

The Role of Big Data and AI In Capital Market Based Accounting

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ABSTRACT

This study used a Systematic Literature Review (SLR) to examine the role and use of Big Data and Artificial Intelligence (AI) in capital market-based accounting and identify factors influencing the effectiveness of their implementation. The study followed the PRISMA 2020 protocol. From 437 records obtained through eight keyword combinations in the Scopus database, 29 studies were selected after filtering based on the 2016–2026 publication period, Q1–Q4 journal quality, and thematic relevance. The study grouped the literature into four main aspects: data infrastructure, analytical processing, disclosure and reporting, and governance and assurance. These four aspects were then integrated into the AI-Accounting Value Chain and Governance Loop (AVC-GL) model. The findings indicate that Big Data expands information sources for accounting and capital market analysis, while AI helps process complex data and supports decision-making. However, the effectiveness of its implementation is highly dependent on data quality, governance, professional oversight, and human ability to evaluate technological outcomes. The use of generative AI also improves the efficiency of corporate disclosures, but introduces new risks, including greenwashing. This study contributes through the development of a functional taxonomy and AVC-GL model to explain the relationship between technology, governance, information quality, and decision-making in capital markets.

Keywords: Big Data; Artificial Intelligence (AI); Capital Market Accounting

INTRODUCTION

The development of modern capital markets is characterized by the increasing complexity, volume, and speed of information flow available to market participants. In this context, the role of accounting is no longer limited to providing historical financial reports, but has evolved into providing strategic information that influences investor decision making and market efficiency. Stock prices are assumed to reflect all available market information, both public and private (Vega, 2006; Goldstein, 2023). However, advances in digital technology indicate that the information processed by the market is no longer limited to traditional accounting data but also includes unstructured data such as news, social media, and various digital based indicators (Liu & Liu, 2023; Mashiro, 2026).

Along with these developments, the concepts of Big Data and Artificial Intelligence (AI) have become increasingly important in supporting large scale information processing and analysis (Almanasra, 2024). Big Data enables the collection and processing of data with high volume, velocity, and variety, while AI, through approaches such as machine learning and natural language processing, is able to identify patterns and extract relevant information from complex data (Qaffas, 2023; Ahmed, 2023). The integration of these two technologies has transformed the design of capital market based accounting, particularly in improving the ability to predict company performance, analyze risks, and interpret financial and non financial information simultaneously.

From a Behavioral Finance perspective, the use of Big Data and AI also opens up opportunities for a deeper understanding of investor behavior (Tetlock, 2007; Mu, 2023). These technologies not only improve the quality of information analysis but also broaden understanding of the dynamics of investor behavior in the capital market (Putri & Tanno, 2024). Investors no longer rely solely on traditional financial reports but also consider various alternative sources of information processed through intelligent algorithms.

However, empirical literature on the role of Big Data and AI in capital market based accounting still shows mixed and inconsistent results (Thanasas & Kapiotis, 2024). Several studies have found that the integration of Big Data and AI can improve the value relevance of accounting information and the accuracy of stock price predictions (Nissim, 2022; Malik, 2024) and (Eachempati, 2021; Zhu, 2025). Conversely, other studies have shown that the complexity of AI based models can create transparency and interpretability issues (black box problems), potentially reducing investor confidence in the information generated (Prasad, 2021; Khan, 2025). This situation suggests a trade off between increasing analytical accuracy and information transparency.

Furthermore, from a Signaling Theory perspective, information generated through advanced technology should provide stronger signals to the market (Spence, 1973). However, the effectiveness of these signals depends heavily on investors' ability to understand and interpret technology based information. Differences in technological literacy levels, information access, and market characteristics can influence investor reactions to information generated by Big Data and AI.

Based on the above description, it can be concluded that although Big Data and AI have great potential in improving the quality of accounting information and capital market efficiency, understanding of their role and effectiveness is still not well described. Therefore, a systematic approach is needed to identify, evaluate, and synthesize existing research findings. This study uses a Systematic Literature Review (SLR) approach to examine how Big Data and AI are used in capital market based accounting, and to identify factors that influence the effectiveness of their implementation. The contribution of this research is as a study of accounting literature theory in the capital market, study material for the government, investors and companies that have interests.

LITERATURE REVIEW

Capital Market Based Accounting and Basic Theory

Capital market based accounting emphasizes the role of accounting information in influencing investor decisions and stock price formation (Lev & Thiagarajan, 1993; Rahmana & Liua, 2021). Furthermore, Signaling Theory explains that information provided by a company serves as a signal for investors in assessing the company's prospects and value (Spence, 1973). In the context of modern capital markets, these signals come not only from financial reports but also from various other, increasingly complex and diverse information sources. Therefore, information quality is key to reducing information discrepancies and increasing investor confidence.

Big Data and Artificial Intelligence in Accounting

Big Data refers to data with high volume, velocity, and variety, enabling the processing of large scale and diverse information (Casado & Younas, 2015; Yaqoob, 2016). In accounting, Big Data expands information sources beyond structured financial data to include unstructured data such as text, news, and digital activity. Meanwhile, Artificial Intelligence (AI) enables automated data analysis through techniques such as machine learning and natural language processing, thereby identifying patterns and generating more accurate predictions (Lin & Lobo Marques, 2024). In the capital markets context, the integration of Big Data and AI increases the relevance and timeliness of accounting information and supports data driven investment decision making. The effectiveness of implementing Big Data and AI in accounting is determined not only by technological capabilities but also by data quality and model transparency.

Big Data, AI, and Investor Behavior

From a Behavioral Finance perspective, investment decisions are not always rational but are instead influenced by psychological factors such as cognitive biases and emotions (Kahneman &

Tversky, 1979). The use of Big Data and AI allows for a more in depth analysis of investor behavior through alternative data such as social media, news, and trading activity.

This technology enables the identification of behavioral patterns such as herding behavior, overreaction, and changes in market sentiment in real time (Barberis et al., 1998; Bollen et al., 2011). Thus, Big Data and AI not only improve the quality of information analysis but also broaden understanding of the dynamics of investor behavior in the capital market. However, on the other hand, the use of intelligent algorithms also has the potential to amplify certain biases if the data or models used are not completely neutral.

