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**Leveraging AI to Enhance Double Materiality Assessment:
Exploration of Opportunities and Constraints**

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Abstract

Novel European compliance standards against greenwashing and selective sustainability reporting entail challenges for many companies. This paper aims to investigate the potential of Artificial Intelligence to enhance Double Materiality Assessments under the Corporate Sustainability Reporting Directive. By analyzing existing AI technologies and their applications in the DMA process, the research identifies opportunities and constraints. The paper uses a mixed methods approach consisting of a Literature Review, Market Scan, and Content Analysis. The findings highlight the potential of Artificial Intelligence in streamline data gathering, process automation and improving the efficiency and quality of DMAs. However, challenges such as data bias, privacy concerns, and the need for transparency and explainability in AI models necessitate careful consideration. This paper contributes to the growing body of knowledge on the intersection of AI and integrated reporting, providing valuable insights for companies navigating the complexities of DMAs and promoting the strategic use of AI for enhanced ESG governance.

Keywords

double materiality assessment, CSRD, financial materiality, impact materiality, integrated reporting, artificial intelligence, machine learning, natural language processing, large language models, generative AI, market scan, content analysis

Content

1	Introduction	1
2	Requirements and Challenges of Double Materiality Assessment	7
3	Artificial Intelligence	11
3.1	Natural Language Processing	15
3.2	Machine Learning, Large Language Models, and Generative AI	17
4	AI Opportunities in Double Materiality Assessments	19
4.1	Improve Efficiency, Productivity, and Reduce Manual Error	19
4.2	Reduce Opportunity Costs	20
4.3	Detecting Greenwashing, Enhancing Transparency, and Stakeholder Watch	21
5	AI Limitations in Double Materiality Assessments	22
5.1	ESG Considerations	22
5.2	Bias, Privacy, and Data Validity	22
5.3	Entity-Specific Considerations and Inclusion of Value Chain Information	23
5.4	Alleviation of AI Limitations in DMAs	24
6	Methodology	25
7	Findings	30
7.1	AI Applications in Step A: Understanding the Context	32
7.1.1	Saving Time	32
7.1.2	Data Centralization and Structuring	33
7.1.3	Compliance with Legal Frameworks	33
7.1.4	Stakeholder and Value Chain Analysis Preparation	34
7.2	AI Applications in Step B: Identification of Sustainability-Related IROs	35
7.2.1	Identification of Opportunities	35
7.2.2	Integration of Management Systems and Company Portfolios	36

7.2.3	Performance Comparison and Benchmarking.....	36
7.3	AI Applications in Step C: Assessment & Determination of Material IROs	37
7.3.1	Process Automation	37
7.3.2	Quantification of IROs	37
7.4	AI Applications in Step D: Reporting Material IROs	38
7.4.1	Text Summarizing and Automated Data Analysis.....	38
7.4.2	Accuracy and Reliability of Data	38
7.5	Systematic Content Analysis Findings.....	39
7.5.1	Variation in Materiality Approaches and CSRD Preparedness	39
7.5.2	Sustainability Reporting Frameworks and AI Adoption	40
7.5.3	AI in Business Functions and DMAs.....	40
8	Discussion.....	43
9	Conclusion.....	49
10	References.....	53

Figures

Figure 1 Overview of Analyzed EFRAG Documents	7
Figure 2 The Relationship Between Different AI Subfields Discussed in Paper	12
Figure 3 AI Levels of Advancement, Learning Types, and Examples	13
Figure 4 The Five NLP Models	16
Figure 5 Machine Learning Forms	17
Figure 6 Three-staged Methodology Process Towards Findings	25
Figure 7 Literature Review Selection Process Stages	27
Figure 8 AI DMA Providers' Value Proposition for Opportunities alongside DMA Steps	31

Tables

Table 1 Content Analysis – Initial Results	41
Table 2 AI Deployment Categories of Largest EU Companies	42

List of Acronyms and Abbreviations

AI	Artificial Intelligence
CRM	Customer Relationship Management
CSRD	Corporate Sustainability Reporting Directive
DMA	Double Materiality Assessment
EFRAG	European Financial Reporting Advisory Group
ERP	Enterprise Resource Planning
ESAP	European Single Access Point
ESEF	European Single Electronic Format
ESG	Environmental, Social, and Governance
EU	European Union
GenAI	Generative Artificial Intelligence
GHG	Greenhouse Gas
GPTs	Generative Pretrained Transformers
GRI	Global Reporting Initiative
HGB	German Commercial Code
IASB	International Accounting Standards Board
IFRS	International Financial Reporting Standards
IG	Implementation Guide
IROs	Impacts, Risks, and Opportunities
LLMs	Large Language Models
ML	Machine Learning
NFI	Non-Financial Information
NFRD	Non-Financial Reporting Directive
NGOs	Non-Governmental Organization
NLP	Natural Language Processing
SASB	Sustainability Accounting Standards Board
SCM	Supply Chain Management
SDGs	Sustainability Development Goals
SMEs	Small and Medium-sized Enterprises
TCFD	Task Force on Climate-related Financial Disclosures
WEF	World Economic Forum
XAI	Explainable Artificial Intelligence
XBRL	eXtensible Business Reporting Language
XML	eXtensible Markup Language

1 Introduction

The EU has undergone a significant change in policy orientation over the past decade. The adoption of the 17 Sustainable Development Goals (SDGs) and the commitment outlined in the Paris Agreement marked a significant transition from a focus on financial recovery following the 2008 financial crisis to a broader emphasis on environmental and social objectives. The Non-Financial Information (NFI) Directive highlighted the necessity of integrating financial and non-financial data in 2017. The objective was to advance a more integrated approach to corporate reporting that aligns with the sustainability objectives of the EU (Baumüller & Sopp, 2022).

The European Green Deal was initiated to facilitate the transition towards sustainability, addressing significant challenges such as climate change, biodiversity loss, and pollution (European Commission, 2019, p. 1). The Corporate Sustainability Reporting Directive (CSRD) is a product of the Green Deal, stemming from the revision of the Non-Financial Reporting Directive (NFRD), which pertains to large, listed companies, banks, and insurers with over 500 employees. This revision of the NFRD was proposed in the design of the Green Deal in 2019, with the objective of implementation in 2020 (European Commission, 2019, p. 4; European Parliament, 2024). A clear description of business models concerning sustainability risks and opportunities is essential in this transition into the Green Deal. This entails analyzing the influence of sustainability issues on the business's long-term viability and their integration with broader economic changes, such as the European Green Deal (EFRAG, 2021b, pp. 63–70).

Materiality is a fundamental concept to the financial industry, referring to the data that businesses are required to provide to investors (Delgado-Ceballos et al., 2023). The International Accounting Standards Board (IASB) defines financially material information as that which, if omitted, misstated, or obscured, could influence the decisions of primary users of financial reports (IASB, 2018, p. A26). The concept of materiality within the European Union (EU) has undergone significant evolution over time. The Non-Financial Reporting Directive (NFRD) permitted reporting entities to establish materiality criteria. The CSRD elaborates on the concept of double materiality and establishes the European Sustainability Reporting Standards (ESRS) to ensure the comparability of disclosures (Miettinen, 2024).

Global Reporting Initiative (GRI) and International Financial Reporting Standards (IFRS) focus on impact materiality and financial materiality, respectively (Miettinen, 2024), whereas the CSRD is founded on the concept of double materiality. The CSRD integrates impact and financial materiality into a unified framework, encompassing financial materiality, impact materiality, and their intersection. Companies must report on material Environmental, Social, and Governance (ESG) issues that significantly affect their financial development and/or the environment as a result of their business activities (EFRAG, 2024a).

The concepts of impact and financial materiality are interrelated, with financial consequences frequently resulting from environmental and social impacts (Audencia et al., 2023). *Delgado-Ceballos et al.* define impact materiality as 'stakeholder materiality,' which pertains to ESG-related business externalities. The authors indicate that impact materiality has increasingly gained traction among both financial and non-financial stakeholders, leading to the emergence of the double materiality concept. The concept of double materiality provides a thorough understanding of the relationship between businesses and their ESG-related externalities regarding impact (2023). 'Dynamic materiality' refers to the process by which initially non-financial ESG impacts may develop into financial risks or opportunities over time (EFRAG, 2021a, p. 8). Linking financial and impact materiality improves the understanding of how sustainability aspects affect financial performance (EFRAG, 2021b, pp. 63–70).

The European Single Access Point (ESAP), a unified EU platform, collects disclosed data and makes it easily accessible. To help stakeholders make investment and policy decisions, ESAP combines corporate sustainability data and other data in one central location (EU, 2023b). Technologies like eXtensible Business Reporting Language (XBRL) help comply with regulatory frameworks like the European Single Electronic Format (ESEF), a key step toward digital information reporting (EFRAG, 2021b, pp. 55–61). XBRL¹ improves web financial data quality and accessibility for consistency and comparability in corporate reporting. Unique tags can be attached to reported information, improving disclosure precision (xbrl.org, n.d.).

¹ XBRL is a variant of XML (eXtensible Markup Language) specifically designed for business reporting, providing explicit semantics in a machine-readable format (Yoon et al., 2011)

The use of ESEF has been broadened to encompass sustainability reporting via the CSRD, aiming to enhance the digital usability of such reporting by improving comparability and establishing a digital taxonomy. The CSRD proposes that sustainability reports be prepared in the ESEF format, facilitating integration with the ESAP (European Commission, 2021). The upcoming incorporation of the ESRS XBRL taxonomy for digital reporting seeks to enable the systematic tagging of sustainability information in a structured, machine-readable format, thereby improving transparency and comparability of sustainability disclosures throughout the EU (EFRAG, 2024c, pp. 5–6). Technologies such as iXBRL² ensure the comparability and transparent representation of integrated reports (EFRAG, 2021c, p. 103).

The CSRD entail challenges for proper data analysis (Wunder, 2023). Companies must report the impact of their operations and how sustainability issues impact their bottom line in a double materiality manner. The CSRD seeks to enhance sustainability-related reporting for companies by establishing foundational standards that promote transparency in sustainability reporting to all stakeholders (European Parliament, 2024). Consequently, reporting of material information is crucial from a strategic perspective, as it requires transparency and public accessibility. The evaluation industry may start the monitoring, comparison, and classification of companies based on their performance in material issues, similar to current ESG rating agencies (Delgado-Ceballos et al., 2023).

The policy context for leveraging AI to enhance Double Materiality Assessments (DMAs) is clearly stated. The EU will endorse initiatives that maximize the potential of digital tools for an effective ecological transition, utilizing data and AI technologies to enhance decision-making processes. The support for digital tools seeks to enhance potential, facilitating improved evidence-based decision-making capabilities within companies (European Commission, 2019, p. 18). The EU's strategy focuses on transforming industries via an integrated ecological and digital transition. The objective of this 'twin' transition is to reshape businesses and industries (European Commission, 2020, p. 1).

² 'inline' XBRL allows data to be both human-readable in addition to machine-readability.

Digital technologies play a crucial role in attaining the sustainability objectives outlined in the Green Deal. The EU is investigating the potential of technologies such as AI to enhance environmental protection, tackle climate change, and improve the monitoring of pollution and resource utilization (European Commission, 2019, p. 9). Artificial Intelligence (AI) impacts the business ecosystem and serves as a fundamental basis for establishing competitive advantages capable of disrupting entire industries. AI is poised to influence power dynamics, reshape relationships, and drive transformative changes within the competitive landscapes across various industries (Canton, 2019, p. 385). *Dhiman et al.* observed a notable rise in publications concerning AI and sustainability over the past five years, reflecting an increasing scholarly and practical focus on the sustainability implications of AI technologies (2024).

Numerous European and EU operating companies must conduct a DMA to comply with the novel EU-integrated reporting regulations since it is a prerequisite of the CSRD (EFRAG, 2024a). The European Financial Reporting Advisory Group (EFRAG) stresses the importance of integrating financial and sustainability reporting and advocates for using advanced technologies like AI to enhance the reliability, accuracy, and comprehensiveness of sustainability reporting (EFRAG, 2021b, pp. 63–70). Remaining up to date with evolving sustainability reporting regulations adds complexity and challenges to companies assessing materiality, e.g., while trying to identify potential ESG-related risks accurately (Miettinen, 2024).

