The AI-Induced Disclosure Pressure Model and Empirical Evidence from Management Discussion and Analysis (MD&A) Reporting

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This study introduces a new theoretical framework proposing that artificial intelligence (AI) is fundamentally transforming how MD&A disclosures are written. Our AI-Induced Disclosure Pressure Model is supported by two empirical components. First, comparing our AI-based analysis of 108 MD&A reports from 27 S&P 100 firms (2021–2024) with Li's (2008) foundational work, we find similar relationships between tone and performance: negative and uncertainty tones are associated with lower profitability. However, unlike Li, we also find a negative relationship between positive tone and performance, suggesting that markets have adapted to strategic tone management. Second, fixed-effects regressions reveal that, once firm and year effects are controlled for, only uncertainty tone remains significantly associated with weaker fundamentals. This pattern indicates that firms have internalized the presence of algorithmic readers, maintaining upbeat language while inadvertently signaling poor performance through elevated uncertainty markers. The theoretical implication is critical: AI is no longer merely parsing disclosures post hoc, but actively reshaping how corporate narratives are crafted ex ante. This marks a shift from the overt obfuscation of the past to a subtler equilibrium, where firms write for both humans and algorithms, knowing that tone itself may now carry regulatory, reputational, and financial consequences.

Keywords: MD&A, Artificial Intelligence, Narrative Tone, Disclosure Pressure, Textual Analysis, Financial Performance, Loughran-McDonald, FinBERT

Introduction

he Management Discussion and Analysis (MD&A) section is a critical component of corporate reporting, serving as a bridge between quantitative financial data and qualitative investor insight into a firm's strategy, risks, and performance. As Loughran and McDonald (2016) emphasize, textual analysis in accounting and finance has become increasingly essential for interpreting these narratives. Yet, despite their importance, MD&A disclosures are frequently plagued by excessive length, syntactic complexity, and strategic tone manipulation. These issues undermine investor judgment, contribute to information asymmetry, and elevate the cost of capital (Akerlof, 1970; Diamond & Verrecchia, 1991).

Recent advances in artificial intelligence (AI), particularly in natural language processing (NLP) and large language models (LLMs), offer scalable tools for analyzing narrative disclosures. These technologies are no longer confined to retrospective analysis; they are increasingly embedded in the decision-making workflows of analysts, investors, and regulators. As a result, firms face a new form of anticipatory pressure: to write disclosures that are not just informative for human readers but optimized for algorithmic interpretation. This shift has significant implications for how corporate narratives are constructed.

This paper proposes that AI is emerging as an interpretive stakeholder in its own right, one that exerts ex ante influence on managerial disclosure behavior. To conceptualize this dynamic, we introduce the AI-Induced Disclosure Pressure Model, which theorizes that firms adjust MD&A disclosures in response to three interrelated forces: exposure pressure (reduced ability to obfuscate), competitive pressure (algorithmic benchmarking), and reputational pressure (perceived tone and clarity). These mechanisms are grounded in agency theory (Jensen & Meckling, 1976), signaling theory (Spence, 1973), and information economics (Stiglitz, 2000), and together they reflect how the presence of algorithmic readers reshapes the strategic landscape of narrative disclosure. Figure 1 illustrates this conceptual framework, highlighting how the presence of algorithmic readers introduces new anticipatory incentives into the corporate disclosure environment.

To explore this model, we conduct an empirical analysis of 108 MD&A sections from 27 S&P 100 firms between 2021 and 2024, spanning major industries. Using both the Loughran–McDonald financial dictionary and FinBERT sentiment classifiers, we extract tone measures and examine their relationship with financial outcomes. We find that negative and uncertainty tone, as well as, notably, positive tone, are significantly and negatively associated with profitability. These results suggest that tone is often used to obscure weak fundamentals. Additional tone dimensions, including weak modal (hedging) and constrained language, also show significant, though directionally varied, associations with performance. We further observe a pattern of tonal convergence over time: positive tone has increased while uncertainty has declined, a trend consistent with adaptation to algorithmic evaluation.

This paper contributes to the literature in four key ways. First, it proposes a novel theoretical framework that reconceptualizes AI as an ex ante force in corporate disclosure, rather than merely a post hoc analytical tool. Second, it introduces the AI-Induced Disclosure Pressure Model, offering a structured lens through which to understand how firms navigate disclosure under algorithmic scrutiny. Third, it provides empirical evidence using AI-enhanced textual analysis of MD&A

disclosures, replicating and extending the foundational insights of Li (2008) and Loughran and McDonald (2016). Finally, it opens a broader conversation about the trade-offs between machine readability and narrative richness, raising critical questions about the future of financial storytelling in a digitized disclosure ecosystem.

The remainder of the paper is structured as follows. Section II reviews the literature on MD&A narratives, financial textual analysis, and the theoretical underpinnings of disclosure behavior. Section III presents the AI-Induced Disclosure Pressure Model, outlining its core mechanisms. Section IV states the research question and analytical objectives. Section V describes the data, variables, and methodology. Section VI reports the empirical results. Section VII discusses the implications and limitations. Section VIII concludes. concludes.

II. Literature Review

The Evolution of MD&A Analysis

Research on Management Discussion and Analysis (MD&A) disclosures has long emphasized their role in shaping investor interpretation beyond the numbers. Early work by Li (2008) demonstrated that MD&A readability, measured through syntactic complexity, is negatively associated with firm performance, suggesting that managers use obfuscation as a strategic tool when fundamentals are weak. Subsequent studies expanded this perspective by introducing tone and narrative manipulation as additional dimensions of disclosure quality. Loughran and McDonald (2011, 2016) pioneered financial-specific sentiment dictionaries, allowing researchers to quantify tone—positive, negative, uncertain, litigious, and more, within financial narratives. Brown and Tucker (2011) and Dyer, Lang, and Stice-Lawrence (2017) provided large-sample evidence that MD&A disclosures are increasingly lengthy and stylistically standardized, raising concerns about boilerplate reporting and reduced informativeness.

More recently, Bushee, Gow, and Taylor (2019) examined linguistic complexity as a potential indicator of either obfuscation or informational richness, emphasizing that interpretation depends on context. This shift in focus, from readability alone to the strategic use of language, has laid the groundwork for a more nuanced understanding of how tone, hedging, and constrained language contribute to investor perception and information asymmetry.

