

Article

Machine-Readable Accountability: eXtensible Business Reporting Language, Artificial Intelligence, and the Institutional Rewriting of Accounting Judgement

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Abstract

Machine-readable financial reporting changes how corporate disclosures become visible, verified, and answerable. Inline eXtensible Business Reporting Language (Inline XBRL) combines a human-readable report with embedded structured data, while artificial intelligence expands automated extraction and screening. The study develops Machine-Readable Accountability as a bounded socio-technical construct organised around dynamic visibility, distributed judgement, and responsibility displacement. A qualitative documentary analysis examines four primary archives: regulatory rules, official filing-evidence records, verification materials, and algorithmic-governance documents. Peer-reviewed studies serve as contextual framing and external corroboration. They do not form primary documentary observations. The corpus covers the mature United States Securities and Exchange Commission regime and the European Single Electronic Format from 2020 to July 2026, with earlier sources retained for historical grounding. A seven-family codebook guides analysis of classification, visibility, validation, judgement, audit, artificial intelligence, and accountability. Results arise from coded rules, official filing observations, assurance requirements, and cross-archive role mapping. Structured reporting reduces extraction costs, supports comparison, and permits automated quality checks. It also places institutional weight on taxonomy fit, extension design, validation logic, and software-mediated review. Documentary evidence supports the relocation of judgement across preparers, taxonomy designers, software vendors, auditors, and regulators. Evidence for deliberate narrative optimisation aimed at artificial intelligence remains indirect, so algorithmic answerability remains a bounded theoretical proposition. The framework links market-efficiency research with studies of quantification, professional judgement, and digital governance, and specifies controls for data lineage, extension approval, model documentation, human review, and responsibility assignment.



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1. Introduction

Corporate reporting now operates through a dual communication channel. Human readers receive formatted annual reports, while software receives structured facts, contexts, dimensions, and narrative blocks. eXtensible Business Reporting Language (XBRL) provides a standard for structuring business-reporting data. Inline XBRL embeds those data

within an eXtensible HyperText Markup Language (XHTML) document, which remains readable in a web browser. The United States Securities and Exchange Commission (SEC) and the European Single Electronic Format (ESEF) require structured reporting under mature regulatory regimes. Their rules place taxonomy selection, extension design, anchoring, validation, and filing architecture inside the reporting process (SEC, 2018, 2026a; ESMA, 2025; European Commission, 2019, 2026; IFRS Foundation, 2025; XBRL International, 2013).

Financial economics research reports several benefits from XBRL. Studies associate structured reporting with lower processing costs, stronger analyst coverage, improved forecast accuracy, greater market liquidity, and lower information asymmetry in some settings (Yoon et al., 2011; Kim et al., 2012; Blankespoor et al., 2014; Liu et al., 2014; Blankespoor, 2019; Tawiah & Borgi, 2022). Data quality studies also identify calculation errors, inconsistent tags, and poor extension practice, especially during early implementation (Bartley et al., 2011; Debreceeny et al., 2010; Janvrin & No, 2012). The evidence therefore resists a simple efficiency narrative. Structured reporting improves access while creating new sites of technical discretion and control.

Research on accountability and calculative practice provides a second route into the problem. Accounting systems do more than transmit facts. They define categories, visibility, and acceptable evidence (Miller & O’Leary, 1987; Roberts, 1991; Power, 1997; Miller, 2001). Digital systems extend those effects into schemas, validation engines, and application programming interfaces. Agostino et al. (2022), Argento et al. (2025), and Ferry et al. (2025) describe how digitalisation redistributes reporting work and public oversight. The present study applies such reasoning to machine-readable corporate reporting.

Machine-Readable Accountability refers to an institutional arrangement in which answerability depends on both accounting meaning and computational legibility. The construct does not replace digital accountability, algorithmic governance, socio-technical systems theory, institutional theory, or the sociology of quantification. It narrows their application to a particular reporting chain. The chain starts with accounting recognition and presentation, passes through taxonomy mapping and validation, and ends with human and automated users. The construct adds a unit of analysis centred on the representation chain, a distinction between syntactic validity and accounting validity, and a traceability question concerning who owns each transformation.

Three analytical axes organise the construct. Dynamic visibility concerns the different treatment of standard tags, extensions, dimensions, and narrative blocks in automated retrieval. Distributed judgement concerns the relocation of discretion across standard-setters, taxonomy teams, preparers, software developers, auditors, regulators, and model users. Responsibility displacement concerns the risk of weak ownership when an error survives several technical and professional checkpoints. Algorithmic answerability forms a related proposition. It concerns disclosure choices made with anticipated machine reading in mind. Existing research proves widespread automated reading and growing human–AI collaboration, although public documents provide limited direct evidence of deliberate lexical rewriting by corporate preparers (Loughran & McDonald, 2011; Estep et al., 2024; Choi & Xie, 2026; Jones & Free, 2026).

The manuscript therefore applies strict claim calibration. Regulatory manuals support claims about formal requirements. Official data-quality records support claims about observed filing patterns. Assurance sources support claims about verification scope. AI governance and accounting studies support claims about model risk and human oversight. Claims concerning managerial intention receive cautious treatment unless the archive records such intention. Constructed examples from the earlier draft have been removed.

The study focuses on the United States Securities and Exchange Commission and European Single Electronic Format regimes because both combine mandatory structured re-

porting, public technical rules, maintained taxonomies, and accessible validation guidance. The period starts in 2020, when European Single Electronic Format implementation entered operational use and the United States Inline XBRL regime had moved beyond its initial phase-in. July 2026 provides the corpus lock date. Earlier literature and technical sources remain in the review where they explain the origin of rules or establish prior evidence.

Four research questions guide the analysis. Research question 1 asks how taxonomy design, extension rules, and validation procedures configure the visibility of corporate reporting facts. Research question 2 asks how machine-readable reporting redistributes accounting and audit judgement across human and technical actors. Research question 3 asks which parts of algorithmic answerability receive direct documentary support and which remain theoretical inferences. Research question 4 asks which governance and assurance controls preserve traceability, contestability, and responsibility across the digital representation chain.

