. Standard errors, clustered by firm and year, are reported in parentheses. All continuous variables, except for *Restatement_Risk* and *Machine Downloads*, are winsorized at the 1% and 99% levels. Variable definitions are provided in Appendix A.

Panel A. Machine Downloads and Machine-sensitive Misreporting

VARIABLES	(1)	(2)	(3)	(4)	(5)
			Restatement Risk		*I_Risk*
Machine Downloads	-0.054***	-0.030***	-0.056***	-0.027***	-1.778***
	(0.010)	(0.007)	(0.008)	(0.007)	(0.223)
Total Downloads	-0.009***	0.002	0.000	0.001	-0.003
	(0.002)	(0.001)	(0.002)	(0.001)	(0.046)
ROA			-0.012	-0.015	-0.332
			(0.010)	(0.009)	(0.228)
MTB			-0.000	0.000	0.000
			(0.000)	(0.000)	(0.010)
Size			-0.003**	0.002	-0.027
			(0.001)	(0.001)	(0.026)
Leverage			0.021***	0.036***	0.578***
			(0.005)	(0.007)	(0.119)
Sales_Growth			0.008***	0.005*	0.197***
			(0.002)	(0.002)	(0.044)
RD			-0.002***	-0.001	-0.039**
			(0.000)	(0.000)	(0.015)
Loss			0.022***	0.013***	0.705***
			(0.004)	(0.002)	(0.071)
Analyst_Following			-0.002	0.001	-0.114***
			(0.003)	(0.003)	(0.042)
Institutional Ownership			0.006	0.007*	-0.052
			(0.004)	(0.004)	(0.094)
Big 4			-0.015***	0.003	-0.449***
			(0.002)	(0.005)	(0.060)
Constant	0.155***	0.082***	0.127***	0.049***	-1.590***
	(0.013)	(0.009)	(0.010)	(0.015)	(0.459)
Observations	33,709	33,371	33,709	33,371	33,709
Adj-R^2/ Pseudo R^2	0.08	0.34	0.12	0.35	0.050
Method	OLS	OLS	OLS	OLS	Logistic
Industry FE	Yes	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes

Panel B. AI Ownership and Machine-sensitive Misreporting

VARIABLES	(1)	(2)	(3)	(4)	(5)
		Restatement_Risk			*I_Risk*
AI_Ownership	-0.109***	-0.030**	-0.022*	-0.036**	-1.251*
	(0.007)	(0.010)	(0.009)	(0.013)	(0.735)
MTB			-0.000	-0.001	-0.013
			(0.001)	(0.001)	(0.039)
ROA			-0.003	-0.000	-0.184
			(0.006)	(0.009)	(0.301)
Size			-0.004***	0.006**	-0.019
			(0.001)	(0.003)	(0.054)
Leverage			0.016***	0.005	0.747***
			(0.005)	(0.011)	(0.221)
Sales_Growth			0.008***	0.003	0.303***
			(0.002)	(0.005)	(0.086)
RD			-0.016	0.009	-0.724
			(0.012)	(0.024)	(0.480)
lag_loss			0.010***	0.002	0.364***
			(0.002)	(0.002)	(0.133)
Analyst_Following			-0.000	-0.002	-0.121
			(0.002)	(0.002)	(0.098)
Institutional Ownership			-0.003	-0.001	-0.251
			(0.005)	(0.007)	(0.275)
Big 4			-0.008**	0.010	-0.348**
			(0.003)	(0.009)	(0.158)
Constant	0.063***	0.055***	0.076***	0.010	-2.574***
	(0.001)	(0.001)	(0.003)	(0.018)	(0.229)
Observations	9,681	9,467	9,681	9,467	9,533
Adj-R^2/ Pseudo R^2	0.04	0.43	0.08	0.44	0.06
Method	OLS	OLS	OLS	OLS	Logistic
Industry FE	Yes	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes

