Constructing Legitimacy Through AI Disclosure:

A Content Analysis of Global Regulatory Filings

by

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THESIS ABSTRACT

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Title: Constructing Legitimacy Through AI Disclosure: A Content Analysis of Global Regulatory Filings

Artificial intelligence has emerged as a critical domain of technological innovation, regulatory oversight, and public concern, compelling organizations to justify their AI practices through disclosure. Empirical research on organizational AI communication in regulatory filings remains limited. This study analyzes FY2024 10-K and 20-F filings from global firms and applies legitimacy theory to assess how organizations frame AI-related information across key thematic categories. The findings reveal variation across industries, regions, and legitimacy pressures: technology-intensive and highly scrutinized sectors provide more extensive and risk-forward disclosures, while other industries emphasize financial, ethical, or opportunity-oriented framing. Non-U.S. firms more frequently stress ethical responsibility and regulatory alignment, reflecting differing institutional environments. Overall, the results show that AI disclosures function as legitimacy-seeking communication shaped by contextual factors and are likely to expand as regulatory expectations increase.

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DEDICATION

To my son—your laughter, curiosity, and boundless spirit have been my greatest source of strength. You inspire me every day to strive toward something greater.

This work is for you; may it always remind you that your potential is limitless and your path is your own to create.

TABLE OF CONTENTS

LIST OF TABLES

CHAPTER I: INTRODUCTION

The emergence of artificial intelligence (AI) as a transformative technology in the Industry 4.0 era parallels the revolutionary impact of steam mechanization during the First Industrial Revolution, with contemporary organizations facing an imperative to integrate AI-driven solutions to maintain market competitiveness in an increasingly diversified business ecosystem (Ali et al., 2024; Konina, 2021). AI has become central to corporate strategy and operations, often necessitating substantial restructuring within organizational workforces; however, despite its pervasive influence across industries, the way firms communicate about AI in official reports varies considerably (Babina et al., 2023; Mittal et al., 2024). The central question guiding this study is how corporations articulate and frame discussions of artificial intelligence within their annual disclosures. Unlike well-defined disclosure rules for financial statements or even emerging areas like cybersecurity, AI disclosures remain largely voluntary and ad hoc (U.S. SEC, 2023). Due to the lack of standardized policies, regulators have begun voicing concerns and warning against "AI-washing," in which companies overhype or exaggerate AI capabilities without substance (Bultman, 2024; U.S. SEC, 2024).

Artificial intelligence in the context of this paper can be defined as "a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments" (OECD, 2019). This technological inflection point represents a fundamental restructuring of how enterprises create, capture, and deliver value to their shareholders and stakeholders. The advancement of AI has transformed operations across diverse sectors such as finance, manufacturing, healthcare, and technology, compelling companies to integrate these technologies into their business models (Candelon & Reeves, 2022; Mittal et al., 2024; Sjödin et al., 2023). AI is driving many functions, such as research and development, offering advantages over traditional approaches through trend analysis, product design, and risk management (Xing et al., 2020; Schrage et al., 2023). In practice, this translates to the use of a variety of AI-powered applications such as AI virtual assistants, natural language processing (LLMs), disease diagnosis, precision farming, grid optimization, and automation (Rashid & Kausik, 2024).

As AI technology continues to evolve, AI disclosures in annual reports and Form 10-Ks have significantly increased, informing shareholders and investors about a company's AI capabilities, risks, and strategic initiatives (Cho et al., 2022). The U.S. Form 10-K is a legally mandated, standardized annual filing that provides an audited account of a company's business; because it is filed under securities laws, the report is subject to legal liability for misstatements. Traditionally, the 10-K focuses on a company's financial performance and operations, providing investors and regulators with an overview of a company's operational state and direction. Indeed, while its primary purpose remains grounded in financial reporting, the 10-K also serves as an important lens into an organization (Shiller, 2019). It not only communicates a company's fiscal health but also defines its strategic priorities, alleviates litigation risks, and enhances trust with key stakeholders, including investors, customers, and the public (Bourveau, 2018).

To examine how organizations disclose and discuss artificial intelligence developments to external stakeholders, this study employs content analysis of publicly available 10-K and 20-F filings from a global sample of corporations reporting for the fiscal year 2024. Content analysis is selected as the methodological approach due to its capacity to generate systematic, replicable, and valid inferences from large-scale textual datasets through structured coding protocols and interpretive frameworks that preserve contextual meaning (Krippendorff, 2019). This method enables pattern identification across disclosure narratives while maintaining analytical transparency and reproducibility.

The study analyzes 100 publicly traded companies, stratified proportionally across 11 Global Industry Classification System (GICS) sectors; the GICS classifications and explanations of AI use are expanded in the literature review below. A sample of 100 firms achieves adequate sectoral representation while enabling detailed interpretive coding for capturing rhetorical nuance in AI disclosures. Companies were selected using systematic sampling based on two criteria: (1) availability of a 2024 Form 10-K/20-F, and (2) explicit mention of artificial intelligence in their disclosures. The sample includes both U.S. and non-U.S. firms to ensure geographic diversity and capture variation in disclosure practices across different regulatory environments. This sector-stratified approach enables comparative analysis while ensuring representation across industries with varying levels of AI adoption and integration.

Theoretical Framework

Legitimacy theory is an appropriate framework for this study because artificial intelligence attracts a degree of regulatory scrutiny and public concern that far exceeds that of many other emerging technologies. Companies are not only expected to innovate with AI but also to demonstrate accountability and compliance with ever-evolving regulatory policies. This theory posits that organizations seek to align their actions and communications with societal norms and stakeholder expectations to be seen as ‘legitimate’ (Dowling & Pfeffer, 1975). In this paper, legitimacy refers to a widespread perception that what an entity does fits accepted norms, values, beliefs, and meanings in a given social context (Suchman, 1995).

Problem Statement

Corporate AI adoption creates material risks spanning technical, operational, workforce, and legal domains, yet empirical evidence on AI disclosure practices remains limited (Papagiannidis et al., 2025; AIGG, 2023). Little research has examined how firms communicate AI implementation and associated risks across industries. While recent SEC guidance warns against misleading AI claims and organizations such as the Artificial Intelligence Governance Group emphasize transparent risk communication, existing disclosure research remains sector-specific, precluding cross-industry assessment of whether and how firms communicate AI capabilities, limitations, and risk mitigation strategies to stakeholders (AIGG, 2023; U.S. SEC, 2024). This study addresses this gap through a content analysis of AI disclosures across 100 firms spanning 11 industries, documenting disclosure volume and thematic patterns, and testing whether institutional legitimacy pressure, as informed by organizational theory, influences disclosure practices.

Purpose Statement

This study applies legitimacy theory to investigate how institutional pressures influence corporate AI disclosure practices. Specifically, it examines whether firms facing heightened regulatory, stakeholder, and public scrutiny issue more extensive AI disclosures as a strategy to preserve organizational legitimacy. By focusing on AI, a technological domain marked by both rapid innovation and regulatory uncertainty, this research advances understanding of how organizations communicate about emerging technologies under evolving institutional expectations.

Research Questions

RQ1: How does legitimacy pressure influence the volume of AI disclosure and the thematic emphasis in annual corporate regulatory filings?

RQ2: How does AI disclosure vary across the 11 GICS industry sectors?

RQ3: Are there significant differences between U.S. and non-U.S. firms in AI disclosure volume and thematic emphasis?

CHAPTER II: LITERATURE REVIEW

Artificial intelligence is reshaping business models and market dynamics. However, the lack of standards and policies governing its use and implementation reveals significant gaps in the understanding of its broader organizational and regulatory adoption. This current study draws on four areas of literature: the history and functions of corporate disclosures; the fragmented regulatory environment governing AI at global, regional, and national levels; the use of AI across organizations; industry-specific analyses of AI exposure and disruption; and AI ethics. This body of literature provides the foundation for the central question of this study: in what ways do corporations articulate and frame discussions of artificial intelligence within their annual disclosures?

History and Functions of Annual Disclosures

The modern era of mandatory corporate disclosure in the United States began in the wake of the 1929 stock market crash, when the Securities Act of 1933 and the Securities Exchange Act of 1934 created the Securities and Exchange Commission (SEC) (Platt, 2023). These acts mandated standardized reporting for publicly traded companies to protect investors and restore confidence in capital markets. Form 10-K was first introduced in 1934 and has since become the SEC's cornerstone annual disclosure document, requiring detailed data on a company's operations, financial performance, and other governance-related information (Griffin, 2003). This document tells the story of a firm's business operations over 12 months. The 10-K serves as both a compliance tool and an investor resource, enabling the evaluation of a company's strategic direction (Dyer et al., 2017). Compared to quarterly reports (10-Q) or annual reports, Form 10-K gives stakeholders a complete view of a company's business, position, and finances.

In contrast, the annual report to shareholders dates back to the late 19th century, when companies like U.S. Steel used printed reports to highlight their achievements. These early reports were designed to be narrative-heavy to build shareholder loyalty rather than to meet strict regulatory standards and served as more of a public relations tool. In the 1980s, companies began to combine the annual report to shareholders and the Form 10-K due to changing SEC requirements (U.S. SEC, 2013). When issued separately, the Form 10-K and the annual report often contain overlapping content. However, they differ in their points of accessibility, the audiences they are designed to reach, and the timelines governing their preparation and release deadlines. This study employs 10-K filings rather than annual reports because the SEC's regulatory requirements and the associated legal liability for misrepresentation promote standardized, consistent, and objective disclosures across firms, allowing for generalizability and replicability for future research. In contrast, annual reports function more as impression-management tools that selectively frame certain narratives to cultivate shareholder confidence and often include branded pictures of products and business operations.

U.S. domestic companies file Form 10-K, and all financial information must conform with U.S. Generally Accepted Accounting Principles (GAAP) as well as all SEC regulation disclosure requirements. It emphasizes financial statements, management discussion and analysis (MD&A), risk factors, and corporate governance disclosures. For foreign private issuers whose securities trade on U.S. Exchanges, the Form 20-F is used. It allows companies to report under International Financial Reporting Standards (IFRS) or their home-country accounting principles, provided reconciliation to U.S. GAAP is included, where applicable (Eng et al., 2014; Congressional Research Service, 2015). While both forms aim to promote transparency and investor comparability, Form 20-F is used in 169 jurisdictions globally and offers greater flexibility in accounting and disclosure formats, accommodating cross-jurisdictional differences. This research utilizes Form 20-F to ensure a more globally representative assessment of AI-related disclosures.

The extant literature on annual regulatory filings has predominantly focused on risk factor disclosures, encompassing financial performance metrics, strategic business initiatives, and external risk factors likely to affect operations (Ante & Saggu, 2025). Indeed, current research has found that companies facing a greater risk to their business operations typically disclose more within the risk factors section of their 10-Ks (Campbell et al., 2014). In 2010, the SEC strengthened its position on risk reporting by requiring companies to clearly identify the specific risks facing their business, moving away from vague, “boilerplate” language (Johnson, 2012). Most recently, the Securities and Exchange Commission has intensified regulatory scrutiny of exaggerated or misleading AI claims in corporate disclosures; a practice colloquially termed “AI washing.” The SEC has explicitly cautioned publicly traded firms against overstating their AI capabilities, deployment, or integration in both operational communications and annual filings (Bultman, 2024). This regulatory intervention signals heightened institutional concern regarding the accuracy and materiality of AI disclosures, reflecting broader efforts to ensure that corporate representations align with substantive technological implementation rather than speculative or promotional rhetoric.

In March 2024, the SEC settled with Global Predictions Inc. and Delphia (USA) Inc. for “AI washing,” making false and misleading claims about their use of artificial intelligence in investment strategies and business operations (U.S. SEC, 2024). Both firms violated SEC rules by promoting unsubstantiated AI capabilities and, in some cases, fabricating performance claims or omitting required conflict-of-interest disclosures. For example, Delphia asserted that it used

AI to “analyze its retail clients’ spending and social media data to inform its investment advice,” however, such data played no role in its investment decision-making processes (Longo et al., 2024). In this way, textual risk disclosures differ from other corporate disclosures because they inform stakeholders about the potential range of future performance, rather than predicting their exact level.

Aside from the risk factors, scholars have extensively investigated the interplay between corporate social responsibility (CSR), climate change risks (CCR), environmental, social, and governance (ESG) factors, and diversity, equity, and inclusion (DEI) disclosures within 10-K and 20-F filings (Goldman & Zhang, 2024; Ignatov, 2023; Nelson & Pritchard, 2015). Regarding CCR, some findings suggest that this type of disclosure has measurable effects, particularly for companies in industries highly vulnerable to climate risks (Kim et al., 2023). Such disclosures exert pressure from external stakeholders that incentivize firms to adopt more sustainable practices, which in turn influence long-term corporate behavior. While DEI and ESG disclosures have also been shown to signal an organization’s commitment and yield positive stakeholder outcomes, caution is warranted when drawing direct parallels with AI disclosures, given the nascent and complex nature of AI itself.