Based on the conceptual framework and literature review outlined above, this study formulates the following research questions:

RQ1. What are the roles and forms of use of Big Data and Artificial Intelligence in capital market based accounting?

RQ2. What factors determine the effectiveness of implementing Big Data and Artificial Intelligence in the context of capital market based accounting?

METHODOLOGY

Research Design

This study uses a Systematic Literature Review (SLR) design that follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 protocol. The SLR design was chosen based on the research objective to systematically and reproducibly map how Big Data and Artificial Intelligence (AI) play a role in capital market-based accounting, while also identifying conceptual gaps and future research agendas. The PRISMA 2020 protocol was chosen because it provides a four-stage reporting structure identification, screening, eligibility assessment, and inclusion that allows the literature selection process to be traced transparently and re-audited by other researchers (Agrawal, 2024).

Data Sources and Literature Search Strategy

The single data source used was the Scopus database, chosen for its extensive coverage of reputable indexed journals in the fields of accounting, finance, information systems, and law, as well as the availability of journal quartile metadata (SJR quartile) required for the quality screening stage in 3.3. The search strategy was constructed from eight keyword combinations representing the conceptual intersection between technology (Big Data, AI) and the capital market accounting domain (accounting, financial reporting, capital market, corporate disclosure). The eight keyword combinations were run separately in the Title-Abstract-Keyword fields, except for the “Corporate Disclosure and AI” combination which produced a much larger record volume (157 records) so the search field was narrowed to Abstract-only to maintain the precision of the results before being combined with the other seven combinations. The details of the number of records per keyword are presented in Table 1.

Table 1. Conceptual Framework for Keyword Selection

No	Search Keywords Search	Search Field	Number of Raw Records	Abstract Restrictions
1	AI and Accounting	Title-Abstract-Keyword	121	No
2	Big Data and Accounting	Title-Abstract-Keyword	104	No
3	Big data capital markets	Title-Abstract-Keyword	7	No
4	AI and Capital Market	Title-Abstract-Keyword	7	No
5	AI and Financial Reporting	Title-Abstract-Keyword	13	No

6	Big Data and Financial Reporting	Title-Abstract-Keyword	9	No
7	Financial reporting capital markets	Title-Abstract-Keyword	19	No
8	Corporate Disclosure and AI	Abstract-only	157	Yes
Total			437	

Inclusion Criteria for Article Selection Process (PRISMA Flow)

The eligibility of retrieved records was determined through five sequential inclusion and exclusion criteria, as summarized in Table 2. The publication period was restricted to 2016–2026 to capture the rapid advancement of research on Big Data analytics and Artificial Intelligence (AI) in accounting and capital market-related studies. Furthermore, only Scopus-indexed journals ranked in Quartiles 1–4 (Q1–Q4) were included to ensure methodological rigor, publication quality, and academic credibility, consistent with established practices in systematic literature reviews within the fields of accounting, finance, and information systems.

Table 2. Inclusion and Exclusion Criteria

Criteria	Inclusion	Exclusion
Publication year	Studies published between 2016 and 2026	Studies published outside the 2016–2026 period
Journal quality	Articles published in Scopus-indexed journals (Q1–Q4)	Articles published in journals without a clearly identified Scopus quartile ranking
Document completeness	Studies with an available abstract for screening and accessible full text	Studies without an abstract for screening or whose full text could not be retrieved after reasonable search efforts
Record uniqueness	A single unique record for each publication	Duplicate records identified within the database
Thematic relevance	Studies examining Big Data and/or Artificial Intelligence in the context of accounting, financial reporting, corporate disclosure, auditing, or capital markets	Studies containing the search keywords but lacking substantive relevance to accounting, financial reporting, or capital market contexts (e.g., AI applications in healthcare, manufacturing, or engineering)

The selection process follows the four stages of PRISMA 2020 identification, screening, eligibility assessment, and inclusion as visualized in Figure 1.