Table 4: Exogenous Variation Using Local AI Talent Supply

This table reports the 2SLS analysis using *AI Talent Supply* as Instrumented *Machine Downloads*. *Machine-sensitive misreporting* measures include *Restatement_Risk* (columns 2) and *I_Risk* (column 3). Instrumented *Machine Downloads* is the standardized value of predicted *Machine Downloads* from the first stage. The sample covers firms from 2011 to 2016 with non-missing financial data. Variable definitions are listed in Appendix A. All continuous variables (excluding *Restatement_Risk* and *Machine Downloads*) are winsorized at 1% and 99%. Control variables include *ROA, MTB, Size, Leverage, Sales Growth, RD, Loss, Analysts Following, Institutional Ownership*, and *Big4*. OLS regressions are estimated with industry/firm and year fixed effects. Logistic regressions are estimated with industry and year fixed effects. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm and year, are reported in parentheses.

VARIABLES	(1) *Machine Downloads*	(2) *Restatement Risk*	(3) *I_Risk*
AI Talent Supply	0.121**		
	(0.000)		
Instrumented		-1.443**	-36.926*
Machine Downloads		(0.447)	(19.793)
Total Downloads		-0.002	-0.159**
		(0.001)	(0.070)
Observations	13,651	13,651	13,589
Adj-R^2/ Pseudo R^2	0.74	0.09	0.06
Method	OLS	OLS	Logistic
Constant	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Industry FE	No	Yes	Yes
Firm FE	Yes	No	No
Year FE	Yes	Yes	Yes

Table 5: Machine readership and TM-sensitive misreporting

This table reports the regression results of *TM-sensitive misreporting* on machine readership (measured by *Machine Downloads* and *AI Ownership*). Proxies for *TM-sensitive misreporting* include (1) Discretionary accruals from the modified Jones model (*MJones*), (2) Discretionary accruals from performance-matched modified Jones model (*PM-Jones*), and (3) F-score as a prediction of material misstatements (*F-score*). Variable definitions are listed in Appendix A. All continuous variables except *Machine Downloads* are winsorized at 1% and 99%. Control variables include *ROA, MTB, Size, Leverage, Sales Growth, RD, Loss, Analysts Following, Institutional Ownership*, and *Big4*. OLS regressions are estimated with firm and year fixed effects. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm and year, are reported in parentheses.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	MJones		*PM-Jones*		*F-score*	
Machine Downloads	-0.004		-0.004		0.036	
	(0.005)		(0.004)		(0.030)	
AI Ownership		0.015		0.017		0.048
		(0.015)		(0.014)		(0.088)
Observations	28,242	10,180	28,179	10,145	28,555	10,297
Adj-R^2	0.23	0.28	0.23	0.25	0.65	0.73
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Machine readership and Restatements

This table examines and reports the regression results between restatement incidence and machine readership. *Restatement* is an indicator variable that equals to one if a firm files a restatement through Form $8-K$ Item 4.02. Proxies for machine readership include *Machine Download* and *AI Ownership*. The sample covers firms over 2004 – 2016 for *Machine Download* (2011 – 2019 for *AI Ownership*) with non-missing financial data. Variable definitions are listed in Appendix A. Column (1) and (3) employ linear probability model, and column (2) and (4) use logistic regression, controlling for firm and year fixed effects, and industry and year fixed effects, respectively. All continuous variables (excluding *Machine Downloads*) are winsorized at 1% and 99%. Control variables include *ROA, MTB, Size, Leverage, Sales Growth, RD, Loss, Analysts Following, Institutional Ownership,* and *Big4*. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm and year, are reported in parentheses.

