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Signal or Cheap Talk?

AI Activity Disclosure and Firm Valuation on Nasdaq Stockholm, 2014–2024

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Abstract: This thesis examines whether disclosed AI activity in annual reports is associated with firm valuation and fundamental performance among Swedish non-technology companies listed on Nasdaq Stockholm Main Market between 2014 and 2024. Using textual analysis of 1,098 annual reports across 102 firms, we construct a firm-year measure of disclosed AI activity and relate it to i) the market-to-book ratio, ii) four measures of fundamental performance over horizons up to three years, and iii) R&D and SG&A intensity. We find that disclosed AI activity is positively associated with the market-to-book ratio only in our strictest specification, with significance at the 10 percent level, implying market-to-book ratios 8% to 23% higher for AI-disclosing firms than non-disclosing peers. It is also associated with subsequent improvements in three of four fundamental performance measures at the three-year horizon (including ROA of 12.5% to 37.5% higher than industry peers), with effects largely absent at shorter horizons. The findings indicate no significant association with R&D or SG&A intensity, suggesting that firms are disclosing AI activity without corresponding investment, so called AI-washing. Taken together, however, the deferred fundamental improvements are the clearest evidence against this AI-washing reading and suggest that markets price real underlying activity, though the small Swedish sample leaves room for the alternative reading.

Keywords: AI disclosure, Textual analysis, Market-to-book ratio, Fundamental performance
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1. Introduction

In only a few years, artificial intelligence has moved from a niche research topic to a common feature of corporate disclosure. Firms across the size spectrum are increasing their disclosed AI activity, from global giants such as Walmart and JP Morgan Chase, which emphasize AI activity throughout their annual reports, to micro-caps reinventing themselves outright. The most extreme example is Allbirds, a footwear maker whose stock surged nearly 600% after announcing that it would pivot away from shoes and become an AI compute infrastructure provider (Markman, 2026). Subtler versions of the same playbook also exist: Domino's Pizza, described by its former CEO J. Patrick Doyle as "a technology company that delivers pizza" (Groysberg, Abbott and Seligson, 2021) has been among the top-performing non-technology stocks of the past decade. The pattern is broader than headline-grabbing anecdotes. Among US-listed non-technology firms, the share disclosing digital activity rose from 8% in 2010 to 30% in 2020 (Chen and Srinivasan, 2024). The trend is clear. Technology disclosure has become widespread and firms that disclose technology activity appear to be rewarded both in market valuations and, increasingly, in fundamental performance.

However, the picture is far less clear for non-technology firms outside the United States, particularly when the focus narrows from broad digital activity to AI specifically. An unanswered question remains: Is the disclosure of their AI activity also associated with higher firm valuations?

1.1 Theoretical and empirical background

Theory offers clear reasons to expect a relationship between disclosed AI activity for non-technology firms and firm valuation.

Accounting systems have long struggled to capture intangible investment, producing a widening gap between book and market values for intangible-intensive firms (Lev and Sougiannis, 1996; Lev and Zarowin, 1999). Under IFRS, development costs can only be capitalized when strict criteria are met (IAS 38). Most AI-related spending fails to meet these criteria. As a result, book value is systematically depressed for AI-investing firms.

Voluntary disclosure and signaling theory predict that firms can improve investor valuation by disclosing value-relevant non-financial information (Spence, 1973; Verrecchia, 1983; Healy and Palepu, 2001), and empirical work confirms that investors price such information (Amir and Lev, 1996; Trueman, Wong and Zhang, 2000; Li, 2010). Together, if AI activity is value-relevant, firms have incentives to disclose it, and markets should reflect that disclosure in valuations.

Empirical evidence on technology disclosure and AI adoption is less settled. The closest precedent is Chen and Srinivasan (2024), who apply textual analysis to US 10-K filings and find that disclosure of digital activity is associated with significantly higher market-to-book ratios. This thesis builds on the methodological and empirical foundation they establish. Focusing on AI activity specifically, studies document positive associations between AI investment and firm growth (Babina et al., 2024), reduced operating volatility (Babina et al., 2025) and enhanced complementary-asset value (Cockburn, Henderson and Stern, 2019). At the same time, benefits may lag investment by years as firms build the intangible capital required to extract value from AI (Brynjolfsson, Rock and Syverson, 2021), echoing the historical lag between IT adoption and measurable productivity gains first documented by Solow (1987). Disclosure may not always reflect underlying activity: Barrios et al. (2025) find that firms disclosing AI activity without corresponding investment, so-called AI-washing, do not experience the fundamental improvements observed among genuine adopters.

1.2 Contribution

This thesis builds on Chen and Srinivasan (2024) but departs from their study in three deliberate ways.

First, the setting shifts from the United States to Sweden, which matters in three distinct ways. The accounting regimes differ, with US adopting GAAP while the Swedish Main Market is governed by IFRS. The technological settings also differ, Sweden has consistently ranked among Europe's digital frontrunners since the Digital Economy and Society Index began in 2014 (European Commission, 2023) and was the third-highest EU country in enterprise AI adoption in 2025 at 35% (Eurostat, 2025), suggesting that Swedish listed firms are well positioned to translate AI investment into realized outcomes. Furthermore, Swedish and US reporting structures differ. Chen and Srinivasan’s methodology was designed for the standardized US 10-K format. This cannot be directly applied to Swedish annual reports given their different requirements and structure.

Second, Chen and Srinivasan's (2024) dictionary captures broad digital technologies, whereas this thesis targets AI specifically. AI is a narrower and more uncertain technology whose valuation signal may differ from that of mature digital infrastructure.

Third, their sample ends before the release of ChatGPT in late 2022, whereas the 2014 to 2024 window adopted here spans both pre-diffusion and post-diffusion periods. Thus, allowing a test of whether the disclosure-valuation relationship holds through the rapid mainstreaming of AI. To our knowledge, no prior study has applied text-based measurement of AI activity to Swedish annual reports.

1.3 Research design and findings

This thesis examines whether disclosed AI activity is associated with firm valuation and fundamental performance among Swedish public non-technology firms listed on Nasdaq Stockholm Main Market between 2014 and 2024. Using textual analysis of annual reports, it constructs a firm-year measure of disclosed AI activity intensity and examines its relationship with market-to-book ratios (MTB) and measures of profitability, productivity/efficiency, while also testing the disclosure-based measure against alternative indicators of underlying AI activity.

The main research question is whether disclosed AI activity in Swedish public non-technology firms' annual reports is associated with higher firm valuations. This question is addressed through three sub-questions:

i) Are non-technology firms that disclose AI activity associated with higher market-to-book ratios than industry peers?

ii) Is disclosed AI activity associated with subsequent changes in fundamental performance, as measured by profitability and productivity/efficiency?

iii) To what extent does disclosed AI activity in annual reports proxy for actual AI activity, as measured by R&D and SG&A spending?

To test our hypotheses stemming from these questions, we construct a firm-year disclosed AI activity score by counting AI-lexicon mentions in each annual report, applying a 50-word context filter to exclude macroeconomic commentary, normalizing by report length, and quantizing into a 0 to 3 score based on within-year terciles. We then estimate three panel regressions: a market-to-book specification, a model linking disclosed AI activity to subsequent changes in profitability and productivity over one-year to three-year horizons, and a test relating disclosed AI activity disclosure to Research & Development (R&D) and Selling, General and Administrative Expenses (SG&A) intensity. In addition, we estimate a determinants regression that identifies the firm characteristics associated with disclosed AI activity and tests its year-to-year persistence. All specifications include industry and year fixed effects, with standard errors clustered at the firm level.

We find that disclosed AI activity is positively associated with firm valuation among Swedish non-technology firms, although the supporting evidence is mixed. The market-to-book association is significant at the 10% level in our strictest specification, with MTB ratios 8% to 23% higher than non-disclosing peers. Disclosed AI activity is also associated with subsequent improvements in three of four fundamental performance measures at the three-year horizon (including ROA 12.5% to 37.5%), with effects largely absent at shorter horizons. This timing pattern is consistent with the lag between AI investment and measurable returns predicted by general-purpose technology theory. However, disclosed AI activity is not associated with R&D or SG&A intensity. This allows for two readings, either that R&D and SG&A are too broad to capture real AI activity or that disclosure does not reflect real AI activity, consistent with AI-washing. Our small Swedish sample leaves room for both readings.

The remainder of the thesis proceeds as follows. Section 2 develops the theoretical grounding, reviews the empirical literature on AI and firm outcomes, and derives the hypotheses. Section 3 sets out the research design, including the construction of the disclosed AI activity measure, variable definitions, and the sample. Section 4 reports descriptive statistics and the main empirical results across the three sub-questions. Section 5 discusses the findings in relation to prior literature. Section 6 concludes with contributions, limitations, and directions for future research.

2. Literature review and theory

This section sets out the foundation for the empirical analysis. Section 2.1 develops the theoretical case for studying disclosed AI activity: why non-financial disclosures are value-relevant, why AI activity is poorly captured in book value, and why market-to-book is the natural dependent variable. Section 2.2 reviews the related literature on AI's effects on firm outcomes, measurement approaches, and the control variables we use. Section 2.3 develops the hypotheses.

2.1 Theoretical foundation

2.1.1 Why non-financial information is value-relevant

A central premise of this thesis is that non-financial disclosures can convey information that investors price beyond what is contained in the audited financial statements. This premise rests on two complementary theoretical frameworks and a body of empirical evidence.

Voluntary disclosure theory suggests that firms disclose information when the benefits of reducing information asymmetry, such as a lower cost of capital and higher valuation, outweigh the costs of disclosure (Verrecchia, 1983). Relatedly, signaling theory further suggests that firms may use disclosure to distinguish themselves from competitors, as credible signals of quality or future prospects can be rewarded by the market (Spence, 1973). Both frameworks rest on a shared assumption. Disclosure must be costly to fabricate, otherwise the signal carries no information. For verifiable claims about past performance, this assumption holds, as false claims carry legal and reputational costs (Healy and Palepu, 2001). For forward-looking AI disclosures, the assumption is weaker. Claims about AI activity can be made in a few sentences, are difficult to falsify in real time, and rarely carry direct legal exposure. The same theory that predicts informative disclosure therefore also predicts cheap talk. Firms can claim AI activity to capture the valuation benefit even when underlying investment is limited or absent, a pattern often called AI-washing.

However, if firms disclose credibly and investors update on that disclosure, we should see that disclosure reflected in valuations. Empirical research confirms this. Amir and Lev (1996) demonstrate that non-financial metrics, such as area population for cell phone firms, were value relevant to investors beyond what accounting numbers could convey. Similarly, Trueman, Wong and Zhang (2000) show that web traffic metrics, such as the number of unique visitors, were value relevant for internet firms beyond traditional accounting variables. As a natural step, studies have applied textual analysis to corporate disclosures to find such value-relevant information not captured in the financial statements. Li (2010) shows that linguistic features in the qualitative section of annual reports are associated with future firm performance and returns. Building on this literature, Chen and Srinivasan (2024) use textual analysis to measure digital activity disclosures. They find that these are associated with significantly higher valuations, further demonstrating that text-based proxies can capture economically meaningful information.

2.1.2 The growing wedge between book and market value

Whether disclosure of AI activity is informative depends in part on the extent to which existing accounting already captures it. If financial statements fully reflected AI investment, voluntary disclosure would add little. Research has long documented, however, a widening gap between the book and market value of firms, driven by the current rules of handling intangible investments in accounting systems. Lev and Sougiannis (1996) show that R&D, when treated as a capitalized asset rather than an expense, helps explain stock prices, suggesting that financial statements omit value-relevant information when intangible investments are expensed. Lev and Zarowin (1999) document that this gap between accounting numbers and stock prices has widened over time as intangibles have become more important to firm value.

This pattern applies directly to AI investment in Sweden. Under IFRS, research expenditures must be expensed, while development costs may be capitalized only when six strict criteria are met simultaneously, including technical feasibility, probable future economic benefits, and reliable measurement of the expenditure (IAS 38). Since AI initiatives are exploratory and costs are spread across functions, most AI-related spending is unlikely to satisfy these conditions. The complementary investments necessary for AI to generate value, such as organizational restructuring and new business processes (Cockburn, Henderson and Stern, 2019) are operating expenses by nature.

Beyond R&D, AI-related spending also flows substantially through SG&A, since enterprise adoption increasingly relies on purchased software and services rather than in-house development (Menlo Ventures, 2025; Wang *et al.*, 2025). For non-technology firms in particular, where AI is rarely a core competitive differentiator, SaaS subscriptions, integration services, and vendor fees concentrate AI expenditure in operating expenses.