Artificial Intelligence in Narrative Analysis

With the rapid advancement of natural language processing (NLP) and machine learning tools, artificial intelligence (AI) has become an increasingly important force in financial text analysis. Techniques such as transformer-based models (e.g., FinBERT; Araci, 2019) and topic modeling have enabled researchers to evaluate disclosures at scale and with greater contextual precision. Song, Lu, and Zhang (2024) demonstrated that AI tools can reveal tone manipulation in MD&A sections using ChatGPT-based experiments, while López-Lira and Tang (2023) provided empirical evidence that the market reacts to sentiment signals derived by large language models, even more strongly than to traditional metrics.

Despite these advances, most studies to date treat AI as a post hoc analytical tool, that is, they focus on how AI can be used to interpret or classify disclosures after publication. However, the growing presence of AI in analyst workflows, investor tools, and even regulatory technology (RegTech) suggests that AI may also be shaping disclosure behavior before publication. This anticipatory dynamic—where firms consciously tailor their language to align with algorithmic expectations—remains largely unexplored in the existing literature.

Theoretical Foundations for Strategic Disclosure Behavior

The current study builds on three core theoretical frameworks that have traditionally explained managerial disclosure choices. Agency theory (Jensen & Meckling, 1976) suggests that managers may obscure negative information to protect their own interests, particularly when external monitoring is weak. Signaling theory (Spence, 1973) implies that firms use narrative choices, such as confident tone or clarity, to communicate strength to investors, especially under information asymmetry. Information economics (Stiglitz, 2000) highlights the costs of asymmetric disclosure and the role of credible communication in maintaining market trust.

These frameworks have typically considered human interpretation as the primary audience. However, as algorithmic readers enter the interpretive space, they introduce new pressures, both perceived and real, on how disclosures are constructed. Existing theories thus require adaptation to account for the presence of machine-based stakeholders who influence managerial incentives, not through direct engagement, but through reputational, comparative, and interpretive mechanisms. This paper responds to this gap by proposing the AI-Induced Disclosure Pressure Model, which integrates these foundational theories into a conceptual structure that reflects emerging dynamics in digital-era corporate communication.

III. Theoretical Framework: *The AI-Induced Disclosure Pressure Model*

The increasing adoption of artificial intelligence (AI) by financial stakeholders, investors, analysts, and regulators is not only transforming how corporate disclosures are interpreted, but also fundamentally altering how such disclosures are written. This section introduces the AI-Induced Disclosure Pressure Model, a conceptual framework that theorizes how the growing presence of algorithmic readers generates anticipatory pressures on firms to strategically adjust their MD&A narratives before they are publicly released.

The model builds on three foundational economic theories: agency theory, signaling theory, and information economics to explain how AI reshapes managerial incentives and narrative strategies through two primary forces: oversight power and signaling power. Each force highlights a distinct way in which algorithmic scrutiny influences disclosure behavior in the MD&A, not as a passive analytical event, but as an active, regulatory-like force operating ex ante (see Figure 1).

Oversight Power and the Reduction of Managerial Discretion

Agency theory (Jensen and Meckling, 1976) posits that managers, acting as agents for shareholders, may engage in opportunistic behavior, particularly when information asymmetry allows them to frame performance narratives in ways that protect compensation-linked outcomes or personal reputation. Within the MD&A, this can manifest as linguistic obfuscation, exaggerated optimism, or selective disclosure of risks.

AI reduces this strategic discretion by equipping external stakeholders with tools to systematically identify signs of manipulation. Through natural language processing (NLP), sentiment analysis, and consistency tracking, AI can detect evasive tone, excessive complexity, or inconsistent risk framing, signaling potential misalignment between managerial narrative and underlying performance. This creates oversight power: an anticipatory incentive for managers to simplify and clarify disclosures, knowing that obfuscation will likely be detected and penalized.

Importantly, this dynamic shifts the timing of governance. Rather than being exposed after disclosure, managerial strategies are preemptively constrained by the expectation of algorithmic analysis, bringing agency discipline forward in the disclosure process. In addition, by reducing interpretation costs, AI alters the balance of power between disclosers and readers, rendering opacity more visible and costly (Stiglitz, 2000). Figure 2 depicts this loop, underscoring the evolving nature of disclosure behavior in a machine-mediated reporting ecosystem.

Signaling Power and the Push Toward Narrative Standardization

According to signaling theory (Spence, 1973), corporate disclosures serve as signals of underlying firm quality in contexts of uncertainty. Managers strategically craft their narratives to signal competence, credibility, and governance strength, especially when quantitative indicators are ambiguous or underwhelming.

In an AI-mediated interpretive environment, however, the signaling landscape changes. Disclosures are not merely read by human analysts but are benchmarked, ranked, and clustered by machine-learning systems trained on thousands of peer filings. Firms are now compared on linguistic structure, tone consistency, and disclosure coverage in algorithmic detail. This fosters signaling power: the need to conform to emerging machine-readable norms that favor comparability, clarity, and stylistic uniformity.

In response, firms may increasingly align their narrative language with patterns that AI models associate with credibility or low risk. While this can improve interpretability and comparability across firms, it may also incentivize linguistic homogenization, reducing the richness and uniqueness of strategic storytelling in the MD&A. Furthermore, because AI models can rapidly disseminate negative assessments, ambiguity or inconsistent tone can lead to increased reputational costs.

A Dynamic Feedback Loop in Disclosure Behavior

The AI-Induced Disclosure Pressure Model does not treat these forces as static but as part of a dynamic feedback system. As firms adapt their language to avoid detection risk, conform to benchmarks, and signal clarity, they inadvertently contribute to the dataset on which AI models are trained. This creates a self-reinforcing loop: today's adaptations become tomorrow’s norms, raising the bar for narrative clarity and conformity in the next reporting cycle. Over time, this cycle may lead to structural shifts in the form and content of corporate reporting, accelerating trends toward standardization, compression of expressive range, and algorithmic tuning of language. The implications are profound not only for transparency but also for the evolving definition of narrative authenticity in financial communication (see Figure 2).