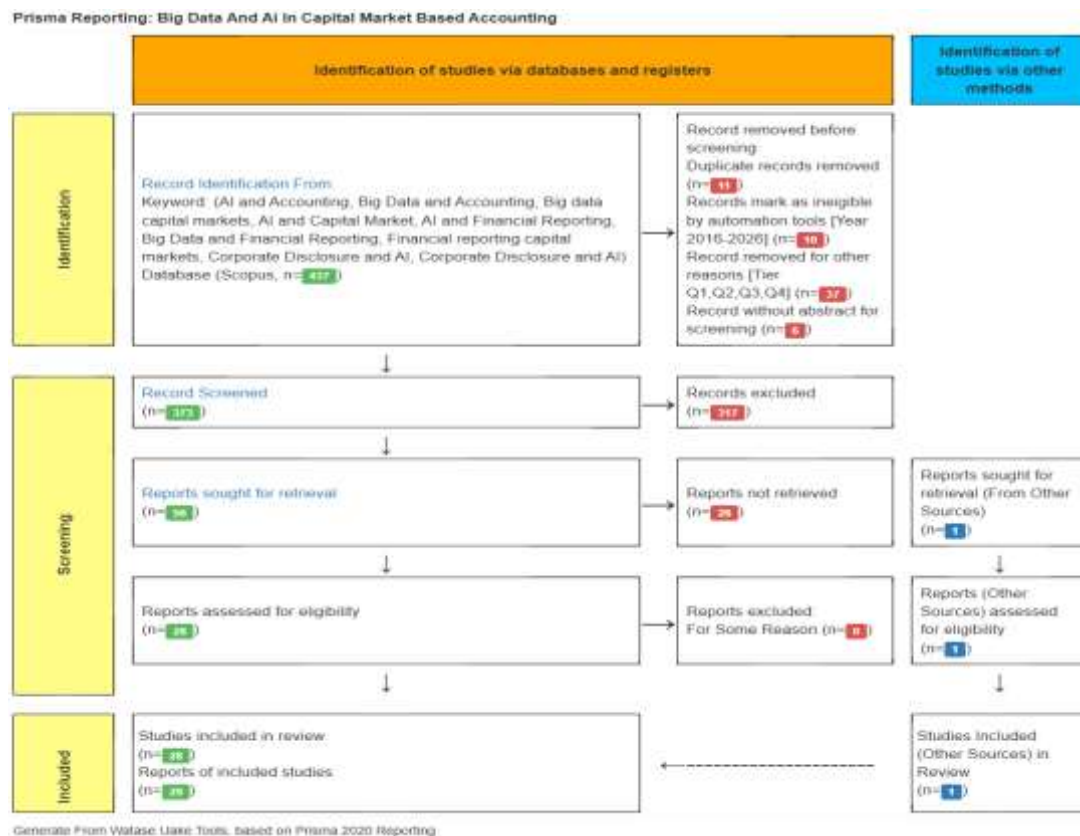


Figure 1. Magnetization

Source: Data Processing From The Wataseuake Website

The search strategy initially identified 437 records from the Scopus database. Following the PRISMA protocol, duplicate records ($n = 11$) were removed. Automated filtering was then applied to include only publications published between 2016 and 2026 ($n = 10$ removed). Furthermore, studies that did not meet the journal quality criteria (non-Q1–Q4 indexed journals) ($n = 37$) and publications without abstracts ($n = 6$) were excluded during the identification stage.

After these procedures, 373 records remained for title and abstract screening. Based on relevance to the research objectives, 317 studies were excluded because they did not specifically address the application of Big Data or Artificial Intelligence within capital market-based accounting. Consequently, 56 reports were retained for full-text retrieval. Of these, 28 articles could not be retrieved due to access limitations, leaving 28 studies for eligibility assessment.

In addition to the database search, one relevant study was identified through manual searching of reference lists and other complementary sources. This study satisfied all eligibility criteria and was incorporated into the final review.

Therefore, the final dataset consisted of 29 studies (28 studies retrieved from Scopus and one study identified through other sources), which formed the basis for the thematic synthesis.

RESULTS

The Scopus search initially identified 437 records. After removing duplicates ($n = 11$), publications outside the 2016–2026 period ($n = 10$), articles from journals not meeting the Q1–Q4 quality criteria ($n = 37$), and records without abstracts ($n = 6$), 373 records remained for title and abstract screening. Of these, 317 were excluded due to irrelevance to Big Data and Artificial Intelligence applications in capital market-based accounting, leaving 56 reports for full-text retrieval. Because 28 reports were inaccessible, 28 studies proceeded to eligibility assessment and met the inclusion criteria. One additional eligible study was identified through complementary searching. Thus, the final dataset comprised 29 studies: 28 retrieved from Scopus and one identified

through other sources, which formed the basis for the thematic synthesis.

Table 3. Presents The 29 Studies

No	Authors (Year)	Research Focus	Primary RQ
1	(Meng & Friginal, 2026)	Stakeholder-targeted engagement strategies in corporate AI ethics statements	RQ2
2	(Jędrzejka, 2026)	Conceptual analysis of AI dependence and erosion of accounting expertise	RQ2
3	(Bashir Elsharif et al., 2026)	AI-enabled accounting intelligence and capital market performance, mediated by disclosure quality and comparability	RQ1 & RQ2
4	(Bustelo-Gracia & Miró-Pérez, 2026)	AI adoption and intangible-asset visibility/valuation, IBEX 35 firms	RQ1
5	(Monteiro et al., 2023)	AI adoption intensity, internal control quality, and accounting information system quality	RQ2
6	(Vilchez Olivares & Astorga De La Cruz, 2026)	SLR of AI/Big Data in sustainable financial reporting and ESG disclosure	RQ1
7	(Xu et al., 2026)	Mechanism linking Generative AI to corporate ESG performance, China	RQ1
8	(Shi et al., 2026)	AI-derived brand visibility and sentiment as drivers of Bitcoin ETF capital flows	RQ1
9	(Haffar et al., 2026)	Framing bias and AI-channel reliance as moderators of investor reaction to disclosures, UAE	RQ2
10	(Alzeghoul & Alsharari, 2025)	AI disclosure and financial reporting/performance, US banks	RQ1
11	(Yu et al., 2026)	Hybrid NLP-deep learning model for corporate performance prediction using strategic text	RQ1
12	Artene, Domil & Ivascu (2024) (Artene et al., 2024)	AI-driven decision support in financial reporting systems	RQ1
13	(Almaqtari, 2024b)	IT governance as a condition for effective AI integration in accounting/auditing	RQ2
14	Huy & Phuc (2024) (Huy & Phuc, 2024)	Big Data analytics, accounting information systems and forensic-accountant skill in the public sector	RQ2
15	(Dimes et al., 2026)	Experimental evidence that Generative AI perpetuates greenwashing in sustainability reports	RQ1
16	(Ye & Li, 2017)	Foundational review of internet Big Data sources and methods in capital market research	RQ1
17	(Bradshaw et al., 2026)	Generative AI use by information intermediaries, Seeking Alpha	RQ1
18	(Ecker et al., 2026)	How investors query Generative AI platforms for stock-related information	RQ1
19	(Blankespoor et al., 2026)	Generative AI content detected in corporate disclosures	RQ1
20	(Katona et al., 2025)	Satellite-based Big Data and information asymmetry in capital markets	RQ1
21	(Yap & Lim, 2022)	Legal framework for AI fairness reporting (comply-or-explain disclosure)	RQ2

22	(Ante & Saggu, 2025)	NLP-based construction of firm-level AI-engagement indices from 10-K filings	RQ1
23	(Kongthon & Sae-Lim, 2026)	Transformer models and Generative AI applied to climate-risk disclosure, banking sector	RQ1
24	(Nissim, 2022a)	Review of Big Data/machine-learning applications in accounting-based valuation	RQ1
25	(Basnet et al., 2025)	Market reaction to actionable vs. speculative AI narratives in corporate filings	RQ1
26	(Qiu et al., 2026)	Generative-AI-based readability as a disclosure-quality proxy, linked to ESG rating divergence	RQ1
27	(C. Liu et al., 2026)	AI-empowered green finance and carbon asset pricing	RQ1
28	(Lehner, 2026)	Foucauldian analysis of how AI reconfigures the production of accounting "truth"	RQ2
29	(Huttunen et al., 2019)*	Foundational review of Big Data, cloud computing, and data science applications in finance and accounting	RQ1

The complete distribution of articles based on the country or region of origin of the research is presented in Table 4. Summarizes the distribution based on the lead or corresponding author's institutional affiliation.