Taken together, AI-related spending depresses book value relative to the firm's underlying economic value, highlighting a growing need for research into value-relevant non-financial information that captures these investments.

2.1.3 Why market-to-book (MTB)?

The preceding sections establish two things: First, AI-related spending is largely absent from book value. Second, markets respond to non-financial information. If both are true simultaneously, book and market value will diverge systematically for AI-adopting firms relative to non-adopting peers, assuming that AI investments are value-relevant. That divergence is precisely what the market-to-book ratio captures. This intuition has a formal theoretical foundation.

Under the framework of Myers (1977), MTB reflects the extent to which firm value is attributable to growth options rather than assets already in place. Thus, a firm whose book value omits AI-related investments while its market value incorporates expectations of future cash flows from those investments will exhibit a structurally elevated MTB ratio relative to non-investing peers. An elevated MTB is, however, consistent with two distinct interpretations. Informative pricing of unrecognized economic assets, or behavioral overpricing of firms disclosing AI activity without substantive investment. MTB alone cannot distinguish the two, which motivates the complementary tests on fundamental performance and on whether disclosed AI activity proxies for actual AI activity.

2.2 Related literature

2.2.1 Why might AI activity increase firm value and fundamental performance?

The literature identifies three channels through which artificial intelligence may increase firm value and improve fundamental performance: (i) increased productivity and process efficiency, (ii) reduced operating risk, and (iii) enhanced value of existing assets.

First, artificial intelligence can increase productivity and process efficiency. The theoretical argument is that AI reduces the cost of experimentation and expands product offerings (Cockburn, Henderson and Stern, 2019; Bustamante, Cujean and Frésard, 2021). In addition, Agrawal et al. (2019) characterize AI as a prediction technology that makes forecasts both cheaper and more accurate, thereby raising the quality of decisions across the firm. This includes operational choices about which products to develop as well as strategic ones about how to allocate resources. Furthermore, AI can improve labor productivity. Brynjolfsson, Li and Raymond (2025) find that generative AI tools increase productivity by approximately 15% in a customer service setting, and the first causal evidence for Europe finds that AI adoption is associated with a 4% increase in labor productivity, driven by capital deepening (Aldasoro *et al.*, 2026). Overall, this means that AI-investing firms experience higher growth in sales and market valuations, driven primarily by new product creation stemming from these improvements (Babina *et al.*, 2024).

Second, AI investments may reduce firm risk by lowering the volatility of operating performance (sales, earnings, and cash flows) (Babina *et al.*, 2025). Corporate finance theory establishes that a reduction in cash flow volatility allows firms to consistently fund attractive investment opportunities, which in turn increases firm value (Froot, Scharfstein and Stein, 1993). This lower risk may thus translate directly into higher market value.

Third, beyond AI's direct contributions, AI may increase firm value and improve fundamental performance by enhancing the value of existing assets. Cockburn et al. (2019) argue that AI, as a general-purpose technology, enables firms to extract substantially more value from resources they already possess. This parallels how electricity transformed manufacturing in the early twentieth century or information technology reshaped business operations in the 1990s (Brynjolfsson and Hitt, 2000).

Taken together, these channels provide the theoretical basis for expecting AI activity disclosing firms to exhibit both higher valuations and, with varying lags, stronger fundamental performance. However, there are also channels as to why AI investment would not yield significant improvements.

2.2.2 Why might AI activity not translate into firm value?

While the previous section outlines several channels through which AI investments may create value, the literature also identifies reasons for possible delay or limitation of these benefits.

Historically, productivity gains from new technologies have been slow to materialize. During the IT revolution in the late 1980s, massive investments were deployed, and computer adoption spread swiftly, yet initially it failed to impact productivity statistics. This is referred to as Solow's paradox (Solow, 1987). Brynjolfsson et al. (2021) suggest that AI is following the same trajectory, where productivity effects from AI are modeled as a J-curve, predicting that initial productivity may decline before surging once the necessary complementary investments are in place.

The main argument for this lag is the missing costly complementary investments. Cockburn et al. (2019) attribute this to AI being a general-purpose technology, and Brynjolfsson et al. (2021) simply state that it is a necessity to generate returns. Building these assets, including new data infrastructure, organizational restructuring, employee training, and redesigned workflows, requires extensive resources in the form of time and capital. These investments are mainly expensed under current accounting standards rather than capitalized, leading to deflated profitability measures such as return on assets and operating margins (Brynjolfsson and Hitt, 2000). In addition, early adopters may face costs of creating new markets for unfamiliar AI-based products and services, since pioneering firms typically bear the costs of buyer education (Lieberman and Montgomery, 1988). The implication is that firms in the early stages of AI adoption may appear less profitable because they are investing in future capabilities.

Consistent with these theoretical arguments, the empirical evidence on AI's impact on fundamental performance is mixed. Chen and Srinivasan (2024) find that while firms disclosing digital activity exhibit significantly higher market-to-book ratios, there is only weak evidence of near-term improvements in fundamental performance. ROA and asset turnover improve on the three-year horizon, but profit margins are unaffected, and sales growth declines compared to peer firms not investing in digital activity (Chen and Srinivasan, 2024). Babina et al. (2024) studied the more relevant niche, AI-investing companies, and also found increased market value and no evidence that AI improves operating margin. However, conversely, they found that growth accelerates among AI-investing firms. Taken together, these findings suggest that even firms that are genuinely investing in AI have yet to translate those investments into consistent and coherent improved fundamentals.

Furthermore, Babina et al. (2024) find that AI-driven growth concentrates disproportionately among larger firms and is associated with rising industry concentration, as measured by increases in HHI (Herfindahl-Hirschman Index) and the market share of the largest firms. Since firms on Nasdaq Stockholm are on average smaller than their US-listed peers, those benefits may be weaker in the Swedish setting.

Separately, there is a distinction between “AI investment” and “disclosed AI activity”. Barrios et al. (2025) address this directly, finding that firms with high AI disclosure but low

AI investment (proxied by employment in their case), so-called "AI-washing", do not experience improvements in efficiency, innovation, or long-term returns, whereas firms that pair disclosure with substantial investment in AI human capital significantly outperform. This finding is consistent with the voluntary disclosure framework outlined in 2.1.1, explaining that disclosures are informative only to the extent that they are costly to fabricate. The AI-washing phenomenon suggests this cost is low for forward-looking AI claims.

Taken together, this literature provides multiple theoretical and empirical grounds on which disclosed AI activity may not translate into superior fundamentals in the short run, even when the underlying AI activity is substantive.

2.2.3 Challenges in empirically measuring AI adoption

This subsection reviews the measurement approaches used in the literature, which shapes the methodological choice developed in Section 3. A central challenge is the absence of firm-level measures that cleanly isolate AI-specific investment from broader technology or operating spending. Aggregate accounting measures such as R&D and capital expenditure capture total investment and are not in themselves AI-specific. They remain useful as correlated indicators, since under IFRS most AI-related spending flows through R&D and SG&A (Section 2.1.1), but they cannot identify AI activity on their own. Studies have therefore relied on four alternative approaches: (i) Survey data; (ii) Patent-based measures; (iii) Labor-based measures; (iv) Text-based measures on IT activity, all with their own shortcomings.

Survey data on AI adoption in Sweden exists through Statistics Sweden's ICT usage in enterprises survey, which has included an AI module annually since 2021. However, the series does not cover the first half of our 2014–2024 sample, measures AI adoption as a simple yes/no or banded category rather than a continuous scale, and the firm-level microdata are confidential, available to researchers only through a separate application process. Other studies have leveraged “The U.S. Census Bureau's Business Trends and Outlook Survey” (Bonney et al., 2024) and industry surveys such as McKinsey's annual Global Survey on AI (Babina et al., 2024) both lacking due to scope misalignment and missing firm-level panel data.

Patent-based measures identify AI activity through keyword searches in patent filings (Webb, 2019; Bloom et al., 2021). While useful for capturing frontier innovation, these measures systematically exclude firms that use AI without patenting it, precisely the non-technology adopters that are the focus of this study.

Labor-based measures proxy for AI or digital-investment through the share of employees in AI or digital-related roles, using resume databases or job-posting data (Rock, 2019; Tambe et al., 2020; Babina et al., 2024). This approach has the advantage of capturing actual AI or digital capability at the firm level. However, as Chen and Srinivasan (2024) note, these data sources cover only a subset of public firms and are not widely available to researchers, particularly outside the United States. For Swedish-listed firms, coverage in these databases is minimal.

Finally, the approach most directly relevant to this study is a text-based measurement. Chen and Srinivasan (2024) construct a measure of digital activity by counting technology-related terms in the business description section of US 10-K filings. This approach offers two main advantages that the other alternatives lack. It relies on publicly available data, and it covers all listed firms. This approach laid the foundation for our methodology.

2.2.4 Literature-based motivation for control variables

Following Chen and Srinivasan (2024), we include a set of controls that capture firm characteristics correlated with both disclosed AI activity and market valuation.

Size, measured as the log of market capitalization, controls for the fact that larger firms have more resources to invest in AI and systematically different valuations (Fama and French, 1993). Leverage, defined as total assets over shareholder equity, controls for capital structure, which affects both the capacity to invest and the level of market valuation. ROA controls for current profitability, which drives valuation independently of AI activity and shapes the firm's ability to fund discretionary investment. Three-year annualized sales growth captures the recent growth trajectory, a key valuation driver that may also correlate with AI adoption. Market-adjusted return controls for recent stock performance, and return volatility for firm risk, both of which may correlate with disclosed AI activity and valuation through investor expectations channels. Cash ratio and capital expenditure intensity, included in the determinants specification (Equation 1), control for liquidity, efficiency in capital allocation, and physical investment, which capture alternative uses of internal resources that may compete with or complement AI spending. Log report length controls for verbosity, since longer reports mechanically contain more AI-related terms (Chen and Srinivasan, 2024). For the extended MTB and fundamental performance regressions, intangibles controls are added

(R&D intensity, SG&A intensity, and a missing R&D indicator), which absorb the capitalization bias arising from AI-related spending being expensed rather than capitalized under IFRS.

Firm age is omitted from our specifications. Year fixed effects absorb the time component of age that varies across the panel and including age alongside industry fixed effects based on GICS sector produced inflated VIFs, indicating collinearity with the industry-level effects.

Finally, all specifications include industry and year fixed effects to absorb unobserved firm-level heterogeneity and common annual shocks.

2.3 Hypothesis development

This thesis aims to examine whether disclosed AI activity in annual reports is associated with higher firm valuations and improved fundamental performance among Swedish non-technology firms listed on Nasdaq Stockholm Main Market. By applying a text-based measure of AI activity to a setting governed by IFRS and covering the period 2014 to 2024, our study seeks to contribute to the broader literature on the value-relevance of non-financial disclosures and the economic implications of AI adoption outside the US market.

Based on the theoretical foundation and related literature reviewed above, we propose the following hypotheses:

H_1 (Valuation): Among non-technology firms listed on Nasdaq Stockholm, higher disclosed AI activity intensity in annual reports is positively associated with the market-to-book ratio.

H_2 (Fundamental performance): Among non-technology firms listed on Nasdaq Stockholm, disclosed AI activity intensity is not associated with improvements in fundamental performance (return on assets, asset turnover, operating margin, and sales growth) over the one to three years following disclosure.

H_3 (Proxy determination): Among non-technology firms listed on Nasdaq Stockholm, disclosed AI activity intensity is positively associated with (i) R&D intensity or (ii) SG&A intensity.

3. Data and methodology

3.1 Sample and data selection

Our study uses four datasets in total. First, we obtained a combined list of all companies whose shares were actively traded on Nasdaq Stockholm during the period 2014–2024 from Nasdaq European Data Support Service, allowing us to distinguish between Main Market and First North listings. We restricted our sample to the Main Market because these firms are required to prepare consolidated financial statements under IFRS as adopted by the EU, whereas firms on Nasdaq First North Growth Market may report under Swedish GAAP (typically the K3 framework). This ensures both report comparability and a feasible sample size. Further, we required firms to have been continuously listed from at least fiscal year 2017 onward, ensuring a minimum of five years of pre-ChatGPT (November 2022) observations per firm. Therefore, we excluded IPOs, take-privates, and other delisting activity after 2017.