The paper contributes a bounded conceptual model, a transparent documentary protocol, an evidence-to-claim matrix, and a control framework for machine-readable reporting. The analysis also provides a balanced account. Structured reporting supports faster retrieval and stronger quality monitoring. Taxonomy mismatch, opaque validation logic, and fragmented ownership introduce different risks. The argument therefore concerns governance design rather than technological pessimism.

2. Literature Review and Conceptual Positioning

2.1. *eXtensible Business Reporting Language Adoption, Reporting Quality, and Capital-Market Effects*

XBRL research started with adoption, implementation, data quality, and assurance. Troshani and Rao (2007) identified organisational drivers and barriers. Plumlee and Plumlee (2008) framed assurance questions before mandatory filing matured. Debreceeny et al. (2010) reported calculation errors in early SEC submissions. Bartley et al. (2011) compared voluntary XBRL filings with 10-K reports and found accuracy concerns. Janvrin and No (2012) documented implementation issues involving software, validation messages, internal readiness, and control ownership.

Later capital-market studies produced a broader record. Yoon et al. (2011) associated XBRL adoption with lower information asymmetry in Korea. Kim et al. (2012) found improvements across several features of the United States information environment. Blankespoor et al. (2014) reported uneven market effects across investor groups, while Liu et al. (2014) linked the mandate with analyst following and forecast accuracy. Blankespoor (2019) showed how lower processing costs feed back into disclosure choice. Tawiah and Borgi (2022) found a positive relation between national XBRL adoption and reporting quality. Such findings support the efficiency case while preserving room for distributional and implementation questions.

Taxonomy extensions provide a focal tension. A standard element supports cross-company retrieval. An extension preserves entity-specific meaning when no suitable standard element exists. Excessive or inconsistent extension use weakens comparison. Hoitash and Hoitash (2018) use XBRL tag counts to measure reporting complexity. SEC custom-tag trend publications track extension rates over time. Kim and Lee (2025) associate excessive custom-tag use with internal-control weakness and stronger SEC oversight. The tension therefore concerns faithful representation and comparability rather than a simple preference for fewer extensions.

2.2. Quantification, Digital Accountability, and Socio-Technical Control

The sociology of quantification treats categories and calculative devices as active parts of governance. Miller and O’Leary (1987) show how accounting constructs governable persons. Roberts (1991) presents accountability as a relational practice. Power (1997) explains how verification routines reorder organisational control. Miller (2001) links calculative practice with political and organisational authority. Such work directs attention towards the categories, routines, and evidence forms embedded in structured reporting.

Digital accountability research extends this reasoning. Agostino et al. (2022) show how digital technologies alter accountability in public services. Argento et al. (2025) examine unrecorded effects of digital transformation in accounting and audit. Carlsson-Wall et al. (2025) analyse promissory narratives around digital technologies. Fortin et al. (2025) locate accountability across ledger design, code, and people. Ferry et al. (2025) connect digital audit with democratic oversight. Machine-readable reporting fits this stream because schemas and validation rules mediate the relation between the reporting entity and external users.

Socio-technical reasoning also prevents technological determinism. Human actors choose taxonomies, draft rules, configure software, approve mappings, review exceptions, and interpret outputs. Technical artefacts constrain later choices, yet no artefact acts without an institutional setting. Machine-Readable Accountability therefore studies distributed agency across a representation chain rather than assigning agency to software alone.

2.3. Artificial Intelligence, Explainability, and Human–AI Audit Work

Artificial intelligence expands the scale of automated disclosure analysis. Financial text research uses dictionaries, natural language processing, machine learning, and large language models to classify tone, risk, topics, and events. Loughran and McDonald (2011) demonstrate how domain-specific dictionaries alter financial text measurement. Issa et al. (2016) identify audit tasks suited to artificial intelligence. Kokina and Davenport (2017) describe early audit automation. Appelbaum et al. (2017) connect large datasets with modern audit design. Fedyk et al. (2022) report associations between artificial intelligence investment and audit outcomes.

Human judgement remains central. Brown-Liburd et al. (2015) warn about information overload, relevance, and pattern recognition. Jarrahi (2018), Dellermann et al. (2019), Raisch and Krakowski (2021), and Choi and Xie (2026) describe forms of human–AI complementarity. Glikson and Woolley (2020) show how trust depends on system features and context. Estep et al. (2024) report how financial executives respond to artificial intelligence in reporting and audit. Jones and Free (2026) review artificial intelligence and machine learning across accounting work.

Explainability research adds a governance condition. Ribeiro et al. (2016) and Lundberg and Lee (2017) provide methods for local and feature-based explanation. The United States National Institute of Standards and Technology (NIST) places validity, transparency, explainability, accountability, and risk management inside its Artificial Intelligence Risk Management Framework (NIST, 2023). Regulation (EU) 2024/1689 sets legal duties for selected artificial intelligence systems and reinforces documentation, oversight, and risk controls. The International Auditing and Assurance Standards Board (IAASB) Technology Position also links audit quality with suitable technology use. Such sources support governance claims. They do not prove corporate preparers rewrite disclosures to manipulate models.

2.4. Distinguishing Machine-Readable Accountability from Adjacent Theories

Machine-readable accountability draws from several established theoretical streams while addressing a distinct problem: the translation of corporate reporting into structured

data processed by software. Table 1 compares its primary focus with digital accountability, algorithmic governance, socio-technical systems, institutional theory, and the sociology of quantification. The comparison identifies how machine-readable accountability connects accounting meaning, taxonomy design, validation procedures, computational interpretation, and responsibility across the reporting chain.

Table 1. Position of Machine-Readable Accountability relative to adjacent theories. Source: Author synthesis from the cited literature.

Adjacent Theory or Stream	Primary Concern	Unresolved Issue for Structured Reporting	Added Focus of Machine-Readable Accountability
Digital accountability	Answerability through digital systems	Limited attention to the accounting representation chain	Links accounting meaning, taxonomy mapping, validation, and use
Algorithmic governance	Rules and decisions implemented through algorithms	Often centres on decision systems rather than regulatory filings	Treats algorithms as readers and validators of corporate disclosure
Socio-technical systems	Joint operation of people, organisations, and technology	Broad unit of analysis	Defines actors and control points across a filing chain
Institutional theory	Rules, legitimacy, diffusion, and organisational response	Limited technical detail on tags and validation	Connects institutional pressure with concrete data structures
Sociology of quantification	Power effects of categories and measures	Less attention to machine parsing and software assurance	Adds computational visibility and traceable transformation ownership

3. Research Design and Documentary Corpus

3.1. Qualitative Documentary and Archival Design

The study uses qualitative documentary and archival analysis. Documentary research treats rules, manuals, standards, technical specifications, public data-quality records, and professional guidance as institutional records. Archival research examines records produced for regulatory, operational, or professional purposes rather than for the present study. Both forms suit a question centred on formal classification, validation, and assurance structures. They also provide a reproducible record of rule changes and public filing requirements. The unit of analysis is a discrete documentary passage recording a rule, regulator observation, assurance requirement, or governance duty.