	(1)	(2)	(3)	(4)
VARIABLES		*Restate*		
Machine Downloads	-0.048**	-1.177***		
	(0.020)	(0.207)		
AI Ownership			-0.226**	-0.200
			(0.082)	(0.675)
Observations	33,371	33,709	8,161	8,387
Adj-R^2/ Pseudo R^2	0.06	0.03	0.44	0.04
Method	LPM	Logistic	LPM	Logistic
Constant	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
Firm FE	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes

Table 7: Machine readership advantage: financial statement complexity

This table reports the relationship between our measure of misreporting and machine readership: between *Machine Downloads* and machine-sensitive misreporting proxies (1) *Restatement_Risk*, and (2) *I_Risk*. Variable definitions are listed in Appendix A. All continuous variables (excluding *Restatement_Risk* and *Machine Downloads*) are winsorized at 1% and 99%. Control variables include *ROA, MTB, Size, Leverage, Sales Growth, RD, Loss, Analysts Following, Institutional Ownership*, and *Big4*. Regressions are estimated with industry/firm and year fixed effects. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm and year, are reported in parentheses.

	(1)	(2)	(3)
VARIABLES	*Restatement Risk*		*I_Risk*
Machine Downloads %	-0.036***	-0.010	-1.404***
	(0.008)	(0.008)	(0.269)
FS Complexity	0.039***	0.035***	0.872***
	(0.007)	(0.006)	(0.183)
Machine Downloads % x FS Complexity	-0.033***	-0.035***	-0.479*
	(0.009)	(0.008)	(0.254)
Observations	33,278	32,936	33,278
Adj-R^2/ Pseudo R^2	0.13	0.35	0.06
Method	OLS	OLS	Logistic
Constant	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Industry FE	Yes	No	Yes
Firm FE	No	Yes	No
Year FE	Yes	Yes	Yes

Table 8: Machine readership advantage: Alternative Data Coverage

This table reports the relationship between satellite data coverage and machine-sensitive misreporting: between *Post_Coverage*, *Alt_Data_Covered*, and machine-sensitive misreporting proxies *Restatement_Risk*. Variable definitions are listed in Appendix A. All continuous variables (excluding *Restatement_Risk* and *Machine Downloads*) are winsorized at 1% and 99%. Control variables include *ROA, MTB, Size, Leverage, Sales Growth, RD, Loss, Analysts Following, Institutional Ownership*, and *Big4*. Column (1) and (2) present OLS regression results with industry and year fixed effects. Column (3) and (4) present OLS regression results with firm and year fixed effects. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm and year, are reported in parentheses.

VARIABLES	(1)	(2)	(3)	(4)
		Restatement Risk		
Machine Downloads	-0.056***	-0.057***	-0.027***	-0.027***
	(0.008)	(0.005)	(0.007)	(0.006)
Post_Coverage		-0.001		0.002
		(0.003)		(0.003)
Post_Coverage x Alt_Data_Covered		-0.006		-0.009**
		(0.005)		(0.004)
Observations	33,709	33,709	33,371	33,371
Adj-R^2	0.12	0.12	0.35	0.350
Constant	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 9: AI-enabled detection: increased misreporting cost from peer restatement

This table reports whether firms with *Peer Restate* displays a different relationship between machine readership and machine-sensitive misreporting. between *Machine Downloads* and misreporting proxies (1) *Restatement_Risk* and (2) *I_Risk*. The sample covers firms over 2004 − 2016 with non-missing financial data and partitioned based on the indicator variable *Peer Restate*. Variable definitions are listed in Appendix A. All continuous variables are winsorized at 1% and 99% except *Restatement_Risk* and *Machine Downloads*. Control variables include *ROA, MTB, Size, Leverage, Sales Growth, RD, Loss, Analysts Following, Institutional Ownership*, and *Big4*. Regressions are estimated with industry/firm and year fixed effects. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm and year, are reported in parentheses.