Table 4. Geographic Distribution of the 29 Included Articles

Country/Region	Number of Articles
China	5
United States	4
Jordan	2
Finland	2
Romania	1
Portugal	1
Spain	1
Peru	1
United Arab Emirates	1
South Korea	1
Yemen	1
Vietnam	1
New Zealand	1
France	1
Singapore	1
Germany	1
Thailand	1
Canada	1
Poland	1
Hong Kong SAR	1
Total	29

A Four-Layer Functional Taxonomy of Big Data and AI in Capital Market Based Accounting

Rather than treat the 29 studies as an undifferentiated list, this review organizes them into four functional layers through which Big Data and AI operate in capital market-based accounting. The layers are cumulative: each depends on the one beneath it, and together they form the backbone of the integrative model presented in the Discussion.

Table 5. Four Layer Functional Taxonomy Cross-Study Synthesis

Layer	Function	Representative Studies	Synthesis Finding	RQ
1. Data Infrastructure	Sourcing and structuring non-traditional data as raw informational input	Ye & Li (2017); Huttunen et al. (2019); Katona et al. (2025); Ante & Saggu (2025); Shi et al. (2026); Basnet et al. (2025)	Internet, satellite, textual-filing, and social-media data have matured into legitimate, quantifiable inputs to capital market research; access to premium sources (e.g., satellite imagery) creates asymmetric informational advantage rather than eliminating it	RQ1
2. Analytical Processing	Converting raw data into decision relevant signals via NLP/ML/transformer models	Yu et al. (2026); Kongthon & Sae-Lim (2026); Qiu et al. (2026); Ecker et al. (2026); Bradshaw et al. (2026)	Hybrid NLP deep learning and transformer architectures materially improve prediction and readability-measurement accuracy over structured-data-only baselines, but investor engagement with GenAI outputs is conditional on conciseness and directional accuracy of the signal produced	RQ1
3. Disclosure and Reporting	Embedding AI output directly into financial and sustainability disclosures	Blankespoor et al. (2026); Artene et al. (2024); Dimes et al. (2026); Xu et al. (2026); Vilchez Olivares & Astorga De La Cruz (2026); Haffar et al. (2026); Alzaghoul & Alsharari (2025); Bustelo-Gracia & Miró-Pérez (2026); Liu et al. (2026)	Generative AI already authors a measurable share of corporate disclosure text and materially shapes how intangible assets, ESG performance, and green-finance instruments are communicated; the same generative capacity that improves consistency can also be exploited or misjudged, as shown experimentally in AI-perpetuated greenwashing	RQ1
4. Governance and Assurance	Institutional, ethical, and legal oversight	Almaqtari (2024); Meng & Friginal (2026); Yap & Lim	Effective AI integration is conditioned on IT	RQ2

	of the preceding three layers	(2022); Lehner (2026); Monteiro et al. (2023); Huy & Phuc (2024); Jędrzejka (2026)	governance maturity, stakeholder-differentiated ethics communication, comply-or-explain fairness reporting, and preservation of professional judgment; absent governance, AI functions as an unaccountable arbiter of accounting "truth"	
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Source: Processed by the author based on thematic analysis (2026)

Of the 29 articles, 19 primarily address RQ1 (roles and forms of use), 8 primarily address RQ2 (determinants of effectiveness), and 2 (Bashir et al., 2026; and, in a mediating sense, Huy & Phuc, 2024) address both simultaneously by explicitly modeling disclosure quality or professional skill as the mechanism linking AI/Big Data adoption to capital market or reporting outcomes.

DISCUSSION

RQ1. The Roles and Forms of Big Data and AI Use in Capital MarketBased Accounting Big Data as a Source of New Information for Capital Market Analysis

Ye & Li, (2017) demonstrated that Big Data obtained from internet forums, microblogs, and search activities can be used to measure investor sentiment and attention in capital market research. This development was further supported by Huttunen et al., (2019), who highlighted the growing role of cloud computing and data science in transforming how financial and accounting information is collected, processed, and analyzed. Katona et al., (2025) extended this development by showing that satellite imagery can provide additional information for capital market analysis and generate informational advantages for investors with access to such alternative data. Taken together, these studies indicate a fundamental expansion in the information environment of capital markets. Information relevant to investment decisions is no longer derived exclusively from standardized corporate reports but increasingly from diverse and high-frequency data sources, including internet activity, satellite imagery, corporate filings, social media, and other alternative data. The significance of this development lies not merely in the greater volume of available information, but in the ability of Big Data and AI technologies to convert previously unstructured and non-traditional signals into analyzable information for accounting, valuation, and investment decision-making. However, the increasing use of alternative data also raises important concerns regarding unequal data access, information asymmetry, and the potential concentration of informational advantages among investors with superior technological and analytical capabilities. Thus, the expansion of Big Data in capital market-based accounting simultaneously creates new opportunities for more timely and comprehensive analysis while potentially introducing new forms of informational inequality.

AI Based Analytical Processing: Transforming Data into Decision-Relevant Information

Beyond expanding the range of available data, the reviewed studies demonstrate that the principal contribution of Big Data and AI lies in their ability to transform heterogeneous information into decision-relevant insights. Rather than relying solely on structured financial indicators, recent AI applications increasingly integrate textual disclosures, sustainability reports, and other unstructured information through Natural Language Processing (NLP), deep learning, and transformer-based models. This shift represents a transition from data collection toward intelligent information processing, enabling accounting information to become more predictive, timely, and context-sensitive.

Yu et al., (2026) show that combining structured financial data with unstructured corporate disclosures through a hybrid NLP and deep-learning framework substantially improves corporate performance prediction compared with conventional models based only on financial variables.

Similarly, Kongthon & Sae-Lim, (2026) demonstrate that transformer-based models enhance the analysis of climate-risk disclosures in the banking sector, while Qiu et al., (2026) show that Generative AI can produce scalable readability measures that provide an alternative indicator of disclosure quality and help explain differences in ESG ratings across agencies. Collectively, these studies indicate that AI is increasingly employed not only to automate analytical tasks but also to extract meaningful patterns from complex accounting and disclosure data that would be difficult to identify using traditional analytical techniques.