The design contains no ethnographic access to preparers, auditors, or software teams. It does not infer private intention from final disclosure wording. The earlier claim of an enumerated 80-firm corporate sample lacked a retained filing register and has therefore been removed. The revised corpus uses identifiable document groups and official filing-evidence records. Public filings serve as document-level illustrations only where a source remains traceable. No firm-level frequencies, sector estimates, or population claims arise from those illustrations. Section 4 draws direct observations only from official and professional documents. Peer-reviewed studies serve as corroborating or boundary evidence in the literature review and discussion.

Documentary analysis supports institutional interpretation because the documents define permitted tags, extension relations, validation outcomes, assurance tasks, and governance duties. The design also has limits. Official texts describe formal systems and regulator observations. They do not reveal every local workaround or private judgement. The analysis addresses the gap through rival readings, negative-case review, and careful separation of observation from inference.

3.2. Jurisdiction, Period, and Inclusion Logic

The United States Securities and Exchange Commission and European Single Electronic Format settings were selected through purposive theoretical sampling. Both regimes require machine-readable reporting, publish technical rules, maintain structured taxonomies, and provide public guidance on validation and extensions. The United States setting supplies a long-running regime under United States generally accepted accounting principles and International Financial Reporting Standards filers. The European setting uses the IFRS Accounting Taxonomy with formal anchoring requirements. The pair supports comparison across two mature architectures without implying global representativeness.

Table 2 compares the SEC and ESEF regimes across their governing basis, covered issuers, reporting scope, filing architecture, and analytical consequences. The SEC framework relies on federal securities rules and the centralised EDGAR system, whereas ESEF operates under European Union legislation with enforcement conducted through national authorities. These institutional differences affect coverage, submission practices, regulatory oversight, and cross-jurisdictional comparison of structured financial data.

The core period runs from January 2020 to July 2026. The start captures operational European Single Electronic Format implementation and a mature phase of United States Inline XBRL use. The end reflects the final corpus lock. Earlier sources enter the corpus only when they establish a rule origin, a foundational empirical result, or a theoretical concept. Later updates supersede earlier manuals where rules changed.

Table 2. Main differences between the United States Securities and Exchange Commission regime and the European Single Electronic Format. Source: Author comparison based on SEC (2018, 2026b), European Commission (2019, 2026), and ESMA (2025).

Dimension	United States Securities and Exchange Commission (SEC)	European Single Electronic Format (ESEF)	Analytical Consequence
Governing basis	Federal securities rules, Regulation S-T, and the EDGAR filing architecture.	Transparency Directive framework and Delegated Regulation (EU) 2019/815, amended through 2026.	A central United States filing system differs from a European rule enforced through national authorities.
Covered issuers and reports	Operating companies subject to SEC structured-data rules, including domestic issuers and eligible foreign private issuers, across specified forms.	Issuers with securities admitted to trading on a European Union regulated market when publishing annual financial reports.	Coverage follows different legal entry points and report cycles.
Electronic document and filing route	Inline XBRL is embedded in HTML and filed through the Electronic Data Gathering, Analysis, and Retrieval system.	The entire annual financial report uses XHTML. Inline XBRL mark-up is embedded for IFRS consolidated financial statements under national filing arrangements.	Both combine human and machine readability, while package and filing architecture differ.
Accounting basis and taxonomy	United States generally accepted accounting principles taxonomy for domestic issuers and the IFRS taxonomy for eligible foreign private issuers.	The ESEF taxonomy extends the IFRS Accounting Taxonomy.	Taxonomy choice follows accounting basis in the United States and a common IFRS-centred European architecture.
Tagging scope	Specified cover-page and financial-statement information, including notes, schedules, and defined auditor information.	Detailed tagging of primary financial statements and block tagging of notes from financial years beginning on or after 1 January 2022.	The European regime combines whole-report XHTML with a defined hierarchy of detailed and block tagging.

Table 2. Cont.

Dimension	United States Securities and Exchange Commission (SEC)	European Single Electronic Format (ESEF)	Analytical Consequence
Issuer-specific extensions	A custom element is used when an appropriate standard element is absent, subject to SEC rules and EDGAR validation.	An extension element is used when the core taxonomy lacks a suitable element and is anchored to the closest wider or narrower core element.	European anchoring creates an explicit taxonomy relationship absent from the United States rule design.
Validation and oversight	EDGAR validation, SEC filing review, and separate custom-tag trend monitoring for United States GAAP and IFRS filers.	Technical validity under the regulatory technical standards and ESMA Reporting Manual, with enforcement by national competent authorities.	Oversight differs in institutional location, while both regimes combine automated checks and regulatory review.

Documents qualified for inclusion when they met at least one of four criteria: the document defined a structured-reporting rule, the document reported official filing-quality observations, the document specified verification or assurance practice, or the document defined artificial intelligence governance or machine-reading methods relevant to financial reporting. Primary documentary status required an official regulatory, standard-setting, enforcement, or professional source. Peer-reviewed studies formed a separate contextual set for theory, historical comparison, and external corroboration. Commentary without a stable source, anonymous web content, vendor marketing claims, and unverifiable citations were excluded.

3.3. Corpus Structure

The primary corpus comprises four official or professional archives. Peer-reviewed research forms a separate contextual set used for theory, historical comparison, and external corroboration. Section 4 draws direct observations from the primary corpus only.

Figure 1 presents the four primary documentary archives used in the study and distinguishes their respective evidential functions. Regulatory materials define formal reporting requirements, technical materials specify data structures and validation rules, corporate filings provide observable reporting practices, and enforcement records document identified deficiencies and regulatory responses.