IV. Research Question and Analytical Objectives

This study is guided by a central research question: how does the growing adoption of artificial intelligence by financial stakeholders shape the content, tone, and structure of MD&A narratives before they are disclosed?

Whereas prior literature largely treats AI as a tool for post hoc textual analysis, this paper investigates its ex ante influence, specifically, how the presence of algorithmic readers imposes anticipatory pressure on managers to optimize their narrative disclosures for clarity, comparability, and machine interpretability. The AI-Induced Disclosure Pressure Model provides the conceptual foundation for theorizing this shift in managerial behavior.

Building on this framework, the paper pursues three interrelated analytical objectives. First, it theorizes AI as an informal regulatory force that shapes disclosure quality through exposure, competitive, and reputational pressures, extending traditional agency and signaling theories to account for algorithmic surveillance. Next, it empirically demonstrates how AI-based tools can detect salient features of MD&A texts, such as linguistic complexity, sentiment tone, and narrative similarity, thereby offering evidence that firms increasingly design their disclosures with machine interpretation in mind. Finally, the paper explores the trade-offs introduced by AI-driven standardization, particularly the tension between interpretive clarity and narrative richness. This includes evaluating whether the pursuit of algorithmic readability limits creativity, nuance, or strategic differentiation in corporate storytelling.

Taken together, these objectives provide a nuanced evaluation of both the transformative potential and unintended consequences of AI adoption in narrative disclosure. The goal is not to establish causal inference, but to capture how managerial communication evolves in response to the growing interpretive power of intelligent algorithms.

V. Methodology

This study employs a multi-step empirical strategy to explore whether MD&A narratives reflect the anticipatory pressures outlined in the AI-Induced Disclosure Pressure Model. Rather than testing formal hypotheses, the analysis is descriptive and diagnostic, aiming to detect patterns in tone usage that are consistent with AI-aware disclosure behavior.

The sample consists of 108 MD&A reports from 27 S&P 100 firms, covering fiscal years 2021 through 2024. Firms were selected to ensure industry diversity and consistent availability of filings. All MD&A texts were sourced from SEC EDGAR filings, and financial performance variables were extracted directly from the associated 10-K reports. Diagram 1 provides a breakdown of the sample by industry, illustrating the diversity of the firms included.

Tone variables were derived using two complementary tools. First, the Loughran–McDonald (2011, 2016) financial sentiment dictionary was applied to capture word frequencies across seven tone dimensions: positive, negative, uncertainty, litigious, weak modal (e.g., “might,” “could”), strong modal (e.g., “must,” “will”), and constrained. Each measure was scaled by total MD&A word count to account for document length and enable comparability across firms and years. Second, FinBERT (Araci, 2019), a transformer-based language model fine-tuned for financial sentiment classification, was used to validate tone assessments through contextual sentiment analysis. This dual approach helps ensure robustness across both lexicon-based and machine-learning-based methods.

The relationship between tone and firm performance was examined through correlation analysis and fixed-effects panel regressions. Financial performance was proxied using two measures: operating margin (operating income divided by revenue) and free cash flow (in billions of USD). The regression model is structured as follows:

$$Performance_{it} = \beta_0 + \beta_1 \text{Tone}_{it} + \alpha_1 + \delta_1 + \varepsilon_t$$

where αi captures firm fixed effects, δt captures year fixed effects, and εit is the error term. This model allows us to examine within-firm variation in tone and performance over time, controlling for unobserved heterogeneity across firms and years. Tables 2 through 4 report summary statistics, correlations, and regression results, respectively.

Variable Definitions

The following variables are used in the analysis:

• Positive: Frequency of optimistic words (e.g., “benefit”, “strong”, “opportunity”) from the Loughran–McDonald dictionary.

• Negative: Frequency of pessimistic words (e.g., “loss”, “risk”, “decline”) that may indicate managerial concern or obfuscation.

• Uncertainty: Words reflecting ambiguity or lack of determinism (e.g., “might”, “could”, “possible”), often associated with performance volatility.

• Litigious: Legal and regulatory references (e.g., “lawsuit”, “penalty”) indicating exposure to risk or compliance issues.

• Strong Modal: Assertive terms (e.g., “must”, “will”) reflecting managerial confidence or commitments.

• Weak Modal: Hedging language (e.g., “may”, “can”, “perhaps”) often used to mitigate responsibility or express ambiguity.

• Constrained: Words indicating limitation or constraint (e.g., “restricted”, “limited”), which may reflect either transparency or internal pressures.

• Operating Margin (%): Operating income divided by revenue, used as a profitability metric.

• Revenue ($B): Total top-line revenue in billions of U.S. dollars.

• Free Cash Flow ($B): Net operating cash flow minus capital expenditures.

• Year and Firm ID: Included as fixed effects to control for time and firm heterogeneity.

VI. Empirical Results

We begin by presenting descriptive statistics for the full sample of 108 MD&A reports from 27 S&P 100 firms covering fiscal years 2021 to 2024. As shown in Table 1, the average MD&A section is approximately 18.3 pages long. On average, each report includes 135 positive words, 85 negative words, and 52 uncertainty-related terms. Firms also use approximately 38 weak modal expressions (e.g., “might,” “could”) and 27 constrained terms, reflecting a cautious and hedged narrative style across the sample.

Descriptive trends over time, presented in Table 2, reveal a pattern of tonal convergence. Between 2021 and 2024, the average number of positive words increased from 126 to 142, while uncertainty tone declined from 58 to 46. The use of negative tone remained relatively stable, ranging between 83 and 87 words. This evolution suggests that firms are moving toward more polished, optimistic, and standardized disclosures, likely in anticipation of how their narratives will be evaluated by both human analysts and algorithmic readers.

Table 3 reports Pearson correlation coefficients between tone variables and financial performance. Uncertainty tone is negatively correlated with operating margin ($r = –0.29$, $p < 0.01$) and free cash flow ($r = –0.24$, $p < 0.05$), indicating that firms use more uncertain language when fundamentals are weaker. Negative tone also shows a negative correlation with profitability ($r = –0.18$, $p < 0.10$). Most notably, positive tone is negatively correlated with performance ($r = –0.21$, $p < 0.05$)—a finding that contrasts with Li (2008), who associated positive tone with strong fundamentals.