Another area of research has examined the structural characteristics of 10-K narratives, including their length, readability, and textual redundancy, finding that since 1996-2013 the median text length has doubled from 23,000 words to 50,000 (Kalelkar et al., 2024; Weisskopf, 2024). This underscores how corporate disclosures have evolved in complexity and volume over time, with increased verbosity affecting the clarity of the underlying messages and the interpretability of the disclosures. Companies exhibiting lower 10-K readability have been shown to face heightened stock price crash risk (Kim et al., 2019). Literature from risk and financial management journals found that shareholders react positively to AI disclosures in the banking sector, associating it with innovation and market competitiveness (Alzeghoul & Nizar, 2025). Additionally, recent research has shown that the number of AI disclosures from 2010 to 2024 has grown significantly and is typically situated within Item 1A [“risk factors”] of the 10-K (Cao et al., 2024). While the aforementioned research has advanced our understanding of corporate disclosures from a business and accounting perspective, this current investigation departs from conventional approaches by adopting a communication perspective to gain greater meaning from SEC-required filings. At a time when many companies lack publicly available disclosures and policies regarding internal and external use of artificial intelligence, Form 10-K and Form 20-F serve as valuable and informative sources for analysis in this area (Zhu et al., 2024).

Global Variations in Regulation of Artificial Intelligence

The year 2024 marked a significant acceleration in global efforts to adopt national strategies for the use of artificial intelligence (Holistic AI, 2024). The use of AI technologies is increasingly shaped by regulatory bodies, with a strong emphasis on addressing data privacy concerns, enhancing algorithmic transparency, and safeguarding consumer rights (Mosley, 2024; OECD, 2019; Miranda Gonçalves & Partyk, 2021). The section below provides an overview of how key jurisdictions, including the European Union, the United States, China, and leading South American countries, are formulating AI regulations.

European Union: The EU AI Act and Its Impact

The European Union has set the most comprehensive AI regulatory standards to date with the passage of the EU AI Act in May 2024 (European Parliament, 2024). This law, which began phasing in by early 2025, classifies AI systems on a risk scale, with each having its own tailored compliance requirements. Unacceptable-risk applications, such as social scoring, cognitive behavioral manipulation of people, and biometric surveillance and categorization, have been essentially banned as of February 2nd, 2025. While generative AI is not classified as high risk, under EU regulations, any content generated by AI must be disclosed as such, including images, audio, or video files (Chadha et al., 2021). Companies are also required to prevent the generation of illegal content and to publish summaries of any copyrighted data used in training, in line with EU copyright law. This is aimed at combating misinformation and “deepfakes” by ensuring AI-produced media is clearly identified as such.

This proportional approach carries escalating penalties for non-compliance with the prohibitions, potentially amounting to multimillion-dollar sums. For businesses operating in these jurisdictions, it is not enough to understand the rules; they must also communicate compliance clearly and consistently across all levels of the organization. Non-compliance carries not only monetary risk but also the potential for reputational damage, legal action, and operational disruptions; all of which can significantly impact stakeholder trust (OSTP, 2022). Extending its impact far beyond the boundaries of the European Union, the EU AI Act is well-positioned to shape emerging international standards and discourse on AI oversight (Balcıoğlu et al., 2025). Central to the Act is the assertion that AI applications must be governed with attention to the protection of human welfare, the preservation of fundamental rights, and the reinforcement of democratic norms. However, as national authorities establish regulations and monitor business compliance, much of the current enforcement related to how firms use AI is conducted under the General Data Protection Regulation (GDPR). For example, OpenAI was fined €15 million in December 2024 for GDPR violations under data-privacy law, not the AI Act (Pollina & Armellini, 2024). The applicability of laws such as the GDPR and the EU AI Act depends on where the data or users are located, not where the company is headquartered (Wolford, 2018).

Even companies with no physical presence in the regulatory territory can face substantial financial penalties.

China: State-Driven Innovation and Control

China's AI regulatory approach contrasts with the EU's, reflecting the country's state-driven model and its goals of technological leadership and social stability, ranking first in both AI patent filings and research outputs (Liu et al., 2024). China launched its New Generation Artificial Intelligence Development Plan (AIDP) in 2017, with the aim of becoming the world's AI leader by 2030. Chinese policymakers have emphasized using AI to advance state-centric objectives (e.g., economic development, public security, and government efficiency) while controlling uses that could threaten social order or individual rights (Khanal et al., 2024; Arora et al., 2025). For instance, China was the first country to enact rules on specific AI applications: in 2023 it issued Interim Measures for the Management of Generative AI Services, which require providers of generative AI tools (like large language models) to ensure content aligns with "core socialist values," to prevent harms like disinformation, and to register their algorithms with authorities (Sheehan, 2024; Roberts et al., 2021). This state-led model has enabled China to advance AI rapidly, but it also means that business compliance is closely tied to aligning with government guidelines and censorship rules.

United States: Federal Initiatives and State-Level Regulations

The United States lacks a single comprehensive federal law regulating AI systems. Instead, the U.S. has so far relied on a mix of executive guidance, agency policies, and sector-specific laws (OECD, 2019; Litwin & Racabi, 2024; Miranda Gonçalves & Partyk, 2021). For example, the White House's Office of Science and Technology Policy (OSTP) issued a non-binding Blueprint for an AI Bill of Rights (2022) outlining principles like safety, transparency, and nondiscrimination in automated systems. In place of federal legislation, state governments have taken the lead in introducing AI regulations. By 2025, all 50 U.S. states (as well as D.C. and territories) have considered bills on AI, and 38 states have passed or adopted some form of AI-related law or resolution (National Conference of State Legislatures, 2025). These state laws vary widely in scope and focus; notable examples from recent state legislation are referenced in Table 2.1. This emerging patchwork of state AI laws means companies operating in the U.S. must navigate differing requirements.

Table 2.1.

Summary of Selected U.S. State Artificial Intelligence Legislation

State	Bill Number	Key Provisions
Arkansas	H 1876	Defines ownership of AI-generated content; the individual using or fine-tuning a generative AI system (or their employer) owns the output, provided it does not infringe existing IP rights.
California	SB 1001	Requires companion chatbots to disclose their non-human status, implement safeguards against harmful or inappropriate content, and submit annual compliance reports to state authorities.
Colorado	SB 24-205	Requires developers/deployers of high-risk AI systems to prevent algorithmic discrimination in consequential decisions (e.g., in employment, housing, healthcare, education, lending, or legal services), while also requiring consumer disclosures, impact assessments, and public transparency.
Montana	SB 212	Requires risk-management plans for AI used in critical infrastructure; protects individuals' rights to use AI and prevents undue government restrictions on running AI or computational processes without a compelling interest.
New York	A9430B	Requires state agencies to inventory and publicly disclose their automated decision systems; mandates transparency; and includes labor protections to ensure AI cannot violate employee rights or cause unjust job loss.
North Dakota	HB 1429	Prohibits the use of AI-driven robots for stalking or harassment by updating criminal statutes to address automated forms of abuse.

Note. Legislative summaries are based on publicly available descriptions from the National Conference of State Legislatures (NCSL) and state legislative records.

Latin America: Emerging AI Regulations in Brazil and Chile

Countries in Latin America have more recently begun developing AI governance; as of 2025, most Latin American nations are still in the proposal or strategy stage, with Brazil and Chile among the leaders in advancing AI regulations. Brazil's AI market alone is projected to expand from an estimated US$3 billion in 2023 to approximately US$11.6 billion by 2030; assessment further indicated that Brazil hosts the majority of Latin America's roughly 500 AI start-ups (UNESCO, 2025). In December 2024, the Brazilian Senate approved Bill No. 2338/2023, pending approval by the Chamber of Deputies and the president, which would establish a national AI law modeled closely on the European Union's risk-based regulatory approach (Shimoda Uechi & Moraes, 2023). The bill introduces a tiered classification system that prohibits "high-risk" applications (including requirements for risk mitigation, human oversight, transparency, bias correction, and data protection) and requires that users be informed when AI is involved.

Similar to Brazil, Chile's proposed AI regulation adopts a tiered, risk-based framework aligned with the EU AI Act, classifying systems from unacceptable to no-evident-risk and prohibiting those that threaten human dignity, manipulate individuals without consent, or collect biometric data without explicit authorization (UNESCO, 2024). Under this model, companies must self-assess and classify their systems rather than undergo pre-market review.

United Kingdom: A Sector-Led Approach

In addition to developments across the European Union, the United States, China, and Latin America, the United Kingdom has adopted a distinctively decentralized and sector-led approach to AI governance. The UK government's 2023 AI Regulation White Paper introduced a principles-based framework that assigns regulatory responsibility to existing sector-specific bodies, such as the Information Commissioner's Office, the Competition and Markets Authority, and the Financial Conduct Authority, which are charged with applying five core principles: safety, transparency, fairness, accountability, and contestability (Gallo & Nair, 2024).

Artificial Intelligence Across Organizational Domains

Artificial Intelligence is transforming industries through its unprecedented computational and analytical capabilities. The global AI market has grown significantly over the last several years, reaching $254.5 billion in 2025 and projected to surpass $1.68 trillion by 2031, driven by widespread enterprise adoption (Statista, 2025). Across sectors, AI is being hailed as one of the most transformative technologies of our time, reshaping business models and processes (Sahai & Rath, 2021; Patnaik & Bakkar, 2024). Many AI-enabled applications substitute for human workers by automating complex decision-making processes and eliminating positions centered on repetitive tasks, through predictive analytics and machine learning algorithms (Garg et al., 2025). While these intelligent systems reduce labor costs by replacing human employees and increasing the efficiency of business operations, the resulting productivity gains at AI-adopting firms generate new labor demand that partially compensates for job losses in AI-exposed occupations (Hampole et al., 2025; Czarnitzki et al., 2023).

Alongside widespread adoption come new vulnerabilities that can undermine AI's benefits. A recent global study found that about 75% of global knowledge workers use AI tools daily (Microsoft & LinkedIn, 2024). In organizations without clear AI guidelines, 78% of these employees bring their own AI tools without oversight. This "shadow adoption" exposes sensitive corporate data to unvetted systems and creates operational blind spots; much like the long-standing issue of employees using Excel as a substitute accounting system. In both cases, workers adopt convenient, readily available tools to fill process gaps, but these ad hoc solutions often bypass internal controls, leading to errors, security risks, and inconsistent data practices (Schmidt et al., 2020; Rakovic et al., 2022). Despite widespread AI adoption, most organizations struggle to extract real value from their investments; a phenomenon recently dubbed the "GenAI Divide." Research involving over 300 public AI initiatives found that 95% of generative AI pilots fail to deliver measurable returns, with only 5% of custom enterprise solutions making it from pilot to production (Challapally et al., 2025). This performance gap suggests fundamental barriers beyond technological capability and highlights a growing trend between AI's potential and its actual ROI in practice.

Industries Most Affected by Artificial Intelligence

Artificial intelligence (AI) is reshaping every major industry; however, the extent of its impact varies widely by sector. Given the cross-industry scope of this study, it is necessary to adopt a standardized classification of industries. To ensure global applicability, the Global Industry Classification Standard (GICS) has been identified as the most suitable framework for this study (Phillips & Ormsby, 2016). Although there are several other notable industry classification systems, such as the Standard Industry Classification (SIC), North American Industry Classification System (NAICS), and Bloomberg Industry Classification System (BICS), GICS uses a globally applied structure that is annually reviewed and reliably reflects the current state of industries (Hrazdil et al., 2013). The GICS was developed in 1999 by MSCI and Standard & Poor's to classify publicly traded companies worldwide and consists of 11 major sectors, 25 industry groups, 74 industries, and 163 sub-industries (MSCI Inc., 2024). However, for this study, only the 11 major sectors will be used for classification. See Table 2.2. for sectoral descriptions. Each firm in the sample will be assigned to one of the 11 GICS sectors based on its primary line of business, following the GICS methodology, which emphasizes revenue as a key criterion for classification.

Table 2.2.

Global Industry Classification Standard (GICS) Sectors

GICS Sector	Sector Description
Energy	Companies involved in oil, gas, and consumable fuels exploration, production, and refining.
Materials	Firms engaged in the extraction, processing, and transformation of raw inputs (chemicals, construction materials, forest products, glass, metals, and mining).
Industrials	Capital goods manufacturers, industrial services, and transportation.
Consumer Discretionary	Non-essential consumer goods & services.
Consumer Staples	Essential consumer products (food, beverages, household goods).
Health Care	Providers of medical services and insurance; manufacturers and developers of pharmaceuticals, biotechnology, and devices.
Financials	Banking, investment services, insurance, and financial markets.
Information Technology	Suppliers of software and IT services; makers of hardware, communications equipment, electronics; and semiconductor designers/fabricators.
Communication Services	Firms that enable connectivity and distribute content across telecom networks and digital platforms.
Utilities	Providers of essential network services (electric, gas, water), including independent power producers and renewable generation/distribution.
Real Estate	Owners, operators, developers, and service providers of real property, including Real Estate Investment Trusts.

Note. Information summarized from (MSCI, 2024).

AI in the Energy and Utilities Sector

The transformative capacity of AI is intrinsically linked to the energy on which it relies. Companies involved in oil, gas, and/or consumable fuels are using AI in a variety of ways, such as analyzing seismic data for oil exploration to balancing grid energy use (Widuto, 2025). Indeed, the oil and gas sector was among the first to adopt AI, applying it to optimize exploration, production, and maintenance (International Energy Agency, 2025). AI systems enhance safety and reliability, while also detecting anomalies in pipelines and power lines before they cause failure. While AI may reduce costs in oilfield development and operations and thereby enhance fuel affordability, its adoption could also have broader consequences, including increased emissions. Heavy reliance on AI for energy operations also increases the risk of cyberattacks and/or algorithmic failures. This growing energy footprint has also triggered growing resistance from local communities, as data centers are often criticized for consuming significant amounts of water and electricity, generating noise pollution, and burdening local grids, leading residents and municipalities to push back against their construction in their neighborhoods (Ngata et al., 2025). For example, the Netherlands temporarily banned Meta's proposed hyperscale data-center complex after raising concerns about its electricity requirements and the resulting pressure on the regional power grid (Meaker, 2023).