VARIABLES	(1)	(2)	(3)
	Restatement Risk		*I_Risk*
Machine Downloads	-0.019*	-0.003	-0.764**
	(0.009)	(0.009)	(0.336)
Peer Restate	0.046***	0.028***	1.215***
	(0.009)	(0.006)	(0.223)
Machine Downloads	-0.050***	-0.034***	-1.219***
x Peer Restate	(0.012)	(0.009)	(0.307)
Observations	33,709	33,371	33,709
Adj-R^2/ Pseudo R^2	0.12	0.35	0.06
Method	OLS	OLS	Logistic
Constant	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Industry FE	Yes	No	Yes
Firm FE	No	Yes	No
Year FE	Yes	Yes	Yes

Table 10: AI-enabled detection: High-litigation industry

This table reports the relationship between our measure of misreporting and machine readership: between *Machine Downloads* and misreporting proxies (1) *Restatement_Risk* and (2) *I_Risk*. The sample covers firms over 2004 − 2016 with non-missing financial data and partitioned based on the indicator variable *Litigate*. Variable definitions are listed in Appendix A. All continuous variables (excluding *Restatement_Risk* and *Machine Downloads*) are winsorized at 1% and 99%. Control variables include *ROA, MTB, Size, Leverage, Sales Growth, RD, Loss, Analysts Following, Institutional Ownership*, and *Big4*. Regressions are estimated with industry/firm and year fixed effects. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm and year, are reported in parentheses.

	(1)	(2)	(3)
VARIABLES	*Restatement Risk*		*I_Risk*
Machine Downloads	-0.044***	-0.017**	-1.626***
	(0.008)	(0.007)	(0.235)
Litigate	0.038***	0.039***	0.523**
	(0.012)	(0.012)	(0.214)
Machine Downloads	-0.045***	-0.041***	-0.543*
x Litigate	(0.014)	(0.012)	(0.277)
Observations	33,709	33,371	33,709
Adj-R^2/ Pseudo R^2	0.12	0.35	0.05
Method	OLS	OLS	Logistic
Constant	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Industry FE	Yes	No	Yes
Firm FE	No	Yes	No
Year FE	Yes	Yes	Yes

Table 11: Alternative measures

Panel A. Alternative measures of machine download.

This table reports the relationship between our measure of misreporting and machine readership: between *Machine Downloads* (alternative definition) and misreporting proxies (1) *Restatement_Risk* and (2) *I_Risk*. The sample covers firms over 2004 − 2016 with non-missing financial data. Variable definitions are listed in Appendix A. All continuous variables are winsorized at 1% and 99% except *Restatement_Risk* and *Machine Downloads*. Control variables include *ROA, MTB, Size, Leverage, Sales Growth, RD, Loss, Analysts Following, Institutional Ownership*, and *Big4*. OLS regressions are estimated with industry/year and firm fixed effects, and logistic regressions are estimated with year and industry fixed effects. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm and year, are reported in parentheses.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
		Restatement_Risk			*I_Risk*	
Machine Downloads_14D	-0.059***		-0.033***		-2.020***	
	(0.009)		(0.007)		(0.226)	
Total Downloads_14D	0.001		0.002		0.014	
	(0.002)		(0.001)		(0.047)	
Machine Downloads_30D		-0.057***		-0.032***		-2.048***
		(0.010)		(0.009)		(0.235)
Total Downloads_30D		0.003		0.004*		0.056
		(0.002)		(0.002)		(0.050)
Observations	33,709	33,709	33,371	33,371	33,709	33,709
Adj-R^2/ Pseudo R^2	0.12	0.12	0.35	0.35	0.06	0.06
Method	OLS	OLS	OLS	OLS	Logistic	Logistic
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	Yes	Yes
Firm FE	No	No	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Alternative measures of machine-sensitive misreporting

This table reports the relationship between machine readership and machine-sensitive misreporting proxies *Fraud Score*. We define *Fraud Score* following the machine learning method in Bao, Ke, Li, Yu, and Zhang (2020). The sample covers firms over 2004 − 2016 with non-missing financial data. Variable definitions are listed in Appendix A. All continuous variables are winsorized at 1% and 99% except *Fraud Score* and *Machine Downloads*. Control variables include *ROA, MTB, Size, Leverage, Sales Growth, RD, Loss, Analysts Following, Institutional Ownership*, and *Big4*. Column (1) controls for industry and year fixed effects, and column (2) controls for firm and year fixed effects. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm and year, are reported in parentheses.