Nevertheless, the reviewed evidence also suggests that greater analytical capability does not necessarily translate into higher informational quality. Ecker et al., (2026) report that investors value AI-generated information primarily when it is concise, relevant, and directionally accurate, indicating that the usefulness of AI depends more on the quality of generated insights than on the sophistication of the underlying model. Likewise, Bradshaw et al., (2026) find that although Generative AI significantly increases the volume of financial commentary and expands coverage of previously under-researched firms, AI generated analyses generally receive weaker market responses than human-produced analyses. This finding implies that automation can improve efficiency and scalability without necessarily enhancing the credibility or informational value perceived by market participants.

Taken together, these studies reveal a common pattern across the literature. AI substantially strengthens the analytical capacity of capital market-based accounting by converting large volumes of structured and unstructured data into actionable information. However, the effectiveness of this analytical process ultimately depends on the relevance, interpretability, and reliability of the generated outputs rather than on computational capability alone. Consequently, the value of AI in accounting should be evaluated not only by its ability to produce more information, but also by its capacity to generate information that improves decision quality for investors and other capital market participants.

Generative AI in Corporate Disclosure and Reporting

The reviewed studies show that Generative AI is increasingly moving beyond the role of an analytical tool and becoming directly involved in the production of corporate disclosures. This represents an important change in the accounting information process because AI is no longer used only to analyze existing information but can also contribute to the generation of information communicated to investors and other stakeholders.

Blankespoor et al., (2026) provide evidence that Generative AI has already been used to produce content in several types of corporate disclosures. Their findings show that AI-generated text has linguistic characteristics that differ from human-written text, indicating that AI is becoming an increasingly visible part of the corporate reporting process. Similarly, Artene et al., (2024) show that AI can improve financial reporting through faster anomaly detection, real-time data processing, and the integration of information from multiple sources. These findings suggest that AI can improve the efficiency and timeliness of financial reporting.

However, the use of Generative AI in disclosure also creates important risks. Dimes et al., (2026) provide experimental evidence that AI can contribute to greenwashing in sustainability reports. Their findings show that AI-generated sustainability statements may appear more credible and positive even when the underlying content is misleading. This finding demonstrates that persuasive language does not necessarily indicate reliable information. AI may therefore improve the presentation of information without necessarily improving its quality or truthfulness. Consequently, AI generated disclosures require effective human review and clear accountability mechanisms.

The evidence from X. Xu et al., (2026) and Vilchez & Astorga, (2026) further indicates that the effects of Generative AI are not uniform. When supported by reliable information, innovation capabilities, and appropriate reporting processes, AI can contribute positively to ESG performance and sustainability reporting. In addition, (Bustelo-Gracia & Miró-Pérez, 2026) show that AI adoption is associated with greater visibility and valuation of intangible assets, while C. Liu et al., (2026) demonstrate that AI-enabled green finance can influence the pricing of carbon-related assets. Overall, these findings indicate that AI is increasingly influencing the preparation of financial and

sustainability information as well as the way investors evaluate emerging forms of corporate value and financial assets.

Governance and Assurance of AI in Accounting

While the previous evidence highlights the expanding role of AI in data processing and disclosure production, the reviewed studies show that technological capability alone cannot guarantee the reliability of AI-enabled accounting information. Governance and assurance therefore represent a separate and essential dimension of AI integration. This dimension determines whether the data used by AI are reliable, whether analytical outputs can be evaluated, whether AI-generated disclosures are sufficiently transparent, and whether human professionals retain the capacity to challenge potentially misleading outputs.

Almaqtari, (2024a) emphasizes the importance of IT governance in ensuring that AI systems are properly aligned with organizational objectives, monitored for risks, and subject to appropriate control mechanisms. Monteiro et al., (2023) further show that AI adoption and internal control quality are closely associated with the quality of accounting information systems. These findings indicate that effective AI implementation requires more than access to advanced technology; it also requires organizational structures capable of monitoring and controlling its use.

Governance also includes ethical and legal considerations. Meng & Frigal, (2026) demonstrate that corporate AI ethics statements use different engagement strategies for different stakeholder groups, suggesting that AI governance communication may reflect strategic stakeholder management rather than uniform transparency. Yap & Lim, (2022), meanwhile, propose a legal framework for AI fairness reporting that emphasizes greater transparency regarding the use and fairness of AI systems. Together, these studies show that the governance of AI in accounting involves not only technical control but also questions of accountability, fairness, transparency, and responsibility.

The role of professional judgment is equally important. Jędrzejka, (2026) warns that excessive dependence on AI may gradually weaken the accounting expertise required to evaluate AI-generated outputs. Huy & Phuc, (2024) show that professional expertise can strengthen the value of Big Data analytics in accounting-related risk management. This issue is particularly important in light of the findings of Dimes et al., (2026), which demonstrate that human involvement does not automatically guarantee effective oversight. Human reviewers may remain formally involved in the process while failing to make meaningful corrections to AI generated content.

Taken together, these findings demonstrate that governance and assurance determine whether the benefits identified in the previous sections can be achieved without compromising the integrity of accounting information. The effectiveness of AI in capital market-based accounting therefore depends on the interaction between technological capabilities and governance capacity. Strong IT governance, ethical and legal safeguards, professional expertise, and meaningful human oversight are necessary to ensure that AI improves the quality and usefulness of accounting information rather than merely increasing the speed and volume of information production

RQ2. Factors Determining the Effectiveness of Big Data and AI Implementation

IT Governance and Internal Controls

The reviewed studies indicate that the effectiveness of AI in accounting depends not only on the adoption of the technology but also on the organization's ability to manage and control it. Almaqtari, (2024b) shows that strong IT governance helps organizations monitor AI systems, evaluate their outputs, identify potential risks, and maintain records of AI-based decisions. This suggests that AI adoption without appropriate governance may increase technological capability without ensuring the reliability of its results.

Monteiro et al., (2023) provide further evidence that AI adoption and internal control quality are positively associated with the quality of accounting information systems. Their findings indicate that the benefits of AI are more likely to emerge when organizations have adequate control mechanisms and organizational capabilities. However, the use of convenience sampling in their study limits the generalizability of the findings. Taken together, the evidence suggests that IT

governance and internal controls are important conditions for effective AI implementation, although they cannot by themselves guarantee high-quality outcomes.