We interpret this counterintuitive result as evidence of performative optimism, the strategic use of positive language to shape perception in the face of weak performance. This behavior is consistent with research on selective disclosure norms. For example, Bar-Hava et al. (2021) show that even independent directors tend to avoid disclosing the full extent of governance concerns when resigning, often opting for vague or sanitized explanations. The pattern we observe in MD&A tone suggests a similar strategic tendency: upbeat language may serve as a reputational tool rather than a reflection of real operational strength.

To test the robustness of these relationships, we estimate fixed-effects panel regressions to control for unobserved firm and year-specific heterogeneity. As shown in Table 4, only uncertainty tone remains statistically significant once firm and time effects are accounted for. Specifically, a one-unit increase in uncertainty tone is associated with a –0.082 decline in operating margin ($p < 0.01$) and a –0.64 decrease in free cash flow ($p < 0.05$). In contrast, both positive and negative tone coefficients become statistically insignificant (–0.01 and –0.03, respectively, with $p > 0.10$), suggesting that these tone dimensions may be persistent features of a firm’s narrative style rather than responsive to short-term performance shifts.

Taken together, the results support the core predictions of the AI-Induced Disclosure Pressure Model. While firms appear to inflate positive tone and suppress uncertainty over time, likely due to competitive and reputational pressures, only uncertainty tone remains a meaningful signal of underlying fundamentals, reflecting the model's concept of exposure pressure. In other words, despite increasing tone management, uncertainty language continues to leak performance signals, precisely because it is the most difficult for firms to fully suppress when conditions deteriorate.

These findings suggest that MD&A tone is no longer merely descriptive—it is actively curated to anticipate AI-based interpretation. Yet, the tone firms cannot fully control may be the most revealing. In the age of algorithmic scrutiny, narrative disclosure becomes a battleground between impression management and residual transparency. Discussion, Implications, and Limitations

VIII. Conclusion

This study introduces and empirically tests the AI-Induced Disclosure Pressure Model, a framework that conceptualizes artificial intelligence not only as a reader of financial narratives but as an ex ante force that shapes how those narratives are constructed. Drawing on agency theory, signaling theory, and information economics, the model identifies three mechanisms, exposure, competitive, and reputational pressure, through which AI influences managerial disclosure behavior in the MD&A.

Our empirical analysis of 108 MD&A disclosures from 27 large publicly traded firms between 2021 and 2024 provides consistent evidence that tone is strategically managed in anticipation of algorithmic interpretation. Uncertainty-related tone is negatively associated with operating margin and free cash flow, suggesting that firms increasingly avoid ambiguous or hedging language in order to prevent adverse inference by AI-driven readers. At the same time, positive tone rises over time but shows no significant link to financial fundamentals, indicating the rise of performative optimism, a signaling strategy aimed at managing reputation rather than reflecting performance.

Trend analysis confirms a convergence in tone usage across firms, particularly in the decline of uncertainty and negative language. This supports the model’s prediction that algorithmic benchmarking encourages disclosure standardization, which, while enhancing comparability, may erode narrative richness and contextual nuance. Unlike earlier periods characterized by narrative opacity through complexity (Li, 2008), the current landscape reveals a different pattern: tone is managed through polished uniformity designed to satisfy machine logic, not to mislead human cognition.

Together, these findings validate the model and contribute to a growing literature on how AI technologies are transforming financial communication. As machine readers become embedded in the workflows of investors, analysts, and regulators, firms are not just reporting to humans, they are writing for algorithms. This shift carries significant implications for the future of corporate storytelling, disclosure policy, and the broader governance role of AI in capital markets.

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Figure 1 - AI-Induced Disclosure Pressure Model