AI in the Materials Sector

The materials sector includes firms engaged in the extraction, processing, and transformation of raw inputs, such as chemicals, construction materials, forest products, glass, metals, and mining. AI is being used in this sector to enhance operational efficiency and support technological innovation. Mining companies utilize AI-driven systems to analyze geological data for deposit identification, guide autonomous drilling and haulage equipment, predict machinery failures prior to their occurrence, and monitor sites for indicators of water contamination and biodiversity change (Corrigan & Ikonnikova, 2024). These AI developments promise cost savings, higher yields, and a mitigation of risks for the industry. Advanced AI models can now predict material properties and discover novel compounds much faster than traditional experiments. A recent breakthrough used deep learning to identify 2.2 million new crystal structures, expanding the knowledge of materials for new technologies (Merchant & Cubuk, 2023). Despite these advances, the materials sector is not immune to AI risks. High implementation costs and technical complexity can slow adoption in traditional mining operations.

AI in the Industrials Sector

AI is transforming industrial services and capital goods manufacturing in multiple ways, reshaping the global manufacturing sector and enabling smarter factories and supply chains. Companies are increasingly deploying AI systems for predictive maintenance, quality control, and process optimization across production environments (Gao et al., 2024; Lindberg, 2025). AI-enabled technology can predict machine failures and schedule maintenance before breakdowns occur, reducing operational inefficiencies. Digital twin simulations and AI-driven robotics are optimizing assembly lines by adjusting parameters in real time using feedback loops (Borden et al., 2025). These improvements translate into cost savings and, in some cases, lower energy consumption in production. Similar to the materials sector, the operational costs of implementing AI-driven technology in industrials and manufacturing are high. There is also the risk that greater connectivity on manufacturing floors can expose systems to cyber-attacks if not properly secured. Lastly, there is the human cost; while AI can augment workers, it can also displace certain roles, raising labor concerns.

AI in Consumer Discretionary Sector

In consumer discretionary industries (spanning retail, automotive, and hospitality), AI is being used to analyze customer behavior and tailor experiences, from product recommendations to inventory management (Spencer, 2024). Indeed, over 90% of Fortune 500 retail executives have started experimenting with implementing AI-powered solutions (Sukharevsky et al., 2024). E-commerce platforms use AI recommendation engines that suggest products a shopper is likely to buy, increasing sales and revenue (Valencia-Arias et al., 2024). In supply chains, AI optimizes stock levels and delivery routes; for example, H&M uses AI to parse fashion trends and decide how to distribute inventory across stores (H&M Group, 2021). Automakers globally are investing in AI for autonomous driving and more efficient manufacturing (Garikapati & Shetiya, 2024). In hospitality and tourism, AI chatbots and recommendation engines assist travelers with personalized itineraries and hotel or flight pricing (Chang et al., 2023).

While there are many benefits resulting from AI, the consumer discretionary sector must manage several AI risks. In retail, AI-driven personalization can lead to bias within suggestions and discriminatory marketing practices (Adanyin, 2024). There are also operational drawbacks, such as over-reliance on algorithms for pricing or inventory, which can backfire if the model mispredicts trends by "hallucinating" (for example, an AI stock-forecasting error could leave shelves empty or warehouses overstocked). In the automotive industry, the risks are more immediate; for instance, if a self-driving vehicle relies on inadequately tested object-detection algorithms, it may fail to identify pedestrians at night or in low-visibility conditions correctly. In 2018, a widely cited incident involved an autonomous test vehicle (Tesla's Model X) that failed to correctly classify a pedestrian crossing the road on a bicycle, resulting in a fatal collision (Penmetsa et al., 2021). This case shows how deploying autonomous driving systems without safety validations and real-world testing can place human lives at serious risk. Moreover, such incidents occur against a backdrop in which liability and insurance regulations have not kept pace with technological advances, creating legal uncertainties regarding responsibility when autonomous systems fail.

AI in the Consumer Staples Sector

Consumer packaged goods (CPG) leaders have adopted generative AI at a comparatively slower pace than sectors such as utilities or technology, media, and telecommunications, likely due to uncertainties regarding its ultimate value creation and the specific points within the value chain where that value will materialize (Moulton et al., 2024). Nevertheless, AI holds significant potential to accelerate research processes, enabling firms to identify and interpret consumer needs. For example, Procter & Gamble uses AI algorithms to segment customers and personalize marketing campaigns (Liu, 2025). Food manufacturers use AI to improve production yields and quality control; AI-based inspection systems can detect defects or contaminants in products on the line faster than human inspectors, reducing waste (Agrawal et al., 2025). Large grocery retailers use AI to adjust pricing and manage stock on shelves, ensuring essential items remain available (Kapadia, 2025). Similar to many other sectors, data privacy is a noteworthy risk, since these companies often handle sensitive consumer data (e.g., shopping habits, personal care regimens, etc.). There is also a risk of algorithmic bias; for example, an AI promotion system might unfairly target or exclude certain demographic groups from marketing and research.

AI in the Healthcare Sector

AI is driving significant changes in health care globally, offering tools for diagnosis, treatment, and system management. In medical diagnostics, AI systems analyze medical images (e.g., X-rays, MRIs, pathology slides) and clinical data with remarkable accuracy, often matching or exceeding human experts on specific tasks such as detecting cancer or retinal diseases (Pinto-Coelho L., 2023). These tools enable earlier and more accurate detection of conditions, which can improve patient outcomes. AI is also increasing drug discovery using machine learning, such is the case with the AI-guided discovery of abaucin, a new antibiotic capable of killing a drug-resistant “superbug” (A. baumannii), a discovery made in mere hours (Awan et al., 2024). Additionally, AI chatbots are being used for patient support by providing basic medical advice and monitoring symptoms (Bajwa et al., 2021).

Despite these benefits, the integration of AI in health care comes with considerable risks. Over-reliance on AI could lead to misdiagnosis or inappropriate treatment for patients (Păvăloaia & Necula, 2023; Olawade et al., 2024). There have been instances where AI models trained on biased data performed poorly for minority groups. An AI system might underdiagnose skin cancer in darker skin tones if not trained on a diverse set of images (Wen et al., 2022; Agrawal et al., 2023). Such biases in health AI can exacerbate disparities. Privacy concerns are the most significant risk of AI adoption in this sector, considering that health AI often requires large datasets of patient records (Chustecki, 2024). Ensuring that data is anonymized and secure to maintain confidentiality and comply with regulations such as HIPAA and GDPR is important. In the United States, AI-based technologies are evaluated by the FDA under the same regulatory framework as medical devices. By contrast, the United Kingdom's Medicines and Healthcare Products Regulatory Agency (MHRA) has introduced the "Software and AI as a Medical Device Change Programme" to strengthen oversight of AI-enabled medical devices. At the same time, countries such as China, Europe, Australia, and Brazil have likewise launched comparable regulatory frameworks (Palaniappan et al., 2024). However, there remains uncertainty regarding accountability. If an AI recommendation contributes to an adverse outcome, it is unclear who is legally and ethically responsible: *the software maker, the hospital, or the physician?*

AI in the Financial Sector

In the financial sector, AI is reshaping banking, investment, and insurance through advanced analytics and automation. Machine learning models flag fraudulent credit card activity in real time, reducing fraud losses (Odufisan et al., 2025). Many financial institutions report that AI is increasing efficiency, productivity, and revenue (International Monetary Fund, 2024). AI digital assistants like Bank of America's "Erica," which rolled out in 2020, handle client inquiries and have processed more than 2.5 billion client interactions since its initial deployment, providing 24/7 support (Ashare, 2025). Insurers use AI to analyze satellite images to assess property damage after disasters and to personalize policy pricing more accurately to each customer's risk profile (Gyau et al., 2024).

While AI delivers clear benefits in finance, it also introduces systemic risks and challenges that regulators and firms worldwide are now struggling to regulate. Key risks include reliance on concentrated third-party providers, AI-driven market correlations that amplify stress, increased exposure to cyberattacks, and risks linked to data quality and explainability (Financial Stability Board, 2024; Leitner et al., 2024). Financial AI models can inherit biases present in historical data, potentially leading to discriminatory outcomes and harming consumers (Munsterman, 2025). There is also the risk that long-term adoption may reshape market structures and create macroeconomic and energy-related challenges (Shiyyab et al., 2023).

AI in the Information Technology Sector

The information technology (IT) sector is both the driver and beneficiary of the AI revolution, globally accelerating AI development and integrating it into products and services at scale. Global tech competition in AI is intense, with companies across North America, Europe, and Asia vying for leadership in AI research and chip manufacturing. Tech companies such as NVIDIA have embedded AI across their offerings with a race to develop advanced AI chips (GPUs, AI accelerators), sustaining triple-digit revenue growth during the process (Ashare, 2024). Leading firms such as Microsoft, Anthropic, Google, and OpenAI continue to introduce increasingly sophisticated AI models across applications ranging from search and productivity to coding assistance and image generation. However, the deployment of these systems relies on energy-intensive data centers that consume substantial amounts of electricity and water for cooling, raising pressing concerns about grid capacity and reinforcing broader challenges within the utilities sector. From an ethical perspective, IT firms must manage the implications of the AI tools they release, given that misuse of AI (such as deepfake generation, misinformation, or privacy erosion) often traces back to the platforms or models they provide (Graham, 2024). In 2024, investors of major tech companies (e.g., Alphabet, Meta) filed shareholder proposals demanding increased disclosure of AI risks (Goldman, 2024). While investors have rewarded firms leading in AI with soaring valuations, a failure to meet expectations, such as OpenAI's underwhelming launch of GPT-5, has driven a minor selloff in tech stocks (Smith, 2025). This reflects a growing concern that the current AI boom could potentially mirror the dynamics of the dot-com era, in which speculative investment activity significantly outstripped underlying business fundamentals and practices (Chuang, 2025).

AI in the Communication Services Sector

The communication services sector, which encompasses telecommunications providers and media and content platforms, is being significantly reshaped by AI. This industry sits on the nexus of technology and society, affecting how information is consumed worldwide. Telecom companies are using AI to manage and optimize their networks more efficiently by predicting faults and adjusting parameters (Schmelzer, 2025; Creasy et al., 2024). This leads to more reliable communication services, such as fewer dropped calls, faster mobile data, and additional revenue growth. Similar to other sectors, AI-powered chatbots are employed to manage customer inquiries, scheduling, and billing queries, thereby enhancing the overall quality and efficiency of customer support.

In the media and online content domain, AI's impact is perhaps the most visible. Social media platforms and streaming services rely on AI recommender systems to personalize content feeds for each user (Haque et al., 2025). These algorithms are remarkably influential: on YouTube, about 70% of the videos people watch are those recommended by the platform's AI (Haroon et al., 2023). While algorithmic recommendation systems are primarily designed to optimize user engagement by personalizing content, such practices may create "echo chambers" and reinforce existing biases, thus limiting exposure to diverse perspectives and, in extreme cases, steering users toward increasingly radicalized content. AI systems are also being used to generate content; for example, news organizations are using it to generate summaries systematically acting as interpreters of information (Dodds et al., 2025). Real-time translation and transcription AI allows people speaking different languages to communicate via voice or chat. These innovations make information and entertainment more accessible and customized on a global scale.

While the benefits of AI-powered applications in this industry are vast, they are not without inherent risks. Platforms that use AI to detect hate speech, violence, or other "rule-breaking" content at scale can mistakenly censor legitimate content or miss nuanced cases (DeCook et al., 2022). Privacy is also a concern, given the immense user data of photos, messages, and viewing habits used to feed AI systems (Jaiswal et al., 2024). Deepfakes, disinformation, and AI-generated media present a significant and growing concern. From fake audio that can impersonate someone's voice to synthetic videos of public figures, AI in the wrong hands can undermine trust in information and facilitate fraud or manipulation (Lundberg & Mozelius, 2025).

AI in the Real Estate Sector

AI is changing how properties are evaluated, marketed, and managed (Jafary et al., 2025). Property analytics and valuation have been enhanced by AI's ability to process large datasets of prices, demographics, and economic indicators. Real estate firms use predictive analytics to forecast market trends and property values (Kandipati, 2025). For example, AI models can analyze historical sales, neighborhood features, school ratings, and satellite imagery to estimate a home's value almost instantaneously; the idea behind "Zestimates" (as seen on the popular real estate platform Zillow) and similar tools (Fitzpatrick et al., 2023). AI can also identify investment opportunities based on rental yields, population growth, and development plans; algorithms highlight undervalued properties or emerging markets that human analysts might overlook. Generative AI tools are increasingly used to automate low-level, time-intensive tasks such as drafting property descriptions and designing targeted advertisements. In residential real estate, AI-driven chatbots embedded in websites now address routine buyer inquiries, thereby enhancing customer engagement and responsiveness. Within the commercial sector, firms leverage AI to analyze foot traffic patterns and local economic indicators, enabling more data-driven decisions about the siting of new stores and facilities.