Ethics, Fairness, and Transparency

The effectiveness of AI also depends on how organizations address ethical and transparency issues. Meng & Friginal, (2026) show that companies communicate their AI ethics practices differently to different stakeholder groups. This finding suggests that corporate AI ethics communication may serve not only as a transparency mechanism but also as a form of strategic stakeholder communication. Therefore, the existence of an AI ethics statement does not necessarily guarantee that an organization's AI practices are fully transparent or accountable.

Yap & Lim, (2022) propose a legal framework that encourages organizations to disclose information about the use and fairness of AI systems. Such disclosure can help stakeholders understand how AI is used and whether its outputs may produce unfair results. Lehner, (2026) extends this discussion by arguing that AI may influence how accounting information is produced and accepted as evidence. As AI increasingly contributes to accounting judgments and reporting processes, questions of responsibility and professional accountability become more important. These studies collectively indicate that effective AI implementation requires not only technical performance but also transparency regarding how AI systems operate and how their outputs are used.

Professional Expertise and Human Oversight

The reviewed studies also highlight the continuing importance of professional expertise. Jędrzejka, (2026) argues that excessive reliance on AI may gradually weaken the accounting knowledge and professional judgment needed to evaluate AI-generated outputs. This creates a potential long-term risk: organizations may become increasingly dependent on AI while simultaneously losing the human expertise required to challenge its errors.

Dimes et al., (2026) provide supporting evidence by showing that users did not always critically revise AI-generated sustainability disclosures, even when encouraged to improve them. This finding demonstrates that simply keeping a human involved in the process does not guarantee effective oversight. In contrast, Huy & Phuc, (2024) show that the skills of forensic accountants can strengthen the contribution of Big Data analytics to risk management. The combined evidence therefore suggests that human expertise remains valuable when professionals possess sufficient knowledge and are actively involved in evaluating AI outputs.

Data Quality, Investor Behavior, and Disclosure Quality

The effectiveness of Big Data and AI also depends on the quality of the data used and how the resulting information is interpreted by investors. Nissim, (2022a) emphasizes that Big Data and machine-learning models are only useful when the underlying accounting information is relevant and properly structured. Large amounts of data do not automatically produce better valuation or decision-making outcomes.

The reviewed studies further show that investor characteristics influence the market consequences of AI-enabled information. Haffar et al., (2026) find that framing bias and reliance on AI-based information channels affect how investors respond to negative financial disclosures. This means that the same information may produce different investor reactions depending on how it is presented and how investors obtain and interpret it.

Similarly, Basnet et al., (2025) show that investors respond more positively to AI-related disclosures when they are supported by specific implementation plans and observable evidence, such as subsequent research and development or patent activity. In contrast, general or speculative AI claims receive limited market attention. Bashir Elsharif et al., (2026) provide further evidence that AI adoption does not directly improve capital market performance. Its effects are realized through improved disclosure quality and greater comparability of financial information.

Theoretical Gaps and Implications for Accounting Theory

The reviewed studies show that AI and Big Data are increasingly changing how accounting information is produced, processed, and communicated to capital market participants. However, the literature has paid limited attention to how these changes affect the assumptions underlying traditional accounting theories. In particular, the role of AI as an intermediary between firms and investors creates challenges for the conventional assumptions of Signaling Theory and Behavioral Finance.

Traditional Signaling Theory assumes that firms communicate information to investors, who then interpret these signals. However, the increasing use of AI in financial reporting and corporate disclosure makes this process more complex. AI can now generate, modify, summarize, and influence the information communicated by firms (Blankespoor et al., (2026); Artene et al., (2024). Therefore, the information received by investors may no longer represent only the firm's original signal. It may also reflect the characteristics and objectives of the AI system used to produce or process that information. This creates a theoretical gap because existing Signaling Theory does not fully explain how the credibility of a signal should be assessed when the signal is partly produced or modified by AI. Evidence that Generative AI may also facilitate greenwashing further demonstrates that greater technological sophistication does not necessarily guarantee greater information quality (Dimes et al., 2026). Thus, future research should examine whether the credibility of AI-mediated accounting information depends not only on the firm's incentives but also on the transparency, reliability, and auditability of the AI system.

A similar issue emerges in Behavioral Finance. Traditional Behavioral Finance primarily explains market bias through human cognitive limitations and investor behavior. However, the reviewed studies suggest that bias may also be introduced before information reaches the investor. AI systems can influence which information is retrieved, how it is summarized, and how it is presented to users Haffar et al., (2026); Ecker et al., (2026). Consequently, a biased investment decision may not result solely from investor irrationality; it may also be influenced by the AI-mediated information channel. This distinction is important because current Behavioral Finance research generally does not clearly separate bias originating from the investor from bias introduced by the technology used to access financial information.

These findings suggest that AI has created a new relationship in capital market-based accounting: the traditional firm–investor relationship is increasingly becoming a firm–AI–investor relationship. This represents an important theoretical implication of the review. AI should not be viewed merely as a technological tool that improves accounting efficiency. It increasingly functions as an information intermediary that can influence the production, interpretation, and communication of accounting information. Therefore, future accounting theory should pay greater attention to the role of AI in shaping information credibility, investor interpretation, and market outcomes. The AI-Accounting Value Chain and Governance Loop (AVC-GL) proposed in this study provides an initial conceptual framework for understanding this process by emphasizing that the effectiveness of AI in accounting depends not only on its analytical capabilities but also on the quality of data, governance, human oversight, and the transparency of the AI process. Nevertheless, this framework should be considered a conceptual contribution that requires further empirical testing.

CONCLUSION

This study aims to examine the role of Big Data and Artificial Intelligence (AI) in capital market-based accounting and identify factors that determine the effectiveness of their implementation. The research was conducted through a systematic literature review of 29 Scopus-indexed studies published between 2016 and 2026 using the PRISMA 2020 protocol. The study grouped research findings into four main aspects: data infrastructure, analytical processing, disclosure and reporting, and governance and assurance. These four aspects then formed the basis for the development of the AI-Accounting Value Chain and Governance Loop (AVC-GL) model. The results show that Big Data expands the sources of information available for accounting and capital market analysis, including internet, satellite, and text data. Meanwhile, AI helps process large amounts of unstructured information to generate insights that can support analysis and decision-making. The

use of AI is also growing in the preparation and disclosure of corporate information. However, the use of this technology does not automatically result in higher-quality accounting information or better market decisions. Its effectiveness is heavily influenced by data quality, IT governance, internal controls, professional expertise, human oversight, and regulatory and ethical support. This study also shows that AI is no longer merely a technical tool but is beginning to influence how accounting information is generated, processed, and received by investors. This creates a more complex relationship between companies, AI, and investors. These findings suggest that accounting theory, which has traditionally explained the direct relationship between companies and investors, needs to consider the role of technology as an information intermediary. Based on these findings, the AVC-GL model proposes that governance should not only be implemented after information is generated but should be applied continuously, from data collection and analysis to disclosure.