Improvement is needed in the conducting of DMAs. *De Cristofaro and Gulluscio* identified a general deficiency in clarity and detail regarding the integration of the double materiality concept. Organizations exhibit varied approaches to topic prioritization, with some neglecting it entirely. Dynamic materiality is infrequently discussed, and numerous companies do not acknowledge it at all. There are notable differences in DMA phases among companies. Materiality matrices exhibit diverse applications, and axes demonstrate considerable variation (2023, p. 19, 21-22, 23, 24, 25).

Conventional approaches to DMAs exhibit deficiencies in various aspects. Some companies occasionally depend exclusively on desktop research and internal expert surveys to assess their operations (Allianz, 2023). Companies and stakeholders prioritize various sustainability issues differently (Fiandrino et al., 2022). Initial implementation experiences of the CSRD uncover several problems and challenges. Companies frequently accept stakeholders' perspectives regarding their environmental and societal impact without adequate objective data and evaluations. This compromises consistency and results in elevated review costs. Systematic comparison of various topics regarding the impact of materiality presents a challenge (Gleissner, 2024, pp. 29, 31).

A minority of the largest global companies undergo third-party validation. This discrepancy points out a significant divergence from financial reporting, which complies with rigorous and widely recognized standards and audits. Despite the substantial rise in companies implementing voluntary sustainability reporting frameworks, such as the GRI, tangible and significant advancements in ESG issues remain lacking. Despite the increasing prevalence of materiality assessments, challenges arise from data quality and methodological transparency. Companies often struggle to deliver detailed reporting on materiality assessments. One reason for this is the varying methodologies of materiality deployment. Greenwashing, voluntary symbolic reporting, and applying financial materiality lenses to sustainability account for the most salient challenges of approaches to materiality reporting. Many sustainability reports still rely on nonstandard and often imprecise metrics, lack comprehensive auditing, and tend to present an exaggerated view of their sustainability performance. A notable concern is the voluntary aspect of traditional sustainability reporting. Companies generally select the standards they adhere to and determine the information they disclose without rigorous external validation. This flexibility has resulted in reports that are frequently misleading and incomplete (Fiandrino et al., 2022; Pucker, 2021).

Given these challenges in conducting effective DMAs, exploring innovative solutions is imperative. The question arises as to whether and how AI technologies might enhance DMAs. With EFRAG advocating for advanced technologies like AI to improve sustainability reporting, exploring this potential could help companies address current complexities and better comply with the CSRD. This paper aims to explain the interplay between AI and DMAs, particularly within the regulatory landscape of the CSRD. It seeks to provide a deeper understanding of how AI can influence the effectiveness of DMAs in meeting regulatory requirements. It explores how AI can be integrated into the DMA process and delineates the potential and limitations of AI technologies in conducting DMAs. The paper tries thus to shed light on both the opportunities and constraints that arise when leveraging AI in this specific context, offering insights relevant for businesses and stakeholders involved in sustainability reporting.

To achieve this, the research will be guided by three specific objectives:

- (1) Identify and analyze available AI products and technologies for conducting DMAs
- (2) Investigate how current AI products and technologies can address the challenges identified in the literature regarding conducting DMAs
- (3) Critically analyze the potential benefits and limitations of AI products and technologies alongside different stages of DMAs

This study employs thus a mixed-methods research design to examine the extent to which AI can assist companies in conducting DMAs under the EU's CSRD. By integrating both theoretical exploration and practical evaluation, the research provides a comprehensive understanding of how AI technologies can enhance the DMA process and address associated challenges. Next, the paper outlines the extensive data requirements and challenges posed by DMAs. The paper provides then a comprehensive overview of AI and discusses its fundamental concepts and key subfields. It highlights AI's applications in addressing complex problems. The ethical considerations, environmental impacts, and challenges associated with AI are also addressed, providing a balanced perspective on the technology's potential and limitations.

The exploration of Natural Language Processing (NLP) focuses on its role as a branch of AI that enables computers to understand and process human language. The shift from rule-based to data-driven approaches in *NLP* is outlined. The discussion on Machine Learning (ML) explains how computers improve their performance based on data and past experiences, detailing the three main forms of *ML*. The relevance of these forms in analyzing complex datasets for DMAs is highlighted. Furthermore, the paper introduces Large Language Models (LLMs) and Generative Artificial Intelligence (GenAI), discussing their advanced capabilities in understanding and generating human-like text.

The paper outlines a three-staged research approach that comprises a Literature Review, Market Scan, and Content Analysis. The Literature Review investigates existing academic discourse on AI and DMAs, providing theoretical insights into the subject. The Market Scan examines current AI technologies and products designed to support DMAs, identifying key tools and providers in the industry. The Content Analysis systematically examines sustainability reports to assess AI integration in sustainability reporting, offering practical insights into current trends and applications.

Presenting the results of the research, the paper details how AI solutions are applied in each step of the DMA process. Real-world applications are included to illustrate the practical benefits and limitations of AI integration. Insights from the Content Analysis highlight trends in AI adoption among leading EU companies. The findings are interpreted in the context of the research objectives, discussing how AI technologies address specific challenges in DMAs. The paper concludes by summarizing the key insights gained from the research and offers recommendations for companies to adopt AI strategically.

2 Requirements and Challenges of Double Materiality Assessment

Materiality per se appears to be a somewhat subjective concept. *Garst et al.* collected multiple materiality definitions, of which one can infer that materiality is a principle of identifying and disclosing a company’s most significant ESG impacts, going beyond just financial concerns. Materiality considers thus how these issues affect the company's financial performance, strategy, stakeholders, and the potential of value creation in the short, medium, and long term (2021, 2022:65–66). To circumvent the challenges of a subjective understanding of the double materiality concept and its assessment, this paper adopts EFRAG’s understanding of materiality. Following a systematic and valid approach, this paper derives DMA requirements from the official finalized Implementation Guidance (IG) documents provided by the EFRAG³ illustrated in [Figure 1](#).

By adhering to these official EU documents, the paper seeks to maintain objectivity and ensure the reproducibility of the findings. While acknowledging alternative methods proposed by practitioners, such as key topics identified by working groups (Audencia et al., 2023), this approach focuses on the official EFRAG guidance to align closely with regulatory requirements. The DMA necessitates an integrated approach where sustainability-related Impacts, Risks, and Opportunities (IROs) are continuously identified, assessed, and managed within the company’s overall governance and strategic frameworks. Each component of this approach ensures that sustainability disclosures are relevant and provide a truthful representation, aiding stakeholders and statement users in making informed decisions (European Commission, 2023a, pp. 8–11).

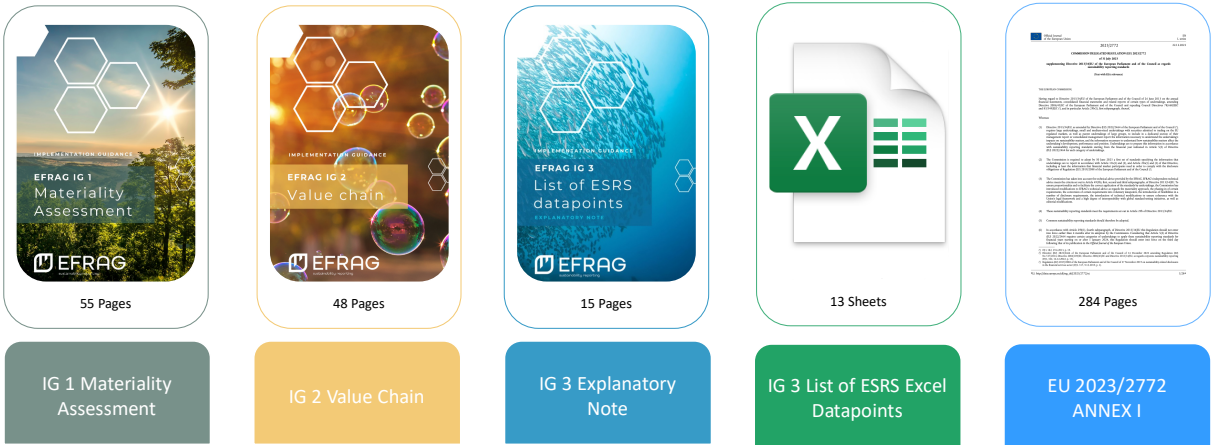


Figure 1 Overview of Analyzed EFRAG Documents

³ Official IG documents pertinent to DMA were finalized on 31 May 2024 (EFRAG, 2024d; Markhahn, 2024)

A DMA helps companies deepen their understanding of previously identified material matters and extend their assessment to new sustainability matters, such as data and methodologies, as some companies have experienced (Allianz, 2023). Stakeholders like financial institutes and insurance can better manage risk with trustworthy data, as material topics can substantively influence stakeholders' assessments and decisions (Garst et al., 2021, 2022, pp. 65–66). Companies must provide disclosures that enable users of sustainability statements to understand IROs related to ESG matters. The CSRD aims to ensure transparency, comparability, and accessibility of reported information for all stakeholders, including governments and NGOs (EU, 2023a). Reported information must be easy to navigate and accessible for report users (European Commission, 2023b). Therefore, stakeholder views and interests expressed during engagement may influence companies' strategy or business model (EU, 2023a).

The double materiality concept encompasses both financial and impact materiality. It requires companies to consider the impacts of their activities on ESG topics and the financial impact of these activities on the company itself. A DMA considers both materiality perspectives, i.e., inside-out (impact materiality) and outside-in (financial materiality). It is essential for accurate sustainability reporting and helps companies identify their and their stakeholders' most significant sustainability issues. While standard setters establish industry-wide or specific sector disclosures based on double materiality, reporting companies perform their own DMA to identify entity-specific sustainability issues considering the 'comply or justify' principle, which allows companies to explain why a mandatory disclosure is irrelevant to their specific situation. However, avoiding important disclosures is not an excuse since companies must provide a strong justification for non-reporting (EFRAG, 2021a, p. 8).

Impact materiality identifies sustainability actual and potential issues that significantly affect people and the environment throughout a company's operations and value chain, considering factors like severity, scale, and irremediability of impacts, positive impacts on people and the environment, and the base urgency on ESG goals and planetary boundaries. Therefore, impact materiality maintains a systemic and macro view of impact. On the other hand, financial materiality identifies sustainability issues that can financially affect a company beyond what is already reported financially, using various sorts of data, e.g., non-monetary, monetary, and qualitative (EFRAG, 2021a, p. 8; European Commission, 2023a, p. 10).

Impact materiality involves recognizing risks and opportunities that might materially affect a company's financial position, such as changes in resource availability or regulatory frameworks (European Commission, 2023a, pp. 10–11). A DMA must consider 622 mandatory and 269 voluntary data points, which organizations may choose to disclose based on their materiality judgments (EFRAG, 2024c, p. 4). The types of data organizations are expected to manage include a mix of narrative, semi-narrative, and numerical data, as well as conditional, alternative, and voluntary data points. This data is essential for tailoring the DMA and reporting to specific organizational contexts and sustainability impacts (EFRAG, 2024c, pp. 6–7). Organizations must consider mandatory and voluntary data points based on the relevance and significance of sustainability matters (EFRAG, 2024c, p. 4).

The inherent dual nature of DMA and value chain upstream and downstream considerations necessitate adequate collection, preparation, and analysis of vast amounts of data. Companies must evaluate the financial impact of ESG-related topics on their cashflows and financial performance considering multiple factors like, for example, social acceptance and resource availability (Wunder, 2023). Regulators expect the inclusion of science-based and evidence-based metrics and targets. These should be tied to specific challenges, particularly for sustainability factors like social issues, e.g., diversity and inclusion. They also expect companies to tie their targets to global challenges, e.g., through alignment with national and international sustainability goals and providing context to the targets set by companies (EFRAG, 2021b, pp. 63–70).