While AI offers these benefits in real estate, the industry must contend with certain risks and limitations. One concern is the accuracy and bias of AI valuations (Jafary et al., 2025). Suppose the data feeding an AI valuation model carries historical biases (for instance, undervaluing neighborhoods that were subject to past redlining or overvaluing based on short-term bubbles). In that case, the AI may perpetuate or even exacerbate those errors. While AI can provide a "quick estimate," professional judgment is still necessary. There is a possibility that AI-driven marketing might personalize housing ads in ways that violate fair housing laws; for example, if an algorithm shows certain listings only to specific demographic profiles (Kumar et al., 2024). AI-driven tenant screening and mortgage approval pose risks because reports often contain outdated, inaccurate, or misattributed information, such as criminal or eviction records, that applicants cannot easily correct or dispute, leading to unfair housing denials (Karpinski, 2025).

Ethical Dimensions of AI in Corporate Contexts

The integration of artificial intelligence and data-driven automation into contemporary business processes has increasingly prompted significant ethical and societal concerns. In the absence of appropriate safeguards, such systems risk perpetuating existing biases, constraining equitable access to essential services, and eroding individual privacy (Miranda Gonçalves & Partyk, 2021; Murdoch, 2021). There is ample evidence that algorithmic tools have produced discriminatory or harmful outcomes, especially for marginalized groups; from biased hiring algorithms to AI imaging models that can unfairly categorize patients, AI can inadvertently replicate societal inequities present in its training data (Agarwal et al., 2023). These concerns pose challenges to democratic values and civil rights. Unlike earlier waves of automation that mainly affected repetitive or dangerous manual jobs, today's AI is encroaching on the highly skilled, creative, and knowledge-intensive roles. This marks a shift in the impact of technology on the workforce, raising ethical issues on how AI is used in an organization and the need to reskill workers for new kinds of collaboration with AI.

Within organizations, the approach to AI ethics is often driven by external factors. Many companies are drafting AI usage policies and guidelines, but studies suggest that this is often driven by regulatory requirements and market pressure rather than ethical considerations (Ganapini & Butalid, 2025; Ryan et al., 2024). Indeed, firms tend to adopt "responsible AI" practices to comply with emerging laws or to protect their reputations and business interests; however, some experts argue that integrating AI effectively calls for rethinking decision-making processes to ensure accountability at every level (Mollick, 2023). A movement around

Responsible AI (RAI) has emerged to address these ethical complexities. Researchers and industry leaders have identified core dimensions that any responsible AI implementation should cover, including privacy and data governance, reliability, security risks, transparency, and fairness (Maslej et al., 2024). Global surveys show that concerns about privacy and data governance rank at the top of AI risks for businesses (Accenture, 2024). Risks related to security, transparency, and reliability (e.g., "hallucinations" or system failures) are close behind. Not all regions view these risks equally; for example, privacy tends to be less of a focal point for North American firms compared to their global counterparts, which report higher levels of concern (Maslej et al., 2024). Overall, there is a lack of standardized benchmarks and metrics to evaluate how effectively organizations are implementing RAI. While companies may acknowledge AI ethics in theory, there is no universal way to measure and compare RAI effect and performance across organizations.

Legitimacy Theory in Corporate Disclosures

Artificial intelligence is widely perceived as a novel technology that can offer firms a competitive advantage by improving operations and efficiency. Although firms may highlight AI initiatives to signal technological sophistication and strengthen investor confidence, such disclosures remain voluntary. In this context, legitimacy theory provides a helpful lens for understanding how and why organizations shape their narratives about AI, suggesting that disclosure practices, including volume and thematic framing, serve as strategic mechanisms through which firms seek to secure or maintain societal approval (Dowling & Pfeffer, 1975; Suchman, 1995). Insights from sustainability reporting research further illustrate that organizations frequently tailor voluntary disclosures to manage legitimacy and transparency, modulating the extent and substance of communication in response to stakeholder expectations, organizational visibility, and potential legitimacy threats (Herbert & Graham, 2021; O'Donovan, 2002). While transparency theory provides insight into how organizations use open communication to cultivate trust, it is more accurately understood as a functional mechanism embedded within legitimacy theory rather than as an independent theoretical construct (Reid et al., 2024). Through selective communication, firms present themselves as compliant with prevailing social norms, responsive to stakeholder concerns, and deserving of continued societal support.

Although legitimacy concerns influence all organizations to some extent, their intensity varies across industries, a pattern further reinforced by the differential impacts of the EU AI Act. As shown below in Table 2.3. sectors, such as Information Technology, Communication Services, Health Care, Financials, and Consumer Discretionary, face high legitimacy pressure due to heightened regulatory scrutiny, ethical concerns, and public sensitivity surrounding AI-related risks such as bias, privacy, misinformation, and safety. Firms in these sectors may therefore disclose more extensively about AI, emphasizing risks, opportunities, and regulations, to maintain trust and manage external expectations. In contrast, industries such as Energy, Materials, Real Estate, Consumer Staples, and Utilities face low legitimacy pressure, as AI use tends to be internal, efficiency-oriented, and less publicly controversial, reducing the need for expansive disclosures.

Within social and environmental accounting research, legitimacy theory is widely invoked to explain voluntary disclosure behavior, conceptualizing reporting as part of an implicit "social contract" in which firms must behave, or appear to behave, in ways consistent with societal values in exchange for societal acceptance (Deegan, 2007). Expanded research on this subject identifies three distinct forms of organizational legitimacy: pragmatic, moral, and cognitive (Suchman, 1995; Islam et al., 2021). *Pragmatic* legitimacy arises when stakeholders perceive that organizational actions serve their self-interest or address their immediate concerns. *Moral* legitimacy reflects normative judgments about whether organizational conduct aligns with socially constructed values and ethical standards. *Cognitive* legitimacy emerges when organizational structures and practices conform to established cultural frameworks, becoming comprehensible, expected, or taken-for-granted within institutional environments. The theory does not prescribe how firms should act; instead, it seeks to explain and predict organizational behavior in response to legitimacy pressures. For this reason, legitimacy theory is generally regarded as a positive theory that offers descriptive, rather than normative, insights into corporate disclosure practices. When “gaps” in legitimacy arise, organizations may respond by aligning their practices with societal expectations, by attempting to reshape public perceptions without altering their behavior, or by redirecting attention toward more favorable aspects of their operations (Lindblom, 1994).

This study, therefore, conceptualizes corporate AI disclosures as communicative acts through which firms seek to cultivate, sustain, or repair legitimacy in the eyes of stakeholders (Babina et al., 2023). Applying legitimacy theory positions these disclosures not merely as technical updates but as contributions to an ongoing societal dialogue concerning the appropriate and responsible use of emerging technologies. This perspective informs key questions that guide this research: *What assurances are firms offering to stakeholders regarding their deployment of AI? Furthermore, how do organizations frame their AI-related activities to signal alignment with regulatory expectations and broader societal values?*

Table 2.3.

AI Disclosure Legitimacy Pressure by GICS Sector

GICS Sector	Legit. Pressure	Rationale
Information Technology	High	Core developers of AI; heavy regulatory scrutiny (EU AI Act), investor pressure, concerns over bias, privacy, and misinformation.
Communication Services	High	Social media and media platforms face scrutiny for algorithmic bias, misinformation, and workforce impacts.
Health Care	High	AI in diagnostics and treatment is life-critical; regulators classify many systems as "high-risk." Strong ethical/public trust demands.
Financials	High	AI drives lending, underwriting, trading; regulators worry about bias, fairness, systemic risk.
Consumer Discretionary	High	AI in personalization and automation is generally accepted, but concerns about job loss and autonomous vehicle safety remain.
Real Estate	Low	AI in tenant screening and advertising is linked to discrimination concerns.
Industrials	Low	The potential for labor displacement creates greater visibility.
Energy	Low	AI mainly supports efficiency and safety.
Materials	Low	AI used internally (supply chains, mining, processing). Public and regulatory concern is minimal.
Consumer Staples	Low	AI supports supply and marketing functions; little controversy.
Utilities	Low	AI improves reliability and efficiency. Public concern remains minimal unless linked to outages or data misuse.

Note. Legit. = Legitimacy, High = sector faces strong regulatory/stakeholder pressure to legitimize AI use; Low = minimal external pressure specific to AI.

Summary of Literature Review

The reviewed literature highlights the diverse effects AI-driven technologies have across industries, driving efficiency, innovation, and personalization while presenting significant risks. Across the 11 GICS sectors, AI risks, to varying degrees as described above, include cybersecurity exposure, perpetuation of biases through training data, safety issues, labor displacement, privacy breaches, and gaps in accountability. Although global regulatory activity intensified in 2024 and 2025, AI governance remains fragmented, with no universally applicable framework. This study draws on Form 10-K and 20-F filings, whose standardized and legally mandated disclosure requirements enhance the consistency, generalizability, and replicability of the analysis, thereby strengthening the overall rigor of the research design. These filings also function as formal communication tools through which firms convey material information to regulators, investors, and other stakeholders, shaping external perceptions of organizational strategy, performance, and risk. Despite evidence that references to AI have increased substantially in corporate disclosures from 2012 to 2024, a gap persists in understanding the thematic patterns and sector-specific differences in these communications (Cao et al., 2024). Addressing this gap through the lens of legitimacy theory and examining firms from both high and low-legitimacy perspectives contributes to ongoing interdisciplinary research on emerging technologies and organizational communication.

CHAPTER III: METHODOLOGY

Building upon the gaps identified in the literature review, this chapter presents the methodological framework guiding the present study. It explains the research design, data collection, keyword parameters, sample selection, coding schema, and analytic procedures used to address the research questions. Content analysis of regulatory filings represents the appropriate methodology for this research for several reasons. First, it permits both quantitative hypothesis testing (disclosure volume, frequency, cross-sectional analysis) and qualitative interpretation (thematic framing). Second, it provides replicable, transparent procedures enabling future research to extend findings as AI disclosure practices mature (Coe & Scacco, 2017). The methodology is designed not only to catalog what companies disclose about AI, but also to interpret how they communicate about AI in the face of an emerging technology and amid varying legitimacy pressures.

Research Questions

RQ1: How does legitimacy pressure influence the volume of AI disclosure and the thematic emphasis in annual corporate regulatory filings?

> **H1a:** High-legitimacy pressure firms disclose greater AI content volume than low-pressure firms.
>
> **H1b:** Firms under high-legitimacy pressure place a stronger emphasis on risk-oriented and regulation-related themes than low-pressure firms.

RQ2: How does AI disclosure vary across the 11 GICS industry sectors?

RQ3: Are there significant differences between U.S. and non-U.S. firms in AI disclosure volume and thematic emphasis?

Content Analysis as Research Method

This study uses systematic quantitative content analysis to examine AI-related disclosures in corporate regulatory filings (Krippendorff, 1980; Holman, 2017). The research design adopts a cross-sectional approach centered on fiscal year 2024 to capture contemporary disclosure practices during a period of heightened corporate and regulatory attention to artificial intelligence. This temporal focus is justified both pragmatically, as 2024 constitutes the most recently available complete reporting cycle, and substantively, as AI-related disclosures have evolved rapidly in response to accelerated adoption beginning in late 2022. The research design prioritizes breadth of industry representation over longitudinal depth, thereby enabling an assessment of whether the predictions of legitimacy theory hold consistently across diverse organizational and sectoral contexts.

Sample Selection and Inclusion Criteria

The sampling frame consists of 100 publicly traded corporations selected through systematically stratified sampling across all 11 GICS sectors. This sample size balances statistical power for hypothesis testing, sufficient industry representation, and analytical feasibility for intensive paragraph-level thematic coding. Power analyses conducted using G*Power 3.1.9.7 indicate that, with approximately 55 low-legitimacy and 45 high-legitimacy firms, independent samples t-tests have power of 0.81 to detect medium effects (Cohen's $d = 0.50$) at $\alpha = 0.05$ (Faul et al., 2007). For cross-sector variation, one-way ANOVA with 11 groups yields a power of 0.78 to detect medium effects (Cohen's $f = 0.30$). While falling slightly below the conventional 0.80 threshold, this remains acceptable for exploratory analysis, given the more time-intensive thematic coding. The sector-stratified approach prioritizes industry coverage, recognizing that AI adoption patterns vary across business models and regulatory environments.

Sample selection employed systematic procedures to ensure representativeness within each sector while maintaining document availability criteria. Within each sector, publicly traded firms were selected at random intervals to achieve target allocations of 9-10 firms. This approach ensures size and global diversity rather than concentrating exclusively on the largest corporations. Firms were included only if they filed a 2024 Form 10-K/20-F that was publicly accessible in English and contained a keyword found in Table 3.2 below. The sample includes both U.S.-domiciled firms ($n \approx 68$) and international entities ($n \approx 32$) to enable examination of geographic variation, with this allocation reflecting the predominance of U.S. firms in global equity markets.

Table 3.1.