We further applied the same tech-exclusion methodology as Chen and Srinivasan (2024), based on three industry classification systems (SIC, NAICS, and GICS). We removed all firms classified as digital under at least one of these systems.

For dual-listed firms with different share classes, we retained only the B share, as it is typically the more liquid class on Nasdaq Stockholm and therefore provides more reliable price and volume data for return calculations.

In the second step, we retrieved annual reports in PDF format for each firm-year using a custom Python crawler that we developed to scrape companies' investor relations pages directly, or, where unavailable, the third-party databases Modular Finance (MFN) and annualreports.com. These reports form the basis of our content analysis for disclosed AI activity. Where the crawler failed to retrieve a report, we manually downloaded the report from the same sources. We also verified that each retrieved file corresponded to the correct firm and fiscal year. We deliberately remained consistent with the language, only including companies publishing their annual reports in English. Swedish reports would require a separate lexicon and parallel macro-context filtering, while introducing translation noise and compromising comparability due to stylistic differences between the two languages.

As a third data source, we used Compustat Global via WRDS to obtain annual fundamentals covering the period 2010 to 2025, which we use to analyze firms' accounting performance. The earlier start date relative to our sample period of 2014 to 2024 is necessary to construct lagged variables and multi-year growth rates used as controls in the regressions below. From this database, we retrieved the accounting variables required to compute our control and dependent variables including, SG&A and R&D intensity, EBIE, total debt, and capital expenditure. Finally, we also obtained monthly stock price data as well as shares outstanding from Compustat Global Security Daily via WRDS, again covering 2010 to 2024.

Thus, for our constructed final sample, we began with the 356 companies listed on Nasdaq Stockholm's Main Market at any point between 2014 and 2024. We excluded 184 firms that were not continuously listed from 2017 onward, 40 tech firms, and a further 30 firms for which annual reports could not be obtained in a machine-readable, English-language format across all firm-years. The final sample therefore consists of 102 non-technology firms and 1,098 firm-year observations (one annual report per firm-year), forming an unbalanced panel spanning from 2014 to 2024.

3.2 Research design

With the collected data we conducted an archival, correlational panel research design. We converted all annual reports to usable *.txt* on which we ran a content analysis by using a lexicon of AI-related terms (see Appendix Table 10). The lexicon is based on two sources, i) Chen & Srinivasan's AI words (2024) and ii) Stanford HAI (Stanford Institute for Human-Centered Artificial Intelligence, no date).

To collect AI activity terms in the annual reports, we encountered one key methodological challenge: European annual reports do not contain a standardized section equivalent to Item 1 of the US 10-K, which in the original paper, Chen & Srinivasan (2024), cleanly separates the firm-specific business description from other content. Many Swedish annual reports include sections describing the broader macroeconomic environment, regarding global demand and trends, central bank policy, and market conditions. These sections are directed at shareholders rather than describing the firm's own activities. Counting AI activity mentions across the full report would therefore generate false positives, reflecting the general rise of AI in public discourse rather than at a firm-level.

We addressed this through a context-window filtering approach. For every lexicon hit, we extracted the 50-word window on each side of the matched term and examined whether it contains any of 58 predefined macro-context signal phrases, terms such as "global economy", "central banks", "European market", or "geopolitical" (see Appendix Table 11 for the full list). These are characteristic of macroeconomic disclosure rather than firm-level activity. Applying this macro context filter produces two parallel counts per firm-year: a raw count including all hits and a clean count restricted to hits outside macro context. Both counts are normalized by report length and constructed as AI terms per 1,000 words. To reduce noise from the continuous intensity measure and ensure comparability across years, each firm-year's clean AI intensity, $AIIntensity_{i,t}$, is quantized into a 0–3 score, denoted $AIRank_{i,t}$, which equals zero if no AI activity terms are disclosed, and one, two, or three for firms in the bottom, middle, and top tercile of disclosers within that fiscal year, where each tercile contains an equal number of disclosing firms. In our regressions **(2)** - **(4)** the coefficient β_1 on $AIRank_{i,t}$ captures the association between firm-level disclosed AI activity and the dependent variables. In regression **(1)** the coefficient β_1 is on one-year lagged $AIRank_{i,t-1}$.

A detailed description of all variables used in each regression is provided in Appendix Table 12, which also reports how each variable is computed, the regression in which it is used, and the expected sign of its coefficient based on Chen and Srinivasan (2024). Our market-based variables, such as $Size_{i,t}$, defined as the natural logarithm of market capitalization in mSEK, are measured over a window ending four months after fiscal year-end. Chen and Srinivasan (2024) measure their market-based variables on the trading day after the 10-K filing date, which Compustat reports for US firms. An equivalent firm-specific publication date is not available for Swedish listed firms in Compustat Global, so we instead anchored our market-based variables to a fixed window of four months after fiscal year-end. We chose this window because Nasdaq Stockholm's Main Market Rulebook requires listed firms to publish their annual reports within four months of fiscal year-end (Nasdaq, 2020) which ensures that, by t+4 months, shareholders have had time to price the disclosed information. We therefore measure all market-based variables including market capitalization $Market\ cap_{i,t}$ (used for Size and MTB), market-adjusted returns Return $Return_{i,t}$ and return volatility $Vol_{i,t}$, at t+4 months. All accounting fundamentals are anchored to fiscal year-end.

3.2.1 Statistical assumptions

All our regressions (**1)** to **(4)** are estimated by ordinary least squares (OLS) on unbalanced firm-year panel data and include industry fixed effects a_j, year fixed effects a_t, and a set of control variables $C_{i,t}$. Standard errors are clustered at the firm level in all specifications. The error term is denoted $\varepsilon_{i,t}$. For the OLS estimator to deliver unbiased and efficient coefficients, the five Gauss-Markov assumptions must hold.

1. Linearity: We assume a linear relationship between AI disclosure and each dependent variable, consistent with Chen and Srinivasan (2024). In addition, the tercile disclosure rank accommodates non-linearity in the underlying continuous intensity measure, since equal steps in rank do not correspond to equal steps in raw intensity.

2. Residual normality: With 1,098 firm-year observations, the sample is sufficiently large that residual normality is not required for valid inference, consistent with the Central Limit Theorem.

3. and 4. Heteroskedasticity and autocorrelation: Standard OLS assumes that errors are independent and identically distributed. Firm-level panel data, however, often exhibit heteroskedasticity across firms and serial correlation within firms. To address this, we cluster standard errors at the firm level, following Petersen (2009) and Thompson (2011), which corrects for both issues simultaneously. As a sanity check for heteroskedasticity, we also conduct a Breusch-Pagan test for each regression.

5. Multicollinearity: Some explanatory variables are mechanically related. For example, R&D and SG&A both capture dimensions of intangible spending, with SG&A defined net of R&D. High correlations among regressors do not bias coefficient estimates, but they may inflate standard errors. We assess this with a correlation matrix and by computing variance inflation factors (VIFs), which should fall below the standard threshold of 5.

3.2.2 Determinants of disclosed AI activity

First, we want to understand which firm characteristics drive disclosed AI activity and thus regress the current disclosed AI activity rank $AIRank_{i,t}$ on a set of lagged firm-level variables, including the lagged disclosed AI activity measure $AIRank_{i,t-1}$.

This analysis serves two purposes. First, it identifies whether firms with specific characteristics are more likely to disclose AI activity. Second, it tests whether disclosure is persistent over time. The regression is specified as follows:

$$AIRank_{i,t} = a + \beta_1 AIRank_{i,t-1} + \beta_2' D_{i,t-1} + a_j + a_t + \gamma' C_{i,t-1} + \varepsilon_{i,t} \quad \textbf{(1)}$$

$D_{i,t-1}$ is the vector of one-year-lagged firm characteristics we wish to investigate, including firm size (log market cap), ROA, sales growth, and past stock return, with corresponding coefficient vector β_2'. $C_{i,t-1}$ contains additional controls, including leverage, cash ratio, and capital expenditure, with coefficient vector γ'.

3.2.3 Market-to-book

To investigate whether shareholders reward disclosed AI activity with higher firm valuations, we regress the market-to-book ratio, which is the firm's market capitalization divided by book value of equity, denoted $MTB_{i,t}$, on our disclosed AI activity measure and a set of control variables (H_1). The regression specification is:

$$MTB_{i,t} = a + \beta_1 AIRank_{i,t} + a_j + a_t + \gamma' C_{i,t} + \varepsilon_{i,t} \quad \textbf{(2)}$$

Following Chen and Srinivasan (2024), we estimate Equation **(2)** across multiple specifications that progressively add controls for firm characteristics. Concretely, we run three specifications: **(2a)** a baseline with our standard valuation controls $C_{i,t}$. Specification **(2b)** adds to $C_{i,t}$ both $RD_{i,t}$ and $SGA_{i,t}$ to control for variation captured by traditional intangible spending, and **(2c)** further adds lagged market-to-book, $MTB_{i,t-1}$, to control for the fact that some firms persistently trade at higher valuations than others for reasons unrelated to disclosed AI activity. Because each specification builds on the previous one, a coefficient that remains stable across columns is unlikely to be driven by omitted controls.

3.2.4 Fundamental performance

We further examine whether disclosed AI activity is associated with subsequent changes in fundamental performance (H_2), denoted $\Delta Y_{i,t+k}$, which is one of four performance measures assessed along two dimensions: *1. Profitability* with Return on Assets, $ROA_{i,t}$ **(3a)**, and Operating margin, $OpMargin_{i,t}$ **(3b)**, and *2. Operational efficiency* with asset turnover $TOA_{i,t}$ **(3c)**, and three-year annualized sales growth denoted by $Sales\ growth_{i,t}$ **(3d)**. The dependent variable $\Delta Y_{i,t+k} = Y_{i,t+k} - Y_{i,t-1}$, measures the change in fundamental performance from the year before disclosure to k years after, with $k \in \{0,1,2,3\}$, allowing for delayed effects.

$$\Delta Y_{i,t+k} = a + \beta_1 AIRank_{i,t} + a_j + a_t + \gamma' C_{i,t} + \varepsilon_{i,t} \quad \textbf{(3)}$$

3.2.5 Proxy determination

Lastly, we want to investigate whether disclosed AI activity is associated with proxies for firm-level AI activity (H_3), we therefore regress two alternative measures on our disclosure variable separately: R&D intensity, $RD_{i,t}$, defined as research and development expenditure scaled by total assets, and SG&A intensity, $SGA_{i,t}$, defined as selling, general, and administrative expenses (net of R&D) scaled by total assets. We test the following two specifications, each linking our AI disclosure measure to a different proxy for intangible spending:

$$RD_{i,t} = a + \beta_1 AIRank_{i,t} + a_j + a_t + \gamma' C_{i,t} + \varepsilon_{i,t} \quad \textbf{(4a)}$$

$$SGA_{i,t} = a + \beta_1 AIRank_{i,t} + a_j + a_t + \gamma' C_{i,t} + \varepsilon_{i,t} \quad \textbf{(4b)}$$

3.3 Robustness testing

We conducted robustness tests at two levels. Section 3.3.1 addresses robustness of data and sample selection. Section 3.3.2 addresses the robustness of each of our regressions.

3.3.1 Data and measurement robustness

Our first robustness measure concerns the consistency of report language and document type. We verified that our sample consists exclusively of machine-readable English-language reports. To detect this, we applied a frequency test on a 2,000-word sample drawn from the middle of each report, flagging the document if more than 1% of tokens were whole-word matches to common Swedish words such as “och”, “att”, and “är”. These words are frequent in Swedish but absent in English, making false positives unlikely. We additionally tested whether each report is scanned or text-based, since scanned PDFs extracted via OCR are more prone to tokenization errors that could bias word-count measures.

We further assess whether our macro-context filter meaningfully isolates firm-specific AI disclosure from broader macroeconomic discussion by re-running our regressions using the raw count in place of the clean count and comparing the results. If the coefficients remain similar, the filter has little effect on inference. If they differ, the filter is removing meaningful macroeconomic noise. Appendix Table 13 illustrates the filter qualitatively, showing examples of AI mentions that pass the filter (firm-level disclosure) alongside examples it removes (macroeconomic context).