VARIABLES	(1) *Fraud Score*	(2) *Fraud Score*
Machine Downloads	-0.192***	-0.126***
	(0.044)	(0.043)
Observations	28,700	28,330
Pseudo R^2	0.70	0.49
Constant	Yes	Yes
Controls	Yes	Yes
Industry FE	Yes	No
Firm FE	No	Yes
Year FE	Yes	Yes

Appendix A. Variable Definitions

Variable	Description
Machine Readership variables	
Machine Downloads	The ratio of the number of download requests made by machine readers of the Form 10-K in the last fiscal year scaled by the number of total downloads of the same form. To measure Machine Downloads, we identify an IP address downloading more than 50 unique firms' filings (Lee et al., 2015). Next, we aggregate the daily raw downloads data for each filing within seven days after it becomes available on EDGAR, and scale by the number of total downloads of the same form.
AI Ownership	The ownership of AI-equipped investment company shareholders at the firm-year- level. Following Cao, Jiang, Yang, and Zhang (2023), we identify investment companies as AI-equipped if they have posted job openings related to AI technology in the past five years, according to Burning Glass job posting data between 2011 and 2016. Then, we aggregate at the firm-year- level.
Misreporting variables	
F-score	Score variable following Dechow, Ge, Larson, and Sloan (2011), implying that a score of 1.00 indicates that the firm has the same probability of misstating than the unconditional probability.
I_Risk	Indicator variable equal to one if R-Risk is above a certain threshold – a yearly cutoff point above which Type I error is at five percent, and zero otherwise.
MJones	The absolute value of residuals from the modified Jones model following Dechow, Sloan, and Sweeney (1995).
PM-Jones	The absolute value of residuals from the performance matched modified Jones model following Kothari, Leone, and Wasley (2005).
Restate	An indicator variable is the firm issued a restatement filing in the Form 8 − K Item 4.02.
Restatement_Risk	The probability of Restatement Risk following Bertomeu, Cheynel, Floyd, and Pan (2021), using Audit Analytics' Restatement data and GBRT model.
Other variables	
AI Talent Supply	Following Jiang et al. (2021) and Cao et al. (2023), we obtain the number of people between 18 and 64 with college or graduate degree in information technology, from Integrated Public Use Microdata Series (IPUMS), a state-level data from 2011 to 2016 scaled by state population. Then, we match the headquarters of the institutional investors and states into an investor-state-year-level AI talents supplies. Last, we aggregate at the firm-level
Alt_Data_Covered	Indicator variable equal to one if the firm is covered by satallite images, following Katona et al. (2022).
Analysts Following	The natural logarithm of 1+ the number of analysts following a firm.
Big 4	Indicator variable equal to one if the firm is audited by the big 4 auditing firm
FS Complexity	Indicator variable equal to one if the number of words in a 10-K is above median, and zero otherwise.
Institutional Ownership	The proportion of shares held by institutional investors.
Leverage	Total liabilities divided by total assets.
Litigate	Indicator variable equal to one if the firm belongs to the biotechnology (SIC codes2833–2836), R&D services (8731–8734), programming (7371–7379), computers (3570–3577), electronics (3600–3674), and zero otherwise.
Loss	Indicator variable equal to one if net income is negative and zero otherwise.

Market-to-Book	The market-to-book ratio.
Peer Restate	Indicator variable equal to one if a firm has restating peer firms.
Post Coverage	Indicator variable equal to one after the initiation of satellite coverage, following Katona et al. (2022).
RD	Total research and development expenses scaled by sales.
ROA	Firms' net income over lagged total assets.
Sales Growth	The one-year percentage change in sales for the year prior to the current fiscal year.
Size	The natural logarithm of market capitalization.
Total Downloads	The natural logarithm of total download requests of the Form 10-K in the last fiscal year.