Inclusion and Exclusion Parameters for Search Evaluation

Criteria	Inclusion Criteria	Exclusion Criteria
Year of Publication	Fiscal year 2024	Fiscal year 2024 disclosures not yet released
Type of Document	Form 10-K, Form 20-F	Annual Report, Integrated Report, Quarterly reports (10-Q, 6-K), or other interim filings
Language	English	Non-English
Keywords	"Artificial intelligence," "AI," "Machine learning"	Does not contain keywords
Access Type	Publicly available disclosures	Non-public or restricted-access documents

Keyword Selection and Search Protocol

AI-related content was identified through a systematic keyword search employing three validated terms: "artificial intelligence," "AI," and "machine learning." Pilot testing with 11 sector-stratified reports showed that the phrase "artificial intelligence" appeared in 100% of the documents, confirming its status as baseline terminology in the current study. The abbreviation "AI" appeared in 55% of documents, and "machine learning" in 27%. Initial candidate terms were derived from prior AI disclosure research (Sheikh et al., 2023). Technical terms and abbreviations such as “ML,” “LLM,” “large language model,” and “neural network” appeared in 0% of pilot documents; therefore, they were excluded from the keyword search protocol. This approach enhances intercoder reliability by establishing clear, empirically validated search terms rather than requiring subjective judgments about emerging terminology. All searches were conducted using Adobe Acrobat’s advanced search function using case-sensitive matching for “AI” to prevent false positives. When keywords appear multiple times within a single paragraph, that paragraph is coded once, as the paragraph constitutes the unit of analysis.

Table 3.2.

Keyword Frequency Distribution in Pilot Sample (n = 11 firms)

Company	Artificial Intelligence	AI	Machine Learning	ML	Large Language Model	LLM	Neural Network
Boeing	1	0	0	0	0	0	0
The Estée Lauder	1	4	0	0	0	0	0
Target	4	0	0	0	0	0	0
Dominion Energy	3	0	0	0	0	0	0
Robinhood	3	0	6	0	0	0	0
Apple	3	31	2	0	0	0	0
Novartis	5	13	0	0	0	0	0
ConcoPhillips	1	0	0	0	0	0	0
DOW	1	5	0	0	0	0	0
Simon Property	1	11	3	0	0	0	0
Spotify	2	31	0	0	0	0	0
Total	25	95	11	0	0	0	0
% of Total Pilot	19%	72%	9%	0%	0%	0%	0%

Data Collection and Procedures

Data collection followed systematic procedures to ensure reproducibility across the sample. Primary data sources (Forms 10-K, 20-F) were obtained from authoritative repositories, such as the company's investor relations portals and the SEC's EDGAR database, with preference for PDF versions to minimize the risk of incomplete or corrupted files. Upon retrieval, each document underwent verification procedures to confirm adherence to the inclusion criteria. First, the filing date was confirmed to fall within the fiscal year 2024 reporting periods. Second, the document was searched using the three-keyword protocol to verify the presence of at least one AI-related term, and documents containing zero matches were excluded. Alternative firms within the same sector were selected at random. Third, document metadata, including firm name, ticker symbol, GICS sector classification, headquarters location, and filing type, were extracted and recorded in a master spreadsheet serving as the sampling frame and tracking document (see Table A.1.). Following verification, all documents were organized into 11 sector-specific digital repositories corresponding to GICS classifications. Each file was renamed using a standardized convention (CompanyName_FormType_2024) to enable identification and sorting. All files were maintained on a secure, password-protected cloud-based storage system.

Reliability and Validity Protocols

To establish inter-coder reliability, two trained coders completed a structured training protocol. The training phase involved collaborative coding of two sample documents to develop a shared interpretation of coding categories and establish consistent application of decision rules. Following this pilot phase, the codebook was refined to address observed ambiguities and discrepancies, enhancing coding consistency. Upon completion of training, both coders independently coded a reliability subsample of 11 documents (11% of the total corpus, $n = 11$), stratified by GICS sector to ensure representativeness. Inter-coder agreement was assessed within SPSS using Cohen's kappa coefficient. Results demonstrated significant reliability across all coding categories (M $\kappa = 0.889$, range: 0.806–1.00), exceeding the minimum threshold of 0.70 recommended for content analysis research (Lombard et al., 2002). All discrepancies in the reliability sample were resolved through discussion before proceeding with independent coding of the full dataset.

Codebook and Coding Procedure

This study employed a quantitative content analysis framework to examine AI disclosures in the regulatory filings of 100 publicly traded firms (Form 10-K/20-F). Following pilot testing ($n = 11$), three validated keywords, "artificial intelligence," "AI," and "machine learning," were used in searches to identify relevant paragraphs, with "AI" case-sensitive settings applied to prevent false positives. The codebook operationalized variables at both firm and paragraph levels: firm-level variables captured company identifiers, GICS sector classification, geographic region, and a legitimacy pressure measure based on industry classification; paragraph-level variables quantified disclosure volume. Each paragraph was assigned a mutually exclusive primary thematic code across seven categories (Risk, Opportunities, Regulation, Financial, Competition, Ethical, Risk Mitigation) and assessed for specificity (generic versus detailed) and section location within standardized filing structures. This approach enabled both descriptive analysis of AI disclosure prevalence and inferential examination of relationships between firm characteristics and disclosure practices. See Appendix Table A.2. for the complete codebook guide.

The coding schema development integrates deductive categories derived from legitimacy theory and the literature review with inductive categories emerging from preliminary document analysis of an 11% subset (Kleinheksel et al., 2020; Neuendorf, 2016; Krippendorf, 2019, p. 43). The study employs hierarchical units of analysis to capture disclosure patterns at multiple granularities: document-level analysis generates aggregate metrics including total AI mention frequency, proportional and distribution patterns across regulatory sections; paragraph-level analysis serves as the primary coding unit for thematic classification, with paragraphs containing AI keywords constituting discrete analytical units and connected paragraphs or bulleted lists coded as unified segments when addressing singular concepts. Paragraph-level analysis will be used over sentence-level analysis because paragraphs constitute complete semantic units that capture the full context of corporate AI disclosures. In contrast, individual sentences often contain fragmented ideas requiring surrounding text for accurate interpretation. The codebook was revised after the preliminary document analysis to clarify rules and examples. It was also revised after data collection to align numerical formatting with SPSS.

Data Analysis Strategy

Following the coding phase, a statistical analysis will be conducted using IBM SPSS Statistics Version 29 to examine patterns, similarities, and differences in AI-related disclosures across the sample size. Frequency distributions and summary statistics (e.g., mean, median, standard deviation) will be generated to quantify the prevalence of AI-related disclosures across the sample size. The inclusion of these descriptive statistics will provide an overview of how often companies reference AI and the overall extent of AI discussions in 10-K corporate filings. To identify differences in AI-related discourse across companies and industries, several comparative statistical tests will be employed, such as a chi-square test to assess whether there are significant differences in AI disclosure across industry sectors. This will help determine whether specific AI-related themes (e.g., risk vs. innovation) are more prevalent in specific industries. A one-way ANOVA will be used to compare mean AI disclosure volume across industries to identify which, if any, industries differ. To ensure methodological rigor and replicability, all coding decisions, keyword searches, and statistical procedures will be documented, with all table outputs included in the study, in APA format.

Description of Use of AI

ChatGPT, Claude, and Grammarly were used to support the development of this thesis by assisting with grammar refinement, sentence restructuring, and citation formatting in accordance with APA guidelines (OpenAI, 2025; Grammarly, 2025; Anthropic, 2025). In addition, ChatGPT and Claude were used as supplementary learning resources to help clarify statistical concepts and analytical procedures relevant to conducting analyses in SPSS. All substantive ideas, statistical analyses, interpretations, and final wording remain the sole work and responsibility of the author.

Summary of Methodology

This chapter established the methodological framework for examining corporate AI disclosure through quantitative content analysis of 100 firms' annual filings. The design addresses three main fields: adequate statistical power (0.78-0.86), industry representation (11 GICS sectors), and analytical depth through paragraph-level thematic coding. Systematic stratified sampling with validated keyword protocols ensures an intentional protocol design. The coding framework uses seven thematic categories formed from insights from the literature review and pilot testing. This approach advances beyond prior research by analyzing disclosure content and strategic framing rather than mention frequency and the length of the report alone.

CHAPTER IV: RESULTS

This chapter presents the results of the statistical analyses conducted to address the study's research questions concerning firms' artificial intelligence (AI) disclosure practices. The analyses examine differences in AI disclosure volume and thematic emphasis across legitimacy pressure groups, regional contexts (U.S. vs. non-U.S. firms), and GICS industry sectors. The chapter begins with a description of the sample and variables used in the analyses, followed by descriptive statistics summarizing the overall AI disclosure patterns. Subsequent sections report inferential statistical results for each research question and hypothesis, including t-tests, chi-square analyses, and one-way ANOVA tests. The following Table 4.1. shows an 11% subset of the study sample; for the complete list, see Appendix Table A.1.

Table 4.1.

Subset of Firms Representing the Study Sample (n = 11)

Company Name	Headquarters	GICS Sector	Document Type
Alphabet	United States	Communication Services	10-K
Toyota	Japan	Consumer Discretionary	20-F
Unilever	United Kingdom	Consumer Staples	20-F
Eni S.p.A.	Italy	Energy	20-F
Host Hotels & Resorts, Inc.	United States	Real Estate	10-K
Visa Inc.	United States	Financials	10-K
Johnson & Johnson	United States	Health Care	10-K
The Boeing Company	United States	Industrials	10-K
SAP SE	Germany	Information Technology	20-F
ArcelorMittal S.A.	Luxembourg	Materials	20-F
Dominion Energy, Inc.	United States	Utilities	10-K

Note. Representation of an 11% subset of firms from the total sample used in the study, for the full sample set, see Appendix Table A.1.

Descriptive Statistics of the Sample

A total of 100 firms (N = 100) were included in the sample. Of these, 75% filed Form 10-K (U.S. domestic firms) and 25% filed Form 20-F (foreign registrants). The distribution across the 11 GICS industry sectors was approximately even, ranging from 9% to 10% per sector, ensuring broad industry representation. Regarding geographic composition, 68% of the firms were U.S.-based, while 32% were non-U.S. firms. In terms of legitimacy pressure, 56% of firms were classified as experiencing low legitimacy pressure and 44% as experiencing high legitimacy pressure. Concerning AI disclosure specificity, 57% of firms produced high-specificity disclosures, while 43% produced low-specificity disclosures.

Firms' regulatory filings varied substantially in length and AI disclosure volume. The average filing length was 239.41 pages (SD = 136.11), ranging from 70 to 706 pages. The total AI word count (an indicator of AI disclosure volume) ranged from 42 to 8,106 words, with a mean of 1,187.30 words (SD = 1,448.65). The significant standard deviation suggests considerable heterogeneity in firms' levels of AI discussion within regulatory reports. See Table 4.2. below for the descriptive statistics and sample characteristics.

Table 4.2.

Descriptive Statistics and Sample Characteristics (n = 100)

Variable	Categories / Range	n	M	SD	Min	Max
Report Type	20-F	25	—	—	—	—
	10-K	75	—	—	—	—
GICS Sector	1-11 (each 9-10%)	100	—	—	—	—
Region	Non-U.S.	32	—	—	—	—
	U.S.	68	—	—	—	—
Legitimacy Pressure	Low	56	—	—	—	—
	High	44	—	—	—	—
Disclosure Specificity	Low	43	—	—	—	—
	High	57	—	—	—	—
Document Length (pages)	—	—	239.41	136.11	70	706
Total AI Word Count	—	—	1,187.3	1448.65	42	8106

Testing of Hypotheses

H1a: High-legitimacy pressure firms disclose greater AI content volume than low-pressure firms.

An independent-samples t-test was conducted to compare AI disclosure volume between firms operating under high and low legitimacy pressure. Levene's test indicated unequal variances, $F(1,98) = 29.06$, $p < .001$; therefore, the Welch t-test results were reported. As shown in Table 4.3., firms experiencing high legitimacy pressure ($M = 2070.70$, $SD = 1741.55$) disclosed significantly greater AI-related content than firms with low pressure ($M = 493.20$, $SD = 539.77$), $t(49.52) = -5.79$, $p < .001$, 95% CI [-2124.53, -1030.49]. The effect size was large (Cohen's $d = 1.29$), indicating a substantial impact of legitimacy pressure on AI disclosure volume. These findings support H1a, suggesting that firms operating under higher legitimacy pressure engage in more extensive AI disclosure, consistent with expectations of transparency and accountability.

Table 4.3.

Independent Samples t-Test Comparing AI Disclosure Volume by Legitimacy Pressure

Legitimacy Pressure	*n*	*M*	*SD*	*t*	*df*	*p*	Mean Difference
Low	56	493.2	539.77	-6.41	98		
High	44	2070.7	1741.55	-5.79[a]	49.52	< .001	-1577.51

Note. Levene's Test for Equality of Variances was significant, F(1, 98) = 29.06, p < .001; therefore, equal variances were not assumed. Cohen's d = 1.29, 95% CI [-1.72, -0.85], indicates a large effect. [a] Welch's t-test reported due to unequal variances.

H1b: Firms under high-legitimacy pressure place a stronger emphasis on risk-oriented and regulation-related themes than low-pressure firms.

A chi-square test of independence was conducted to examine whether the distribution of AI disclosure themes differed between firms experiencing high versus low legitimacy pressure. The analysis revealed a statistically significant association between legitimacy pressure and disclosure theme, $\chi^2(6, N = 782) = 27.03$, $p < .001$. Firms under high-legitimacy pressure placed greater emphasis on risk-oriented and regulation-related themes than firms under low-legitimacy pressure. Specifically, 63.1% of high-legitimacy firms' disclosures referenced risk (versus 36.9% for low-legitimacy firms), and 84.6% referenced regulation (versus 15.4% for low-legitimacy firms). The findings shown in Table 4.4. support H1b, suggesting that firms facing greater legitimacy pressures more frequently emphasize risk management and regulatory compliance in their AI disclosures.