3.3.2 Regression specification robustness

To address the linear scaling assumption embedded in the 0–3 tercile score, we re-estimated our main regressions using three alternative measures of disclosed AI activity. i) A continuous intensity measure (AI terms per 1,000 words), ii) a binary disclosure indicator, and iii) the year-on-year change in tercile rank. The change-based measure serves as a diagnostic for persistent firm style or industry-specific language in AI disclosure. If level-based disclosure primarily reflects such persistent patterns, changes should better isolate the new information that investors respond to. Across all three alternatives, the coefficient on disclosed AI activity remained consistent in sign and significance, indicating that our findings are not driven by the tercile scoring methodology.

To mitigate any influence driven by outliers, we winsorized all continuous variables at the 1st and 99th percentiles, which prevents extreme observations from dominating coefficient estimates given our modest sample size.

We further examined the robustness of our results across alternative sample partitions, exploring three dimensions of variation: i) Within-industry (firms within the same GICS sector), ii) cross-industry (retaining only industry and year fixed effects), and iii) a time-series split between 2014–2018 and 2019–2024, motivated by the relative scarcity of AI mentions before 2019. For Equation **(4)**, we additionally restrict the sample to firms with non-missing R&D and SG&A data. Our main findings are unchanged across these specifications.

Since H_2 is tested across four dependent variables ($Y \in \{ROA,\ OpMargin,\ TOA,\ Sales\ growth\}$) and four horizons ($k \in \{0,1,2,3\}$) in regression **(3)** giving 16 tests in total. Under the null, this implies 1.6 expected false positives at α=0.10 and 0.8 at α=0.05. We therefore apply within-horizon Bonferroni and Holm corrections, full-panel Bonferroni, and Benjamini-Hochberg FDR corrections as a conservative benchmark, and a clustering test. All significant coefficients survive, both individually and as a joint pattern. Due to excessive length these are not part of the appendix.

3.4 Hypothesis testing

We base our statistical analysis on the three hypotheses outlined in Section 2.3.
For each hypothesis, we test the null that the coefficient on our disclosed AI activity measure equals zero (H_0: $\beta_1 = 0$).

To assess whether disclosed AI activity is associated with higher market-to-book ratios in accordance with H_1, we conduct the hypothesis tests summarized in Table 1 across our three model specifications. Here β_1 denotes the coefficient on our disclosed AI activity measure, $AIRank_{i,t}$, as defined in Equation **(2)** in Section 3.2.3 *Market-to-Book.*

Table 1: Hypothesis tests for H_1 - Market-to-book

Specification	Null hypothesis (H_0)	Alternative hypothesis (H_1)
Baseline	H_0: β_1=0	H_1: β_1>0
With intangibles	H_0: β_1=0	H_1: β_1>0
Lagged MTB	H_0: β_1=0	H_1: β_1>0

With H_2 we assess whether disclosed AI activity is associated with significant changes in fundamental performance. We conduct the hypothesis tests summarized in Table 2 for each fundamental performance measure across four-time horizons. Here β_1 denotes again the coefficient on our disclosed AI activity measure, $AIRank_{i,t}$, as defined in Equation **(3)** in Section 3.2.4 *Fundamental Performance*. Since we are investigating a non-directional change, we apply a two-tailed test, meaning we are open to finding either a positive or a negative association between disclosed AI activity and fundamental performance, rather than predicting upfront which direction the effect will go. This helps to examine whether any significant association between disclosed AI activity and accounting performance materializes over time. We are aware that frequentist hypothesis testing cannot confirm a true null. Therefore, a non-significant result for H_2 indicates the absence of a detectable effect, not evidence that the true effect is zero.

Table 2: Hypothesis tests for H_2 - Fundamental performance

Specification	Horizon	Null hypothesis (H_0)	Alternative hypothesis (H_1)
$\Delta Y_{i,t+k}$	Current, 1-, 2-, 3-year	H_0: β_1=0	H_1: $\beta_1 \neq 0$

Note: $Y \in \{ROA,\ OpMargin,\ TOA,\ Sales\ growth\}$

Finally, we assess whether disclosed AI activity is associated with intangible spending, Table 3. We regress two proxies for AI-related activity on our disclosure score and a set of controls: (i) R&D intensity and (ii) SG&A intensity. This is reflected in equation **(4)** in Section 3.2.5.

We apply a one-tailed test, where a positive and significant coefficient on the disclosed AI activity score in each specification would support the interpretation that our text-based measure identifies firms' spendings on AI-related activity.

Table 3: Hypothesis tests for H_3 – Proxy determination

Specification	Null hypothesis (H_0)	Alternative hypothesis (H_1)
R&D intensity	H_0: β_1=0	H_1: β_1>0
SG&A intensity	H_0: β_1=0	H_1: β_1>0

4. Findings and analysis

This section presents our empirical results. We begin with an overview of the sample, including descriptive statistics and a correlation matrix, followed by diagnostic tests for multicollinearity and heteroskedasticity. We then report the results on the firm characteristics that determine disclosed AI activity, before presenting our findings for each of our three hypotheses.

4.1 Descriptive evidence

4.1.1 Descriptive statistics and statistical assumptions

Table 4 provides an overview of the distribution, central tendencies, and dispersion of the main variables used in our analysis.

Table 4: Descriptive statistics

Variable	N	Mean	SD	Min	P1	P25	Median	P75	P99	Max
$AIRank_{i,t}$	1098	1.627	1.253	0	0	0	2	3	3	3
$AIIntensity_{i,t}$	1098	0.073	0.119	0	0	0	0.028	0.092	0.292	0.706
$RD_{i,t}$	1088	0.03	0.072	0	0	0	0.004	0.029	0.158	0.469
$SGA_{i,t}$	1088	0.182	0.142	0.005	0.02	0.086	0.145	0.243	0.481	0.738
$MTB_{i,t}$	1086	4	8.088	0.157	0.446	1.232	2.063	3.731	12.034	71.748
$ROA_{i,t}$	1087	0.064	0.147	-0.686	-0.192	0.049	0.083	0.122	0.216	0.344
$OpMargin_{i,t}$	1023	0.1	0.118	-0.907	-0.016	0.054	0.091	0.136	0.294	0.515
$TOA_{i,t}$	1087	0.947	0.518	0	0.083	0.626	0.91	1.238	1.869	2.728
$Sales\ growth_{i,t}$	774	0.077	0.192	-0.767	-0.203	0.027	0.079	0.138	0.329	0.88
$Size_{i,t}$	1086	8.998	1.738	3.99	6.26	7.659	8.929	10.297	11.946	13.394
$Return_{i,t}$	1080	0.003	0.325	-1.05	-0.562	-0.167	0.012	0.202	0.504	0.822
$Leverage_{i,t}$	1088	2.378	1.296	1.024	1.114	1.644	2.152	2.72	4.211	10.803
$Cash_{i,t}$	1088	0.909	2.07	0.015	0.04	0.137	0.257	0.628	4.15	13.7
$Capex_{i,t}$	1059	0.028	0.033	0	0.001	0.009	0.017	0.034	0.082	0.203
$Missing\ RD_{i,t}$	1088	0.42	0.494	0	0	0	0	1	1	1
$Vol_{i,t}$	1080	0.098	0.042	0.036	0.047	0.069	0.088	0.116	0.181	0.265
$LogWords_{i,t}$	1098	10.842	0.385	8.389	10.269	10.59	10.852	11.125	11.413	11.765

We find that AIRank has a mean of 1.63 and a median of 2, reflecting the 0–3 quantized construction described in Section 3.2. AIIntensity per 1,000 words is right-skewed, with the mean (0.073) higher than the median (0.028) and a P99 of 0.292 which indicates that a small group of firms disclose AI much more than the rest of the sample. We see a similar right-skewed pattern for MTB, with a mean of 4.00 and a median of 2.06, where a small number of firms with very high market-to-book ratios drive the right tail. Firm size, measured as the log of market capitalization, has a median of 8.93 and ranges from 3.99 to 13.39, showing wide dispersion across the sample. Annual stock returns average close to zero with high variation and return volatility averages around 10%.

For our accounting fundamentals, ROA has a mean of 6.4% and a median of 8.3%, with a long-left tail driven by a subset of loss-making firm-years. Operating margin shows a similar pattern, with a mean of 10% and a median of 9.1%, and a comparable right tail. Asset turnover averages 0.95. Sales growth has only 774 observations, which is expected since it is constructed as a three-year backward-looking measure and cannot be computed for firms listed fewer than three years before a given observation. The variable has a mean and median of around 8%, a roughly symmetric distribution. LogWords shows low variation across firms, with the middle 50% of observations spanning 10.59 to 11.13.

The capital structure and intangible-investment variables vary across firms. Leverage, measured as total assets to shareholder equity, has a mean of 2.38 and a median of 2.15. The cash ratio is right-skewed, with a mean of 0.91 and a median of 0.26, while the P99 of 4.15 shows that a smaller group of firms have stronger short-term liquidity. Capital expenditures average 2.8% of total assets. R&D intensity averages 3% but has a median of only 0.4%, indicating that R&D is driven by a smaller group of firms. The missing R&D indicator equals one for 42% of observations, in line with this concentration. Finally, SG&A intensity is more evenly distributed, with a mean of 18.2% and a median of 14.5%.

4.1.2 Tests of statistical assumptions

This section reports formal tests of the OLS assumptions outlined in Section 3.2.1. We assess multicollinearity through a correlation matrix and Variance Inflation Factor (VIF) test, and heteroskedasticity through a Breusch-Pagan test.

We first inspect the pairwise correlations between the main variables, reported in Appendix Table 14. None of the pairwise correlations exceed the 0.7 threshold commonly used as an indicator of problematic multicollinearity. Two patterns are worth highlighting. First, the two disclosed AI activity measures, AIRank and AIIntensity, are correlated at $\rho = 0.60$, since AIRank is constructed directly from AIIntensity. We therefore use only one of the two as the explanatory variable in any given regression. Second, AIRank correlates positively with Size (0.29), ROA (0.22), and LogWords (0.22), suggesting that larger and more profitable firms with longer reports disclose more AI activity, a pattern we return to in Section 4.1.4. The correlation structure therefore does not threaten the no-perfect-multicollinearity assumption underlying OLS.

We next compute variance inflation factors (VIFs), reported in Appendix Table 15. All VIFs fall below the conventional threshold of 5, with the highest value of 2.47 for $Size_{i,t}$. This confirms that the explanatory variables are not excessively correlated. We do not report a VIF for $OpMargin_{i,t}$ and $TOA_{i,t}$ since these are dependent variables only.

Finally, we run a Breusch-Pagan test, displayed in Appendix Table 16, which rejects the null of homoskedasticity (LM = 125.79, $p < 0.001$). This does not affect the validity of our results, as all our regressions use heteroskedasticity-robust standard errors clustered at the firm level, which correct for both heteroskedasticity and within-firm correlation. We ran the test on 774 observations rather than the full sample of 1,098, due to the previously discussed loss of observations from the three-year backward-looking construction of Sales growth.

4.1.3 AI disclosure trends, 2014–2024

Before turning to the hypothesis tests, this section describes how disclosed AI activity has developed in our sample. The descriptive evidence motivates the macro-context filter introduced in Section 3.2 and provides time-series context for the regressions that follow. Each of the four Figures distinguishes between raw AI term counts and counts after the macro-context filter.

