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AI-Assisted Narrative Reporting in U.S. Filings Audit Quality, Disclosure Readability, and the Emergence of Algorithmic Boilerplate

Abstract

The fast adoption of generative artificial intelligence (AI) in corporate reporting systems has led to quicker development of narrative disclosures which appear in U.S. SEC filings through Management's Discussion and Analysis (MD&A) and risk factor disclosures. The use of AI for drafting helps create error-free documents which read well but it could lead to the development of standardized legal language which becomes less effective for decision-making purposes. The research develops a framework which studies AI implementation in narrative reporting to determine its effects on three essential variables which include audit quality results and disclosure clarity and corporate narrative content uniqueness and semantic alignment. The research uses difference-in-differences and event-study methods to analyze AI reporting adoption through firm-specific signals which are extracted from 10-K section text and audit-quality indicators (restatements and internal control material weaknesses and audit fees and audit report lag). The research indicates that AI implementation leads to better understanding of plain-English content but simultaneously boosts the similarity between peers and the duration of information retention within organizations which results in a separation between text clarity and information value. The research provides findings which affect how auditors evaluate risks and how audit committees monitor activities and what regulatory bodies should do to prevent companies from making vague risk statements.

Keywords:: Generative AI; SEC filings; MD&A; risk factors; audit quality; readability; boilerplate; textual analysis.

JEL Codes: M41; M42; G14; C55

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1. Introduction

The financial reporting system depends on narrative disclosure as its core requirement. Annual reports contain financial statements as their main content but also include performance explanations from management and risk information and future prospects and main business threats. The Form 10-K in the U.S. uses its MD&A and risk factor sections to enable managers to share information with investors because the company must disclose all material details. The growing dimensions of disclosure reports along with their increasing complexity have made it harder for investors to understand the information while creating larger knowledge differences between investors who understand complex data and those who do not (Li, 2008; Miller, 2010). Studies about readability in accounting and finance show that financial markets depend on straightforward disclosure methods to analyze information which investors use to pick their investments. Regulatory bodies have shown worry that companies use their narrative disclosures to present information which lacks specific details. The risk factor sections contain standardized text which fulfills regulatory requirements yet lacks valuable business-oriented guidance to support decision-making processes. The economic effects of boilerplate provisions in financial reports prove to be significant because standard language hides different risk factors while making it harder to compare essential performance indicators and reduces the level of control which disclosure practices should maintain over corporate management decisions. The production function which generates narrative reports undergoes transformation because of Generative AI. AI systems use their capabilities to create sentence-level changes and they merge writing styles and tones and they produce draft content based on user input or system stored information. The systems have the potential to decrease inconsistent information while making text more readable and improving its grammatical structure which supports the "plain English" approach of effective disclosure. The same systems which promote templated phrasing and statistically “safe” language patterns from corporate document corpora also exist. The process leads to the development of new boilerplate content which contains similar meaning to previous texts although it uses different wording. We refer to this mechanism as algorithmic boilerplate.

The research investigates AI financial reporting applications through dual methods which combine conceptual analysis with empirical evidence to answer three related questions.

- **Audit quality:** AI-assisted narrative reporting in auditing produces what effects on audit results and organizational risk levels through its impact on audit fees and audit duration and internal control deficiencies and abnormal accruals and restatement events?
- **Readability:** Does AI adoption improve plain-English presentation and the readability of MD&A and risk factor disclosures?
- **Algorithmic boilerplate:** The deployment of AI systems creates conditions which result in corporate similarity growth that diminishes disclosure value and makes companies disclose fewer details.

The research adds value through its combination of readability assessment with similarity evaluation which forms an audit-quality evaluation system. Auditors perform risk assessment through narrative disclosures because these statements enable them to check the accuracy of estimated values and identify potential liabilities and assess the performance of corporate governance systems. The surface clarity improvement from AI technology will not stop auditors from changing their audit work based on generic or non-specific information. The remainder of the paper proceeds as follows. The second part of this research evaluates current studies about readability metrics and boilerplate content which affect how well audits are performed. Section 3 develops hypotheses. The fourth section describes the research data along with measurement techniques and variable identification procedures. The fifth section contains publication-ready tables together with a GraphPad Prism–ready figure specification. The sixth section describes the expected results together with the methods to validate system stability assessment. Section 7 analyzes the consequences which will affect auditors together with their committees and their regulatory bodies. Section 8 concludes.