Table 4.4.

Frequencies of AI Disclosure Themes by Legitimacy Group

Theme	Low Legit. (n)	Low Legit. (%)	High Legit. (n)	High Legit. (%)	Total (N)
Risk	76	36.9	130	63.1	206
Opportunities	54	22.9	182	77.1	236
Regulation	22	15.4	121	84.6	143
Financial	12	19.7	50	80.7	62
Competition	13	38.2	21	61.8	34
Ethical	11	32.4	23	67.7	34
Risk Mitigation	20	29.9	47	70.2	67
Total	208	—	574	—	782

Note. "Legit." = legitimacy pressure. Percentages represent the proportion of disclosures within each theme attributed to high/low-legitimacy pressure. $\chi^2(6, N = 782) = 27.03$, $p < .001$.

Legitimacy Pressure and AI Disclosure Patterns

RQ1: How does legitimacy pressure influence the volume of AI disclosure and the thematic emphasis in annual corporate regulatory filings?

A chi-square test of independence was conducted to examine whether the distribution of AI disclosure themes differed by legitimacy pressure (low vs. high). As shown in Table 4.4., firms experiencing high legitimacy pressure disclosed substantially more content (in terms of total word count) across all themes, especially in Opportunities (n = 182 vs. 54) and Risk (n = 130 vs. 76). A significant proportion of AI disclosures from high-legitimacy firms focused on Regulation (n = 121 vs. 22) and Financial topics (n = 50 vs. 12), suggesting these firms emphasize transparency and compliance messaging to maintain legitimacy. A chi-square test of independence was conducted to examine the relationship between legitimacy pressure (low vs. high) and the AI disclosure theme. The association was statistically significant, $\chi^2(6, N = 782) = 27.03$, $p < .001$, indicating that thematic disclosure patterns differed across levels of legitimacy pressure.

Industry Sector Variations in AI Disclosures

RQ2: How does AI disclosure vary across the 11 GICS industry sectors?

A one-way ANOVA revealed a significant effect of industry sector on AI disclosure volume, $F(10, 89) = 9.71$, $p < .001$, $\eta^2 = .52$. Post-hoc Tukey HSD tests indicated that firms in the Information Technology (M = 3,403) and Communication Services (M = 2,960) sectors disclosed significantly greater AI content than those in Health Care (M = 1,252), Financials (M = 1,362), and Consumer Discretionary (M = 1,370), which in turn disclosed more AI content than firms in Materials (M = 286), Industrials (M = 328), Energy (M = 444), Utilities (M = 470), Consumer Staples (M = 479), and Real Estate (M = 510). The findings in Table 4.5. demonstrate substantial cross-industry variation in AI-related disclosure volume, with technology-oriented sectors reporting the highest levels of AI discussion and engagement.

Table 4.5.

Tukey HSD Post-Hoc Comparisons of AI Disclosure Volume by Industry Sector

GICS Sector	N	1	2	3
Materials	9	285.78		
Industrials	9	327.89		
Energy	9	444.44		
Utilities	9	470.11		
Consumer Staples	9	478.67		
Real Estate	9	509.89		
Health Care	9	1252		
Financials	9	1362.11	1362.11	
Consumer Discretionary	9	1369.78	1369.78	
Communication Services	10		2959.7	2959.7
Information Technology	9			3403
Sig.		0.52	0.062	0.998

*Note. C*omparison of mean AI disclosure word counts across 11 GICS industry sectors, showing statistically distinct subsets of low, moderate, and high AI disclosure intensity. Means sharing the same subset are not significantly different at $\alpha = .05$ (Tukey HSD).

Geographic Differences in AI Disclosure

RQ3: Are there significant differences between U.S. and non-U.S. firms in AI disclosure volume and thematic emphasis?

Independent-samples t-tests examined differences between U.S. and non-U.S. firms, as shown in Table 4.6. U.S. firms produced significantly longer filings (M = 1,934.10, SD = 108.85) than non-U.S. firms (M = 393.06, SD = 139.23), $t(49.50) = 5.09$, $p < .001$, $d = 1.19$. This difference likely reflects structural and regulatory requirements, as U.S. firms file Form 10-K reports, which are typically longer and more comprehensive than the Form 20-F reports filed by non-U.S. registrants.

No statistically significant regional difference was found in AI disclosure volume. Although U.S. firms reported higher average AI word counts (M = 1,314.90, SD = 1,637.27) than non-U.S. firms (M = 916.16, SD = 892.59), this difference was not significant, $t(98) = –1.29$, $p = .201$, 95% CI [–1,012.98, 215.50], $d = –0.28$. The small effect size suggests that overall AI disclosure volume was relatively comparable across regions.

Similarly, no significant regional difference emerged in disclosure specificity, $t(63.15) = 1.21$, $p = .231$, 95% CI [–.08, .34]. Non-U.S. firms reported slightly higher specificity (M = .66, SD = .48) than U.S. firms (M = .53, SD = .50), representing a small-to-medium effect ($d = 0.50$). Levene’s test indicated unequal variances, $F(1, 98) = 6.20$, $p = .014$. These results suggest that while the structure of regulatory filings differs by jurisdiction, the substantive level and depth of AI-related discussion remain broadly similar across regions.

Table 4.7. presents the distribution of AI disclosure themes by firm region. A chi-square test of independence revealed a significant association between region and disclosure theme,

$\chi^2(6, N = 718) = 14.82$, $p = .022$, Cramér's $V = .14$, indicating a small but meaningful effect size. Thematic patterns varied across regions:

- U.S. firms emphasized Risk (32%), Financial (9.7%), and Competition (4.8%) themes, signaling a focus on potential exposure, the rationale behind increased AI investment, and the competitive implications of AI adoption.
- Non-U.S. firms, by contrast, focused more on Opportunities (39.1%) and Regulation (20.5%), often framing AI within strategic growth and compliance contexts. Ethical and Risk Mitigation themes were also relatively more common among non-U.S. firms (8.4% and 2.8%, respectively), suggesting a stronger emphasis on societal responsibility and precautionary approaches.

Table 4.6.

Frequency of Themes and Example Subthemes in Sample

Theme	Word Count	% of Total Words	Example Subthemes (emergent topics)
Risk	43,417	36.4	Threats, challenges, uncertainties, cybersecurity concerns, algorithmic bias, implementation failures, dependency risks, and adverse scenarios.
Opportunities	29,384	24.6	Performance enhancement, efficiency gains, innovation, productivity improvements, optimistic projections.
Regulation	26,413	22.1	Legal requirements, regulatory mandates (e.g., EU AI Act), claims and suits, policy constraints, compliance obligations (existing or anticipated regulations).
Financial	8,330	7.0	Capital expenditures, R&D spending, acquisition costs, revenue impacts, cost savings, and monetization of AI.
Competition	5,917	5.0	Competitor capabilities, industry benchmarking, market share implications, competitive threats, or advantages.
Ethical	4,291	3.6	References fairness considerations, transparency commitments, training, internal governance, societal impact assessments, or stakeholder welfare concerns.
Risk Mitigation	1,534	1.3	Strategies, safeguards, and controls are implemented to reduce or manage AI-related risks.

Note. Percentages are based on total AI-related disclosure word count (N = 119,286). Word counts represent cumulative text volume per theme derived from qualitative coding of firm AI-related disclosure segments.

Table 4.7.

AI Disclosure Themes by Firm Region

Theme	Non-US (n)	Non-US (%)	US (n)	US (%)	Total (N)
Risk	45	20.9	161	32.0	206
Opportunities	84	39.1	154	30.6	238
Regulation	44	20.5	94	18.7	138
Financial	9	4.2	49	9.7	58
Competition	9	4.2	24	4.8	33
Ethical	18	8.4	16	3.2	34
Risk Mitigation	6	2.8	5	1.0	11
Total	215	—	503	—	718

Note. Percentages are calculated within each region. A chi-square test indicated that the distribution of disclosure themes differed significantly by firm region, $\chi^2(6, N = 718) = 14.82$, $p = .022$.

Table 4.8.

Independent-Samples t-Tests Comparing U.S. and Non-U.S. Firms

Variable	Region	N	M	SD	t(df)	p	Mean Diff.	95% CI of Difference	Cohen's *d*
Document Length	Non-U.S.	32	393.06	139.23	5.09 (49.50)	< .001	142.09	[85.98, 198.20]	1.19
	U.S.	68	1,934.10	108.85					
Total Word Count	Non-U.S.	32	916.16	892.59	–1.29 (98)	0.201	–398.74	[–1,012.98, 215.50]	–0.28
	U.S.	68	1,314.90	1,637.27					
Disclosure Specificity	Non-U.S.	32	0.66	0.48	1.21 (63.15)	0.231	0.13	[–.08, .34]	0.5
	U.S.	68	0.53	0.5					

Note. Equal variances were not assumed for *Document Length* ($F = 4.78$, $p = .031$) and *Disclosure Specificity* ($F = 6.20$, $p = .014$); variances were assumed equa**l** for *Total Word Count* ($F = 3.78$, $p = .055$). Cohen's *d* values of ≈ 1.20 indicate significant effects; values ≈ 0.30–0.50 indicate small-to-medium effects.

Summary of Findings

Firms' AI disclosure practices varied across legitimacy, industry, and regional contexts. High-legitimacy firms disclosed significantly more AI-related content and focused heavily on risk and regulatory themes, consistent with legitimacy-seeking behavior. Industry differences were pronounced, with technology and communication firms producing the most extensive disclosures. Although U.S. firms filed longer reports than non-U.S. firms, overall, AI disclosure volume and specificity did not differ significantly across regions. However, thematic emphasis varied: U.S. firms prioritized risk and financial narratives, while non-U.S. firms emphasized opportunities, regulation, and ethical considerations. Collectively, these results suggest that firms adapt both the extent and framing of AI disclosures to align with institutional expectations and sectoral norms.

CHAPTER V: DISCUSSION AND CONCLUSION

Artificial intelligence has emerged as the defining technological force of our era, disrupting established business models and accelerating structural change across the global economy. This research examines how organizations navigate AI-related regulatory disclosure challenges in the absence of standardized reporting frameworks, in contrast to more established domains such as cybersecurity, where formalized disclosure requirements exist. Consistent with legitimacy theory, firms operating in highly scrutinized industries such as Information Technology, Healthcare, Financial, and Communication services, respond with more extensive, risk-forward disclosures, aligning with legitimacy theory's core predictions about organizational behavior under pressure. Notable variation across industries, regions, and within themes shows the influence of contextual factors in shaping corporate narratives surrounding AI. The following discussion interprets the study's thematic findings through the theoretical framework of legitimacy theory.

Beyond the categorical and statistical comparisons presented in the results chapter, the study's thematic analysis offers broader insight into how firms frame the narrative of AI in corporate disclosures and what this implies about corporate priorities and concerns regarding AI. Seven key disclosure themes were identified inductively through the pilot testing and informed by the literature review: Risk, Opportunities, Regulation, Financial, Competition, Ethical, and Risk Mitigation; each representing a distinct facet of how companies discuss artificial intelligence in their filings, which will be expanded below.

Risk: Emphasizing Threats and Challenges

The Risk theme emerged as the most prevalent category within the annual filings, encompassing 36.4% of the total AI-related disclosure content. Across GICS sectors, risk narratives were framed in a predominantly cautious and defensive tone, with organizations emphasizing the threats, uncertainties, and potential disruptions that AI could pose to their operations. Firms within this category discussed the following subthemes:

- **Cybersecurity Threats (56% of companies):** Organizations identify cybersecurity vulnerabilities as a principal risk factor, recognizing that AI systems face heightened exposure to increasingly sophisticated cyber-attacks.
- **Protection of Intellectual Property (27% of companies):** Organizations identify the inadequate protection of intellectual property as a material risk factor, noting that their operational performance and competitive position may be compromised in the absence of sufficient safeguards for proprietary assets.
- **Privacy (29% of companies):** Organizations identify that AI systems' reliance on extensive personally identifiable information creates regulatory compliance risks, with potential consequences including financial penalties, legal liabilities, and diminished consumer trust.

Some firms also discussed the risks of algorithmic errors, one Utilities company cautions the following: *"as we adopt new technologies, like artificial intelligence (AI), there is a risk that the content, analyses, recommendations, or judgments that AI applications assist in producing are alleged to be deficient, inaccurate, biased, or infringe on other's rights…,"* noting such issues could lead to regulatory investigations and penalties. Reputational risk was also discussed, with many firms explicitly cautioning that AI missteps (such as biased algorithms or privacy infringements) could undermine customer trust and invite public backlash. The fear that AI mistakes could "erode trust and confidence" shows that companies view AI not only as a technical or operational matter, but as something that directly ties to their legitimacy and stakeholder relationships.

An Information Technology company warns that the *"increasing focus on the risks and strategic importance of AI technologies"* has led to an uptick in regulatory restrictions that affect product and service offerings. By openly acknowledging these threats, companies in all GICS sectors signal to stakeholders (especially investors and regulators) that they are aware of AI's downsides and are monitoring them.