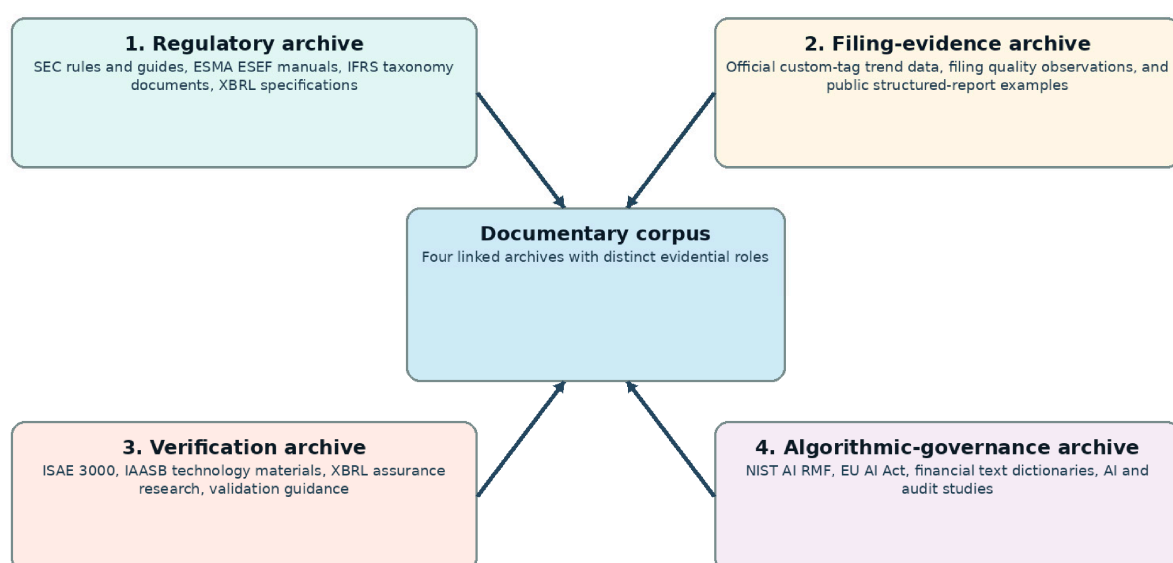


Figure 1. Structure of the four primary documentary archives and the distinct evidential role of each archive. Peer-reviewed studies provide contextual framing and corroboration outside the primary documentary results. Source: Author design based on the corpus register.

Following the documentary structure presented in Figure 1, Table 3 lists the document groups, temporal coverage, and analytical role assigned to each archive. Such classification supports a transparent link between the research questions, source selection, and documentary analysis.

Table 3. Primary documentary corpus registers and analytical roles. Source: Official materials listed in the References. Peer-reviewed studies form a separate contextual set.

Archive	Document Groups	Temporal Coverage	Analytical Role
Regulatory	SEC Inline XBRL final rule and EDGAR XBRL Guide; ESMA ESEF Reporting Manual and taxonomy documentation; IFRS Taxonomy Architecture; final XBRL specifications	Foundational rules plus updates through July 2026	Defines filing architecture, tagging, extensions, anchoring, and validation
Filing evidence	SEC United States GAAP and IFRS custom-tag trend records; regulator data-quality observations; traceable filing examples cited in official materials	Fiscal years mainly 2017–2024, accessed through July 2026	Tests whether formal concerns appear in observed filing records
Verification	International Standard on Assurance Engagements 3000; IAASB technology materials; official and professional assurance guidance	2008–2026	Defines evidence, assurance scope, controls, and professional judgement
Algorithmic governance	NIST Artificial Intelligence Risk Management Framework; European Union Artificial Intelligence Act; IAASB Technology Position	2023–2026	Defines machine-reading governance, model risk, explainability, traceability, and human review

3.4. Coding Protocol, Source Separation, and Researcher Validation

First-cycle coding assigned primary documentary passages to one or more code families. Second-cycle coding linked rules, observed filing evidence, assurance duties, and model-governance requirements. Peer-reviewed studies entered a separate corroboration pass after primary coding. The findings report coded documentary patterns, not citation counts or literature frequencies. The analysis then tested rival readings. A custom extension, for example, might represent poor taxonomy discipline or faithful entity-specific reporting. A validation warning might indicate a weak filing or a useful quality-control mechanism. Rival readings remained in the record until the source permitted a narrower interpretation.

A single researcher completed the coding. No intercoder coefficient is reported. Researcher validation relied on a written codebook, source-level citations, a second review after the initial coding pass, negative-case analysis, and an evidence-to-claim matrix. Each direct result in Section 4 traces to a primary document group. Claims lacking traceable support were downgraded to theoretical propositions or removed. The draft examples involving bespoke software revenue tags and lexical substitutions such as severe to ongoing were removed because their filing-level provenance was not documented.

Figure 2 summarises the six-stage documentary analysis workflow. The procedure moves from research-scope definition and corpus construction to first-cycle coding, cross-archive analysis, claim calibration, and theory development. Each stage preserves a clear distinction between documentary observations, interpretive inferences, and theoretical propositions.

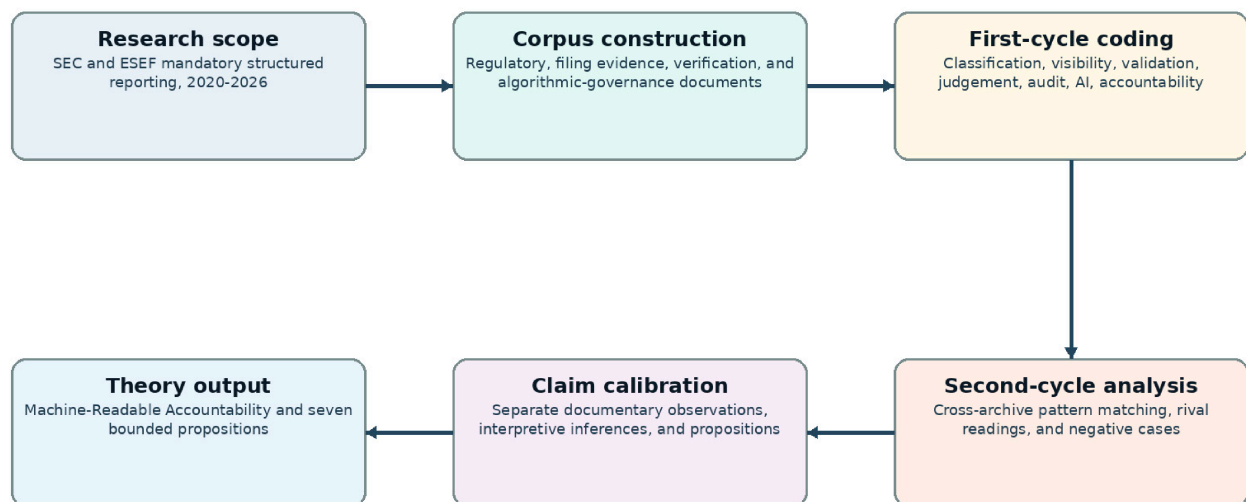


Figure 2. Documentary analysis workflow from scope definition to bounded theory development. Source: Author design.