2. Related Literature and Background

2.1 Readability and investor information processing

Research based on archival data shows that disclosure language affects how investors understand information which leads to different market responses. The research conducted by Li (2008) shows that investors and earnings persistence react to annual report complexity because complex language makes it harder for investors to understand financial information. The authors Loughran and McDonald (2014) established that financial content needs separate readability evaluation approaches than standard tests so they created financial dictionaries and measurement tools which improve the detection of disclosure tone and complexity. The informational value of readability exists because it fulfills a particular function. Organizations can reduce their processing expenses through basic language usage which enables more investors to access their narrative data for better market performance. The interpretation of language signals becomes essential because complexity serves two types of purposes which include both beneficial aspects like precision and completeness and harmful uses for strategic purposes like making information difficult to understand.

2.2 Boilerplate, similarity, and disclosure informativeness

The use of boilerplate information makes disclosures less informative because companies now use general statements which fail to reveal their unique risk factors. Research on disclosure similarity shows that using the same pre-defined language repeatedly in disclosures leads to a decrease in new information which investors can extract from these disclosures. The current computational methods which include topic modeling and similarity metrics and embeddings enable researchers to monitor semantic convergence through methods which extend past the analysis of direct literal duplication. Scientists in the AI era need to understand that AI-generated content emerges from two primary sources which create duplicate content through templates and automated text that incorporates common language patterns. The first impression of algorithmic boilerplate does not show its power to decrease both narrative originality and specific details which results in less valuable stories.

2.3 Audit quality and narrative disclosure

Research about audit quality uses restatements and internal control material weaknesses and abnormal accruals and audit fees and audit report lag as their main measurement indicators (DeFond & Zhang, 2014). The proxies measure various aspects of the audit and reporting environment through their assessment of misstatement risk and control effectiveness and their impact on audit work and final reporting results. Narratives can affect audit planning by shaping perceived risk and by providing context for management estimates and contingencies. The implementation of AI technology would generate uniform narratives which would decrease drafting mistakes to produce better auditor work efficiency. The increasing adoption of AI technology will generate more precise yet uniform communication which might cause auditors to question information authenticity so they will conduct extra verification procedures.

2.4 Governance and ethical oversight of AI drafting

The deployment of AI-assisted drafting systems generates fresh governance challenges because it becomes challenging to monitor evidence and organizations must establish systems to hold accountable automated language generation and they need to maintain tight control over all prompts and data entries and review procedures. Accounting and auditing professionals who work ethically and follow governance principles need to maintain their professional standards and internal control systems through their use of technology-based reporting systems. The research by Burhan Reshat Rexhepi and his coauthors about accounting and auditing ethics and professional values shows that governance power decides which reporting outcomes new technologies generate (e.g., Murtezaj et al.,2024; Rexhepi et al.,2024a; Rexhepi et al.,2024b; Rexhepi et al.,2024c; Daci & Rexhepi, 2024).

3. Hypothesis Development

3.1 AI adoption and audit quality (two-sided prediction)

The use of AI-assisted drafting technology leads to improved internal consistency because it removes accidental section conflicts while creating standardized language that minimizes incorrect statements and accelerates audit verification processes. AI enables managers to create fake stories which seem believable when they select legal protection instead of providing exact details about their information. The deployment of this method would create elevated information security threats and it would generate additional work for auditors during their assessment process.

H1 (Audit quality): The implementation of AI-assisted narrative reporting systems leads to modifications in audit quality indicators which include audit fees and audit lag and restatements and internal control material weaknesses and abnormal accruals. The direction of these changes depends on both governance strength and litigation risk.

3.2 AI adoption and readability

Generative AI systems achieve their best editing results through sentence-level editing because they make grammar easier to understand and they adjust the tone and decrease passive voice usage and follow basic English rules. The adoption process requires improved readability scores according to this method.