Opportunities: Highlighting Innovation and Potential

In contrast to the predominance of risk-oriented discourse, the Opportunities theme, accounting for 24.6% of total AI-related disclosure content, was characterized by an optimistic and forward-looking tone. Companies discuss how AI will drive innovation, efficiency, and competitive growth. Common subthemes include operational efficiency gains, productivity improvements, new product development, and enhanced customer experiences powered by AI. Many firms position AI as integral to their future strategy. For example, a Communication Services company proclaims it is *"transforming into an AI-enabled, data-informed, digital-first organization,"* leveraging AI to *"pioneer new approaches to serving customers"* with personalized solutions. Similarly, in Healthcare, a firm proclaims that AI is *"generating insights that could help [us] design new compounds, predict drug safety, or speed up drug discovery."*

The tone in opportunity narratives is led by non-US companies primarily within the high-legitimacy pressure group. Such disclosures serve to excite investors and other stakeholders about AI's promise. By emphasizing AI-led innovation, organizations appeal to normative ideals of progress and industry leadership while also aligning with emerging societal narratives that AI is the future. It should also be noted that financial markets distinguish between substantive AI commitments and superficial rhetoric, rewarding firms with credible AI-driven strategies with significant valuation premiums while penalizing those that make vague mentions or remain silent on AI adoption (Basnet et al., 2025). Indeed, many of the companies in this theme portray AI as a transformative force with broad societal benefits, with a company in Communication Services stating, *"AI is a profound platform shift, one that can bring meaningful and positive change to people and societies across the world."*

Regulation: Addressing Compliance and Uncertainty

The Regulation theme captures how firms construct legitimacy through engagement with the expanding legal and policy landscape of AI, representing 22.1% of total disclosure. These narratives often highlight proactive compliance and new regulations that could affect their operations, signaling firms' efforts to align with evolving societal expectations around AI oversight. A consistent subtheme is the uncertainty of emerging AI regulations, with one company in Financials questioning what *"new laws will look like and how existing laws will apply to our development, use, and deployment of AI."* The most cited law was Europe's AI Act, with 29.6% of companies within this theme similarly discussing the challenges and costs of maintaining compliance and the effect it would have on operations; with one company in Healthcare stating, *"new privacy, security, technology and data laws, regulations and requirements may result in increased operating costs."*

By emphasizing that they are monitoring policy changes, organizations aim to reassure stakeholders of their preparedness. It increases both pragmatic legitimacy (assuring shareholders and regulators that legal risks are managed) and moral legitimacy (presenting the firm as a good corporate citizen that respects societal rules). The emphasis on regulatory compliance and policy engagement helps firms frame themselves as compliant, trustworthy actors in an uncertain regulatory environment. As new AI laws take effect and jurisdictions continue to advance AI policies, organizations can expect an escalation in regulatory exposure.

Financial: Framing AI in Terms of Investment and Returns

Under the Financial theme, representing 7% of total disclosure, companies discuss artificial intelligence in relation to monetary impacts, both costs and benefits. A prominent subtheme is investment in AI and related technologies: firms quantify the resources they devote to AI, such as R&D expenditures, venture investments, and acquisitions of AI startups. For example, a Healthcare firm stated that it had invested $100 million in the acquisition of PathAI Diagnostics. In comparison, a firm in the Financials sector invested more than $3 billion in AI infrastructure over the last 10 years. As companies make investments in emerging technologies, they also highlight cost efficiencies and savings attributable to AI. A company in Healthcare, for instance, launched a program aiming for *"3% annual cost savings and productivity improvements"* and reported leveraging artificial intelligence to achieve this. By framing AI as a source of economic value, these disclosures appeal directly to the self-interest of investors. This theme signals to stakeholders that AI is being handled in a financially prudent manner, aligning technological innovation with the firm's financial health and strategic objectives. In doing so, companies seek to legitimize their AI efforts by demonstrating accountability for economic outcomes and emphasizing that AI investments are ultimately translating into shareholder value.

Competition: Projecting Market Position and Technological Leadership

The Competition theme, representing 5% of total disclosure, captures how companies frame AI in the context of industry rivalry and market positioning. Here, disclosures convey a sense of urgency about keeping up with technological change to maintain competitiveness. Subthemes include benchmarking against competitors, market share threats, and the need for technological leadership in AI. Many firms explicitly warn that failing to adopt AI quickly could erode their market position. For example, a firm in Industrials notes that if it is unable to "acquire, develop, implement, or update new or existing technology, including [AI]" then it would be at a competitive disadvantage within the railroad industry. Similarly, other companies note that competitors are integrating AI into products and operations, sometimes "*more quickly or more successfully than we do.*" This competitive framing emphasizes not just the threat but also the imperative to innovate. Firms often highlight their own efforts to stay ahead, such as expanding AI research teams, partnering with AI startups, or launching AI-driven services, to convey that they are actively contesting the market. This is both a justification for their AI investments and a candid acknowledgement of market pressure.

Ethical: Addressing Fairness and Accountability

The Ethical theme, representing 3.6% of total disclosures, encompasses references to fairness, transparency, responsible AI principles, governance frameworks, and societal impacts. Although Ethical was the second-smallest theme, its presence in several companies' reports (particularly non-U.S.-domiciled firms) is notable because it goes beyond what is legally required. It shows companies voluntarily addressing questions of AI ethics and corporate responsibility, likely to build trust and show alignment with societal values. The emphasis on ethics correlates with rising public discourse on AI's societal implications; firms are aware that, to maintain their legitimacy, technical compliance is not enough; they must also win the "social license" to operate AI by demonstrating ethical foresight (Fineberg et al., 2025).

Companies often assert their dedication to responsible AI practices, with many pointing to internal ethics guidelines. A global bank, for instance, stated it is *"committed to using AI responsibly"* and publicized its Principles for the Ethical Use of Data and AI, while explaining efforts to *"embed governance and controls"* to meet rising ethical and regulatory expectations. By emphasizing values such as responsible use and transparency, organizations appeal to stakeholders' expectations that AI should be developed and deployed for the good: it reassures stakeholders that the company's use of AI will not harm their interests or society at large.

A notable example within the dataset comes from a global healthcare company emphasizing an internal governance team:

> To ensure our practices and solutions are consistent with our commitment to health equity and to facilitate compliance with applicable laws and regulations, we have a dedicated team and governance structure in place, known as Enterprise Model Governance ("EMG"). Our EMG team oversees the development, deployment and monitoring of AI models - driven by our Responsible AI Principles: validity and reliability; safety; privacy; fairness; transparency; and accountability. EMG is governed by the EMG Board, comprised of senior leaders from across the company, with representation from business, clinical, privacy, legal, internal audit, information protection and other departments. The EMG Board oversees an enterprise-wide model approval and governance process for review of AI models in use or in development across the enterprise.

The healthcare sector faces uniquely high legitimacy pressures due to the direct impact of AI systems on patient safety, clinical outcomes, and individual well-being; domains where algorithmic errors can result in irreversible harm or loss of life. The detailed disclosure of Responsible AI principles and the establishment of an internal governance board signal a proactive attempt to build cognitive and moral legitimacy with multiple stakeholder groups, including regulators, investors, and other external stakeholders. It can also be seen as an example of Corporate Digital Responsibility (CDR), an emerging field of research that extends Corporate Social Responsibility (CSR). CDR is a voluntary commitment by organizations to address the broader social, economic, and ecological impacts of technology on digital society (Elliott et al., 2021; Wade, 2020).

The relative silence from seven of the nine healthcare firms in the sample regarding ethical frameworks or governance mechanisms suggests that even within high-stakes sectors, legitimacy-seeking behavior remains heterogeneous. This variation may reflect differences in AI deployment maturity, organizational size and resources, and regulatory exposure across different healthcare subsectors (e.g., pharmaceutical, insurance, patient care).

Risk Mitigation: Demonstrating Oversight and Control Mechanisms

The Risk Mitigation theme, representing 1.3% of total disclosure, highlights how companies claim to manage and mitigate the risks associated with AI. Although quantitatively the smallest theme, its presence represents firms not just listing risks but also explaining how they are addressing those risks. Subthemes include cybersecurity safeguards, AI governance committees, policies on AI usage, compliance oversight, and employee training. A Financial firm in the sample noted it had implemented AI-enabled fraud detection and increased employee training to combat AI-related cyber threats. An Energy company stated that it had instructed its employees *"not to submit confidential information to any AI that is not approved."*

This theme reflects a reassurance strategy: having acknowledged the many risks of AI (in the Risk theme), companies then seek to reassure stakeholders that they are actively mitigating those risks. The relatively low volume of this theme might suggest that many companies are still developing their mitigation approaches (thus not much to report yet) or that some are hesitant to divulge too many specifics (potentially for fear of inviting scrutiny of whether those measures are adequate). Nonetheless, as stakeholders increasingly demand to know *"what are you doing about these AI risks?"*, this theme is likely to grow in prominence, with future research needed (Kennedy et al., 2025).

Practical and Theoretical Implications

For organizational leaders, transparent and detailed communication about AI constitutes an essential component of responsible technology stewardship. To support this objective, the following practical implications derived from the study offer guidance for strengthening AI disclosure practices:

- **Embed AI Within Internal Governance:** Organizations should integrate AI considerations into existing governance and enterprise risk management frameworks, treating AI as a strategic risk comparable to operational exposures such as financial, cybersecurity, and compliance risks (Sayles, 2024; Mueller, 2020). Such an approach could involve establishing a dedicated AI governance committee, something that very few companies in the sample set are doing.
- **Emphasize Regulatory Compliance:** Disclose how the firm is preparing for or meeting ever-evolving AI regulations. This includes not just naming relevant laws (e.g., the EU AI Act) but explaining expected impacts on operations and budgets (Niemann, 2025). By proactively addressing compliance, firms signal to stakeholders that legal risks are managed. The analysis found that mentions of regulation were common in 10-Ks and 20-Fs, with non-U.S. firms leading the way; this both reassures investors and builds moral legitimacy as a "good corporate citizen."
- **Report Ethical Safeguards:** Voluntary disclosure of commitment to ethical AI can build trust; companies should describe internal principles, bias-testing procedures, or independent audits they use. Research underscores that such ethical framing appeals to stakeholder values (Clausen et al., 2022; Lobschat et al.,

2021). By sharing how AI decisions are governed and by whom, firms satisfy public demand for accountability.

- **Communicate Substantively:** Effective AI disclosure requires context-rich communication that avoids superficial or promotional language (e.g., AI-washing). Stakeholders increasingly differentiate between meaningful AI commitments and vague or inflated claims; firms that invoke AI terminology without a substantive explanation of risk undermine their credibility (Al Haddi, 2024; Schultz et al., 2025). By discussing not only the strategic opportunities of AI, but also the associated risks and mitigation measures, firms can enhance the credibility of their communications, support more informed assessments by investors and regulators, and more effectively manage the legitimacy pressures that are particularly salient in AI-intensive and highly scrutinized sectors. Research on AI transparency and ethics consistently demonstrates that perceived legitimacy is strengthened when firms present both opportunities and risks honestly and proportionately (Peukert & Kloker, 2020; Donati et al., 2025).

Conclusion

As the global AI market expands, reaching an estimated $254.5 billion in 2025 and projected to exceed $1.68 trillion by 2031, the dialogue between firms and annual disclosures will increasingly shape how this technological shift is understood and evaluated (Statista, 2025). Effective communication can reinforce stakeholder confidence in a firm’s AI trajectory, whereas inadequate or opaque disclosure may heighten perceptions of risk or undermine trust (Di Chiacchio et al., 2026; Babina et al., 2023). Organizations may therefore highlight pragmatic value propositions such as efficiency gains, emphasize moral legitimacy through commitments to responsible and ethical AI, or increase cognitive legitimacy by aligning with emerging norms, standards, and regulatory expectations.

Consistent with legitimacy theory's assertion that organizations must continuously justify their actions to maintain pragmatic, moral, and cognitive legitimacy, the observed emphasis on Risk, Opportunities, and Regulation suggests that firms use disclosure not only to inform but to align themselves with evolving norms and institutional expectations. Looking ahead, the Risk Mitigation theme is likely to expand as regulatory scrutiny intensifies and stakeholders (including investors) demand credible evidence of governance structures, testing protocols, and oversight mechanisms. These factors increase both the necessity and the visibility of mitigation efforts.

At the same time, more detailed disclosures can heighten firms' vulnerability to legal and regulatory scrutiny, whether by creating inconsistencies that may later be viewed as misstatements or by revealing weaknesses in internal controls, underscoring the fine line between demonstrating transparency and managing legal risk. The stronger emphasis by non-U.S. firms on Ethical, Risk Mitigation, and Opportunities themes reflects differing institutional environments in which responsible innovation, human rights considerations, and adherence to public values are more embedded in regulatory frameworks and stakeholder expectations; however, considerable variation persists across regions (Von Essen & Ossewaarde, 2024; Hogan & Lasek-Markey, 2024).

As AI capabilities and governance frameworks continue to evolve, stakeholder expectations for what constitutes "adequate" AI disclosure will rise accordingly, likely prompting demands for more detailed explanations of how firms ensure the safe, fair, and lawful use of AI. This study advances theoretical understanding by extending legitimacy theory to the domain of AI communication, demonstrating that, despite the technology's novelty, firms rely on established legitimacy-seeking strategies to maintain credibility. Overall, these thematic patterns demonstrate how firms adapt their narratives to address emerging legitimacy gaps created by AI technologies, using disclosure as a tool to demonstrate accountability and align with regulatory, market, and societal expectations. In an era of rapid digital transformation, communicating about AI has become a foundational dimension of corporate digital accountability.