Practically, the study's findings suggest that companies need to develop the use of AI in alignment with governance, internal controls, and professional expertise. Regulators also need to consider clearer rules regarding the use of AI in the preparation and disclosure of corporate information. For investors, the use of technology to generate information requires critical consideration, as faster and more information does not necessarily mean more accurate or useful information. This study has limitations because it only used the Scopus database and included 29 studies, most of which were from specific countries and capital markets. Furthermore, research on organizational and governance factors that determine the effectiveness of AI implementation is still more limited than research on its role and use. Future research should empirically test the AVC-GL model, examine how technology can influence investors' information interpretation processes, and conduct longitudinal studies on the impact of AI use on accounting information quality and professional expertise.

REFERENCES

- Agrawal, S. (2024). PRISMA guidelines in business and accounting research: A systematic literature review approach. *International Journal of Research Methodology*, 18(2), 145–158.
- Ahmed, A. (2023). Artificial intelligence and machine learning in financial markets: A review. *Journal of Financial Technology*, 15(2), 112–125.
- Almanasra, M. (2024). Big Data analytics in accounting and finance: Frameworks and opportunities. *International Journal of Accounting Information Systems*, 52, 100650.
- Almaqtari. (2024a). Determinants of artificial intelligence adoption in accounting and auditing practices. *Journal of Financial Reporting and Accounting*, 22(1), 112–135.
- Almaqtari, F. A. (2024b). The Role of IT Governance in the Integration of AI in Accounting and Auditing Operations. *Economies*, 12(8). <https://doi.org/10.3390/economies12080199>
- Alzeghoul, A., & Alsharari, N. M. (2025). Impact of AI Disclosure on the Financial Reporting and Performance as Evidence from US Banks. *Journal of Risk and Financial Management*. <https://doi.org/10.3390/jrfm18010004>
- Ante, L., & Saggi, A. (2025). Quantifying a firm's AI engagement: Constructing objective, data-driven, AI stock indices using 10-K filings. *Technological Forecasting and Social Change*. <https://doi.org/10.1016/j.techfore.2024.123965>
- Artene, A. E., Domil, A. E., & Ivascu, L. (2024). Unlocking Business Value: Integrating AI-Driven Decision-Making in Financial Reporting Systems. *Electronics*, 13(15). <https://doi.org/10.3390/electronics13153069>
- Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, 49(3), 307–343.
- Bashir Elsharif, M. S., Afaneh, M. K. K., Allahham, M., & Almajali, M. (2026). AI-enabled accounting intelligence and capital market performance: The mediating role of disclosure quality and financial information comparability. *Decision Science Letters*. <https://doi.org/10.5267/j.dsl.2026.6.005>
- Basnet, A., Elias, M., Salganik-Shoshan, G., Walker, T., & Zhao, Y. (2025). Analyzing the market's reaction to AI narratives in corporate filings. *International Review of Financial Analysis*. <https://doi.org/10.1016/j.irfa.2025.104378>
- Blankespoor, E., DeHaan, E., & Li, Q. (2026). Generative AI in Financial Reporting. *Journal of*

- Accounting Research*. <https://doi.org/10.1111/1475-679X.70050>
- Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computer Science*, 2(1), 1–8.
- Bradshaw, M. T., Ma, C., Yost, B. P., & Zou, Y. (2026). Generative AI Use by Capital Market Information Intermediaries: Evidence from Seeking Alpha. *Journal of Accounting Research*. <https://doi.org/10.1111/1475-679x.70053>
- Bustelo-Gracia, J. L., & Miró-Pérez, A. (2026). Artificial intelligence and intangible asset valuation in public markets: Evidence from IBEX 35 firms. *Intangible Capital*. <https://doi.org/10.3926/ic.3545>
- Casado, R., & Younas, M. (2015). Emerging trends and technologies in Big Data processing. *Future Generation Computer Systems*, 48, 4–15.
- Dimes, R., de Villiers, C., Denny, P., & Leinonen, J. (2026). The Impact of Generative AI on the Perpetuation and Detection of Greenwashing in Sustainability Reports: Insights From an Experiment. *Business Strategy and the Environment*. <https://doi.org/10.1002/bse.70983>
- Eachempati, P. (2021). Can AI improve stock price prediction accuracy? Evidence from capital market accounting. *Annals of Operations Research*, 303(1), 215–238.
- Ecker, F., Li, X., Li, Y., & Wu, F. (2026). How Stock Market Participants Use Generative Artificial Intelligence: Evidence from User-Platform Interaction Data. *Journal of Accounting Research*. <https://doi.org/10.1111/1475-679x.70051>
- Goldstein, I. (2023). Information flow and market efficiency in modern capital markets. *Review of Financial Studies*, 36(4), 1455–1490.
- Haffar, M., Hussain, S. M., Alaya, A., Emik, S., & Jammal, M. (2026). Financial Accounting Disclosures (FAD) in the UAE: Investor Reactions to Negative Financial News, Framing Bias and AI Channel Reliance. *Journal of Risk and Financial Management*. <https://doi.org/10.3390/jrfm19060438>
- Huttunen, J., Jauhiainen, J., Lehti, L., Nylund, A., Martikainen, M., & Lehner, O. M. (2019). Big Data, Cloud Computing and Data Science Applications in Finance and Accounting. *ACRN Journal of Finance and Risk Perspectives*, 8, 16–30. <https://www.datamation.com/big-data/structured-vs-unstructured-data.html>
- Huy, P. Q., & Phuc, V. K. (2024). Optimization of Accounting Information System in Public Sector for Sustainable Risk Management under Big Data Analytics. Does Forensic Accountants' Skill Generate Differences? *Foundations of Management*. <https://doi.org/10.2478/fman-2024-0005>
- Jędrzejka, D. (2026). The AI paradox: How AI dependence may erode accounting expertise. *Zeszyty Teoretyczne Rachunkowości*. <https://doi.org/10.5604/01.3001.0055.6632>
- Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), 263–291.
- Katona, Z., Painter, M. O., Patatoukas, P. N., & Zeng, J. (2025). On the Capital Market Consequences of Big Data: Evidence from Outer Space. *Journal of Financial and Quantitative Analysis*. <https://doi.org/10.1017/S0022109023001448>
- Khan, S. (2025). The black box problem in financial AI: Transparency versus accuracy. *Journal of Behavioral and Experimental Finance*, 45, 100890.
- Kongthon, A., & Sae-Lim, P. (2026). Analyzing climate risk disclosures in the banking sector using transformer models and generative AI. *Journal of Open Innovation: Technology, Market, and Complexity*. <https://doi.org/10.1016/j.joitmc.2026.100815>
- Lehner, O. M. (2026). AI and the production of truth in accounting practices: A Foucauldian analysis. *Critical Perspectives on Accounting*. <https://doi.org/10.1016/j.cpa.2026.102862>
- Lev, B., & Thiagarajan, S. R. (1993). Fundamental information analysis. *Journal of Accounting Research*, 31(2), 190–215.
- Lin, Z., & Lobo Marques, J. (2024). Artificial intelligence in accounting: Automated data analysis and future directions. *Accounting and Business Research*, 54(1), 45–72.
- Liu, C., Gao, J., Liu, Z., & Liu, K. (2026). Green finance development empowered by artificial intelligence: Evidence from the perspective of carbon asset pricing. *International Review of Economics and Finance*. <https://doi.org/10.1016/j.iref.2026.105145>