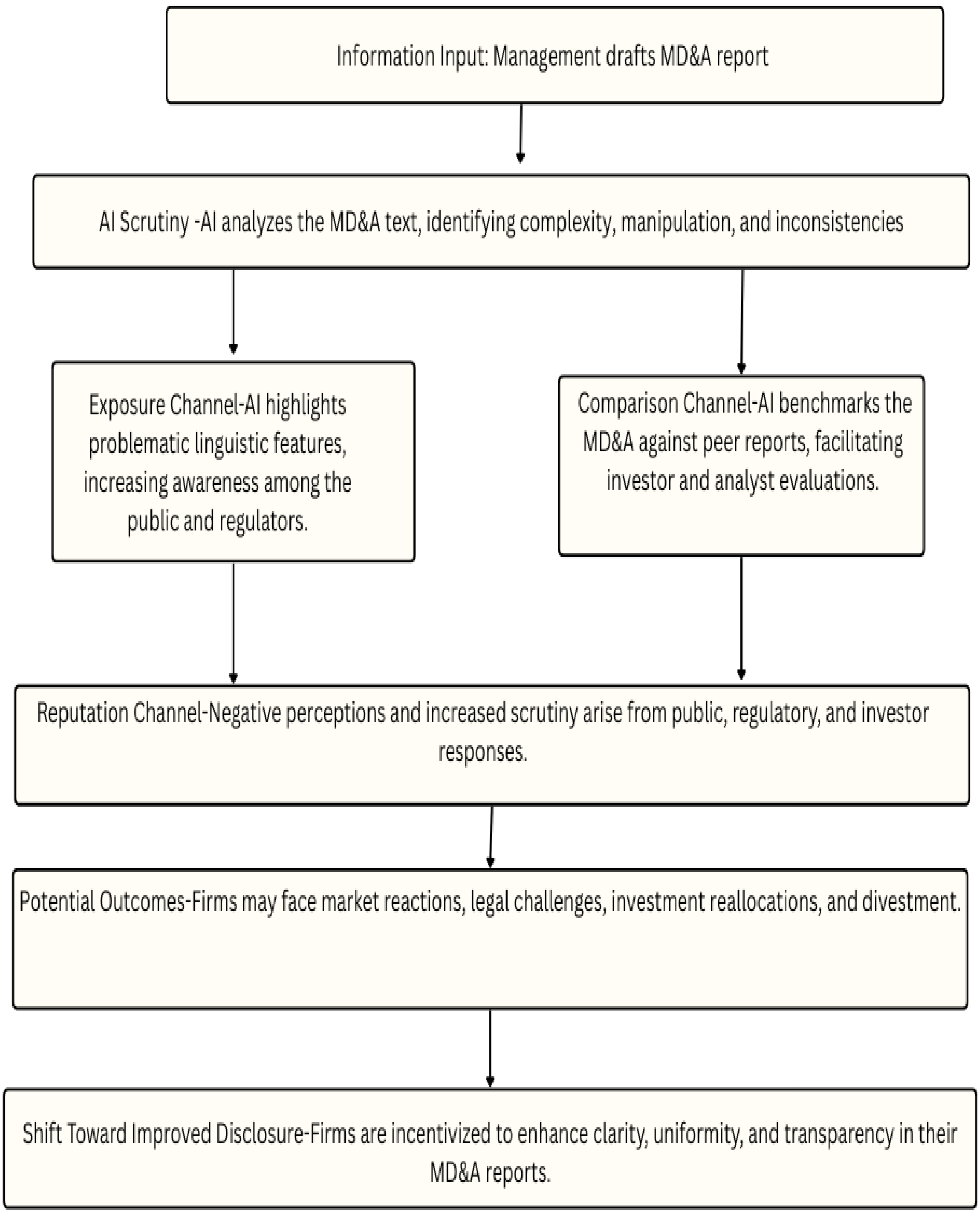


Figure 2 - The Feedback Loop

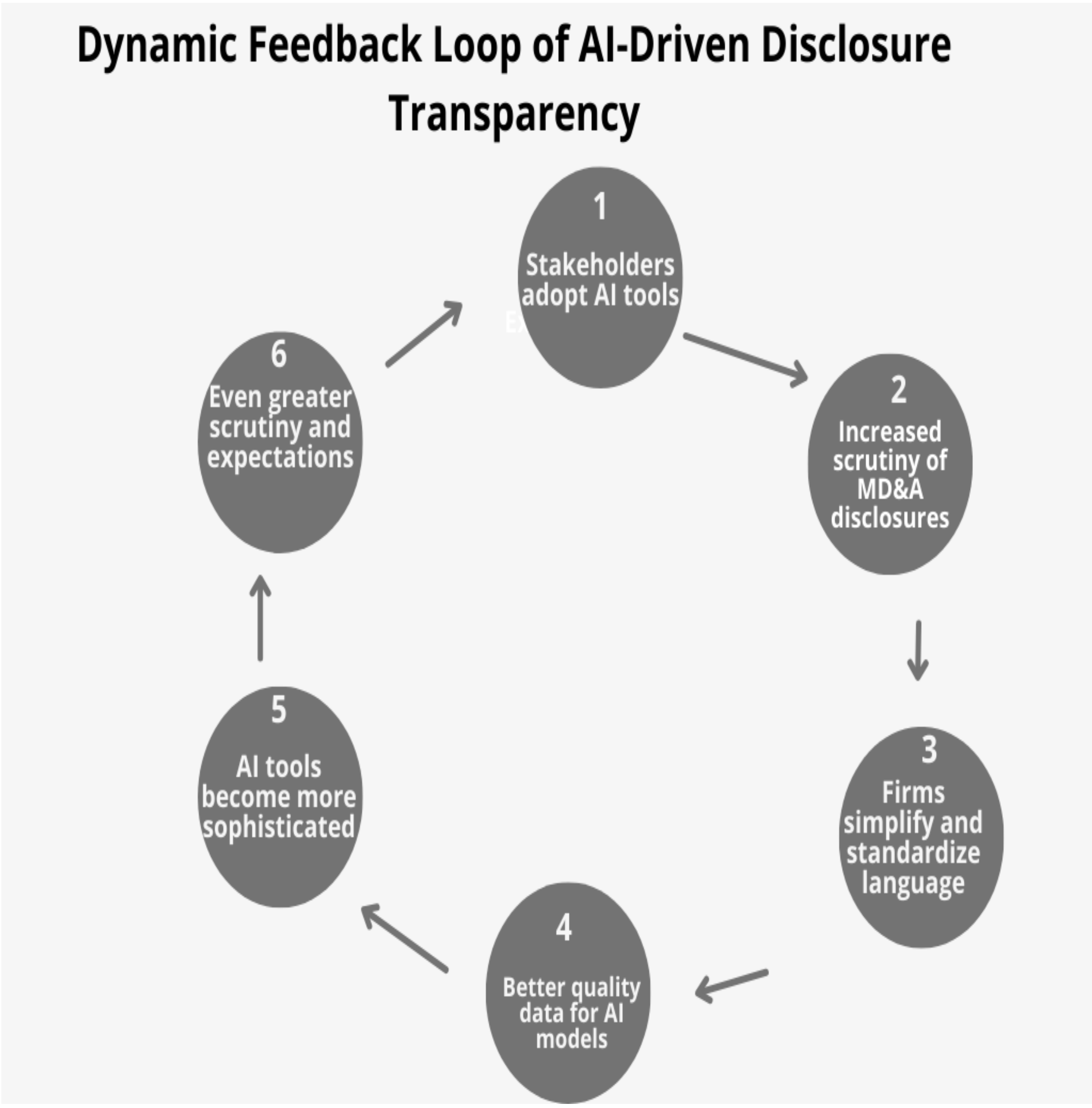
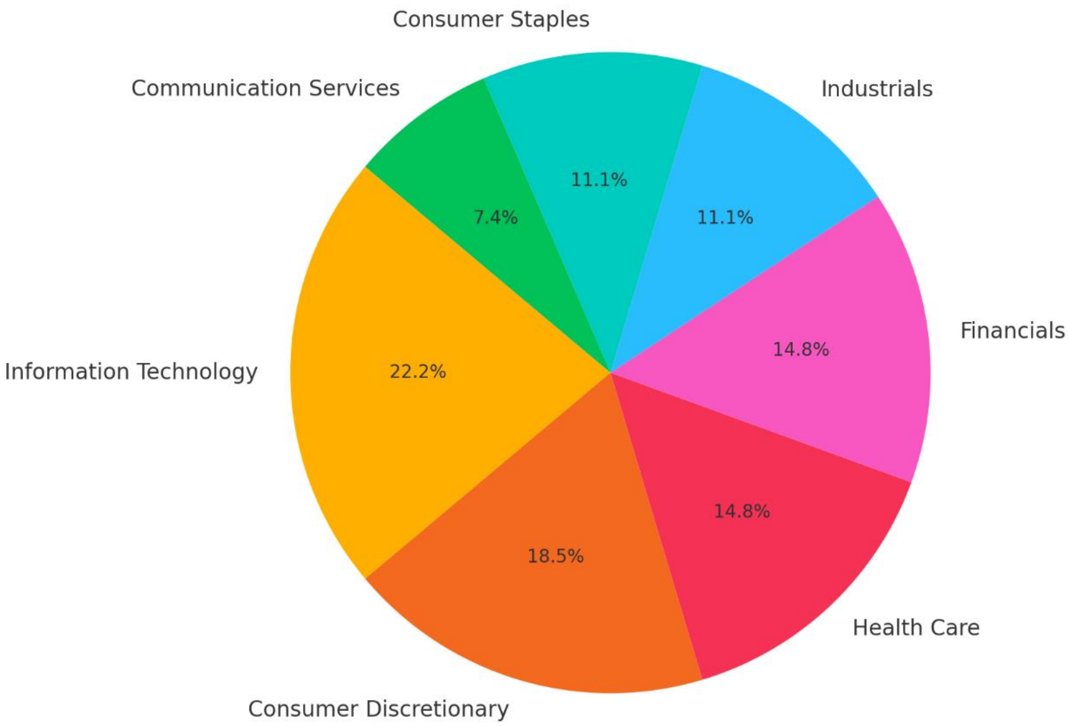