The DMA process should reflect the company's specific facts and circumstances. It may include understanding the context, identifying actual and potential IROs, assessing and determining material IROs, and reporting (EFRAG, 2024a, pp. 19–20). The DMA should further engage with affected stakeholders to inform them of the process and help substantiate the significance of sustainability from their perspective (EFRAG, 2024a, p. 6). Companies must establish suitable quantitative and qualitative thresholds for reporting, guided by criteria including the severity and likelihood of impacts, as well as the expected financial effects of risks and opportunities. The outcomes of the DMA, including methodologies, assumptions, and exercised judgment, must be disclosed transparently. This encompasses the application of thresholds and additional criteria for assessing materiality (EFRAG, 2024a, p. 10).

Engaging stakeholders is essential for DMAs, as it affects the identification and prioritization of material sustainability topics for reporting. Companies must systematically engage with stakeholders to align materiality assessments with the actual impacts and concerns pertinent to the business and its strategic direction (European Commission, 2023a; Fiandrino et al., 2022, p. 684). Conducting a DMA necessitates the assessment of sustainability issues from various stakeholder viewpoints (Latos et al., 2024). Stakeholders' insights help validate the materiality determinations and ensure the reporting aligns with stakeholder concerns (EFRAG, 2024a, pp. 6, 24).

Having explored the requirements and challenges of DMAs, it becomes clear that traditional methods may not suffice to manage the vast amounts of data and complex stakeholder interactions. This is where AI enters the conversation as a potential game-changer. The following section delves into the world of AI to understand its foundational concepts. Examining AI's subfields and their applications aims to illuminate how integrating AI technologies can address the challenges identified.

3 Artificial Intelligence

The core idea behind artificial intelligence (AI) is rational behavior, where a computer program or other intelligent agent chooses the best course of action in a given circumstance (Russell & Norvig, 2021, p. 34). Unlike past technologies, AI benefits from existing digital infrastructure, allowing rapid deployment and integration into various business processes. Some experts even compare the AI revolution to other significant human inventions like electricity, steam engines, or the internet (A. McAfee et al., 2023). Contributions to AI lie back to the 1940s (McCulloch & Pitts, 1943), yet *Turing* managed to influence AI most when he introduced significant contributions to the field like *ML* and addressed many of the problems expressed regarding the potential of AI at early stages (Russell & Norvig, 2021, p. 18; Turing, 1950). AI research has matured considerably, evolving from hand-crafted knowledge to data-driven *ML* (Russell & Norvig, 2021, p. 35). The AI industry boomed in the 1980s but faced a period called the 'AI winter' in the late 1980s, mainly due to unfulfilled promises. This led to a new, more scientific approach using probability, *ML*, and experimental results (Russell & Norvig, 2021, p. 24).

The common distinction between 'weak' and 'strong' AI is traced back to a discourse in 1980 by the philosopher *John Searle* (1980). Weak or narrow AI refers to machines that can perform intelligent tasks in a specific domain. Strong or human-level AI or general AI refers to machines with human-like intelligence that can solve various problems, including novel ones. While conceptually strong AI is possible, it does not actually exist yet (Glover, 2024; Russell & Norvig, 2021, p. 981). [Figure 2](#) illustrates the nested relationship between the AI subfields discussed in this paper.

AI is advancing medicine beyond language applications, with a continuous rise in approved AI medical applications. AI algorithms are achieving or exceeding human experts in diagnosing many medical conditions, especially based on images (Russell & Norvig, 2021, p. 30). Medical AI applications include Alzheimer's disease (Ding et al., 2018), metastatic cancer (Esteva et al., 2017; Liu et al., 2017), ophthalmic disease (Gulshan et al., 2016), and skin diseases (Liu et al., 2020). AI is critical in addressing mitigation and adaptation climate change strategies through electricity power system efficiency improvements, supply chain optimization, and energy-efficient production processes leading to reduced greenhouse gas (GHG) emissions (Rolnick et al., 2019). AI robots could ultimately free humanity from repetitive work, dramatically increase productivity, and accelerate scientific research, leading to cures for diseases and solutions for climate change and resource shortages (Russell & Norvig, 2021, pp. 30, 31).

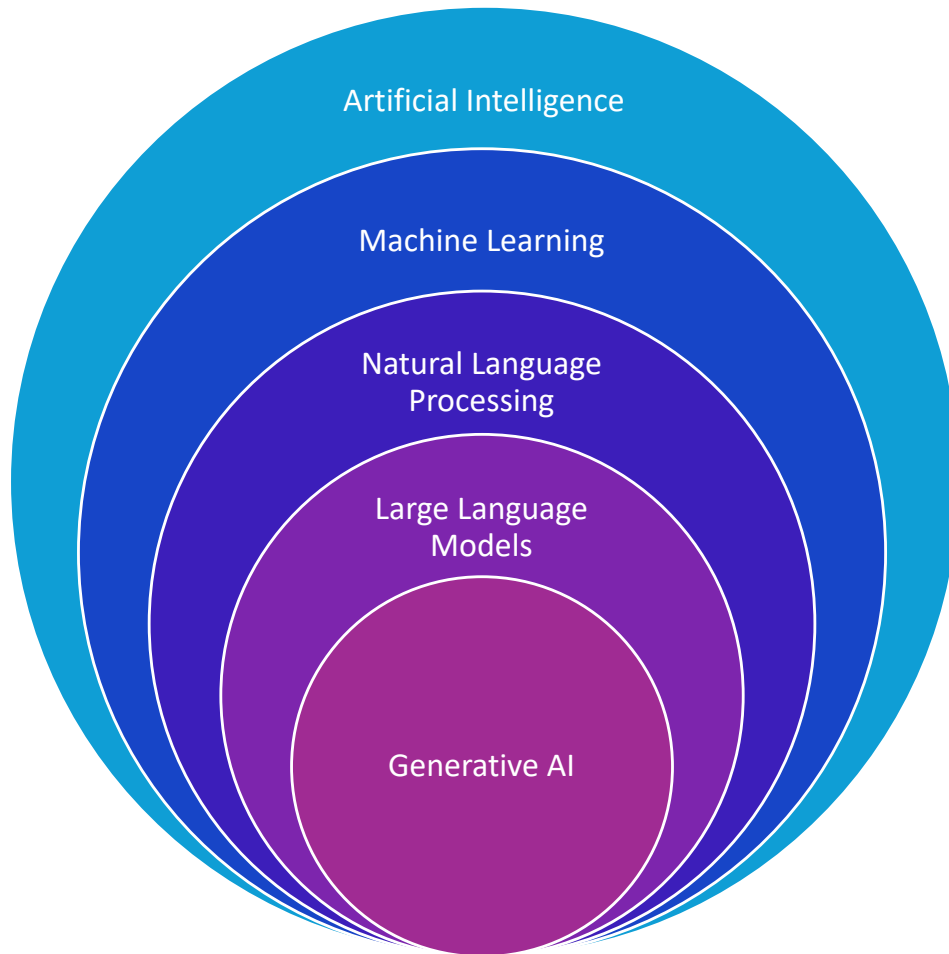


Figure 2 The Relationship Between Different AI Subfields Discussed in Paper

AI and its tools can be powerful for addressing the SDGs and tackling complex problems like poverty by enabling better resource management, healthcare, and education (Tomašev et al., 2020). AI can positively contribute to SDGs by managing resources more efficiently, predicting environmental changes, optimizing energy consumption, and monitoring environmental indicators (Tripathi et al., 2024; van Wynsberghe, 2021). For example, AI can improve understanding and response to climate change by analyzing complex environmental data and forecasting climate trends, contributing to SDG 13 climate action (Cowls et al., 2023). *Ametepey et al.* found a positive impact of AI across most SDGs. The authors identified specific high positive effects on SDG 6, clean water and sanitation by optimizing water distribution; SDG 7, affordable and clean energy by predicting maintenance and energy consumption optimization; and SDG 11, sustainable cities and communities by supporting traffic management and pollution levels management through AI-driven analysis (2024).

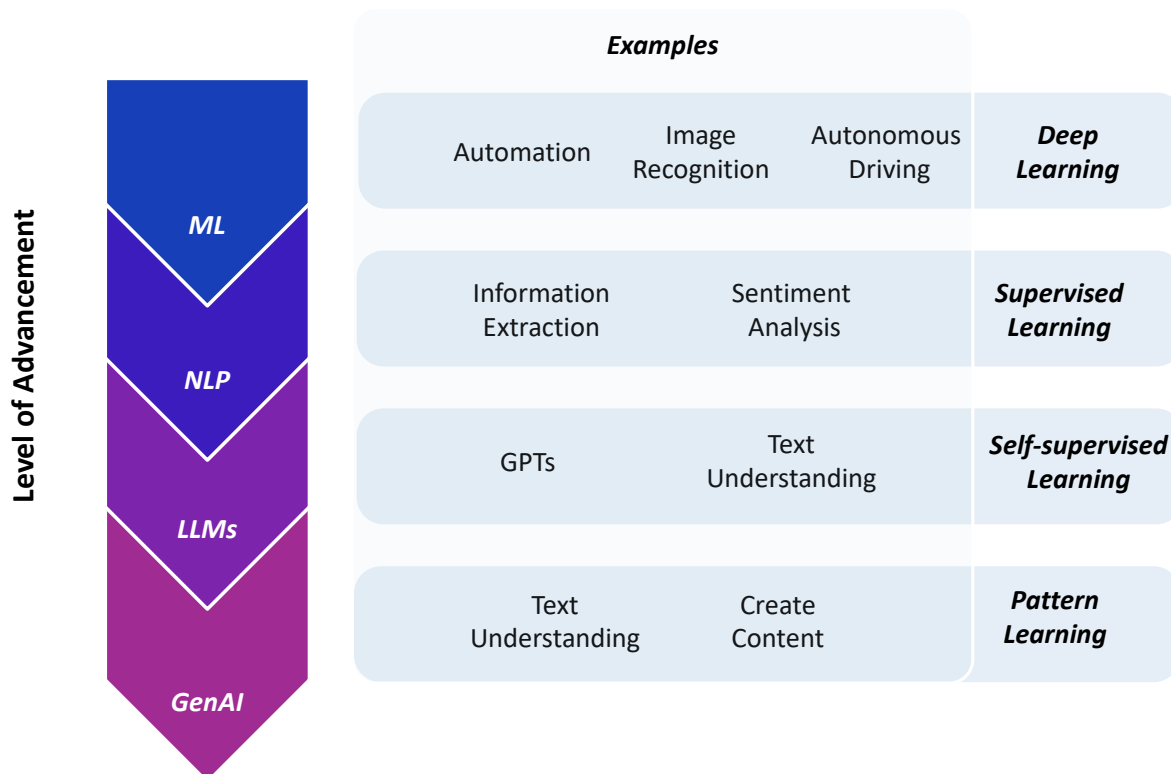


Figure 3 AI Levels of Advancement, Learning Types, and Examples (Russell & Norvig, 2021)

AI used in applications such as software management systems can handle routine tasks and free humans for complex and creative tasks (A. McAfee et al., 2023), which helps the workforce work more efficiently when adequately managed. *Ramprasad et al. & Stergiou et al.* found that *ML* can help optimize the processes for manufacturing building materials and predict and enhance material properties without the need for physical experiments while simultaneously reducing production costs and environmental impact like CO2 emission reduction (2017; 2023). [Figure 3](#) demonstrates the advancement levels of different AI subfields and their learning types.

Deep Learning for example utilizes human brain-inspired *Neural Networks* to process complex data and enable *NLP* (McKinsey & Company, 2024c). *Deep Learning* methods employ multiple layers of simple, adjustable computing elements, achieving notable success in speech and image recognition over the past decade. *Deep Learning* methods employ multiple layers of simple, adjustable computing elements, achieving notable success in *Speak* and *Image Recognition* over the past decade. The release of ChatGPT has led to a notable rise in AI publications. Artificial intelligence and its subfields have significantly impacted marketing and psychology through social media analytics and AI-driven consumer behavior analysis (Mariani et al., 2022; Perrault et al., 2019; Russell & Norvig, 2021, pp. 26–28; Shoham et al., 2018; Torfi et al., 2021; L. Wu et al., 2024).