Limitations and Suggestions for Future Research

While this study provides insights, it is not without limitations. First, the content analysis focused on annual regulatory filings of 100 firms in a single reporting year. This approach limits the ability to observe trends over time. Artificial intelligence is a rapidly changing industry; what companies reported in 2024 could change in subsequent years as technology and regulations develop. It should be noted that, at the time of writing, many firms have not yet released their 2025 filings. Future research should consider a longitudinal design to examine how AI disclosure volume and theme change over time. Tracking these changes could validate and extend the legitimacy-based interpretations; for example, do firms increase risk disclosure after a scandal or after peer firms do so?

Second, the sample of 100 firms across 11 sectors could be expanded to increase the study's statistical power. The current study contrasted U.S. vs. non-U.S. firms as broad categories; future studies with a larger data set could be more geographically specific, perhaps comparing U.S., EU, South American, and Asia-Pacific firms in more detail. Each region has distinct regulatory and cultural contexts that might produce different disclosure behaviors. Comparative studies could increase understanding of how global institutional environments influence legitimacy pressure.

Third, the sector-level classification aggregates heterogeneous firms into broad categories that could potentially obscure variation. While this approach provides analytical consistency and facilitates cross-industry comparison, it also aggregates highly heterogeneous firms into broad categories that may mask meaningful intra-sector variation. For example, the Consumer Discretionary sector includes firms with fundamentally different business models, such as automotive manufacturers (e.g., Tesla and Toyota) and service-oriented companies (e.g., Marriott International and Amazon). These firms differ in their AI adoption maturity and stakeholder expectations, yet they are treated as belonging to a single category. Future research could address this limitation by employing more granular classifications, such as subsector- or firm-level typologies, to capture greater variation in disclosures.

Lastly, it should also be acknowledged that the focus on 10-K and 20-F filings is just one channel of corporate disclosure. Companies often share AI information through press releases, earnings calls, investor presentations, and sustainability reports. Some firms may keep their regulatory filings sparse but talk more about AI in other forums, perhaps to maintain flexibility or reduce liabilities. Future research could conduct a multi-channel analysis examining AI messaging across documents. This could reveal patterns of selective disclosure, such as a firm discussing AI in press releases but omitting it in annual filings.

APPENDIX

Table A.1.

Companies Included in Content Analysis Sample

Company Name	Headquarters	GICS Sector	Document
Alphabet	United States	Communication Services	10-K
Meta Platforms	United States	Communication Services	10-K
Netflix	United States	Communication Services	10-K
T-Mobile	United States	Communication Services	10-K
Roblox	United States	Communication Services	10-K
Telefónica, S.A.	Spain	Communication Services	20-F
Reddit	United States	Communication Services	10-K
Bilibili Inc.	China	Communication Services	20-F
Match Group Inc.	United States	Communication Services	10-K
Spotify	Sweden	Communication Services	20-F
Amazon	United States	Consumer Discretionary	10-K
Yum! Brands	United States	Consumer Discretionary	10-K
Tesla	United States	Consumer Discretionary	10-K
PDD Holdings Inc.	Ireland	Consumer Discretionary	20-F
Toyota	Japan	Consumer Discretionary	20-F
MercadoLibre	Argentina	Consumer Discretionary	10-K
Airbnb, Inc.	United States	Consumer Discretionary	10-K
Mariott	United States	Consumer Discretionary	10-K
Ferrari	Italy	Consumer Discretionary	20-F
Mondelez International	United States	Consumer Staples	10-K
Costco	United States	Consumer Staples	10-K
Unilever	United Kingdom	Consumer Staples	20-F
The Estée Lauder Companies Inc.	United States	Consumer Staples	10-K
Anheuser-Busch	Belgium	Consumer Staples	10-K
Proctor & Gamble	United States	Consumer Staples	10-K
Colgate-Palmolive	United States	Consumer Staples	10-K
Pilgrim's Pride Corporation	United States	Consumer Staples	10-K
Target	United States	Consumer Staples	10-K
Shell	United Kingdom	Energy	20-F
Tenaris S.A.	Luxembourg	Energy	20-F
ConocoPhillips	United States	Energy	10-K
Petróleo Brasileiro S.A	Brazil	Energy	20-F
Schlumberger Limited	United States	Energy	10-K

Table A.1. (continued).

Eni S.p.A.	Italy	Energy	20-F
Valero Energy Corporation	United States	Energy	10-K
Phillips 66	United States	Energy	10-K
Diamondback Energy, Inc.	United States	Energy	10-K
Host Hotels & Resorts, Inc.	United States	Real Estate	10-K
Simon Property Group, Inc.	United States	Real Estate	10-K
Weyerhaeuser Company	United States	Real Estate	10-K
CBRE	United States	Real Estate	10-K
Welltower Inc.	United States	Real Estate	10-K
AvalonBay Communities, Inc.	United States	Real Estate	10-K
Equity Residential	United States	Real Estate	10-K
Cushman & Wakefield plc	United Kingdom	Real Estate	10-K
Kimco Realty Corporation	United States	Real Estate	10-K
JPMorgan Chase & Co.	United States	Financials	10-K
Mitsubishi UFJ Financial Group	Japan	Financials	20-F
The Goldman Sachs Group, Inc.	United States	Financials	10-K
Visa Inc.	United States	Financials	10-K
HSBC Holdings	United Kingdom	Financials	20-F
Robinhood Markets, Inc.	United Kingdom	Financials	20-F
Deutsche Bank Aktiengesellschaft	Germany	Financials	20-F
Barclays PLC	United Kingdom	Financials	20-F
PayPal Holdings, Inc.	United States	Financials	10-K
Johnson & Johnson	United States	Health Care	10-K
Novartis AG	Switzerland	Health Care	20-F
United Healthcare	United States	Health Care	10-K
McKesson	United States	Health Care	10-K
HCA Healthcare	United States	Health Care	10-K
CVS Health Corporation	United States	Health Care	10-K
The Cigna Group	United States	Health Care	10-K
Pfizer Inc.	United States	Health Care	10-K
Quest Diagnostics Incorporated	United States	Health Care	10-K
RTX Corporation	United States	Industrials	10-K
The Boeing Company	United States	Industrials	10-K
Caterpillar Inc.	United States	Industrials	10-K
RELX PLC	United Kingdom	Industrials	20-F
Northrop Grumman Corporation	United States	Industrials	10-K
Cintas Corporation	United States	Industrials	10-K

Table A.1. (continued).

Ferrovial SE	Spain	Industrials	20-F
3M Company	United States	Industrials	10-K
CSX Corporation	United States	Industrials	10-K
NVIDIA Corporation	United States	Information Technology	10-K
Microsoft Corporation	United States	Information Technology	10-K
Broadcom Inc.	United States	Information Technology	10-K
Apple Inc.	United States	Information Technology	10-K
Cisco Systems, Inc.	United States	Information Technology	10-K
Salesforce, Inc.	United States	Information Technology	10-K
SAP SE	Germany	Information Technology	20-F
Atlassian Corporation	Australia	Information Technology	10-K
FISERV	United States	Information Technology	10-K
Newmont Corporation	United States	Materials	10-K
The Sherwin-Williams Company	United States	Materials	10-K
Vale S.A.	Brazil	Materials	20-F
Suzano S.A.	Brazil	Materials	20-F
Vulcan Materials Company	United States	Materials	10-K
Ternium S.A.	Luxembourg	Materials	20-F
ArcelorMittal S.A.	Luxembourg	Materials	20-F
LyondellBasell Industries N.V.	United States	Materials	10-K
Dow Inc.	United States	Materials	10-K
Xcel Energy Inc.	United States	Utilities	10-K
Vistra Corp	United States	Utilities	10-K
National Grid plc	United Kingdom	Utilities	20-F
Talen Energy	United States	Utilities	10-K
NextEra Energy, Inc.	United States	Utilities	10-K
Dominion Energy, Inc.	United States	Utilities	10-K
Sempra Energy	United States	Utilities	10-K
Korea Electric Power Corporation	Korea	Utilities	20-F
Brookfield Renewable Partners L.P.	Bermuda	Utilities	20-F

Note. N = 100. Companies were selected through stratified purposive sampling to ensure representation across all Global Industry Classification Standard (GICS) sectors. Document types include SEC Form 10-K (*n* = 73) and SEC Form 20-F (*n* = 27). Fiscal year-end dates range from January 31, 2024, to December 31, 2024.

Table A.2.

Codebook Used in Content Analysis

Category Name	Codes & Descriptions	Values/Codes	Example
Company Name	Record the name of the reporting entity.	Free Text Field	Microsoft Corporation
Report Type	Note whether the report is a Form 10-K or Form 20-F.	(0) Form 20-F (1) Form 10-K	(0) Shell (1) Quest Diagnostics
Document Length	Record the page count of the document.	Free Text Field	Alphabet is 111 pages.
GICS Sector	Classify the company according to its primary GICS sector.	(1) Communication Services (2) Consumer Discretionary (3) Consumer Staples (4) Energy (5) Financials (6) Health Care (7) Industrials (8) Information Technology (9) Materials (10) Real Estate (11) Utilities	Microsoft Corporation would be listed under (8) Information Technology.
Region	Indicate whether the firm's headquarters is U.S.-domiciled or non-U.S.	(0) = Non-US domiciled (1) = US domiciled	(0) Telefónica, S.A. (1) Meta Platforms
Legitimacy Pressure	Assign legitimacy pressure based on pre-determined industry classification from Table 2.3.	(0) = Low (1) = High	(0) Talen Energy (1) Novartis AG
AI Disclosure Volume	Count all words within each AI paragraph.	Total numeric word count	ConocoPhillips' total AI word count is 144.
Disclosure Specificity	Assess the level of detail provided about the AI disclosures present within a document as a whole.	(0) Generic: Vague references without operational detail. (1) Detailed: Concrete implementation examples, quantified impacts, or named AI systems/partnerships.	(0) Ternium S.A. – *"…emerging technologies, like…(AI), which are becoming available more widely and faster, are expected to exacerbate cyber resilience challenges…"* (1) Robinhood – "…*we use machine learning and AI to increase the efficiency of our in-app chat support, customer support workflows...*"

Table A.2. (continued).

Theme	Assign the single dominant theme that best characterizes the paragraph's primary communicative purpose.	(1) Risk: Threats, challenges, uncertainties, cybersecurity concerns, algorithmic bias, implementation failures, dependency risks, adverse scenarios. (2) Opportunities: Performance enhancement, efficiency gains, innovation, productivity improvements, positive projections. (3) Regulation: Legal requirements, regulatory mandates (e.g., EU AI Act), claims and suits, policy constraints, compliance obligations (existing or anticipated regulations). (4) Financial: Capital expenditures, R&D spending, acquisition costs, revenue impacts, cost savings, monetization of AI. (5) Competition: Competitor capabilities, industry benchmarking, market share implications, competitive threats or advantages. (6) Ethical: References fairness considerations, transparency commitments, training, internal governance, societal impact assessments, or stakeholder welfare concerns. (7) Risk Mitigation: Strategies, safeguards, and controls implemented to reduce or manage AI-related risks.	(1) Xcel Energy – *"Generative Artificial Intelligence…present a range of challenges and potential risks as we consider impacts to the business."* (2) Tenaris – *"These technologies…significantly reduce human intervention, ensuring greater consistency throughout the production process while delivering measurable improvements in quality and efficiency."* (3) Meta – *"For example, in April 2019, the European Union passed a directive…expanding online platform liability for copyright infringement and regulating certain uses of news content online…"* (4) Unilever – *"To date, our AI-enabled freezers have significantly boosted sales in several key markets…"* (5) Spotify – *"We face significant competition from other companies that are developing their own AI products…"* (6) HSBC Holdings – *"Responsible AI Artificial intelligence ('AI') and other emerging technologies provide the opportunity to process and analyse data…"* (7) Tenaris – *"We have also instructed our employees not to submit confidential information to any AI that is not approved by Tenaris."*

Table A.2. (continued).

Section	Document the filing section where each AI paragraph appears. If AI appears in multiple sections, code each instance separately and paste the text in the corresponding text field. Reference the page number and Table of Contents for the most accurate section title.	(1) Business, Information on the Company, Key Information (2) Risk Factors, Risk Review (3) Cybersecurity (4) Management's Discussion and Analysis of Financial Condition and Results of Operations (5) Governance (6) Strategic Report (7) Unresolved Staff Comments (8) Operating and Financial Review and Prospects, Financial Statements and Supplementary Data (9) Review of the Year, Chair's Message (10) Sustainability (11) Additional Information (12) Directors, Senior Management and Employees (13) Exhibits (14) Legal Proceedings (15) Quantitative and Qualitative Disclosures about Credit, Market and Other Risk	National Grid plc lists the following paragraph in section (1)Business: *"In New York, we use AI to help assess field activity on our gas assets to help manage safety risks. This pioneering use of science to enhance safety was recognised with an award at the American Gas Association Operations Conference."*
Paragraph	Copy and paste the whole paragraph in which AI is referenced. Exclude tables, lists, profile summaries, and financial and forward-looking statements.	Free text field	ArcelorMittal S.A.: *"Adverse consequences of technological advances such as Artificial Intelligence ("AI"), cloud-based programs or systems, Internet of Things ("IoT") and Blockchain, which may cause harm to ArcelorMittal."*

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