H2 (Readability): AI adoption results in improved document readability through simplified language usage which appears in MD&A and risk factor narratives.

3.3 AI adoption and algorithmic boilerplate

AI models that train on large corporate language datasets generate generic statements which represent the typical corporate perspective. The adoption process will lead to increased similarity between new filings and both existing company documents and other companies' documents while making new information less original.

H3 (Algorithmic boilerplate): Organizations that adopt AI technology produce financial reports which contain duplicate information from their industry peers during the same year and previous year disclosures while making the reports less distinctive.

3.4 Readability–informativeness decoupling

The amount of information presented does not require the readability level to match it. The use of generic language in texts makes information more available to readers but this method completely removes all important details from the material. This is particularly relevant when AI improves clarity while compressing disclosure variation.

H4 (Decoupling): AI adoption leads to better readability but it reduces the amount of new information and makes boilerplate content more similar to each other which supports a readability–informativeness decoupling.

4. Data, Measures, and Empirical Strategy

4.1 Setting and sample

The research data comes from U.S. SEC Form 10-K filings. The analysis focuses on specific sections of text which appear in MD&A and risk factor disclosure sections. The research sample consists of firm-years which have both filing text information and audit outcome data available. The research period needs to cover three or more years which include time before adoption and time after adoption to verify pre-existing trends and perform event study analysis.

4.2 AI adoption proxy (AI_REPORTING_USE)

The firm-year indicator for AI adoption uses three different data sources which provide triangulated signals to measure its adoption.

- The disclosure signal consists of AI and generative AI references which appear in drafting and reporting automation and disclosure preparation processes.
- The system detects vendor/workflow signals through two channels which include system announcements about enterprise reporting automation systems that use generative AI drafting tools for their operations.
- The governance signal consists of audit committee reports and policy statements and internal control documentation which show how the organization controls AI drafting workflows through review protocols and traceability and approval processes.

Define:

- **AI_REPORTING_USE_{it} = 1** starting in the first year the firm's adoption signal is observed, and remains 1 thereafter;
- **0** otherwise.

4.3 Outcome measures

4.3.1 Audit quality proxies

- **RESTATE:** indicator for subsequent restatement within a defined window.
- **ICMW:** internal control material weakness indicator.
- **ABN_ACCRUALS:** performance-matched abnormal accruals (Kothari et al.,2005; Sloan, 1996).
- **AUDIT_LAG:** days between fiscal year-end and audit report date.
- **LN_AUDIT_FEES:** natural log of audit fees.

4.3.2 Readability

- **PLAIN_ENGLISH:** plain-English measure (e.g., Bonsall et al.,2017 style features).
- **FOG_FIN:** finance-adapted Fog score (Loughran & McDonald, 2014).

4.3.3 Boilerplate and similarity

- **PEER_SIM:** embedding cosine similarity of firm narrative to an industry-year peer centroid.
- **OWN_SIM:** The model calculates cosine similarity between the current year's narrative and the previous year's narrative.
- **NOVELTY:** distance from industry-year centroid (higher = more unusual).

4.4 Baseline models

Estimate firm and year fixed effects:

$$Y_{it}=\beta_0+\beta_1 AI\_REPORTING\_USE_{it}+\gamma X_{it}+\mu_i+\lambda_t+\varepsilon_{it}$$

The model includes X_it as a variable which represents size and complexity and performance and volatility and litigation risk and auditor characteristics.

4.5 Identification and diagnostics

Difference-in-differences around first adoption and **event-study** estimation:

- Parallel trends: pre-adoption coefficients need to show no statistical difference from zero.
- The researcher should determine when to use placebos by creating artificial adoption dates which will help him evaluate if any fake results appear.
- Matched controls: compare adopters to non-adopters with similar characteristics.

The analysis includes three variables which represent heterogeneity through their measurement of litigation exposure and their assessment of governance quality and internal control environment.