Despite AI's potential, significant challenges include the resource consumption of AI systems. The environmental impact of AI development is frequently underestimated. AI can be resource-intensive and consume significant energy during development and usage. AI environmental footprint, e.g., when training large and *Deep Learning* AI models, requires considerable computing power, resulting in high energy consumption and carbon emissions (van Wynsberghe, 2021). Thus, balancing between AI benefits to climate action and its negative environmental impact is critical as AI consumes a considerable amount of energy through the power required to run data centers and computational processes needed for AI research and deployment (Cowls et al., 2023).

Furthermore, the technology is prone to 'unconscious bias' and discrimination arising from the deployment of AI as certain companies observed (SAP, 2023, p. 293). Biased decision-making, may arise from *ML* algorithms used for tasks like evaluating parole or loan applications, potentially reflecting societal biases present in the data. Safety-critical applications using AI techniques, like self-driving cars or managing city water supplies, require addressing formal verification and statistical risk analysis challenges. The AI field lacks technical and ethical standards comparable to other engineering and healthcare disciplines (Russell & Norvig, 2021, pp. 31–32).

AI can be used to defend against cyberattacks and create more potent malware. For instance, *Reinforcement Learning* methods have already been used to develop tools for automated personalized blackmail and phishing attacks (Russell & Norvig, 2021, p. 32). There are significant concerns regarding the development of superintelligent machines, which may result in humans losing control over their future. This situation can be likened to the lack of control gorillas have compared to humans. *Turing* pointed out that it is not obvious that we can maintain control over machines that surpass human intelligence (Russell & Norvig, 2021, p. 33). Some sentimental vibes of public journal titles were simply hard to perceive in the past, particularly within the IT industry. Experts warn of the 'risk of extinction' (Lukpat, 2023; Roose, 2023), especially in light of the recent revolutionary steps such as ChatGPT passing the famous Turing test (Biever, 2023).⁴

⁴ Imitation Game or Turing test was designed by Alan Turing and described in his 1950 paper titled 'Computing Machinery and Intelligence.' It proposes assessing machine intelligence through a test where an interrogator determines which hidden participant is human. If a machine's responses are indistinguishable from a human's, it passes the test, challenging traditional notions of thought and consciousness in machines.

3.1 Natural Language Processing

AI is deeply connected to human or ‘natural’ language. Natural language serves as a vast repository of human knowledge, and information is primarily documented in it. *NLP* empowers computers to extract and interpret this knowledge. Yet, adequately representing the complexity of natural language through logical grammar and principles is intricate (Russell & Norvig, 2021, pp. 823, 851). *NLP* is a branch of AI that enables computers to understand and process human language (Gruetzemacher, 2022). Understanding language is challenging and requires understanding the subject matter, context, and sentence structure. Natural languages are challenging, complex, and ambiguous compared to ‘formal’, i.e., programming languages. Advancements in computational power and the availability of large linguistic datasets have shifted *NLP* from a pre-defined rule-based approach to a data-driven approach (Russell & Norvig, 2021, pp. 17–18; Torfi et al., 2021).

NLP goals include communication with humans, acquiring knowledge from natural language, and scientific advancement in language understanding. It focuses on enabling machines to comprehend human language and facilitate effective. A *Language Model* defines the probability of different word sequences in a language and is used for various tasks like text completion, spell check, translation, and question answering (Russell & Norvig, 2021, pp. 2, 823–824). Hierarchical structures enable models to selectively focus on the most informative parts of a text, improving classification performance by highlighting which words and sentences the model deems most important for classification (Yang et al., 2016).

Multiple technologies underpin a *Language Model*. For example, *Tokenization* is the process of dividing a text into a sequence of words, *N-gram Models* can effectively classify texts and do sentiment analysis (Russell & Norvig, 2021, pp. 825, 826), and *Part-of-Speech* tagging plays a fundamental role in *NLP*, aiding the performance of more complex tasks, e.g., answering questions and translation texts (Russell & Norvig, 2021, pp. 829–830). [Figure 4](#) illustrates the five models of *NLP* and their respective use cases. The *NLP* field encompasses tasks like Speech Recognition, Text-to-Speech, Machine Translation, Information Extraction, Information Retrieval, and Question Answering (Russell & Norvig, 2021, pp. 849–850). These five forms of *NLP* allow computers to process, understand, and generate human language in a meaningful and useful way for specific tasks. For example, *Eaton* leveraged *NLP* while conducting its DMA to identify sustainability-related IROs and gain stakeholder insights (Eaton, 2023, p. 38).

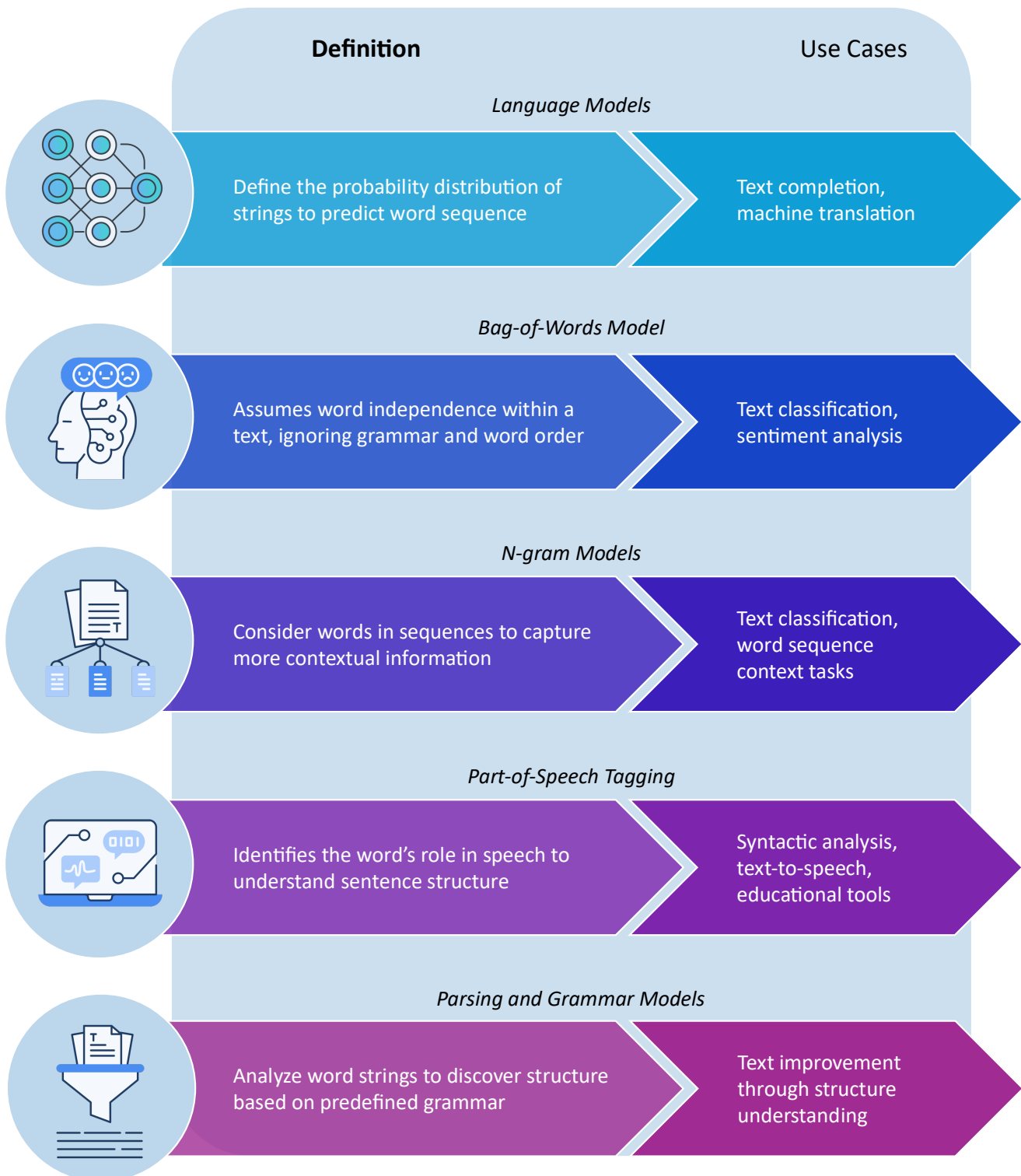


Figure 4 The Five NLP Models (Russell and Norvig 2021)

3.2 Machine Learning, Large Language Models, and Generative AI

ML refers to a computer capable of improving its performance based on studying past experiences and data. ML is used when programmers can not anticipate all future situations or do not know how to program a solution in the first place. In ML, agents improve their performance through observations of the world in a process where computers, build models based on observe data to solve problems (Russell & Norvig, 2021, p. 651). ML principles are traced back to the 1950s. However, its practical applications have significantly expanded in recent decades due to advancements in computing power and data availability (McKinsey & Company, 2024c). ML encompasses three primary forms: *Supervised Learning*, *Unsupervised Learning*, and *Reinforcement Learning* (Russell & Norvig, 2021, p. 653). Figure 5 demonstrates the three forms of ML, its feedback through humans, technology objectives, and deployment examples. Emphasis on data and ML has led to the convergence of different AI subfields, which has led to a better understanding of AI and to leveraging unprecedented quantities of data produced by the World Wide Web, i.e., Big Data (Russell & Norvig, 2021, pp. 25–26).

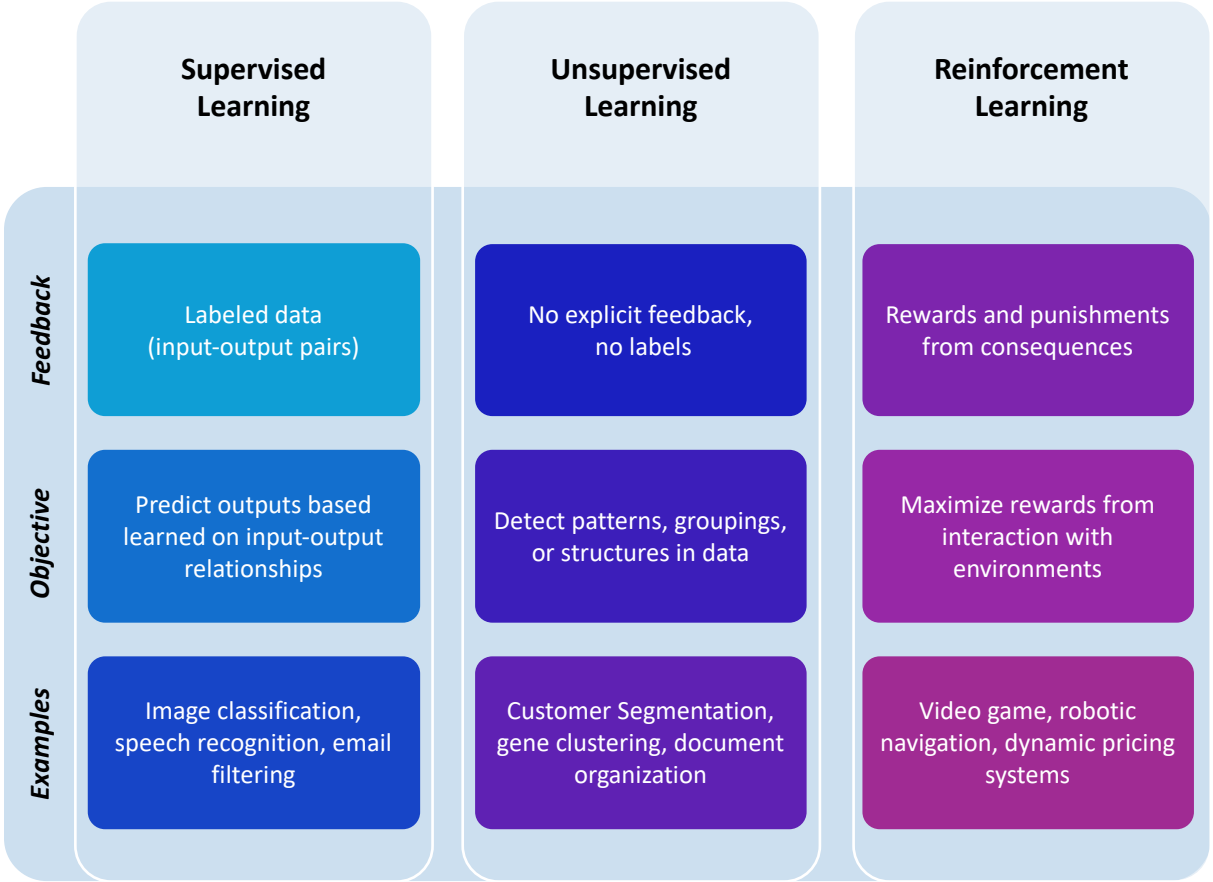


Figure 5 Machine Learning Forms (Russell and Norvig 2021)