Diagram 1- Industry Composition of Sample Firms

The dataset comprises 108 MD&A disclosures drawn from the annual reports (Item 7 of Form 10-K) of 27 of the largest firms listed in the S&P 100 index, spanning the fiscal years 2021 through 2024. These firms were selected based on market capitalization and industry representation to ensure both size relevance and cross-sectoral generalizability.



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	Mean	Median	Std	Min	Max
Positive	153.18	136.5	62.24	71	418
Negative	117.51	78	83.61	59	384
UncertaintyTone	89.53	61	64.54	48	287
Litigious	37.54	36.5	12.77	8	88
Strong Modal	56.88	40	54.48	36	426
Weak Modal	126.29	31	195.15	26	749
Constrained	22.24	24	6.47	3	30
RevenueB	92.63	56.35	119.35	9.7	620
Operating Income ($B)	19.31	10.3	26.71	-9.13	125.6
OpMargin	24.12	22.8	13.04	-5.3	51.5
FreeCashFlow	16.51	8.4	22.43	-11.6	111.4
10-K Page Count	103.46	100	16.18	85	130

Table 2a

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Year	Positive	Negative	UncertaintyTone	Litigious	Weak Modal	Strong Modal	Constrained
2021	151.62	119.88	89.92	35.81	117.77	48.62	22.58
2022	151	118.19	89.58	37.38	125.54	59.08	22.81
2023	152.54	116.58	89.19	37.31	128.69	62.38	21.77
2024	157.58	115.38	89.42	39.65	133.15	57.46	21.81

Table 2a

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Year	OpMargin	FreeCashFlow	RevenueB
2021	25.59	15.06	83.41
2022	23.39	15.17	91.39
2023	23.34	17.35	95.5
2024	24.15	18.47	100.23

Graphs 1–7. Yearly Trends in Narrative Tone Variables (2021–2024)