Figure 3 presents the operational code families and their relationships across the four archives.

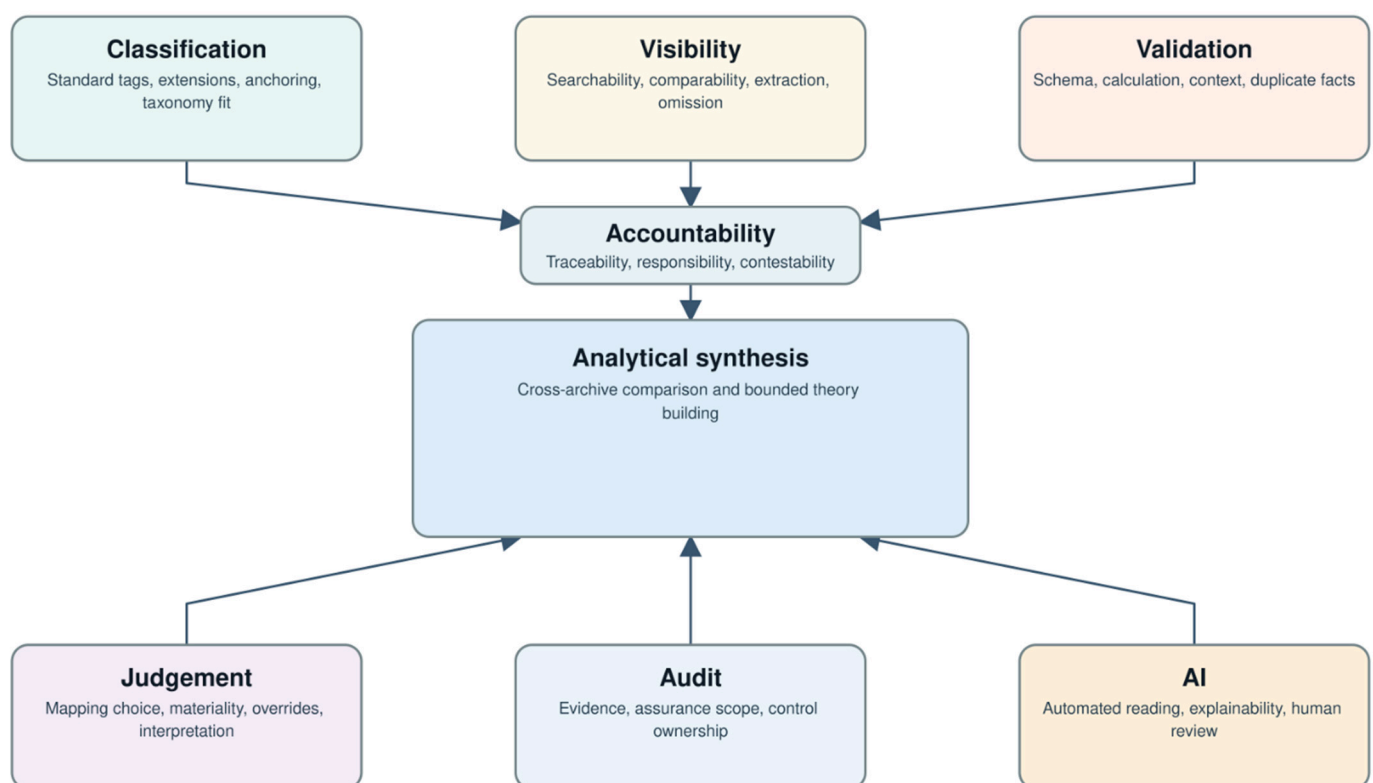


Figure 3. Seven operational code families used across the four archives. Source: Author design.

The coding process applied three code families: classification, visibility, and validation. Table 4 defines each family, states the inclusion and exclusion rules, and provides representative evidence types. These rules supported consistent coding and reduced the risk of assigning general disclosure observations to technically specific categories.

Table 4. Operational codebook with inclusion rules and representative evidence types. Source: Author design.

Code Family	Operational Definition	Include	Exclude
Classification	Choice and structure of reporting concepts	Standard elements, extensions, anchoring, dimensions	General discussion of disclosure without a classification rule
Visibility	Conditions affecting retrieval and comparison	Searchability, standardisation, extraction, omission, extension rates	Visual prominence without machine retrieval relevance
Validation	Formal tests applied to structured reports	Schema, calculation, context, duplicate facts, technical warnings	Substantive audit conclusions without a validation link
Judgement	Discretion in mapping, review, and override	Tag choice, materiality, exception approval, interpretation	Purely mechanical processing
Audit	Assurance scope and evidence	Control ownership, audit trail, digital evidence, review procedures	General technology discussion without assurance relevance
Artificial intelligence	Automated reading and model governance	Text classification, anomaly detection, explanation, human review	Unsupported claims about model use
Accountability	Assignment and contestability of responsibility	Data lineage, approval, escalation, liability, blame allocation	Technical errors without an ownership question

3.5. Evidence Standards for Documentary Results and Propositions

The study distinguishes three evidential levels. Level A consists of direct documentary observation from official or professional sources, such as an anchoring rule or an official custom-tag trend. Level B consists of an interpretation supported across several primary archives, such as the relocation of review work from printed statements towards a digital representation chain. Level C consists of a theoretical proposition requiring field or behavioural testing, such as deliberate disclosure wording aimed at model sentiment. Published empirical studies serve as external corroboration, and the text labels such status explicitly. Section 4 reports Levels A and B. The discussion states Level C propositions with explicit limits.