Like *NLP*, *LLMs* can also store various types of knowledge, e.g., factual knowledge, common sense knowledge, and question-answering knowledge, serving as a knowledge base (Petroni et al., 2019). *LLMs* are advanced AI systems that leverage *NLP* and *ML* techniques, representing a significant leap forward in AI. The transformer architecture is the backbone of *LLMs*. It allows us to weigh the importance of different parts of the input sequence when generating each element of the output sequence, e.g., word order and position in a sentence (Ertel, 2021; NVIDIA, 2024). *LLMs* can understand and handle human language as they are trained on massive datasets that enable them to perform various tasks like understanding and generating human language, and unveiling abilities not observed in smaller models. *LLMs* have thus a transformative impact on the field of AI (L. Wu et al., 2024).

Early *LLMs* were capable of pre-training on large datasets without extensive task adjustments, making them highly versatile for different language processing applications. For example, Bidirectional Encoder Representations from Transformers, known as '*BERT*', was designed to pre-train deep bidirectional representations from unlabeled text. This design enables the model to simultaneously consider context from both the left and right, thereby improving its language comprehension relative to earlier unidirectional models (Devlin et al., 2019; Devlin & Chang, 2018). *LLMs* are typically trained using the *Unsupervised Learning* form of *ML* (Figure 5). This allows them to discover patterns in data without explicit labels and function as base models, capable of performing a wide array of tasks without needing to be trained specifically for each one (NVIDIA, 2024; Petroni et al., 2019).

This flexibility opens the door to deploying *LLMs* for various task sets like sustainability and integrated reporting. Transformers allow *LLMs* to find relationships within the data, allowing for faster and more efficient processing of long pieces of information. The transformer model revolutionized *LLMs* by outperforming previous models while requiring significantly less training time, allowing *LLMs* to look at the data from various angles, helping to understand complex patterns and to remember the sequence of information (Vaswani et al., 2017). *LLMs* constitute Generative Pretrained Transformers (GPTs), which can understand complex contexts and generate contextually relevant text (Ertel, 2021). Generative AI (GenAI) refers to AI that creates new content. *GenAI* models like ChatGPT are trained on massive datasets, enabling them to generate human-like text (McKinsey & Company, 2024a).

Having established a foundational understanding of AI, the paper explores next how these advancements can be harnessed to address the specific challenges identified in DMAs.

4 AI Opportunities in Double Materiality Assessments

4.1 Improve Efficiency, Productivity, and Minimize Manual Errors

AI data enhancement might generate positive effects in the short term, like improved efficiency and increased productivity due to process facilitation and cost advantages. For example, it might reduce non-performance costs and predict maintenance (Grebe et al., 2023) through automation, as some AI DMA providers promise cost cuts and the need for ESG consultants (Hiel, 2024), internal workforce time (Louis, 2023), and automating CSRD tasks that typically require significant human effort (Moran et al., 2024). Utilizing knowledge graphs (Ji et al., 2022) enables AI to comprehend and represent a company's diverse entities, including suppliers and partnerships, along with the underlying semantics, such as the relationships between suppliers and NGOs. Social media text mining serves as an example where analysts utilize AI to extract valuable insights from social media data, such as reviews and conversations, to enhance understanding of customer preferences and feedback (Mariani et al., 2022). *Klein et al.* contend that analysis bias arises during data collection when attention is directed towards issues that align with existing strategies in the execution of DMAs. This results in companies overlooking the evaluation of all pertinent material issues as a consequence of human bias (2023).

The quality of DMA data and the transparency of the data collection methodology are critical, as DMAs are subject to audits (Hiel, 2024). AI DMA providers claim that AI can effectively aggregate and organize extensive publicly available data to represent stakeholder opinions on material issues. This method could mitigate the bias associated with manual data collection (Moran et al., 2024). The EFRAG PTF-RNFRO⁵ found that AI helps companies in conducting materiality assessments by leveraging it, e.g., to support objective data scanning for relevance and bias minimization. According to the report, AI-based scans underpin the consideration of a wider array of stakeholder perspectives (EFRAG, 2021c, p. 93). AI technologies such as *NLP* and *ML* are used in various ways, along with integrated reporting. This includes automating repetitive tasks, heterogeneous and large data analysis, and pattern detection, which is only sometimes readily recognizable for human analysts. AI technology deployment helps efficiently gather, analyze, and report sustainability information (EFRAG, 2021b, pp. 55–61).

⁵ EFRAG's PTF-RNFRO is the 'Project Task Force on Reporting of Non-financial Risks and Opportunities' whose aim is to identify good practices in reporting (EFRAG.org, n.d.)

4.2 Reduce Opportunity Costs

AI has been widely adopted across multiple sectors, including healthcare, finance, education, manufacturing, and legal services. This widespread integration demonstrates its role as a major force in modern business practices (Babashahi et al., 2024). The extensive application of AI in these diverse industries highlights AI's significant impact on modern business operations. By entering various fields, AI has established itself as an essential component in today's business landscape. Adopting AI technologies might prevent relatively high opportunity costs and enhance operational efficiency by automating routine tasks and improving data accuracy in the short term. Over the long term, integrating AI transforms organizational capabilities, fostering a culture of data-driven innovation. The ongoing improvement of AI adoption can enhance customer experiences, product innovation, and market positioning (Enholm et al., 2022).

The shift from Big Data⁶ to valuable Big Data could theoretically yield significant and unprecedented insights from the vast quantities of data held by companies (A. P. McAfee & Brynjolfsson, 2012). AI utilization is highlighted as one success factor among others in enhancing DMAs through more accurate and comprehensive data analysis and efficient DMA processes. Insufficient AI utilization is a pitfall some companies make when preparing for DMAs (Klein et al., 2023). Large international companies are adapting DMA AI products to enhance ESG governance and identify material issues, efficiency, and reliability in ESG assessments (Datamaran, 2024). AI DMA providers promise to reduce complexities associated with legally mandatory DMA frameworks like CSRD by simplifying the process and automating steps to help companies navigate novel directives. As many companies might struggle with new and evolving standards and directives, AI DMA providers capitalize on the opportunity and promise to deliver value for conducting a DMA (VERSO, 2023, 2024).

⁶ Big data is distinguished from normal traditional data analytics via the three characteristics 'volume, velocity, and variety' (A. P. McAfee & Brynjolfsson, 2012)

4.3 Detecting Greenwashing, Improving Transparency, and Stakeholder Watch

Scholars and NGOs deploy *NLP* to streamline the screening of sustainability reports for potential red flags that indicate greenwashing and inconsistencies. *Bingler et al.* used *NLP* to extract relevant information and enhance the efficiency and scalability of analysis assessment processes. The authors used *NLP* to classify corporate climate commitments and filter out greenwashing. This enhanced stakeholder scrutiny shifts focus to companies risking being exposed for their misleading statements in sustainability reports (2023). *NLP*-based assessment tools can streamline screening sustainability reports for potential inconsistencies or greenwashing. Financial supervisors and regulators can leverage *NLP*-enhanced tools to automate the identification of potentially misleading claims and statements. The ability of *NLP*-enhanced tools to flag investments in companies with inconsistent transition plans helps financial supervisors identify potential risks (Bingler et al., 2023, p. 16).

Sustainability reporting is gaining importance as stakeholders demand greater transparency regarding companies' ESG performance. Investors are likely to have a major stake in using AI in the context of sustainability reporting. While other stakeholders, e.g., customers and NGOs, have varying information needs and likely fewer resources to dedicate to analyzing corporate information. Consequently, AI may disproportionately benefit—relative to other stakeholder groups—investors who have the resources to leverage AI tools for analysis and are already leveraging the technology to analyze financial information (De Villiers et al., 2024).

The role of AI in evaluating disclosures is rapidly expanding. Various stakeholders utilize AI to facilitate the analysis of countless documents. For example, ESG rating agencies and investors are using AI to analyze sustainability reports and identify greenwashing potential. AI's insights into a company's ESG strategy have far-reaching implications for sustainability reports. Machine-readable representation and clear language usage are vital for ensuring accurate AI interpretation by stakeholders. Conflicting statements can lead to unfavorable AI assessments. Companies should leverage AI to better understand stakeholders' evaluation of their ESG performance (Zivin et al., 2023). The gap between AI experimentation and real value creation is evident, with the majority of companies unable to create and capture value from AI (Grebe et al., 2023). Despite significant investments in AI, many companies struggle to integrate it into existing processes and to scale beyond pilot projects, failing to reap expected AI benefits like increased revenue, cost reduction, and enhanced decision-making capabilities (Enholm et al., 2022). This leads us to the limitations of AI in DMAs.

5 AI Limitations in Double Materiality Assessments

5.1 ESG Considerations

Ethical concerns around AI and its role in privacy, social impact, and transparency are gaining attention. The adoption of AI raises ethical issues that need to be adequately addressed, including job displacement, protecting privacy, accountability, and algorithmic biases (Babashahi et al., 2024; Tomašev et al., 2020; Tripathi et al., 2024). AI development entails social challenges, e.g., issues related to discrimination and societal bias. AI can amplify existing social inequalities if not carefully managed (Cowls et al., 2023). Researchers are exploring raising concerns about the trust of AI technology users (Mariani et al., 2022) and stressing the need for a policy framework to assess AI applications. For example, AI models that consume high energy should not be deployed for ethically questionable purposes, such as employee monitoring (van Wynsberghe, 2021).

5.2 Bias, Privacy, and Data Validity

Reports highlight the potential of AI models to memorize and leak sensitive information from their training data accidentally (P. Wu, 2022). This is particularly relevant since there is a strong correlation between data appearance frequency while training and model recalling accuracy (Petroni et al., 2019). AI has the potential to reinforce pre-existing social biases. This arises from the training of AI systems on data that mirrors the status quo, which includes its intrinsic biases (Raso et al., 2018). AI-generated content, whenever trained on biased or incomplete data, may perpetuate greenwashing by replicating the positive tone prevalent in existing sustainability disclosures, potentially understating negative impacts (De Villiers et al., 2024, p. 29).

Companies are instructed to disclose how materiality decisions are made, including the criteria and thresholds applied. The goal of transparency and documentation is to ensure that stakeholders understand the basis of the reported information (EFRAG, 2024a, pp. 10, 24). Traditional AI technologies discussed in this paper, e.g., *unsupervised ML*, might struggle to meet regulator expectations for the transparency of approaches used in DMA processes since traditional, non-XAI models are commonly described as 'black boxes' (Theil & Brutian, 2024). Overreliance on historical data may not be predictive of future conditions. Uncertain human behavioral responses to AI interventions (e.g., workers' reaction to lighting or heating after an AI energy optimization program takes place) remain uncertain, and there are increased cybersecurity risks. Measuring the effectiveness of AI interventions remains difficult (Nishant et al., 2020).