Figure 1: Total AI term mentions per year

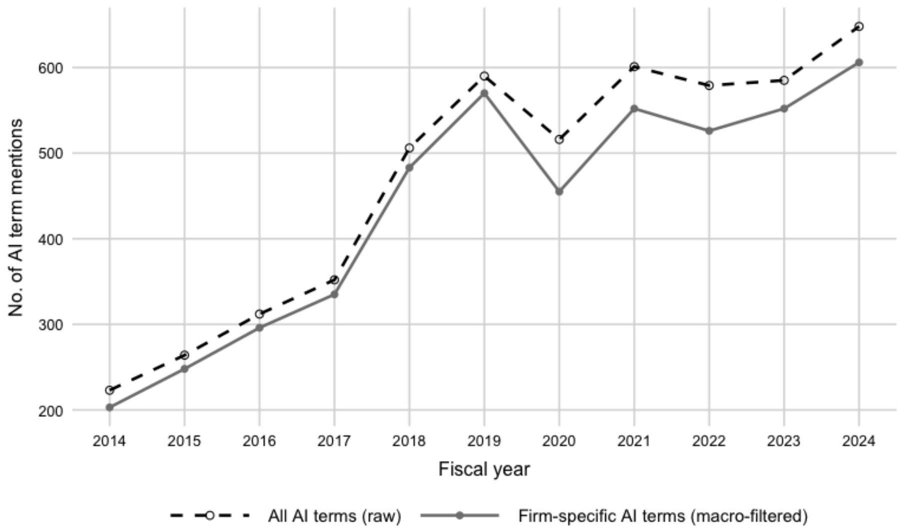


Figure 2: Share of firms disclosing at least one AI term per year

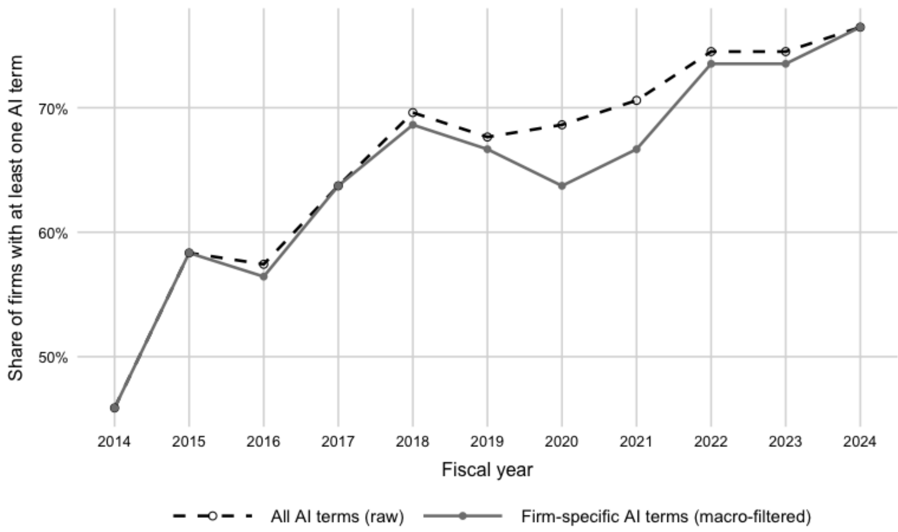


Figure 3: Mean AI terms per 10,000 words

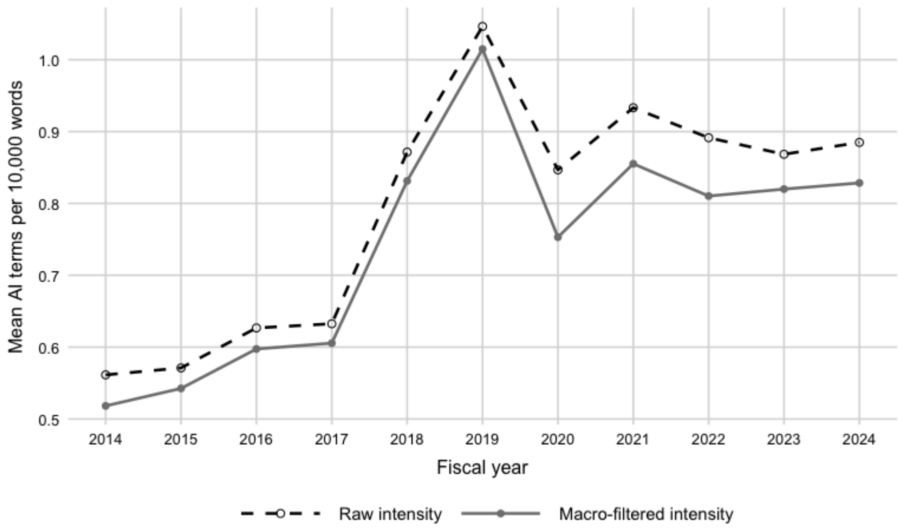
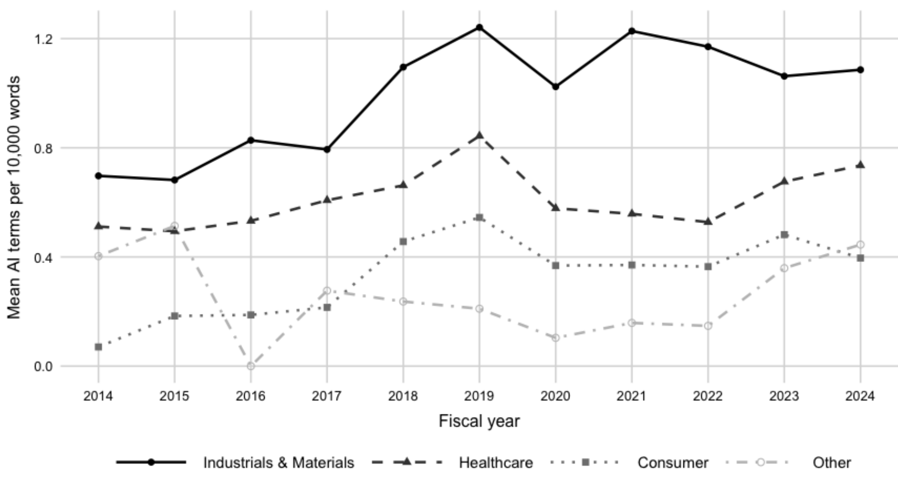


Figure 4: Mean AI terms per 10,000 words by GICS industry group (Macro-filtered)



Disclosed AI activity has increased significantly over the panel. Total AI mentions across the sample roughly tripled between 2014 and 2024, rising from approximately 205 to 605 macro-filtered mentions (Figure 1). The proportion of firms making at least one AI disclosure each year roughly doubled over the same period, from approximately 40% to 75% under both the macro-filtered and raw measure (Figure 2), suggesting that disclosing one's AI activity is becoming a common norm for firms across the stock market. This rising proportion is consistent with Chen and Srinivasan (2024), who document a similar trend among US non-tech firms. The largest part of the acceleration happens between 2017 and 2019, indicating that AI entered corporate disclosures long before the public hype associated with ChatGPT in late 2022. No visible step change appears in 2022 or 2023, suggesting that the post-ChatGPT period did not produce a jump in firm-level AI language.

Mean AI terms per 10,000 words climb steadily from 2014, peak sharply in 2019 at roughly 1 (filtered), then drop in 2020 and plateau at around 0.8 to 0.85 through 2024 (Figure 3). Once again, the 2019 peak pre-dates the public AI breakout by three years. The plateau in intensity after 2020, together with continued growth in firm coverage, indicates that AI language has spread widely across firms without becoming more concentrated within each disclosing firm. More firms now mention AI, but each firm's report is not becoming increasingly AI-dense.

The macro-context filter removes a meaningful amount of noise from the raw counts without changing the overall pattern. The persistent gap between the raw and filtered series across Figures 1, 2, and 3 indicates that the filter is doing work rather than reshaping the underlying trends.

All four industry groups disclose AI activity throughout the panel, but with clear differences in level and growth. Industrials & Materials disclose AI most intensively in every year of the panel, followed consistently by Healthcare (Figure 4). Industrials & Materials roughly increased intensity by 50% over the period, from approximately 0.70 to 1.10, while Consumer firms expanded from roughly 0.10 to 0.40, a large relative increase from a low base. The "Other" group is more volatile, particularly in the early years, reflecting both the smaller number of firms and the fact that the pooled sectors differ widely from each other. The 2019 peak and 2020 dip visible in Figure 3 appear in Industrials & Materials, Healthcare, and Consumer firms alike, indicating that the time pattern reflects a common shift across most of the market rather than the dynamics of any single sector. All four groups disclose AI activity to some degree throughout the panel, consistent with the characterization of AI as a general-purpose technology in Cockburn et al. (2019).

4.1.4 Determinants of disclosed AI activity

This section reports a determinants regression that identifies firm characteristics associated with disclosed AI activity and tests whether disclosure is persistent over time. This descriptive analysis characterizes AI-disclosing firms before the hypothesis tests in Section 4.2. Table 5 reports the determinants regression specified in Section 3.2.2, which regresses the disclosed AI activity rank in year t on a set of one-year-lagged firm characteristics.

Table 5: Determinants of disclosed AI activity

$AIRank_{i,t}$	Determinants **(1)**
$AIRank_{t-1}$	0.594*** (0.036)
$Size_{i,t}$	0.082*** (0.021)
$ROA_{i,t}$	0.758*** (0.251)
$Sales\ growth_{i,t}$	0.010 (0.007)
$Return_{i,t}$	0.161* (0.083)
Observations	950
Adj. R^2	0.527
Controls	Yes
Industry FE	Yes
Year FE	Yes

Note: Lagged determinants of primary interest (Size, ROA, Sales growth, Past stock return) are reported individually; control variables are absorbed into Controls. Standard errors are shown in parentheses. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The strongest predictor of current disclosed AI activity is the firm's own disclosed AI activity in the prior year. The coefficient on lagged disclosed AI activity rank is 0.594, significant at the one percent level. While lagged ROA carries a numerically larger coefficient of 0.758, this reflects the different scales of the two variables, the AI disclosure rank ranges from 0 to 3 while ROA is bounded near zero. In standardized terms, a one-standard-deviation change in lagged disclosure moves the rank by approximately 0.74 points, compared to 0.11 points for ROA, making lagged disclosure the dominant predictor by a factor of roughly seven. The coefficient is well below one, so disclosure ranks are not fixed, but the year-to-year stickiness is high. This supports the inclusion of firm-level controls and firm-clustered standard errors in the MTB and fundamental performance regressions.

Among the remaining firm characteristics, ROA is the strongest predictor and significant at the one percent level. Firms that were more profitable in year t-1 are more likely to disclose AI in year t. Firm size has a positive coefficient of 0.082 and is significant at the one percent level. Larger firms disclose more AI, consistent with Babina et al. (2024) who document that AI investment concentrates among larger firms in the US setting. Lagged sales growth has a coefficient of 0.010 and is not statistically different from zero. Past growth does not predict disclosed AI activity once size and profitability are controlled for.

A short comparison with Chen and Srinivasan (2024) is useful as a reference point. Their full-sample determinants regression on US non-technology firms reports a higher persistence coefficient (0.865) and smaller coefficients on size (0.018) and ROA (0.055). The direction of the size and ROA effects is the same in both studies, but the magnitudes are larger in our setting. Part of the persistence gap is mechanical, their sample (2010 to 2020) covers a period in which digital disclosure had already stabilized, while our panel covers a period of rapid AI adoption in which disclosure ranks are still shifting.

The adjusted R-squared is 0.527, most of this is driven by the lagged dependent variable (0.229 without the lagged variable). The sample contains 950 firm-year observations, reflecting the loss of one year to the lag structure. Industry and year fixed effects absorb common sector-level and time-level shocks.

Taken together, disclosed AI activity is a behavior clustered among large, profitable firms with strong recent stock performance, and it is persistent from year to year.

4.2 Hypotheses testing

This section reports the regression results for the three hypotheses developed in Section 2.3. Together, the three tests address the main research question in sequence: H_1 determines whether disclosure is associated with valuation. H_2 examines whether disclosure translates into subsequent changes in fundamental performance, and H_3 determines whether our disclosed AI activity measure captures genuine activity.

4.2.1 Disclosed AI activity and market-to-book (H_1)

Table 6: Disclosed AI activity and market-to-book

$MTB_{i,t}$	Baseline **(2a)**	With intangibles **(2b)**	Lagged MTB **(2c)**
$AIRank_{i,t}$	0.357 (0.417)	0.538 (0.486)	0.313* (0.174)
Controls			
$Sales\ growth_{i,t}$	-0.307 (0.446)	-0.836 (0.556)	-0.207 (0.235)
$Size_{i,t}$	2.111*** (0.790)	2.141*** (0.727)	0.501** (0.203)
$Vol_{i,t}$	16.837 (13.460)	15.057 (14.473)	8.134* (4.708)
$Return_{i,t}$	1.676*** (0.609)	1.057 (0.651)	2.744*** (0.491)
$Leverage_{i,t}$	0.491 (0.484)	0.552 (0.492)	0.222*** (0.076)
$LogWords_{i,t}$	-10.285** (4.803)	-9.646** (4.589)	-2.993** (1.211)
$RD_{i,t}$		45.759** (20.958)	10.419* (5.878)
$SGA_{i,t}$		3.618 (5.570)	1.304 (1.986)
$MissingRD_{i,t}$		2.351 (1.677)	0.610 (0.412)
$MTB_{i,t-1}$			0.706*** (0.091)
Observations	1098	1098	981
Adj. R^2	0.197	0.265	0.805
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Note: The hypothesis underlying this regression is shown in Table 1 in Section 3.4, Hypothesis Testing. Standard errors are shown in parentheses. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6 reports the market-to-book regressions specified in Equations **(2a)** to **(2c)**, which test H_1, whether disclosed AI activity is positively associated with firm valuation. The coefficient on AI disclosure rank is positive in all three specifications, ranging from 0.313 in **(2c)** to

0.538 in **(2b)**. Only specification **(2c)**, which adds the lagged market-to-book ratio, reaches statistical significance, and only at the 10 percent level. We therefore reject the null in **(2c)** and fail to reject it in the baseline **(2a)**, and the intangibles specification **(2b)**.