The revised evidence protocol changes the status of the seven propositions. They follow the cross-archive results in Section 5.3. Each proposition includes an evidence grade and a boundary condition.

4. Results of the Documentary Analysis

Section 4 reports outputs from the coded primary documentary corpus. Each subsection begins with direct observations from rules, manuals, regulator records, or professional standards. Peer-reviewed studies appear only where they corroborate a documentary pattern or define its boundary. The research design contains no interviews, survey evidence, or representative firm samples.

4.1. Taxonomy Design Produces Conditional Visibility: Cross-Regime Documentary Results

Cross-archive coding identified four recurring visibility mechanisms: taxonomy selection, permitted extension use, anchoring or relationship rules, and retrieval through filing infrastructure. Regulatory documents in both jurisdictions treat structured taxonomies as instruments for comparison and automated use. The IFRS Accounting Taxonomy reflects International Financial Reporting Standards presentation and disclosure requirements. The European Single Electronic Format extends the taxonomy for European filing. United States

Securities and Exchange Commission taxonomies serve a parallel function under United States filing rules. Standard elements support predictable extraction through stable concept identifiers, period types, balance attributes, data types, and dimensional relations.

The comparison in Table 2 shows a shared use of Inline XBRL with different institutional designs. The United States regime tags specified filing content within SEC forms and accepts United States generally accepted accounting principles or International Financial Reporting Standards taxonomies according to filer status. The European regime requires the entire annual financial report in XHTML and requires Inline XBRL mark-up for IFRS consolidated financial statements. Both regimes permit issuer-specific elements where the core taxonomy lacks a suitable concept. European rules add a formal anchoring requirement linking extensions to wider or narrower core elements. United States rules limit custom elements through appropriateness criteria and EDGAR validation.

Official custom-tag trend records form the filing-evidence result. Separate SEC analyses for United States generally accepted accounting principles and International Financial Reporting Standards filers track extension use across fiscal years. The records show sustained regulatory monitoring because custom tags preserve entity-specific meaning while reducing immediate cross-company comparability. The result supports conditional visibility. Standard tags enter automated comparisons more directly, while custom tags require extra mapping and review. Kim and Lee (2025) provide external firm-level corroboration linking excessive custom-tag use with control weakness and SEC scrutiny. Their study sits outside the primary documentary result.

Coding therefore supports a visibility gradient shaped by taxonomy alignment, extension design, anchoring, and user software. A well-designed extension remains machine-readable. It receives less immediate cross-firm comparability and often demands extra mapping logic. The documentary result rejects a binary visible–invisible divide.

4.2. Validation Improves Data Quality Without Proving Accounting Truth: Documentary Results

Coding of validation manuals and technical guides produced seven recurrent control objects: schema conformity, contexts, units, calculations, duplicate facts, dimensions, and filing-package integrity. Both regulatory regimes use automated tests to identify malformed structures and inconsistent relationships at scale. The official documents define a technical control layer with reproducible rules and exception messages. Historical studies by Debreceeny et al. (2010), Bartley et al. (2011), and Janvrin and No (2012) provide external evidence of the error types motivating those controls.

Cross-archive comparison also identified a stable boundary between syntactic validity and substantive accounting validity. A schema-valid fact might still use an unsuitable accounting concept. A calculation might add correctly while recognition or measurement remains wrong. A standard tag might pass validation while obscuring entity-specific meaning. The distinction arises from the coded relationship between technical manuals and assurance guidance.

The coded documents allocate repetitive structural testing to software and accounting meaning, materiality, context, and faithful representation to professional review. The resulting control design uses separate technical and substantive sign-offs and records ownership for every unresolved exception.

4.3. Professional Judgement Moves Across a Digital Representation Chain: Role-Mapping Results

Cross-archive role mapping generated a representation chain with ten stages: ledger data, financial-statement preparation, taxonomy mapping, extension design, context selection, dimensional modelling, validation, rendering, filing, and downstream extraction. Official assurance and technology materials assign decisions and evidence requirements

across these stages. The chain extends the audit object beyond displayed statements towards the data and metadata transformations preceding external use.

The coded role map locates judgement at six actor groups. Standard-setters define taxonomy content. Regulators define filing constraints. Preparers select concepts and extensions. Software designers encode mapping and validation logic. Auditors assess evidence, control design, and exception resolution. Data users configure extraction and analytical models. The documentary result concerns distributed decision rights across the representation chain. Plumlee and Plumlee (2008), Janvrin and No (2012), Vasarhelyi et al. (2012), Brown-Liburd et al. (2015), Appelbaum et al. (2017), and Samiolo et al. (2024) provide historical or empirical corroboration outside the primary documentary result.

Two governance outcomes follow from the role map. Specialist knowledge enters several control points. Weak documentation makes ownership harder to trace. Decision rights, version control, approval evidence, and escalation routes therefore form observable governance requirements across the archive.

4.4. Algorithmic Answerability Receives Uneven Documentary Support: Governance Results

Official governance documents confirm machine reading as an established use context for financial reporting. The coded material covers automated text classification, structured-data extraction, anomaly screening, explanation, documentation, and human review. Peer-reviewed work on natural language processing, machine learning, and large language models provides contextual evidence of wider use in accounting and audit (Loughran & McDonald, 2011; Issa et al., 2016; Kokina & Davenport, 2017; Estep et al., 2024; Choi & Xie, 2026; Jones & Free, 2026).

Cross-archive coding produced four recurring governance duties: intended-use documentation, performance validation, explanation suited to the method, and defined human-review thresholds. The NIST framework, the European Union Artificial Intelligence Act, and IAASB technology materials support traceability, oversight, and risk-management requirements. Ribeiro et al. (2016) and Lundberg and Lee (2017) provide contextual methods for explaining model output.

The primary corpus provides weak direct evidence of deliberate lexical rewriting in public corporate filings. The earlier draft used constructed phrase substitutions as empirical examples. The revision removes those examples. The documentary result is narrower: preparers operate in an environment of automated readers, creating a plausible incentive for machine-oriented drafting. Direct testing requires interviews, draft-to-final document pairs, or software logs. Algorithmic answerability therefore remains a theoretical proposition. The corpus does not establish it as observed practice.