5.3 Entity-Specific Considerations and Inclusion of Value Chain Information

Companies must tailor the materiality assessment process to their specific context, reflecting their unique operational, financial, and environmental conditions (EFRAG, 2024a, pp. 19–20). This can be challenging for AI DMA providers since establishing and modifying the DMA platform to the specific entity might necessitate substantial upfront human and capital expenditures. A mismatch between skills employers require and those employees possess poses challenges for effective AI integration within organizations (Babashahi et al., 2024). A skilled and change-welcoming workforce is particularly important since organizations that excel in AI dedicate a significant portion of their workforce to digital roles, invest heavily in upskilling, and employ innovative working methods (Enholm et al., 2022; 2023).

Including relevant value chain information is necessary to understand material IROs, which may require considering indirect business relationships, not just contractual ones (EFRAG, 2024b, pp. 26–28). This can also challenge AI DMA providers since value chain information is not always available for various reasons (Bateman & Bonanni, 2019). EFRAG directs companies to employ reasonable estimates and proxies to represent the material IROs in the case that direct data from value chain actors is unavailable (EFRAG, 2024b). Methodologies and assumptions for these estimates must be disclosed, contrasting the black box situation of typical, non-XAI models.

Having explored the opportunities and limitations of integrating AI into DMAs, the paper proceeds with the presentation of the innovative methodology used. The following section outlines the structured approach adopted. The methodology provides the foundation for the subsequent findings and discussion, enabling a systematic assessment of AI's role in enhancing DMAs under the CSRD framework.

5.4 Alleviation of AI Limitations in DMAs

As AI utilization and integration increase, ethical concerns arise as a significant theme, particularly around privacy, data security, and transparency (Mariani et al., 2022). AI DMA providers must ensure compliance with privacy laws, protecting sensitive data since privacy issues must be managed appropriately. Responsible AI use and regulations are essential for ethical and accountable AI development (A. McAfee et al., 2023; McKinsey & Company, 2024b). Ethical AI practices are crucial to ensuring that AI implementation does not amplify existing inequalities or introduce new biases (Ametepey et al., 2024). The increasing complexity of *ML* models demands more computational resources and results in higher economic costs, leading to large companies controlling major AI developments (Bolón-Canedo et al., 2024).

AI providers highlight the importance of ethical AI use, addressing issues like factuality and adherence to ethical standards in sustainability-related assessments like DMA (Theil & Brutian, 2024). Continuous efforts are needed to ensure trust and accuracy to make AI models more transparent and understandable. One way is the adoption of Explainable AI (XAI) of evolving models (Louis, 2023; Theil & Brutian, 2024) since companies lack details on data management tools (De Cristofaro & Gulluscio, 2023, p. 23).

XAI refers to a set of techniques that aim to make AI systems more understandable and interpretable to humans, for example, when an AI model's internal decision-making is not transparent (Hassija et al., 2024; IBM, 2023). Institutes and frameworks are trying to address AI-related ethical and governance and ethical confederations. For example, the Responsible AI Institute assesses and validates AI system processes to uphold rigorous standards for responsible AI development and helps members, e.g., by conducting a gap analysis (Responsible AI Institute, n.d.). Another example is the ESG-AI framework, a novel tool designed to ensure that AI technologies are used responsibly by integrating ESG considerations. It evaluates AI's impact in various industries (Lee et al., 2024). These institutes and framework initiatives are important since AI governance mechanisms largely ignore sustainability risks, focusing instead on ethical issues such as fairness, transparency, and non-discrimination (Galaz et al., 2021). *Stahl et al.* marked an increasing implementation of AI impact assessments across various sectors to manage both AI technologies' positive and negative impacts. AI impact assessments are a structured process to evaluate the potential consequences of deploying AI technologies, considering both positive and negative outcomes (2023).

6 Methodology

This paper follows a structured three-staged approach to ensure a comprehensive understanding of AI's effectiveness in enhancing DMAs, grounding the findings in theoretical exploration and real-world application. Integrating theoretical insights from the Literature Review, practical analysis from the Market Scan, and empirical data from the Content Analysis offers valuable contributions to academic discourse and industry practice. This methodology enables the study to address its objectives systematically and provides a robust foundation for the findings and discussions in subsequent sections (Figure 6).

First, a Literature Review was conducted using the academic database Google Scholar and multiple AI tools to identify seminal papers on the underlying matter. This phase focused on theoretical frameworks and existing discourse on AI's role in DMAs, employing rigorous exclusion criteria to ensure the relevance and credibility of the sources. Second, a Market Scan was conducted to review AI DMA provider solutions designed explicitly for DMAs, critically evaluating their various value propositions. This helped to bridge theoretical insights with practical applications, identifying products that align with the specific needs of DMAs. Third, a Content Analysis of sustainability and integrated reports from the 25 largest EU companies assessed the current use of AI in DMAs. This involved systematic keyword searches and a detailed review to analyze the extent of AI integration in sustainability practices and the potential for DMA deployment.

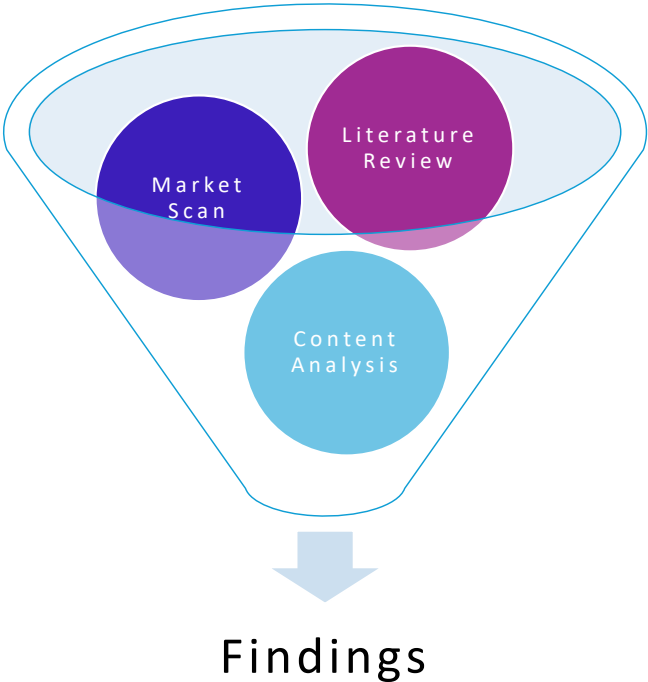


Figure 6 Three-staged Methodology Process Towards Findings

The Literature Review investigates existing academic discourse on the intersection of AI and DMAs, focusing on how AI technologies can address challenges in DMAs. Data for the Literature Review was collected from the academic database Google Scholar, using keywords including 'Artificial Intelligence,' 'Double Materiality Assessment,' 'Sustainability Reporting,' 'Machine Learning,' and 'Natural Language Processing.' Additionally, three AI chatbots—OpenAI's ChatGPT, Google's Gemini, and Microsoft's Copilot—were utilized to identify academic papers relevant to the four steps of the DMA process prescribed by the EFRAG.

An iterative prompt development process was used to query the chatbots effectively. Four prompts based on the DMA steps' keywords asked each chatbot to identify ten seminal papers for each step. This resulted in a total of 120 outputs (12 prompts × 10 papers per prompt). The results were systematically organized in a spreadsheet ([Appendix A](#)), including the title, publication year, author(s), and a link to each paper. After applying exclusion criteria—such as invalid links due to AI chatbot inaccuracies, restricted access, and irrelevance of the topic—95 papers were excluded, leaving 25 eligible papers for further analysis. This ensured the Literature Review was based on credible, accessible sources relevant to the research objectives.

The exclusion criteria for the initial screening were invalid links caused by AI chatbot errors (hallucinations), restricted access to papers not available through existing licenses, and titles irrelevant to the topics of AI and DMA. These criteria helped ensure the final selection of papers was relevant and usable for further study. After applying these criteria, 95 papers were excluded, leaving 25 eligible papers for further analysis. The methods used in the Literature Review involved thematic analysis to understand how AI technologies can help address the challenges identified. Insights were mapped onto the four-step DMA process prescribed by EFRAG. [Figure 7](#) illustrates the stages of the Literature Review selection process.

The methods used in the Literature Review involved thematic analysis to understand how AI technologies can help address the challenges identified. Insights from the literature were mapped onto the four-step DMA process prescribed by EFRAG: understanding the company's context, identification of sustainability-related IROs, assessment and determination of material IROs, and reporting on material IROs. This mapping facilitated a structured understanding of how AI can enhance each step and address specific challenges like inconsistencies in materiality assessments, human bias, operational difficulties in implementing the CSRD, and the need for transparency and stakeholder engagement.

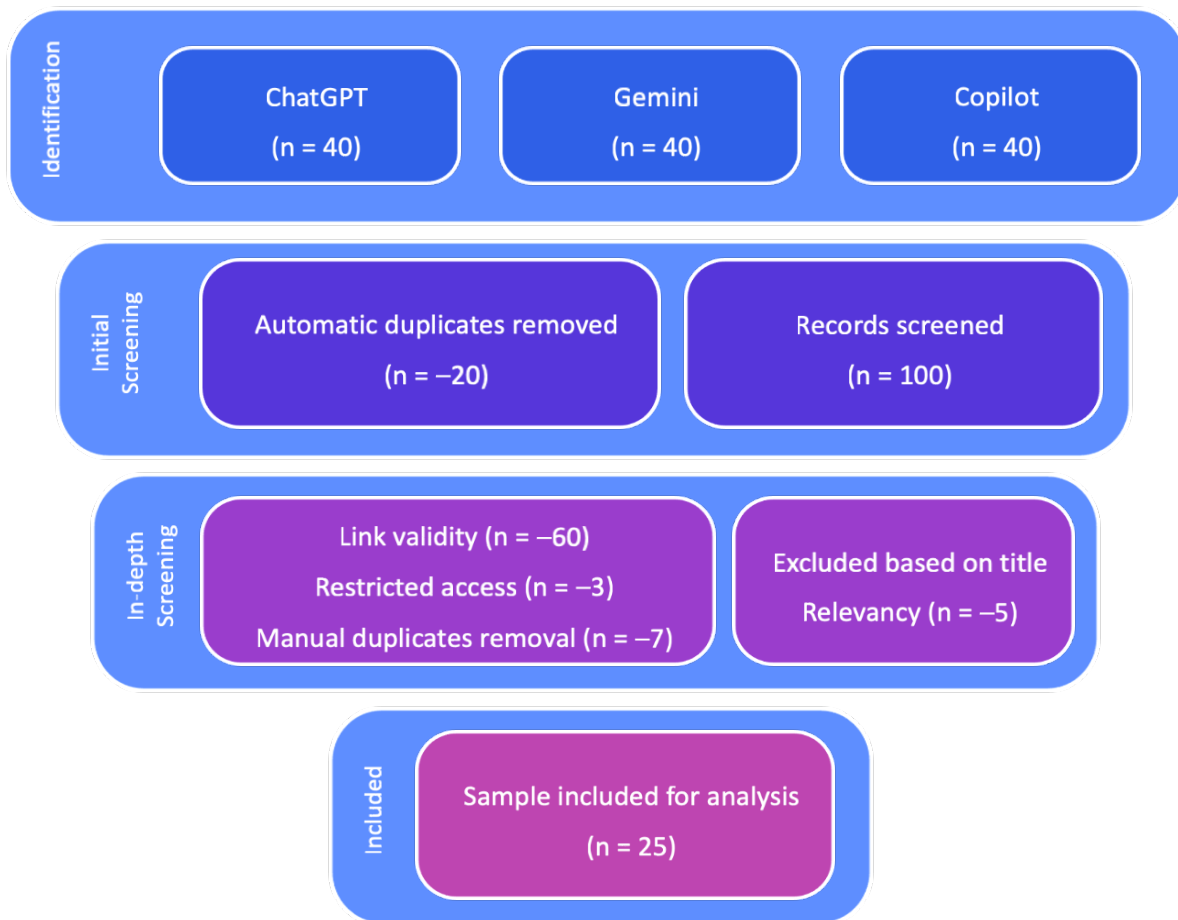


Figure 7 Literature Review Selection Process Stages

A Market Scan is conducted to examine current AI technologies and products specifically designed to support DMAs. AI solutions offered by various providers are explored, focusing on those that explicitly offer AI tools tailored to DMA processes. The main criterion for selecting AI DMA providers is their direct relevance to DMAs, ensuring that their capabilities align with the specific needs of the DMA process. Many AI or software providers target customers as general ESG platforms, but selected providers address DMAs directly on their websites and product marketing materials. Information was gathered from providers' official websites, product brochures, and supplementary sources such as LinkedIn. The potential bias toward marketing sentiments is acknowledged as a limitation of this approach.