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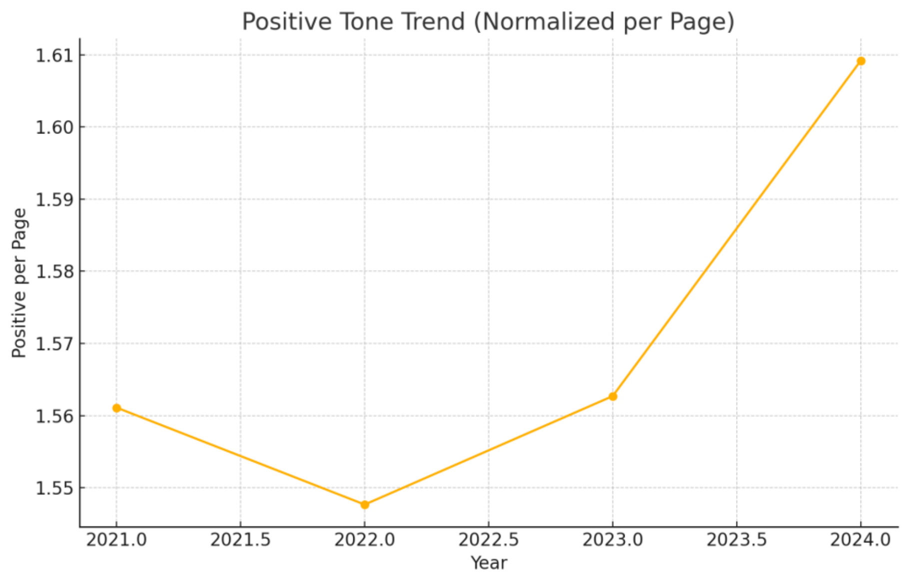
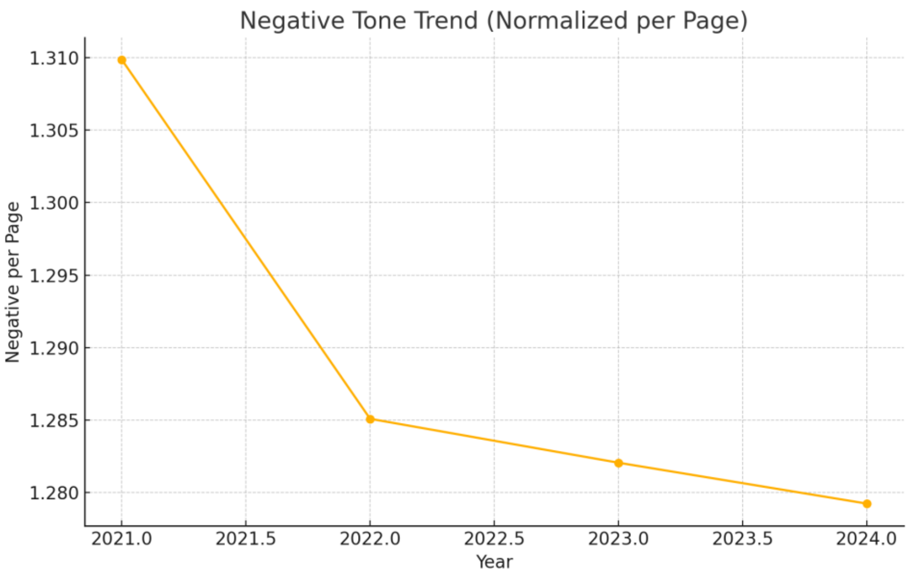
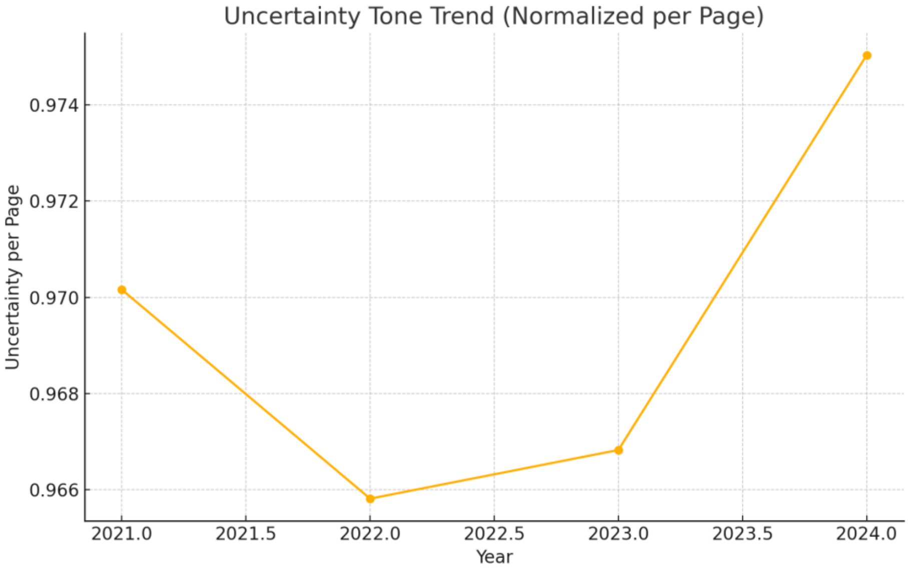
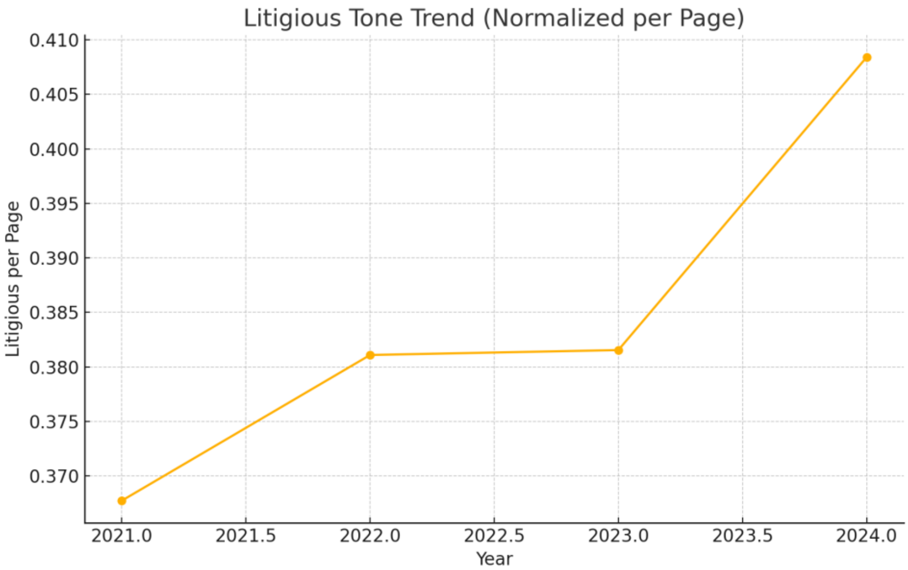
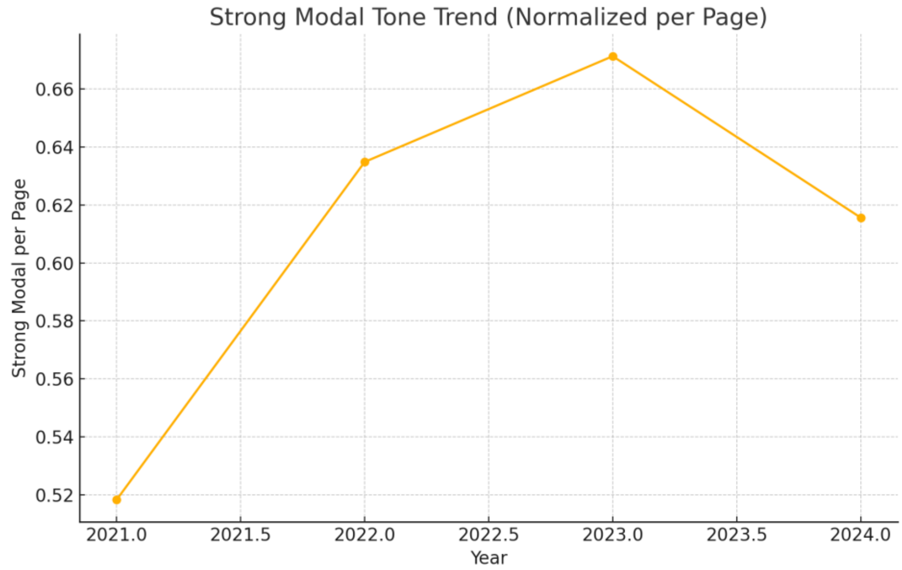
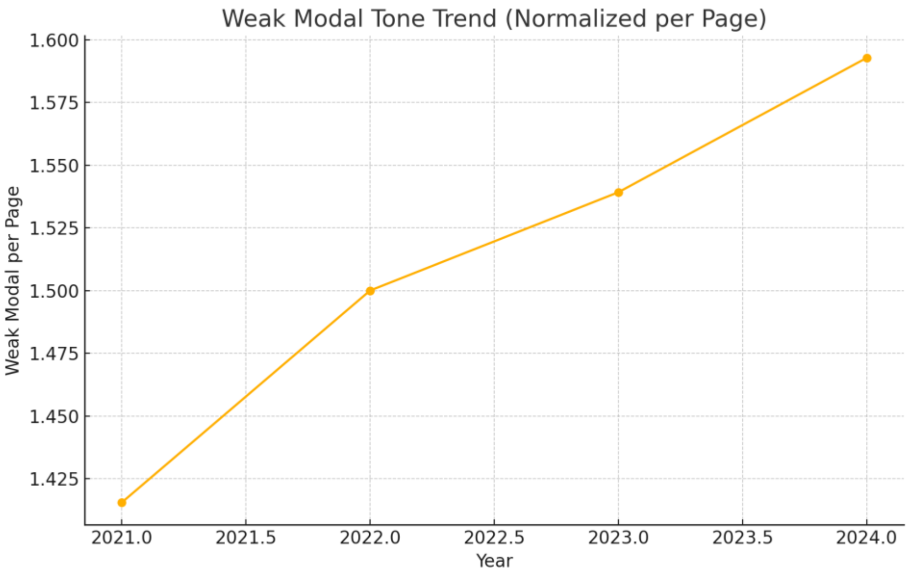