- Liu, Y., & Liu, J. (2023). Unstructured data processing in capital markets: News, social media, and stock prices. *Journal of Financial Data Science*, 5(3), 88–104.
- Malik, A. (2024). Value relevance of accounting information in the era of Big Data and AI. *The Accounting Review*, 99(2), 311–335.
- Mashiro, K. (2026). Digital-based indicators and traditional accounting data: A comparative study. *Asian Journal of Accounting and Finance*, 8(1), 12–29.
- Meng, Y., & Frigal, E. (2026). Engaging stakeholders, shaping AI ethics: Targeted engagement in corporate AI ethics statements. *PLOS ONE*. <https://doi.org/10.1371/journal.pone.0340796>
- Monteiro, A., Cepêda, C., Da Silva, A. C. F., & Vale, J. (2023). The Relationship between AI Adoption Intensity and Internal Control System and Accounting Information Quality. *Systems*. <https://doi.org/10.3390/systems11110536>
- Mu, Y. (2023). Behavioral finance in the era of AI: Deepening the understanding of investor behavior. *Journal of Banking & Finance*, 154, 106920.
- Nissim, D. (2022a). Big data, accounting information, and valuation. *The Journal of Finance and Data Science*, 8, 69–85. <https://doi.org/10.1016/j.jfds.2022.04.003>
- Nissim, D. (2022b). Machine learning in financial analysis: Predicting performance and returns. *Columbia Business School Research Paper*, 22(14).
- Prasad, A. (2021). Model interpretability and investor confidence in AI-driven capital markets. *Journal of Financial Regulation and Compliance*, 29(5), 510–525.
- Qaffas, A. (2023). Natural language processing in capital market-based accounting. *IEEE Access*, 11, 45210–45222.
- Qiu, X., Gan, X., & Zhang, C. (2026). Generative AI-based readability as a measure of disclosure quality: Evidence from ESG rating divergence. *International Review of Economics and Finance*. <https://doi.org/10.1016/j.iref.2026.105364>
- Rahmana, A., & Liua, X. (2021). Capital market-based accounting: A review of information relevance. *International Journal of Finance & Accounting*, 10(2), 77–89.
- Shi, J., Wang, Z., Ding, D., Wang, Y., Xia, C., Ding, Q., & Lim, T. (2026). Who Gets the Flows? AI-Based Brand Visibility, Social Media Sentiment, and Capital Allocation in the U.S. Spot Bitcoin ETF Market. *Mathematics*. <https://doi.org/10.3390/math14111959>
- Spence, M. (1973). Job Market Signaling. *The Quarterly Journal of Economics*, 87(3), 355. <https://doi.org/10.2307/1882010>
- Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, 62(3), 1139–1168.
- Thanasas, G., & Kapiotis, T. (2024). Big Data and AI in capital markets: A systematic literature review of mixed empirical evidence. *Journal of Financial Reporting and Accounting*, 22(3), 601–625.
- Vega, C. (2006). Stock price reaction to public and private information. *Journal of Financial Economics*, 82(1), 103–133.
- Vilchez Olivares, P. A., & Astorga De La Cruz, B. J. (2026). AI and Data Analytics in Sustainable Financial Reporting and ESG Disclosure: A Systematic Literature Review. *Sustainability*. <https://doi.org/10.3390/su18115393>
- Xu, X., Li, H., & Zhang, J. (2026). How Can Generative AI Promote Corporate ESG Performance? Evidence from China. *Sustainability*. <https://doi.org/10.3390/su18062853>
- Yap, J. Q., & Lim, E. (2022). A Legal Framework for Artificial Intelligence Fairness Reporting. *Cambridge Law Journal*. <https://doi.org/10.1017/S0008197322000460>
- Yaqoob, I. (2016). Big Data analytics: Architecture, opportunities, and open research challenges. *Computers in Human Behavior*, 59, 288–298.
- Ye, M., & Li, G. (2017). Internet big data and capital markets: a literature review. *Financial Innovation*. <https://doi.org/10.1186/s40854-017-0056-y>
- Yu, Q., Xing, C., He, Y., Ahn, S., & Na, H. J. (2026). Intelligent Information Processing for Corporate Performance Prediction: A Hybrid Natural Language Processing (NLP) and Deep Learning Approach. *Electronics*. <https://doi.org/10.3390/electronics15020443>
- Zhu, W. (2025). The integration of AI algorithms in capital market research. *Journal of Corporate Finance*, 90, 102710.