In examining the Market Scan data, the alignment of each AI solution with DMA requirements were assessed, key capabilities were identified, and potential benefits and limitations were considered. The theoretical insights from the Literature Review are integrated with practical findings from the Market Scan, identify gaps between academic recommendations and market offerings, and develop recommendations for companies based on these combined insights.

The Content Analysis examined the 2023 sustainability reports of the 25 largest EU companies by market capitalization, identified through CompaniesMarketcap.com (2024). These companies were chosen to ensure a representative sample of major industry players likely to be at the forefront of adopting new regulations and technologies, including AI and DMAs. The reports were collected, and a spreadsheet was created to systematically catalog each company's information, facilitating data management throughout the analysis. The goal was to investigate the integration of AI within conducting DMAs.

The analysis phase was executed sequentially: an initial screening and an in-depth examination. In the initial screening, each sustainability or integrated report was electronically searched for keywords related to DMAs and AI technologies. For DMAs, terms such as 'materiality assessment,' 'DMA,' 'GRI,' 'ESRS' and 'CSRD' were used, including variations like 'dual' and 'double' to ensure comprehensive coverage. Regarding AI, keywords included 'AI,' 'ML,' 'NLP,' and 'GenAI.' This step aimed to identify relevant sections within the reports for further analysis. Pages containing these keywords were flagged for the in-depth analysis phase. Additionally, the specific double materiality frameworks employed by each company were documented. All findings, citations, and corresponding page numbers were extracted and recorded in an Excel spreadsheet ([Appendix B](#)).

The in-depth analysis involved a thorough review of the previously identified sections. This phase had multiple objectives. First, citations were extracted by carefully reading the flagged pages to ensure an accurate representation of the companies' statements regarding DMAs and AI applications. Second, specific AI utilization was identified by searching for detailed descriptions of how AI technologies are employed within each company's business operations. Third, a critical assessment of the statements was conducted by evaluating the clarity and specificity of the reported information, filtering out any vague or non-substantive statements to focus on concrete examples of AI deployment. Fourth, the connection between AI deployment and DMAs was examined to understand how AI influences or enhances DMAs. Lastly, a condensed categorization scheme was developed to classify the different types of AI applications identified across the companies.

The extracted data, including citations and page references, were systematically recorded in the Excel spreadsheet. Citations and their corresponding page numbers were highlighted to ensure a transparent and reliable approach to analysis. This organized dataset served as a foundation for enriching the Market Scan and complementing the findings from the Literature Review. The compiled results provided a nuanced understanding of current trends in AI integration within sustainability reporting among leading EU companies. By combining quantitative data from the initial screening with qualitative insights from the in-depth examination, the study offers a comprehensive overview of how AI technologies are being leveraged in the context of DMAs and broader sustainability practices. Transparency is maintained by clearly documenting methodologies and acknowledging limitations. Potential biases are carefully considered throughout the research. Case studies are consulted to mitigate this since providers' marketing materials were expected to be biased.

7 Findings

This study aimed to fulfill three specific objectives: to conduct a comprehensive Market Scan of AI DMA providers, to investigate how current AI can address DMA challenges, and to critically analyze the potential benefits and limitations of AI in relation to the stages of DMAs. The primary criteria for selecting AI DMA providers included direct targeting of DMAs and a straightforward AI approach. A comprehensive Market Scan identified AI DMA providers such as *DATAMARAN*, *KAROMIA*, *MORNINGSTAR SUSTAINALYTICS*, *C3*, and *FINGREEN*, which streamline the DMA process through data collection and analysis (Hiel, 2024; SAP, 2023; Theil & Brutian, 2024). These tools address critical challenges in DMAs, such as inconsistencies in materiality assessments, operational difficulties, and stakeholder engagement issues, by offering standardized, data-driven approaches and enhancing transparency and efficiency (EFRAG 2021c; Louis, 2024).

AI DMA providers like *KAROMIA* promise to enhance traceability and transparency by linking insights to their sources, while AI technologies improve stakeholder engagement by analyzing communications and sentiments (Hiel, 2024; Theil & Brutian, 2024). *MORNINGSTAR SUSTAINALYTICS* has developed its proprietary *LLM* to tailor AI capabilities specifically for ESG information processing to minimize inaccuracies, which general-use AI models are usually prone to (Theil & Brutian, 2024). In a similar vein, *DATAMARAN* uses *GenAI* and a proprietary *LLM* specifically designed for ESG to provide real-time, accurate insights and enhance information reliability (Datamaran, 2024). In an alternative approach, i.e., not solely built on a general-use AI model, *KAROMIA* is built on an AI engine rather than a mere ESG-customized AI chatbot (Hiel, 2024). However, remains unclear whether this approach differs from those of other AI DMA providers like *MORNINGSTAR SUSTAINALYTICS* and *DATAMARAN*.

Real-world applications by *SAP* and *Eaton* illustrate AI's practical benefits in DMAs, enhancing data collection and analysis while emphasizing the importance of human control. The Content Analysis of 2023 sustainability reports from the 25 largest EU companies reveals that merely 8% utilized AI for DMAs, signaling a potential for broader AI implementation to improve efficiency, accuracy, and regulatory compliance in DMAs.

In the following, the paper derives findings strictly alongside EFRAG's prescribed process for DMAs (2024a). [Figure 8](#) provides an overview of the various value propositions of AI DMA providers in relations to different DMA steps. Companies subject to the CSRD can achieve practical advantages by incorporating AI into their DMA process.






Step A Understanding The Context

Saving Time

Data Centralization and Structuring

Compliance with Legal Frameworks

Stakeholder and Value Chain Analysis Preparation

Step B Identification of Sustainability-Related IROs

Identification of Opportunities

Integration of Management Systems and Company Portfolios

Performance Comparison and Benchmarking








Step C Assessment and Determination of Material IROs

Process Automation

Quantification of IROs

Step D Reporting Material IROs

Text Summarizing and Automated Data Analysis

Accuracy and Reliability of Data










Figure 8 AI DMA Providers' Value Proposition for Opportunities alongside DMA Steps

7.1 AI Applications in Step A: Understanding the Context

Understanding the company's context is the essential first step in kickstarting the DMA process. Step A requires analyzing internal and external factors influencing sustainability issues and their impacts and dependencies (Deloitte, 2023). Hence, customization is crucial in this step since a one-size-fits-all approach does not work due to the unique circumstances across different industries and companies (Klein et al., 2023). Factors such as company size, industry type, country of operation, and sustainability performance all play a role in shaping what is considered material for any given organization (Fiandrino et al., 2022). Varying interpretations and applications across different companies and sectors increase this complexity (Nielsen, 2023). Step A also involves gaining a clear overview of the business environment and stakeholder interests, directly impacting a company's sustainability considerations (EFRAG, 2024a, pp. 20–21). This process of contextual understanding can be significantly enhanced through the use of *NLP*. By analyzing large volumes of data, *NLP* can help companies uncover insights about internal and external factors, thereby enriching their understanding and fostering creative thinking early in the materiality assessment process (Latos et al., 2024). In Step A, the findings suggest that AI DMA providers underpin DMAs in various ways, e.g., saving time, data centralization and structuring, compliance, and stakeholder and value chain analysis preparation, as discussed next. This technological boost helps frame IROs within the company's unique context.

7.1.1 Saving Time

Time is critical in DMAs, as many companies underestimate the significant workload required to complete the process effectively (Chirez & van Vrede, 2024). Timely and comprehensive data collection and analysis is essential due to increasing regulatory pressure and stakeholder demand for transparent and accurate sustainability reporting. Numerous AI and data analytics providers offer solutions that promise to streamline this process by reducing the time required to gather and analyze vast amounts of data. *KAROMIA* has created a solution that substantially decreases the time required for data collection by simultaneously processing thousands of document pages. *KAROMIA* automatically scans, analyzes, and extracts key insights from large volumes of data, which would otherwise take substantial time and manual effort to process (Hiel, 2024). This efficiency in data collection allows companies to gain a clearer understanding of their sustainability context more quickly. Companies can save time and allocate their resources more strategically. This reduces the risk of delays in the DMA process, enabling organizations to focus more on interpreting insights.

7.1.2 Data Centralization and Structuring

AI builds a broad initial topic universe and gathers vast amounts of diverse data points to create a long list of potentially relevant topics, which is assessed for relevance in subsequent steps, allowing for a more holistic DMA approach. By mapping extensive, collected data to relevant guidelines, e.g., ESRS, AI facilitates quantitative and qualitative assessment of various relevant issues (Moran et al., 2024). *SAP* leveraged AI in its materiality assessment by employing the *DATAMARAN* product. This allowed the company to expand and enhance upon its existing long list of relevant topics, ensuring it was both comprehensive and up to date by analyzing vast amounts of data. *DATAMARAN* helped incorporate insights from additional external sources, such as corporate peer reports and mandatory and voluntary regulations specific to the software sector. By doing so, *SAP* efficiently identified and mapped critical topics related to its operations, supply chain, and solutions. Thus, integrating AI into the process enhanced the thoroughness and relevance of the assessment by utilizing AI's capability to process and analyze large datasets effectively (SAP, 2023).

Other AI DMA providers claim to systematically centralize and structure data to create value out of heterogeneous data sets. *FINGREEN* collects data from diverse sources, particularly where data collection is complex due to a poorly structured business nature, e.g., in SMEs. *FINGREEN* organizes unstructured data like web pages, documents, or emails and employs *NLP* to understand and interpret human language. For example, collecting datasets like Scope 3 emissions might involve multiple external partners and formats, enhancing multiple-format data extraction (Louis, 2024).

7.1.3 Compliance with Legal Frameworks

Compliance requires the collection, organization, and presentation of standardized data in accordance with established guidelines. *FINGREEN* offers to automate these tasks, allowing companies to efficiently collect and process data from various sources, from internal documents to external sustainability reports and stakeholder communications (Louis, 2024). The platform's advanced capabilities go beyond basic data collection. It enables companies to filter, compare, tag, and monitor large volumes of data precisely, ensuring that only the most relevant and accurate information is used for reporting. This automated approach helps reduce the risk of human error, which can be expected when manually handling complex data sets required by regulatory frameworks. Moreover, *FINGREEN's* solution is designed to continuously monitor evolving regulatory standards, ensuring that companies remain compliant as laws and guidelines are updated. This feature facilitates staying up-to-date for organizations, knowing that their sustainability reporting aligns with the latest legal expectations (Louis, 2024).

7.1.4 Stakeholder and Value Chain Analysis Preparation

Appropriate stakeholder involvement is crucial for the success of DMAs, as it ensures that all relevant perspectives are considered when identifying key IROs (Deloitte, 2023). Engaging the right stakeholders allows companies to gain a comprehensive understanding of how various stakeholder groups perceive and prioritize sustainability issues. Incomplete or inadequate stakeholder selection and survey processes can significantly undermine the effectiveness of DMAs, leading to skewed or incomplete results that fail to capture the full spectrum of material ESG factors (Chirez & van Vrede, 2024). The AI DMA provider *C3* addresses this challenge by providing advanced tools for analyzing trends in stakeholder ESG priorities in near real-time. This capability allows organizations to quickly adapt to changing external expectations. By continuously monitoring trends, *C3* helps companies stay ahead of shifts in market sentiment and regulatory changes, allowing them to make informed decisions that resonate with their key stakeholders. This ability to rapidly adjust to external input enhances the responsiveness of an organization's sustainability efforts (C3.ai, 2023).