The analysis separates findings drawn directly from the four documentary archives from claims supported through external research. Table 5 records the primary evidence, evidential status, and stated boundary for each claim. Such separation limits overstatement and shows where conclusions depend on corroboration, technical assumptions, or user behaviour.

Table 5. Evidence-to-claim matrix distinguishing primary documentary results from external corroboration. Source: Author analysis of the four primary archives.

Claim	Primary Evidence	Evidential Status	Boundary
Standard tags support automated comparison	Regulatory taxonomies and final XBRL specifications; capital-market studies as external corroboration	Direct documentary result with corroboration	Comparison still depends on correct mapping and user software
Extensions require extra interpretation	European anchoring rules and SEC custom-tag trend records; custom-tag studies as external corroboration	Direct documentary result with corroboration	Extensions also preserve entity-specific meaning

Table 5. Cont.

Claim	Primary Evidence	Evidential Status	Boundary
Validation differs from accounting verification	Validation manuals and assurance guidance; historical data-quality studies as external corroboration	Direct and cross-archive interpretation	Automated checks remain useful control evidence
Judgement is distributed across actors	Cross-archive role map from official and professional documents; implementation studies as corroboration	Cross-archive interpretation	Actor roles differ across firms and jurisdictions
Preparers rewrite disclosures for artificial intelligence sentiment	Machine-reading literature and governance documents only	Theoretical proposition	Needs draft–final pairs, interviews, or system logs
Fragmented chains create responsibility gaps	Control requirements and cross-archive role mapping	Interpretive proposition	Strong governance might reduce the gap

5. Discussion

5.1. Machine-Readable Accountability as a Bounded Construct

The documentary results support Machine-Readable Accountability as a bounded construct centred on the digital representation chain. The construct links three questions: which facts receive reliable computational visibility; where professional judgement enters the chain; and who remains answerable for each transformation and exception.

Dynamic visibility now refers to a gradient shaped by standard tags, extensions, anchoring, dimensions, filing quality, and extraction design. Distributed judgement refers to the allocation of discretion across human and technical roles. Responsibility displacement refers to a governance risk arising when decision rights and evidence do not follow the same allocation. The construct therefore differs from a claim of automatic accountability loss. Strong controls may make a distributed chain more traceable than a manual process.

The framework also joins two research traditions. Capital-market studies explain processing and information effects. Interdisciplinary studies explain category formation, professional work, and answerability. The combined view treats structured reporting as both information infrastructure and institutional control.

5.2. Benefits, Risks, and Rival Interpretations

A positive reading stresses democratised access, lower extraction cost, more consistent checks, and richer analytical use. Blankespoor et al. (2014), Liu et al. (2014), Blankespoor (2019), and Tawiah and Borgi (2022) provide support. A sceptical reading stresses data-quality errors, extension inconsistency, software dependence, and dispersed ownership. Debreceeny et al. (2010), Bartley et al. (2011), Janvrin and No (2012), and Kim and Lee (2025) support such concerns.

Both readings fit the archive. Outcomes depend on implementation quality, taxonomy fit, control design, user capability, and regulatory review. Machine-readable reporting therefore operates as a governed infrastructure. It does not produce transparency or opacity on its own.

Machine-readable reporting produces operational benefits alongside technical, organisational, and accountability risks. Table 6 assesses these effects across access, comparability, data quality, audit work, artificial intelligence, and accountability. Each documented benefit is paired with an associated risk and a corresponding governance response.

Table 6. Balanced assessment of machine-readable reporting. Source: Author synthesis from the cited evidence.

Dimension	Documented Benefit	Associated Risk	Governance Response
Access and processing	Faster extraction and lower processing cost	Unequal user capability and software dependence	Open taxonomies, accessible tools, user guidance
Comparability	Standard concepts support cross-firm analysis	Poorly fitted standard tags distort meaning	Extension policy, anchoring review, peer comparison
Data quality	Automated validation detects structural errors	Validator success may be mistaken for accounting correctness	Separate technical and substantive sign-off
Audit work	Population-level tests and reproducible exceptions	Opaque rules and alert overload	Rule inventory, thresholds, exception ownership
Artificial intelligence	Large-scale reading and anomaly screening	Model error, weak explanation, automation bias	Model documentation, human review, monitoring
Accountability	Digital logs support traceability	Fragmented roles weaken ownership	Responsibility matrix and end-to-end data lineage

5.3. Bounded Propositions Derived from the Documentary Findings

Proposition 1. *Strong documentary support. Machine-readable reporting relocates part of professional discretion from recognition and presentation towards taxonomy mapping, extension design, contexts, dimensions, and validation review.*

Proposition 2. *Strong documentary support. Standard taxonomy alignment increases automated comparability, while extensions preserve local meaning and require extra interpretation, anchoring, or mapping.*

Proposition 3. *Strong documentary support. Syntactic validation and substantive accounting verification address different failure modes and require separate control ownership.*

Proposition 4. *Strong documentary support. Digital assurance extends the audit object from displayed statements towards the representation chain linking source data, tags, metadata, validation, rendering, and filing.*

Proposition 5. *Moderate to strong support. Professional judgement is distributed across standard-setters, regulators, preparers, software designers, auditors, and users. The distribution varies with governance and outsourcing arrangements.*

Proposition 6. *Limited direct support. Anticipated machine reading creates incentives for algorithm-aware drafting, although deliberate lexical optimisation requires behavioural evidence beyond public final filings.*

Proposition 7. *Moderate support. Distributed responsibility increases the risk of blame transfer when data lineage, decision rights, exception ownership, and model accountability remain weak. Strong documentation and approval controls reduce this risk.*

5.4. Audit and Governance Controls

A practical control model follows from the analysis. The first control layer covers taxonomy governance. A documented policy should define standard-tag preference, extension criteria, anchoring review, and peer comparison. The second layer covers data lineage.

Each reported fact should link to source data, transformation logic, context, unit, dimensions, and approval. The third layer covers validation governance. Organisations should maintain a rule inventory, severity criteria, exception owners, and evidence of resolution.