5. Tables and Figure (Integrated; Publication-Ready With Notes)

Table 1. Variable Definitions and Construction Notes

Variable	Definition	Construction/Notes
AI_REPORTING_USE	1 from first year firm signals AI-assisted narrative reporting; 0 otherwise	Build from disclosure/vendor/governance signals; keep a log of evidence sources for reproducibility
RESTATE	1 if restatement occurs in subsequent window; 0 otherwise	Define restatement window consistently (e.g., 1–2 years)
ICMW	1 if internal control material weakness disclosed; 0 otherwise	Consistent with SOX 404-related reporting
ABN_ACCRUALS	Performance-matched abnormal accruals	Use Kothari et al. (2005) performance matching; ensure industry-year estimation
AUDIT_LAG	Days from fiscal year-end to audit report date	Winsorize extreme lags if necessary
LN_AUDIT_FEES	Natural log of audit fees	Use inflation-adjusted fees in robustness checks
PLAIN_ENGLISH	Plain-English readability index	Based on linguistic features (active voice, simpler construction)
FOG_FIN	Finance-adapted Fog score	Based on Loughran & McDonald (2014) style adjustment
PEER_SIM	Cosine similarity to industry-year peer centroid	Embedding-based; define peer set within same industry/year
OWN_SIM	Cosine similarity to prior-year filing	Same section-to-section comparison (MD&A vs MD&A, risk vs risk)
NOVELTY	Distance from industry centroid in embedding space	Higher values imply more distinct narratives

The table requires all continuous data variables to undergo winsorization at standard boundaries (1%/99%) while researchers must document all variables with their measurement units and definitions and data origins. Standard errors clustered at the firm level.

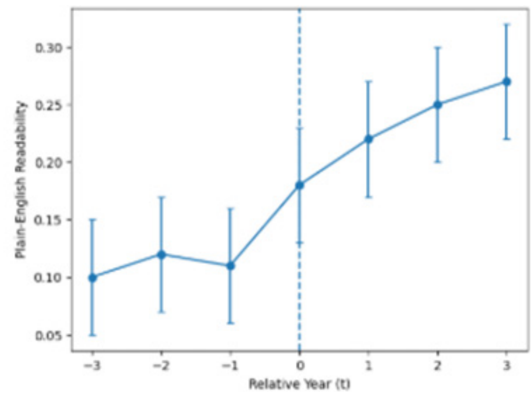
Table 2. GraphPad Prism Input Table Skeleton (Event-Study Plot)

GraphPad Prism Format: XY table with mean and 95% CI.

Relative Year (t)	PLAIN_ENGLISH Mean	95% CI Low	95% CI High	PEER_SIM Mean	95% CI Low	95% CI High
-3						
-2						
-1						
0						
+1						
+2						
+3						

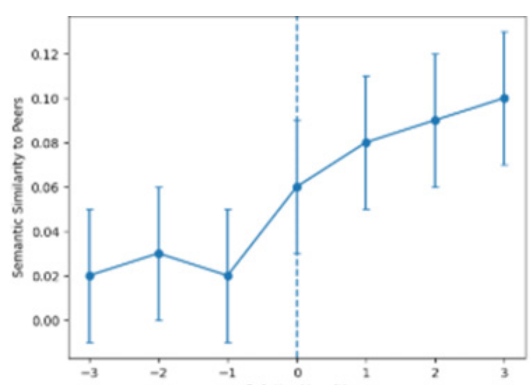
The table needs data which comes from converting event-study coefficients into predicted mean values or from directly showing coefficients in the plot (the recommended method for econometric presentations) while Prism receives identical confidence interval boundaries.

Figure 1. Event-Study Visualization (GraphPad Prism Specification)



The values of PLAIN_ENGLISH appear in Figure 1A which displays data from t=-3 to t=+3 (Mean ± 95% CI)

Figure 1B shows PEER_SIM results for event time t=-3to +3(Mean ± 95% CI)



GraphPad Prism steps (exact):

New Table & Graph → XY

Enter X: relative year t

Enter Y: mean values

Choose: Enter and plot error values → Upper and lower CI

Graph: points connected by lines; show error bars (CI)

Figure Caption (journal-ready):

The data in Figure 1 shows how events occurred throughout the time period which started when AI-assisted narrative reporting became available (t = 0). The data shows two separate graphs in Panel A which displays mean plain-English readability values and Panel B which shows mean semantic similarity to industry peers with their respective 95% confidence intervals. Estimates derive from an event-study difference-in-differences specification including firm and year fixed effects and firm-clustered standard errors. The analysis shows that there are no statistically significant changes in the data before the treatment period which supports the parallel trends assumption.