Uncertainty Tone Trend (Normalized per Page)
Uncertainty per Page
0.974
0.972
0.970
0.968
0.966
2021.0
2021.5
2022.0
2022.5
2023.0
2023.5
2024.0
Year


Litigious Tone Trend (Normalized per Page)
Litigious per Page
0.410
0.405
0.400
0.395
0.390
0.385
0.380
0.375
0.370
2021.0
2021.5
2022.0
2022.5
2023.0
2023.5
2024.0
Year


Strong Modal Tone Trend (Normalized per Page)
Strong Modal per Page
0.66
0.64
0.62
0.60
0.58
0.56
0.54
0.52
2021.0
2021.5
2022.0
2022.5
2023.0
2023.5
2024.0
Year


Weak Modal Tone Trend (Normalized per Page)
Weak Modal per Page
1.600
1.575
1.550
1.525
1.500
1.475
1.450
1.425
2021.0
2021.5
2022.0
2022.5
2023.0
2023.5
2024.0
Year

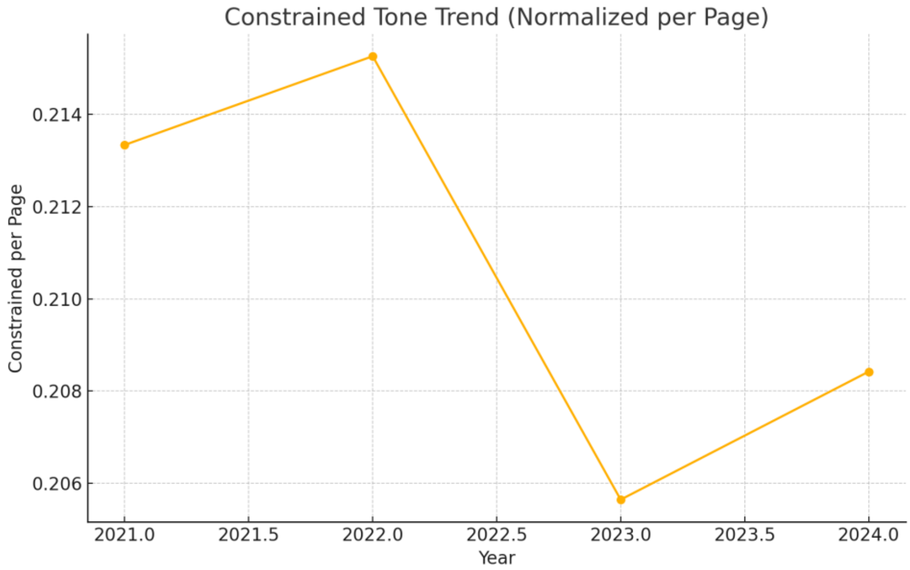

Constrained Tone Trend (Normalized per Page)
Constrained per Page
0.214
0.212
0.210
0.208
0.206
2021.0
2021.5
2022.0
2022.5
2023.0
2023.5
2024.0
Year

Table 3- Correlation to Margin Operation

The dataset comprises 108 MD&A disclosures drawn from the annual reports (Item 7 of Form 10-K) of 27 of the largest firms listed in the S&P 100 index, spanning the fiscal years 2021 through 2024. These firms were selected based on market capitalization and industry representation to ensure both size relevance and cross-sectoral generalizability. The MD&A sections were extracted directly from the SEC's EDGAR database. ***, **, and * denote the significance at the level of 1%, 5%, and 10%, respectively

Tone Variable	**Correlation**	**p-value**
Positive	-0.21**	0.03
Negative	-0.24**	0.01
Uncertainty	-0.2**	0.04
Litigious	0.01	0.88
StrongModal	-0.1	0.32
WeakModal	-0.12	0.21
Constrained	0.2**	0.04

Table 4

The dataset comprises 108 MD&A disclosures drawn from the annual reports (Item 7 of Form 10-K) of 27 of the largest firms listed in the S&P 100 index, spanning the fiscal years 2021 through 2024. These firms were selected based on market capitalization and industry representation to ensure both size relevance and cross-sectoral generalizability. The MD&A sections were extracted directly from the SEC's EDGAR database. ***, **, and * denote the significance at the level of 1%, 5%, and 10%, respectively

Dependent Variable	**Tone Variable**	**Coefficient**	R^2
Operating Margin (%)	Uncertainty_norm	-16.12***	0.039
Free Cash Flow	Uncertainty_norm	-37.96***	0.006
Revenue	Uncertainty_norm	-53.59*	0.001