The economic magnitude in **(2c)** is meaningful but statistically weak. The coefficient implies an 8% increase in MTB per one-rank step relative to the sample mean of 4.00, or 23% for top-tercile disclosers compared to non-disclosers. This range of 8% to 23% is broadly in line with the 8% to 26% Chen and Srinivasan (2024) report for US non-technology firms, though our estimate carries much weaker statistical support.

The shift in significance between **(2b)** and **(2c)** is driven by the standard error rather than the point estimate. The coefficient declines from 0.538 to 0.313 when lagged MTB is added, while the standard error contracts from 0.486 to 0.174. The adjusted R-squared jump from 0.265 to 0.805 indicates that lagged MTB absorbs most of the across-firm variation in valuation, leaving a smaller residual variance against which the AI disclosure coefficient is estimated. Specification **(2c)** therefore tests whether disclosed AI activity predicts MTB beyond a firm's own pre-existing valuation level, rather than the level itself, and the marginally significant coefficient is consistent with markets assigning incremental value to AI disclosure.

4.2.2 Disclosed AI activity and fundamental performance (H_2)

In this subsection, we examine whether disclosed AI activity is associated with subsequent changes in fundamental performance. This is a direct test of H_2, and the result also helps interpret whether the MTB test results bear substance from fundamentals.

Table 7: Disclosed AI activity and subsequent changes in fundamental performance

	Current $k = 0$	$\Delta y1$ $k = 1$	$\Delta y2$ $k = 2$	$\Delta y3$ $k = 3$
Panel A: Disclosed AI activity and development of ROA over time; $\Delta ROA_{i,t+k}$ **(3a)**				
$AIRank_{i,t}$	0.010 (0.007)	0.001 (0.003)	0.005 (0.003)	0.008** (0.004)
Observations	1077	883	782	681
Adj. R^2	0.280	0.273	0.243	0.304
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Panel B: Disclosed AI activity and Operating margin; $\Delta OpMargin_{i,t+k}$ **(3b)**				
$AIRank_{i,t}$	0.006 (0.006)	0.035 (0.022)	0.081 (0.075)	0.063* (0.037)
Observations	1014	825	732	636
Adj. R^2	0.968	0.336	0.139	0.198
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Panel C: Disclosed AI activity and Asset turnover over time; $\Delta TOA_{i,t+k}$ **(3c)**				
$AIRank_{i,t}$	0.023 (0.024)	0.012 (0.007)	0.021** (0.009)	0.028*** (0.010)
Observations	1077	883	782	681
Adj. R^2	0.202	0.275	0.271	0.309
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Panel D: Disclosed AI activity and Sales Growth; $\Delta Sales\ growth_{i,t+k}$ **(3d)**				
$AIRank_{i,t}$	0.018* (0.010)	0.008 (0.010)	0.010 (0.013)	0.011 (0.012)
Observations	722	572	472	372
Adj. R^2	0.253	0.356	0.545	0.501
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: The hypothesis underlying this regression is shown in Table 2 in Section 3.4, Hypothesis Testing. Standard errors are shown in parentheses. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Two features of the Table 7 merit brief comment before turning to the panel results. The number of observations declines with the horizon because firm-years near the end of the sample cannot be matched to outcomes k years later (a 2023 disclosure has no 2026 follow-up). Adjusted R^2 values range from roughly 0.20 to 0.55 across the panels, indicating that fixed effects and controls absorb a moderate share of variation in fundamental changes, the exception is k=0 in Panel B (0.968), where the year-zero change in operating margin is mechanically tied to current-year fundamentals captured by the controls.

We first examine the profitability measures in Panels A and B. For ROA, we find no significant association at horizons k = 0, k = 1, or k = 2, but a coefficient of 0.008 significant at the 5 percent level at k = 3. The point estimate corresponds to a 0.8 percentage point increase per one-rank step, or 2.4 percentage points for top-tercile disclosers compared to non-disclosers. Relative to the sample mean of 6.4%, this is a range of 12.5% to 37.5%. For operating margin, we find no significant association at k = 0, k = 1, or k = 2, and a coefficient of 0.063 significant at the 10 percent level at k = 3. The point estimate corresponds to a 6.3 percentage point increase per one-rank step, or 18.9 percentage points for top-tercile disclosers compared to non-disclosers, a range of 63% to 189% relative to the sample mean of 10%. The estimate is large in magnitude but only marginally significant; we treat it as directional rather than a precise effect size. Both profitability measures therefore show improvement only at the three-year horizon.

We next examine the operational efficiency measures in Panels C and D. For asset turnover, we find no association at k = 0 or k = 1, but coefficients of 0.021 (5 percent level) at k = 2 and 0.028 (1 percent level) at k = 3. Relative to the sample mean of 0.95, the per-one-rank increases are 2.2% and 3.0%, extending to 6.7% and 8.9% for top-tercile disclosers compared to non-disclosers. For sales growth, we find a coefficient of 0.018 significant at the 10 percent level at k = 0, but no significant association at k = 1, k = 2, or k = 3. The point estimate corresponds to a 1.8 percentage point increase per one-rank step, or 5.4 percentage points for top-tercile disclosers compared to non-disclosers, a range of 23.4% to 70.1% relative to the sample mean of 7.7%. This contrasts with Chen and Srinivasan (2024), who report 13% to 40% lower sales growth among digital disclosers. Both the direction and the absolute magnitude differ from theirs.

Taken together, the four panels show scattered significance in the early horizons and a clustered pattern of improvement at the three-year horizon, where three of four measures show significant associations.

4.2.3 Disclosed AI activity and intangible spending (H_3)

Table 8: Disclosed AI activity and intangible spending

Dependent variable	R&D **(4a)**	SG&A **(4b)**
$AIRank_{i,t}$	-0.005 (0.004)	0.010 (0.006)
Observations	1081	1081
Adj. R^2	0.536	0.291
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes

Note: The hypothesis underlying this regression is shown in Table 3 in Section 3.4, Hypothesis Testing. Standard errors are shown in parentheses. Significance: * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 8 reports the proxy regressions specified in Equations **(4a)** and **(4b)**, which tests H_3, whether disclosed AI activity is positively associated with R&D or SG&A intensity. The coefficient on AI disclosure rank is -0.005 for R&D intensity and 0.010 for SG&A intensity. Neither coefficient is significant, so we fail to reject the null in either specification.

4.2.4 Summary of hypothesis tests

Table 9: Summary of hypothesis tests

Hypothesis	H_1			H_2				H_3	
Regression	**(2a)**	**(2b)**	**(2c)**	**(3a)**	**(3b)**	**(3c)**	**(3d)**	**(4a)**	**(4b)**
Fail to reject H_0	✓	✓		For $k \in \{0,1,2\}$	For $k \in \{0,1,2\}$	For $k \in \{0,1\}$	For $k \in \{1,2,3\}$	✓	✓
Reject H_0			✓	For $k \in \{3\}$	For $k \in \{3\}$	For $k \in \{2,3\}$	For $k \in \{0\}$		
Significance level			*	*	*	** ($k = 2$) *** ($k = 3$)	*		

Note: Significance: * p < 0.1, ** p < 0.05, *** p < 0.01.

5. Discussion

5.1 Discussion of individual results

5.1.1 Market-to-Book Valuation

Our first result is that non-technology firms disclosing AI activity are associated with higher market-to-book ratios than industry peers, but only in our strictest specification with significance at the 10 percent level. The result allows for two explanations.

The first explanation is that the effect is real, but the test lacks the power to detect it cleanly. The coefficient is economically meaningful, with a range of 8% to 23% broadly comparable to the 8% to 26% Chen and Srinivasan (2024) report for US non-technology firms. The test in **(2c)** is also the strictest in the panel, asking whether AI disclosure predicts MTB when accounting for a firm's own past valuation. The result suggests that markets are placing some additional value on AI disclosure, but it cannot distinguish between two different interpretations of an elevated MTB ratio (Myers, 1977): informative pricing of unrecognized AI investments, or behavioral overpricing of firms disclosing AI activity without supporting investment. The fundamental performance results in Section 5.1.2 are essential for separating the two.

The second explanation is that markets are correctly pricing disclosed AI activity as cheap talk. If a meaningful share of disclosing firms are AI-washing in the sense of Barrios et al. (2025), markets that recognize this would not bid up valuations in response to disclosures. The weak statistical support across all three specifications would then reflect the market correctly seeing through empty claims. With this explanation, the marginal coefficient in **(2c)** is closer to noise than to a real valuation effect.

5.1.2 Fundamental performance

Our second result is that disclosed AI activity is associated with deferred improvements in fundamental performance, with effects largely absent in the first two years and emerging at the three-year horizon across three of four measures.

The literature on AI as a general-purpose technology predicts this lag: complementary investments must be in place before AI generates measurable returns (Cockburn, Henderson and Stern, 2019; Brynjolfsson, Rock and Syverson, 2021) echoing the IT productivity lag in the 1990s (Brynjolfsson and Hitt, 2000). Chen and Srinivasan (2024) document a similar pattern in their US sample, with improvements in ROA concentrated at the three-year horizon. H_2 was framed as non-association because these papers predict no near-term effect, and the k=3 improvements we observe match the longer-run effect they also predict.

Sales growth is the one measure that does not fit the deferred-improvement pattern. The marginally significant association at k=0, however, is consistent with the theoretical channel through which AI, as a general-purpose technology, lowers the cost of experimentation and expands product offerings (Cockburn, Henderson and Stern, 2019), and matches the empirical pattern in Babina et al. (2024), who find that AI-investing firms grow on the top line without corresponding gains in productivity or operating margin. However, there is no theoretical explanation for why this top-line effect fades in the following years.

5.1.3 Proxy determination

Our third result is that disclosed AI activity does not proxy for genuine AI activity as measured by R&D or SG&A intensity. The result allows for two interpretations.

The first interpretation is that R&D and SG&A are weak proxies for genuine AI activity in this setting. SG&A is broad by construction, and AI vendor fees may be a small share of total operating expenses for the average non-technology firm. R&D captures only firms with material in-house development, and our determinants result (Section 4.1.4) shows that disclosure concentrates among large firms, which are seldom first movers in new technology areas and are more likely to procure AI than to build it. Both inputs into the test may therefore fail to register real activity. Our test is also stricter than comparable validations in the literature: Chen and Srinivasan (2024) validate against patent filings and IT-worker share, and Babina et al. (2025) use a resume-based AI-worker measure, both truly isolating AI activity. A failure of the R&D and SG&A test therefore does not confidently establish that disclosure is disconnected from underlying AI activity.

The second interpretation is that the tests do establish that disclosure is disconnected from underlying AI activity. Genuine AI activity by disclosing firms would be expected to show up in either R&D or SG&A in a structurally different manner than peers, even if small. Barrios et al. (2025) document that firms can disclose AI activity without making corresponding investments, and the H_3 failure is consistent with this AI-washing channel.

Section 5.2 returns to which reading is more plausible.

5.2 Synthesis

Taken together, the three results are mixed. Disclosed AI activity is marginally associated with a higher market-to-book ratio once we control for past valuation (H_1). Fundamental performance improves three years after disclosure across three of four measures (H_2). The R&D and SG&A tests do not validate disclosed AI activity as a proxy for genuine AI activity (H_3). We see two possible explanations.

The most plausible reading is that disclosure tracks genuine AI activity, but the value materializes slowly. The k=3 fundamental improvements across three measures are the strongest evidence. Disclosure that is cheap talk should not predict fundamental improvements three years later, and Barrios et al. (2025) show that AI-washing companies do not exhibit such improvements. The deferred timing aligns with the literature on AI as a general-purpose technology, in which complementary investments must mature before AI generates measurable returns. The marginal H_1 result is consistent with markets pricing disclosed AI activity modestly while waiting for fundamentals to confirm the signal, and its magnitude reinforces this reading: our implied 8% to 23% range tracks Chen and Srinivasan's 8% to 26%, with the weak statistical support consistent with what a smaller sample estimating a similar underlying effect would produce. The fundamental performance results also suggest that the H_3 null reflects the limits of R&D and SG&A as proxies, rather than the absence of underlying activity.