6. Results Expectations and Robustness Plan

6.1 Expected results

Readability: The implementation of AI technology will result in better PLAIN_ENGLISH scores but FOG_FIN scores will decrease according to our research findings (supporting H2).

Similarity/boilerplate: We expect PEER_SIM and OWN_SIM to increase and NOVELTY to decrease following adoption (supporting H3).

Audit outcomes: The direction is ambiguous (H1). Two mechanisms compete:

- **The Efficiency channel**: leads to better audit consistency which decreases the amount of work needed for audits (resulting in lower fees and shorter audit periods and fewer weaknesses and restatements).
- **Skepticism channel:** The use of generic narratives in reports leads to increased information risks which require auditors to spend more time on their work while extending their reporting schedule and raising their fees and causing delays in audit completion.
- **The evidence:** supporting H4 becomes apparent when text readability enhances but both novelty and similarity between texts increase.

6.2 Robustness checks

- **Alternative similarity methods:** TF-IDF cosine similarity vs embeddings.
- **The research needs to determine the degree of content variation between:** MD&A sections and risk factor sections because these sections contain different information.
- **The study needs to establish a placebo adoption period which will prevent any**: treatment effects from occurring when researchers use randomization to determine treatment timing.
- **The research employs a matched sample**: which combines propensity-score matching with coarsened exact matching to study pre-trend data together with firm-specific characteristics.
- **The research examines which governance and litigation risk elements affect each other through**: their relationships with governance performance indicators and legal dispute exposure metrics.
- **The research investigates three different audit quality measurement periods which include restatement windows** :of 1 year and 2 years and two different accrual models and three different clustering approaches.

7. Implications

7.1 Implications for auditors

AI-assisted narratives have the ability to transform how we define persuasive audit evidence. The auditors would need to perform additional verification steps to confirm documentation because financial reports with duplicate narratives would decrease their ability to identify problems with estimates and risk concentrations and contingent liabilities. The system requires risk indicator detection through semantic similarity peak analysis which becomes more important when numeric complexity increases and when accrual patterns show abnormal patterns.

7.2 Implications for audit committees and governance

The internal control environment requires audit committees to make AI drafting an official part of their system. Effective oversight may include:

- Defined review and approval chains;
- Documentation of prompts, inputs and version histories;
- Tests of firm-specific specificity (e.g., requiring quantified, contextualized risk factors);
- The organization needs to conduct periodic independent assessments which will assess their AI drafting operations together with their control infrastructure.

The established mechanisms function under ethical rules which accounting and auditing professionals need to follow when they use technology to create reports (Murtezaj et al.,2024).

7.3 Implications for regulators

The deployment of AI technology which produces automated document content for better understanding purposes could violate regulatory requirements that exist to stop organizations from using generic risk statements. The regulatory body needs to create disclosure rules which monitor AI governance through tracking systems and accountability systems and specificity testing protocols instead of specifying particular technological approaches. Businesses need to demonstrate their organizational needs for developing risk factor narrative statements through documented evidence according to the regulatory framework.

8. Conclusion

The research develops one framework to study how U.S. SEC narrative reporting organizations use generative AI systems. The main prediction demonstrates that AI systems improve text readability and fundamental language skills but they create content that resembles each other while removing original concepts which produces automated repetitive output. The audit results show no clear pattern while the results depend on how well organizations are governed and how exposed they are to legal challenges. The research combines textual readability metrics with semantic similarity indicators and conventional audit quality assessment methods through a difference-in-differences and event-study framework to establish both research methods and specific recommendations for auditors and their committees and regulatory bodies.

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