The fourth layer covers assurance. Technical compliance and substantive accounting review should receive separate sign-offs. Audit procedures should test change management, access, version control, rendering consistency, and filing completeness. The fifth layer covers artificial intelligence. Model inventories, intended-use statements, validation results, explanation methods, human-review thresholds, and monitoring records should accompany automated reading or drafting tools.

A responsibility matrix should name the owner, reviewer, approver, and escalation route for each stage. Such controls reduce responsibility displacement and support later contestability. NIST (2023), the IAASB Technology Position, and Regulation (EU) 2024/1689 provide related governance principles, although entity-level application requires proportional design.

Figure 4 consolidates the three components of machine-readable accountability: dynamic visibility, distributed judgement, and responsibility displacement. The model traces corporate disclosure through the taxonomy and tagging layer to machine users, validators, regulators, and artificial intelligence systems. Reporting choices therefore affect data retrieval, the allocation of accounting judgement, and the attribution of responsibility when errors arise.

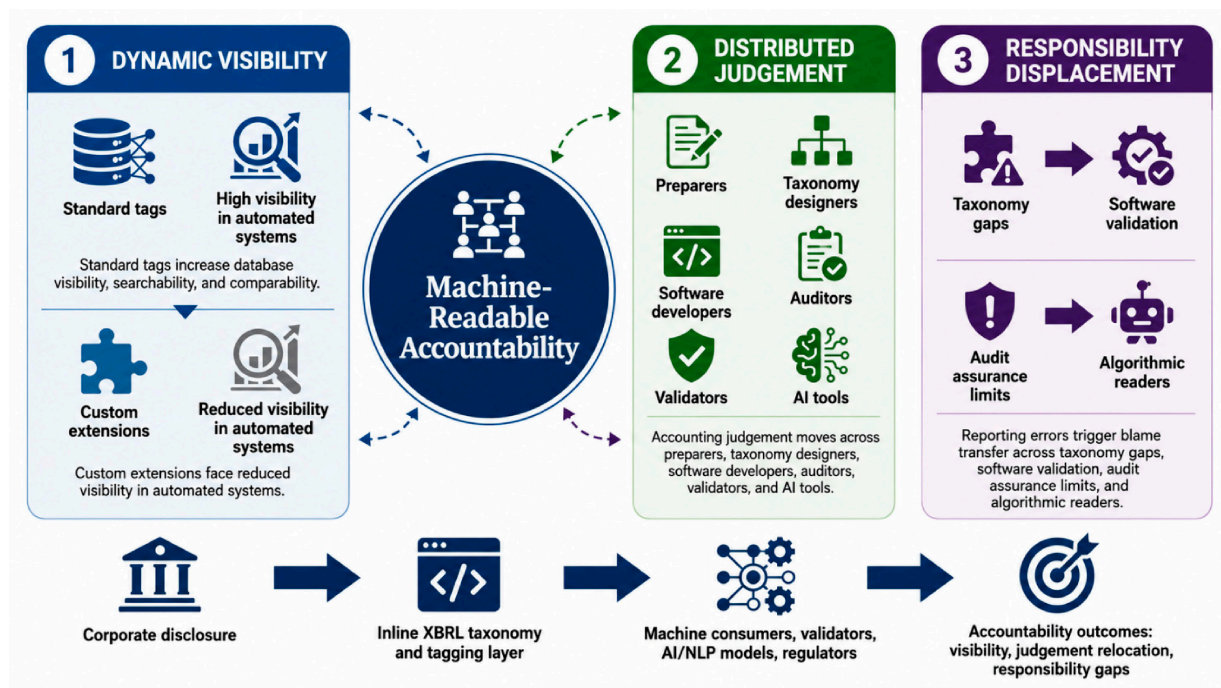


Figure 4. Machine-Readable Accountability. Dynamic visibility concerns retrieval treatment, distributed judgement concerns decision allocation, and responsibility displacement concerns weak ownership across the representation chain. Solid arrows show document and data movement. Dashed links show feedback between reporting choices and institutional users. Source: Author synthesis based on Sections 4 and 5.

6. Limitations

The study relies on public documents. Formal rules and official records provide traceability, yet they omit private negotiations, undocumented workarounds, and tacit professional reasoning. Interviews, observation, and system logs would provide direct behavioural evidence.

The United States Securities and Exchange Commission and European Single Electronic Format regimes are mature mandatory settings. Results do not represent smaller markets, voluntary regimes, private companies, or jurisdictions with limited enforcement and technical capacity. Differences between United States taxonomies and European anchoring also restrict simple cross-jurisdiction transfer.

The revised corpus does not claim a representative firm sample. Public filing examples and official trend records support document-level interpretation. They do not support sector frequencies or causal estimates. The removal of the earlier 80-firm claim narrows the empirical reach and improves source traceability. Peer-reviewed studies serve as contextual and corroborating evidence. The primary results arise from coded official and professional documents.

A single researcher coded the corpus. A codebook, second-pass review, negative cases, and source-level evidence reduce interpretive drift. They do not replace independent coding. Later studies should use multiple coders or publish a full coded repository where licencing and filing formats permit.

Artificial intelligence changes quickly. Current governance sources and accounting studies capture a defined period ending in July 2026. New models, agentic workflows, or reporting rules will require renewed analysis. Public final filings also provide weak evidence about preparer intention. The study therefore presents algorithmic answerability as a proposition requiring direct field testing.

7. Conclusions

Machine-readable reporting changes accountability through the structure of the reporting chain. Standard tags, extensions, contexts, validation rules, rendering, assurance, and automated use all influence how a disclosure travels from accounting records to external judgement. The documentary analysis supports three linked results. Visibility depends on taxonomy and retrieval design. Judgement moves across a network of professional and technical actors. Responsibility requires explicit ownership across every transformation.

Structured reporting also produces measurable benefits. It reduces extraction costs, supports comparison, and permits automated quality checks. Risks arise when standard tags fit poorly, extensions lack disciplined review, validation replaces substantive verification, or artificial intelligence operates without traceable human oversight. Governance design determines which effect dominates.

Machine-Readable Accountability provides a focused construct for studying those conditions. Future research should pair public archives with interviews, draft-to-final disclosure comparisons, audit workpapers, software logs, and cross-market replication. Such work would test algorithm-aware drafting, quantify responsibility gaps, and compare control designs across the United States Securities and Exchange Commission, European Single Electronic Format, emerging-market, and smaller-entity settings.

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