The alternative reading is that disclosure does not track real activity, and the H_1 effect is closer to noise than to a real signal. Barrios et al. (2025) document that firms can disclose AI without investing in it, and the H_3 failure is consistent with this. The marginal significance of **(2c)** and the insignificance of **(2a)** and **(2b)** leave room for this reading. The k=3 clustering is the main piece of evidence against it but does not rule it out. Firms disclosing AI activity could be improving on fundamentals for reasons unrelated to AI, possibly explained by the fact that they are also the larger and more profitable firms in the sample (Section 4.1.4).

Of the two readings, the deferred fundamental improvements at k=3 tilt the evidence most strongly toward the first, with the small Swedish sample leaving room for the second.

6. Conclusion and limitations

6.1 Final conclusion

This study examines whether disclosed AI activity in annual reports is associated with firm valuation and fundamental performance among Swedish non-technology firms listed on Nasdaq Stockholm Main Market between 2014 and 2024. Using textual analysis of 1,098 annual reports, we construct a firm-year measure of disclosed AI activity and link it to market-to-book ratios, fundamental performance and R&D and SG&A intensity. Our analysis yields three findings.

Disclosed AI activity is associated with a higher market-to-book ratio (8% to 23%) at the 10% level once we control for past valuation, with a magnitude broadly comparable to the US study of Chen and Srinivasan (2024). Fundamental performance shows no association at horizons of one or two years but improves three years after disclosure across three of four measures (including ROA 12.5% to 37.5%), aligning with theory that AI gains take years to materialize. Disclosed AI activity is not significantly associated with either R&D or SG&A intensity. This could mean that disclosed AI activity does not reflect real AI activity, or that R&D and SG&A are too broad to capture it.

Together, these findings indicate that disclosed AI activity is positively associated with firm valuation among Swedish non-technology firms, even where the market-to-book effect itself is statistically weak. The deferred fundamental improvements are the clearest evidence against AI-washing, and they suggest that the marginal valuation effect reflects markets pricing real activity rather than overpricing empty claims. The small Swedish sample, however, leaves room for both readings.

These findings have implications for both investors and researchers. For investors, disclosed AI activity is best interpreted alongside fundamental performance over a multi-year horizon rather than as a standalone valuation cue. For researchers, the US evidence on disclosure and firm value extends to smaller IFRS-governed markets, although the signal is detected most clearly in deferred fundamentals rather than in market prices.

6.2 Limitations

Our text-based measure of AI activity has clear limits. Firms can conduct AI activity without disclosing it and disclose AI activity without conducting it. Swedish reports also lack a section equivalent to Item 1 of the US 10-K, so AI mentions are spread across the report, and the macro-context filter cannot catch marketing, sustainability, or aspirational framing that does not reflect firm-level activity. We also cannot run the cleaner validation tests (e.g. patents) used in the literature due to scope of the thesis and limited coverage. The R&D and SG&A test we run is therefore stricter, but a failure leaves more room for genuine activity than a failure of the cleaner tests would.

Our sample of 102 firms and 1,098 firm-year observations is small and narrowly scoped, making it hard to cleanly detect small effects. This is the main reason that the second interpretation of the synthesis cannot be ruled out. The English-only and continuous-listing-from-2017 requirements may also bias the sample toward larger, more internationally exposed firms with longer track records.

Our FYE+4 month measurement window contrasts with Chen and Srinivasan (2024) , who measure MTB on the trading day after each firm's 10-K filing, tying the price directly to the disclosure event. Because Swedish publication dates vary within our window, the disclosure-to-measurement gap differs across firms, and for early publishers, other news will have moved the share price.

Two further extensions would strengthen the MTB analysis. First, we do not compute a conservatism-corrected MTB (McNichols, Rajan and Reichelstein, 2014), which would have isolated how much of the MTB difference reflects unrecognized intangible investment as opposed to the disclosure signal itself. Secondly, we also do not implement an instrumental variable strategy: Chen and Srinivasan use industry-level AI patent exposure as an IV, an approach that could in principle be applied to Swedish data but falls outside the scope of this thesis.

Regression **(2c)** is exposed to Nickell (1981) dynamic panel bias: the lagged dependent variable $MTB_{i,t-1}$ is mechanically correlated with the within-firm error, distorting the coefficient on AI disclosure. The standard approach is Arellano-Bond or Blundell-Bond Generalized Method of Moments (GMM). However, implementing and validating these estimators falls outside the scope of this thesis. This might impact significance of **(2c)** as potentially affected by dynamic panel bias.

Finally, we test horizons only up to k=3. Two panel constraints shrink coverage even at this window: a 2023 discloser cannot be observed at k=3 (2026 data does not yet exist), and a 2018 discloser listed in 2016 lacks the pre-2015 fundamentals needed to anchor the sales growth baseline. We therefore cannot say whether the k=3 improvements persist beyond three years or fade.

6.3 Future research

Several directions for future research follow from our findings and the limitations discussed above.

Firstly, if the data permits, future research should pursue cleaner proxies for genuine AI activity. A labor-based measure built on Swedish resume data would offer a direct external benchmark that the R&D and SG&A test cannot provide. A patent-based measure could complement disclosure for firms with substantial patent portfolios. Both would also enable a separate analysis of AI-washing and genuine adopters in the Swedish setting, which would directly address the interpretation we cannot rule out.

Secondly, future research should also work with larger samples. Replication in other European markets such as Germany, France, or the Nordics would show whether the weak valuation result is specific to Sweden or appears elsewhere and a pooled European panel would increase statistical power further.

Finally, several robustness tests would strengthen the results: an MTB measure that adjusts for unrecognized intangibles (McNichols, Rajan and Reichelstein, 2014), an instrumental variable approach to address selection bias, an extension of the fundamental performance test beyond three years, and a dynamic panel GMM estimator to address Nickell bias in **(2c)**.

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Appendix

Table 10: AI term regex definitions

<table>
<tr><th>AI term</th><th>Regex expression</th><th>AI term</th><th>Regex expression</th></tr>
<tr><td>AI core:</td><td></td><td>Generative:</td><td></td></tr>
<tr><td>artificial intelligence</td><td>(\bartificial intelligence\b)|(\bAI[\-]?tech\b)|(\bAI[\-]?related\b)</td><td>generative AI</td><td>(\bgenerative[\-]?ai\b)|(\bgen[\-]?ai\b)</td></tr>
<tr><td>conversational AI</td><td>(\bconversational ai\b)</td><td>large language model</td><td>(\blarge[\-]?language[\-]?model[s]?\b)|(\bLLM[s]?\b)</td></tr>
<tr><td>evolutionary AI / computing</td><td>(\bevolutionary ai\b)|(\bevolutionary computing\b)</td><td>foundation model</td><td>(\bfoundation[\-]?model[s]?\b)</td></tr>
<tr><td>cognitive computing</td><td>(\bcognitive computing\b)</td><td>transformer model</td><td>(\btransformer[\-]?model[s]?\b)</td></tr>
<tr><td>computer vision</td><td>(\bcomputer[\-]?vision\b)</td><td>diffusion model</td><td>(\bdiffusion[\-]?model[s]?\b)</td></tr>
<tr><td>intelligent system</td><td>(\bintelligent[\-]?system[s]?\b)</td><td>multimodal AI</td><td>(\bmultimodal[\-]?ai\b)|(\bmulti[\-]?modal[\-]?ai\b)</td></tr>
<tr><td>ML:</td><td></td><td>GPT</td><td>(\bGPT[\-\d]*\b)</td></tr>
<tr><td>machine learning</td><td>(\bmachine[\-]?learning\b)</td><td>ChatGPT</td><td>(\bChatGPT\b)</td></tr>
<tr><td>deep learning</td><td>(\bdeep[\-]?learning\b)</td><td>copilot</td><td>(\bco[\-]?pilot\b)</td></tr>
<tr><td>NLP</td><td>(\bnatural[\-]?language[\-]?processing\b)|(\bNLP\b)</td><td>chatbot</td><td>(\bchat[\-]?bot[s]?\b)</td></tr>
<tr><td>image recognition</td><td>(\bimage[\-]?recognition\b)|(\bfacial[\-]?recognition\b)</td><td>hallucination</td><td>(\bhallucination[s]?\b)</td></tr>
<tr><td>speech recognition</td><td>(\bspeech[\-]?recognition\b)</td><td>prompt engineering</td><td>(\bprompt[\-]?engineering\b)|(\bprompt[s]?\b)</td></tr>
<tr><td>biometric</td><td>(\bbiometric[s]?\b)</td><td>retrieval-augmented generation</td><td>(\bretrieval[\-]?augmented[\-]?generation\b)|(\bRAG\b)</td></tr>
<tr><td>supervised learning</td><td>(\bsupervised[\-]?learning\b)</td><td>fine-tuning</td><td>(\bfine[\-]?tun(ing|ed)\b)</td></tr>
<tr><td>unsupervised learning</td><td>(\bunsupervised[\-]?learning\b)</td><td>pre-training</td><td>(\bpre[\-]?train(ing|ed)\b)</td></tr>
<tr><td>data mining</td><td>(\bdata[\-]?mining\b)</td><td>attention mechanism</td><td>(\battention[\-]?mechanism[s]?\b)|(\bself[\-]?attention\b)</td></tr>
<tr><td>decision tree</td><td>(\bdecision[\-]?tree[s]?\b)</td><td></td><td></td></tr>
</table>

<table>
<tr><td></td><td></td><td>Analytics</td><td></td></tr>
<tr><td>random forest</td><td>(\brandom[\-]?forest[s]?\b)</td><td>predictive analytics</td><td>(\bpredictive[\-]?analytics\b)</td></tr>
<tr><td>gradient boosting</td><td>(\bgradient[\-]?boosting\b)</td><td>prescriptive analytics</td><td>(\bprescriptive[\-]?analytics\b)</td></tr>
<tr><td>Deployment</td><td></td><td>data science</td><td>(\bdata[\-]?science\b)|(\bdata[\-]?scientist[s]?\b)</td></tr>
<tr><td>AI-powered / AI-driven</td><td>(\bai[\-]?powered\b)|(\bai[\-]?driven\b)</td><td>AI-driven insights</td><td>(\bai[\-]?driven[\-]?insight)</td></tr>
<tr><td>AI assistant</td><td>(\bai[\-]?assistant\b)</td><td>reinforcement learning</td><td>(\breinforcement[\-]?learning\b)</td></tr>
<tr><td>AI agent / agentic AI</td><td>(\bai[\-]?agent\b)|(\bagentic[\-]?ai\b)</td><td>transfer learning</td><td>(\btransfer[\-]?learning\b)</td></tr>
<tr><td>AI model</td><td>(\bai[\-]?model\b)</td><td>federated learning</td><td>(\bfederated[\-]?learning\b)</td></tr>
<tr><td>predictive AI</td><td>(\bpredictive[\-]?ai\b)</td><td>data augmentation</td><td>(\bdata[\-]?augmentation\b)</td></tr>
<tr><td>recommendation engine</td><td>(\brecommendation[\-]?engine[s]?\b)</td><td>contrastive learning</td><td>(\bcontrastive[\-]?learning\b)</td></tr>
<tr><td>intelligent automation</td><td>(\bintelligent[\-]?automation\b)</td><td>robotic process automation</td><td>(\brobotic[\-]?process[\-]?automation\b)|(\bRPA\b)</td></tr>
<tr><td>responsible AI</td><td>(\bresponsible[\-]?ai\b)|(\bai[\-]?ethics\b)</td><td>industrial AI</td><td>(\bindustrial[\-]?ai\b)</td></tr>
<tr><td>explainable AI</td><td>(\bexplainable[\-]?ai\b)|(\bXAI\b)</td><td>autonomous vehicle</td><td>(\bautonomous[\-]?vehicle[s]?\b)|(\bself[\-]?driving\b)</td></tr>
<tr><td>AI-enabled</td><td>(\bai[\-]?enabled\b)</td><td>autonomous robot / system</td><td>(\bautonomous[\-]?robot\w*\b)|(\bautonomous[\-]?system[s]?\b)</td></tr>
<tr><td>automation</td><td>(\bautomation\b)|(\bautomation[\-]?solution[s]?\b)|(\bmarketing[\-]?automation\b)|(\bprocess[\-]?automation\b)</td><td>digital twin</td><td>(\bdigital[\-]?twin[s]?\b)</td></tr>
<tr><td>human-in-the-loop</td><td>(\bhuman[\-]?in[\-]?the[\-]?loop\b)</td><td>collaborative robot</td><td>(\bcollaborative[\-]?robot[s]?\b)|(\bcobot[s]?\b)</td></tr>
<tr><td>AI governance</td><td>(\bai[\-]?governance\b)|(\bai[\-]?safety\b)|(\bai[\-]?alignment\b)</td><td>inference</td><td>(\binference\b)</td></tr>
</table>

Table 11: Macroeconomic context filter terms

global economic / economy	trade tariff
macroeconomic	supply chain disruption
macro environment	pandemic
macro-economic	covid
eurozone	market risk
euro zone	industry risk
central bank	regulatory risk
central banks	competitive risk
global demand	sector risk
global growth	risk factor
global market	risk factors
global markets	material risk
european market	principal risk
european markets	industry-wide
emerging market	sector-wide
emerging markets	competitive landscape
interest rate	competitive environment
interest rates	industry trend
inflation	industry trends
monetary policy	market trend
fiscal policy	market trends
gdp	our peers
economic slowdown	peer group
economic downturn	peer companies
economic growth	compared to peers
economic outlook	relative to peers
economic conditions	forward-looking statement
geopolit	forward looking statement
trade war	cautionary statement

Table 12: Variable definitions, usage, and expected coefficient signs

Macro term	Variable description	Underlying calculation	Equation used	Sign
$AIRank_{i,t}$	Within-year tercile rank of disclosed AI activity intensity (0–3)	0 if $AIIntensity_{i,t}$ = 0 1, 2, or 3 for the bottom, middle, or top tercile of disclosers	DV **(1)**; DE **(2)**, **(3)**, and **(4)**	+
$AI\ Intensity_{i,t}$	Disclosed AI activity continuous per 1,000 words	$\frac{AIIntensity_{i,t}}{Total\ words} * 1{,}000$	R **(1)**, **(2)**, **(3)**, and **(4)**	+
$RD_{i,t}$	R&D intensity	$\frac{R\&D_{i,t}}{Total\ assets_{i,t}}$	DV **(4a)**; CV **(2b)-(2c)**, and **(3)**	+/-
$SGA_{i,t}$	SG&A intensity	$\frac{SG\&A_{i,t} - R\&D_{i,t}}{Total\ assets_{i,t}}$	DV **(4b)**; CV **(2b)-(2c)**, and **(3)**	+
$MTB_{i,t}$	Market-to-book ratio at FYE+4 months	$\frac{Market\ cap_{i,t+4\ mon}}{Book\ value\ of\ Equity}$	DV **(2)**; CV **(3)**	+
$ROA_{i,t}$	Return on asset	$\frac{EBIE_{i,t}}{Avg.\ total\ assets_{i,t}}$	DV **(3a)**; DE **(1)**	+
$OpMargin_{i,t}$	$Operating\ margin$	$\frac{EBIT_{i,t}}{Sales_{i,t}}$	DV **(3b)**	+
$TOA_{i,t}$	Asset turnover	$\frac{Sales_{i,t}}{Avg.\ total\ assets_{i,t}}$	DV **(3c)**	+
$Sales\ growth_{i,t}$	Three-year annualized sales growth	$\left(\frac{Sales_{i,t}}{Sales_{i,t-3}}\right)^{\frac{1}{3}} - 1$	DV **(3d)**; DE **(1)**; CV **(2)**, **(4)**	+
$Size_{i,t}$	Firm size	$Log(Market\ cap_{i,t+4\ mon})$	DE **(1)** CV **(2)**, **(3)**, and **(4)**	+/-
$Return_{i,t}$	Past stock return (market-adjusted)	$Log(12mon\ Return)_{i,t+4mon} - \overline{Return_t}$	DE **(1);** CV **(2)**, **(3)**, and **(4)**	+
$Leverage_{i,t}$	Financial leverage	$\frac{Total\ assets_{i,t}}{Shareholder\ Equity_{i,t}}$	DE **(1);** CV **(2)**, **(3)**, and **(4)**	-
$Cash_{i,t}$	Cash ratio	$\frac{Cash\ and\ short\ term\ investments_{i,t}}{Current\ liabilities_{i,t}}$	CV **(1)**	+
$Capex_{i,t}$	Capital expenditure intensity	$\frac{Capex_{i,t}}{Total\ assets_{i,t}}$	CV **(1)**	+/-
$Missing\ RD_{i,t}$	R&D non-disclosure indicator	1 if R&D expenditure is missing in Compustat, 0 otherwise	CV **(2b)-(2c)**, **(3)**, and **(4a)**	-
$Vol_{i,t}$	Stock return volatility	Standard deviation of $Log(12mon\ Return)_{i,t+4mon}$	CV **(2b)-(2c)**, **(3)**, and **(4)**	+/-
$Log\ Words_{i,t}$	Log report length	Natural log of total words in annual report	CV **(2), (3)**, and**(4)**	+/-

Note: DV: Dependent variable; DE: Primary determinant; CV: Control variable; R: Robustness

Table 13: Anecdotes / examples disclosed AI activity in selected annual reports

Examples of disclosed AI activity:
Assa Abloy, Fiscal Year 2014 "The rate of automation of administrative flows, Seamless Flow, also increased during the year. Other cost-reduction activities contributed positively to stable margin growth." "This vision includes manufacturing using intelligent machinery and robots with reading capacity and sensors for processing and movement of materials."
Securitas AB, Fiscal year 2018 "Currently, the focus is on further strengthening our technology capability, consolidating the IT infrastructure, providing innovative client solutions and adding additional competencies within big data, digitization and artificial intelligence to support the strategy going forward."
Bravida Holding AB, Fiscal year 2022 "The running of the systems is optimised using logical rules or artificial intelligence. This creates synergies that reduce energy consumption and optimise the net operating income."
Axfood AB, Fiscal year 2023 "Digitalisation, AI and automation are advancing rapidly. These areas are essential for creating high levels of efficiency and strong customer offerings." "During the coming year, work with integrating AI into the Group's processes and ways of working will be accelerated. A particular focus will be on opportunities with generative AI." "Priorities 2024: Accelerate advanced analysis, AI and digital ways of working"
Sandvik AB, Fiscal Year 2024 "Solutions launched a Manufacturing Copilot based on generative artificial intelligence (AI)." "The business area agreed on a common roadmap for the development of software integrations, AI, and the modernization of products, and started to expand its R&D hub in India to ensure a cutting-edge position within AI and cloud solutions."

Examples of excluded macro-related AI disclosures:
Loomis AB, Fiscal Year 2021 "Development in machine learning and artificial intelligence (AI) is quickly advancing. This type of fintech is creating new possibilities in the payment market, above all in - security and flow management, but also in everyday consumer transactions, such as the development of voice-activated payment solutions."
Atlas Copco, Fiscal Year 2022 "Markets trends: The combination of cloud technology, big data and machine learning increases the demand for data-driven service solutions"
Volvo AB, Fiscal Year 2024 The Volvo Group is subject to a broad array of regulations concerning data protection, cyber resilience, data availability and transfer, as well as other consumer protection regulations that govern the impact of products and digital services on consumers, such as the processing of personal data and the use of artificial intelligence.

Table 14: Correlation matrix

Variable	$AIRank_{i,t}$	$AIIntensity_{i,t}$	$RD_{i,t}$	$SGA_{i,t}$	$MTB_{i,t}$	$ROA_{i,t}$	$OpMargin_{i}$	$TOA_{i,t}$	$Sales\ grow$	$Size_{i,t}$	$Return_{i,t}$	$Leverage_{i,t}$	$Cash_{i,t}$	$Capex_{i,t}$	$Missing\ R\&L$	$Vol_{i,t}$	$LogWords_{i}$
$AI\ Rank_{i,t}$	*1*																
$AI\ Intensity_{i,t}$	*0.595****	*1*															
$RD_{i,t}$	*-0.147****	*-0.045*	*1*														
$SGA_{i,t}$	*-0.034*	*-0.071***	*-0.068***	*1*													
$MTB_{i,t}$	*-0.003*	*0.054**	*0.340****	*0.057**	*1*												
$ROA_{i,t}$	*0.218****	*0.161****	*-0.543****	*0.001*	*-0.164****	*1*											
$OpMargin_{i,t}$	*0.166****	*0.085****	*-0.421****	*0.037*	*-0.021*	*0.562****	*1*										
$TOA_{i,t}$	*0.107****	*0.049*	*-0.309****	*0.468****	*-0.061***	*0.433****	*0.282****	*1*									
$Sales\ growth_{i,t}$	*0.128****	*0.097****	*0.164****	*0.001*	*0.029*	*0.109****	*0.090***	*0.129****	*1*								
$Size_{i,t}$	*0.293****	*0.297****	*-0.143****	*-0.272****	*0.085****	*0.270****	*0.222****	*-0.012*	*0.081***	*1*							
$Return_{i,t}$	*0.044*	*0.083****	*-0.063***	*-0.02*	*0.067***	*0.248****	*0.148****	*0.110****	*0.02*	*0.169****	*1*						
$Leverage_{i,t}$	*-0.002*	*0.003*	*-0.153****	*-0.058**	*-0.003*	*0.036*	*0.139****	*0.268****	*-0.039*	*0.103****	*-0.025*	*1*					
$Cash_{i,t}$	*-0.156****	*-0.092****	*0.377****	*-0.160****	*0.094****	*-0.348****	*-0.399****	*-0.403****	*-0.017*	*-0.181****	*-0.095****	*-0.286****	*1*				
$Capex_{i,t}$	*-0.062***	*-0.098****	*-0.139****	*-0.062***	*0.025*	*0.107****	*0.097****	*0.098****	*-0.097****	*0.061***	*-0.042*	*-0.057**	*-0.059**	*1*			
$Missing\ RD_{i,t}$	*-0.189****	*-0.170****	*-0.356****	*0.186****	*-0.042*	*0.088****	*0.108****	*0.271****	*-0.036*	*-0.195****	*-0.009*	*0.124****	*-0.132****	*0.177****	*1*		
$Vol_{i,t}$	*-0.159****	*-0.079****	*0.311****	*0.016*	*0.108****	*-0.389****	*-0.316****	*-0.268****	*-0.068**	*-0.307****	*-0.148****	*-0.059**	*0.254****	*-0.103***	*-0.097****	*1*	
$Log\ Words_{i,t}$	*0.223****	*0.104****	*-0.164****	*-0.269****	*-0.215****	*0.108****	*0.120****	*0.018*	*0.095****	*0.603****	*-0.012*	*0.249****	*-0.224****	*0.028*	*-0.097****	*-0.188****	*1*

Table 15: Variance inflation factors

Variable	VIF
$AIRank_{i,t}$	1.4
$AIIntensity_{i,t}$	1.25
$RD_{i,t}$	2.25
$SGA_{i,t}$	1.57
$MTB_{i,t}$	1.37
$ROA_{i,t}$	1.96
$OpMargin_{i,t}$	n/a
$TOA_{i,t}$	n/a
$Sales\ growth_{i,t}$	1.18
$Size_{i,t}$	2.47
$Return_{i,t}$	1.2
$Leverage_{i,t}$	1.28
$Cash_{i,t}$	1.4
$Capex_{i,t}$	1.74
$Missing\ R\&D_{i,t}$	1.51
$Vol_{i,t}$	1.69
$LogWords_{i,t}$	2.46

Table 16: Breusch-Pagan test

N	Lagrange multiplier	p-value	f-value	f p-value
774	125.7949	< 0.0001	5.3642	< 0.0001

The use of generative AI

For this thesis, we utilized generative artificial intelligence (AI) via ChatGPT (version 5.5) Claude (Opus 4.7), and Google Scholar Labs throughout the writing of the thesis (Jan-May 2026). The tools were primarily applied in the coding process in RStudio and Visual Studio, including troubleshooting and formatting, and were also used to confirm our existing understanding of certain sources. Additionally, they supported text refinement, revision, and proofreading, offering suggestions to improve language, clarity, and grammar. Overall, the use of AI enhanced the efficiency of the process. However, using AI involved risks such as inaccurate suggestions or outdated information. To mitigate these risks, all outputs were critically reviewed, coding suggestions were tested by us, and all factual content was verified against credible academic sources.

Link:

1. https://chatgpt.com
2. https://claude.ai
3. https://scholar.google.com/scholar_labs