MORNINGSTAR SUSTAINALYTICS enhances the entire information value chain by employing *ML* and *NLP* technologies to collect and analyze vast amounts of data. The platform uses predictive analytics to forecast future ESG trends, while sentiment analysis through *NLP* allows for a deeper understanding of stakeholder concerns as reflected in Big Data sources (Theil & Brutian, 2024). This helps companies monitor and better understand ESG metrics across industries. Consequently, companies can gain a deeper understanding of their specific context by utilizing AI tools, making the DMA process more accurate and aligned with their operational environment. While AI enhances Step A by providing a broad and up-to-date view of the sustainability landscape, potential hindrances exist.

7.2 AI Applications in Step B: Identification of Sustainability-Related IROs

Identifying IROs involves compiling a comprehensive list of actual and potential IROs associated with ESG matters. This process requires a detailed analysis of how these IROs manifest within the company's operations and broader context (EFRAG, 2024a, pp. 21–22). The DMA should identify material IROs that extend throughout the entire value chain. This includes direct operations and indirect impacts that take place upstream and downstream of the value chain. By doing so, a DMA ensures that the company addresses material IROs that may otherwise be overlooked (EFRAG, 2024b, p. 26). Reports should emphasize opportunities and focus on risks and opportunities that arise from sustainable practices. They should also include details on how business strategies align with and capitalize on these opportunities (EFRAG 2021b, pp. 63–70). Opportunities may be identified through *NLP* AI tools that analyze diverse information sources, including corporate reports, news articles, and social media. Such a data-driven approach can help companies ensure a comprehensive and auditable DMA process (EFRAG, 2021b).

Companies should leverage their existing text data assets, such as emails and reports, to generate value through AI. Training specialized *NLP* models for specific divisions or business units enables companies to enhance insights and efficiency (Gruetzemacher, 2022). In addition to avoiding negative impacts, companies should adopt an IRO mindset, proactively seeking to report not only on risks but also on opportunities that may enhance sustainability and business performance. This approach aligns with EFRAG, which emphasizes a forward-looking strategy in sustainability reporting (2021b, pp. 63–70).

In Step B, the findings demonstrate data integration and management potential for AI DMA providers by identifying opportunities, integrating management systems, and benchmarking.

7.2.1 Identification of Opportunities

The AI DMA provider *C3* employs *NLP* not only to monitor and manage sustainability risks but also to proactively alert users to emerging risks by continuously analyzing a variety of data sources, including company reports, stakeholder data, news, and social media feeds. This real-time monitoring allows companies to better avoid potential ESG risks before escalating. In addition, *C3* identifies opportunities for improvement across ESG domains, offering data-driven recommendations to users on enhancing sustainability performance (C3.ai, 2023). Through the analysis of data trends and patterns, *C3* can identify areas where a company has significant potential to mitigate negative impacts and enhance positive outcomes.

For example, through operational efficiency, energy use optimization, or improved social initiatives and better governance practices. The recommendations encompass not only the identification of weaknesses but also the exploration of opportunities that may foster innovation and facilitate long-term value creation. C3 facilitates the alignment of corporate sustainability strategies with prospective opportunities, extending beyond mere compliance (C3.ai, 2023).

7.2.2 Integration of Management Systems and Company Portfolios

C3 integrates ESG data across various enterprise systems like ERP, CRM, and SCM platforms. By creating a 'singular data entity,' C3 ensures that ESG performance is continuously tracked and managed across different business functions. This integration allows companies to centralize their sustainability efforts, facilitating real-time ESG metrics monitoring. C3 consolidates data from various systems, allowing organizations to achieve a comprehensive and unified view of their ESG performance, which supports informed decision-making and facilitates compliance with sustainability frameworks (C3.ai, 2023). *MORNINGSTAR SUSTAINALYTICS* takes a portfolio-based approach, offering predictive analytics to anticipate material ESG topics for companies operating multiple entities or engaging in diverse activities. By assessing the ESG risks and opportunities across a company's entire portfolio of operations, *MORNINGSTAR SUSTAINALYTICS* provides deeper insights into individual risks associated with specific business units, locations, or activities. This approach helps companies prioritize ESG efforts where they are most needed. For example, the product can analyze geolocation and physical risks, such as climate-related threats, by processing data to determine which locations are most vulnerable to environmental hazards (Theil & Brutian, 2024).

7.2.3 Performance Comparison and Benchmarking

Using evidence-based and science-based targets enables better comparability to other companies in the same industry and benchmarking among them (EFRAG, 2021b, pp. 63–70). C3 compares performance on priority ESG metrics within the industry to ESG benchmarks to peers (C3.ai, 2023). *KAROMIA* also leverages external documents to gain insights and benchmarking against competitors and industry standards (Hiel, 2024). *VERSO* leverages big data, including tens of thousands of benchmark data points and hundreds of materiality analyses from various industries, to facilitate comprehension and comparison with DMAs (VERSO, 2023, 2024).

7.3 AI Applications in Step C: Assessment and Determination of Material IROs

Assessing the materiality of IROs involves applying specific criteria such as severity, likelihood, and potential financial impact. This process requires careful evaluation to determine which IROs are significant enough to warrant further action (EFRAG, 2024a, pp. 23–24). In Step C, AI DMA providers help companies through automation and quantification. This allows companies to focus on interpreting the results and making decisions based on the findings rather than being trapped by manual data handling (C3.ai, 2023; Hiel, 2024).

7.3.1 Process Automation

The AI DMA provider *KAROMIA* automates the preparation part of the assessment process by extracting quantitative and qualitative insights from large datasets and organizing and categorizing data into relevant subtopics. The product enables organizations to consistently apply predefined criteria across all data sets, accelerating the process and helping minimize human error and bias. Thus, it enhances objectivity and reliability in identifying material IROs (Hiel, 2024). *C3* employs automation to handle calculations for GHG emissions across scopes 1, 2, and 3. This automation reduces reliance on manual data handling, enhancing the reporting process's precision, auditability, and efficiency (C3.ai, 2023). *C3* enhances emissions tracking efficiency, aiding organizations in meeting environmental standards while reducing the likelihood of human error. Similarly, *KAROMIA* offers to simplify traditionally labor-intensive tasks such as research and interdepartmental coordination by alleviating the burdens of manual data gathering and enhancing the overall efficiency of sustainability reporting through automation (Hiel, 2024).

7.3.2 Quantification of IROs

DMAs in Step C and an understanding of the business model are both improved by the quantification of IROs and the effect that they have on cashflows (EFRAG, 2021b, pp. 63–70). Qualitative insights must not be underemphasized since they are as valuable as quantitative insights (Klein et al., 2023). *KAROMIA* performs automatic scans of internal and external documents to extract pertinent information, encompassing quantitative insights, such as total energy consumption measured in MWh, and qualitative insights, including the management of customer complaints and governance matters. The product organizes insights into subtopics, such as water pollution (Hiel, 2024).

7.4 AI Applications in Step D: Reporting Material IROs

Step D involves the reporting, documenting, and disclosing the materiality assessment process and its results, including how decisions were made regarding materiality (EFRAG, 2024a, pp. 24–25). The reported sustainability statement should cover all relevant actors in the value chain, including indirect business relationships (EFRAG, 2024b, p. 28). The findings in Step D relate closely to typical *LLM* chatbot text processing capabilities like text summarization and data analysis, as well as the accuracy and reliability of generated data.

7.4.1 Text Summarizing and Automated Data Analysis

MORNINGSTAR SUSTAINALYTICS is committed to generating comprehensive summaries of sustainability-related risks and management practices. Its objective is to deliver clear, concise, and easily digestible information that caters to a wide range of stakeholders (Theil & Brutian, 2024). Alternatively, *FINGREEN* adopts a more data-driven and technologically advanced approach, pledging to analyze large volumes of historical data to predict corporate responses to emerging sustainability challenges. The platform automates significant portions of the sustainability reporting process by leveraging *ML* and predictive analytics. *FINGREEN* assists companies maintain compliance with evolving regulations, such as the ESRS and other frameworks. This allivates the burden on companies, streamlines reporting, and improves the overall accuracy and timeliness of sustainability disclosures (Louis, 2024).

7.4.2 Accuracy and Reliability of Data

AI facilitates report generation and compliance with regulatory frameworks. For example, *MORNINGSTAR SUSTAINALYTICS* generates summaries of sustainability-related risks and management practices (Theil & Brutian, 2024). *KAROMIA* ensures that each data-generated insight can be traced back to its retrieval source, such as the specific page of a document, thereby promoting transparency. This systematic approach to documentation supports precise and reliable DMA reporting and data quality (Hiel, 2024). *DATAMARAN* promises to manage DMA material issues identification complexities by providing reliable and traceable sources of information to ensure stakeholder and auditor scrutiny. This should be achievable through customizable and explainable processes to support transparent stakeholder and auditor communications (Datamaran, 2024).

7.5 Systematic Content Analysis Findings

A systematic Content Analysis was performed on the 2023 sustainability reports of the 25 largest EU companies by market capitalization to assess their readiness for the CSRD, their adoption of materiality matrices, the reporting frameworks employed, and the application of AI across various business functions, particularly in conducting DMAs. The objective was to examine how companies can leverage AI applications in their DMA processes.

7.5.1 Variation in Materiality Approaches and CSRD Preparedness

The analyzed sample of companies covers a broad spectrum of EU countries: 10 from France, four from Germany, three from Ireland, three from the Netherlands, two from Spain, one from Denmark, one from Belgium, and one from Sweden. Their market capitalizations range from \$90.38 billion (*Investor AB*) to \$522.13 billion (*Novo Nordisk*), reflecting a diverse representation of industries and economic scales within the EU market. The analysis revealed that almost all the analyzed companies (21 out of 25) are actively preparing to comply with the CSRD requirements, indicating a significant shift towards embracing the new regulatory landscape. However, only 11 out of the 25 companies presented a materiality matrix of some kind in their reports. Among these, two companies—*SAP* and *Inditex*—illustrated their materiality matrices as tables, while Allianz mentioned having one but did not supply a visual representation.

Notably, only three companies—*Inditex*, *Eaton*, and *Anheuser-Busch InBev*—adopted a strict inside-out/outside-in perspective in their materiality matrices as proposed by the CSRD. The remaining companies employed alternative approaches (a comprehensive list is provided in [Appendix B](#)). For instance, *Schneider Electric* used an internal stakeholders/external stakeholders' framework, while *SAP* combined GRI standards with the German Commercial Code (HGB) requirements to constitute its materiality matrix. This variation demonstrates the diversity in methodologies and interpretations of materiality among leading EU companies and various approaches to materiality matrices, supporting findings of previous empirical studies of DMA assessments. The limited adoption of a double materiality approach is consistent with findings from previous studies. Only 17% of companies incorporated double materiality into their 2021 non-financial reports, with even fewer doing so in the preceding two years (De Cristofaro & Gulluscio, 2023).

7.5.2 Sustainability Reporting Frameworks and AI Adoption

In terms of sustainability reporting frameworks, the companies exhibited varied preferences. 24 companies reported against Task Force on Climate-related Financial Disclosures (TCFD) guidelines, indicating a solid emphasis on climate-related financial risk disclosure. 20 companies aligned their reports with GRI standards, 20 utilized SASB metrics reflecting a commitment to comprehensive sustainability reporting, and eight reported against WEF guidelines (Table 1). Six companies—*SAP*, *Accenture*, *Prosus*, *Siemens*, *Allianz*, and *Medtronic*—submitted reports for all four frameworks concurrently. None of these companies are in the top three by market capitalization, indicating that extensive reporting across various frameworks is not exclusively limited to the largest firms. Conversely, two companies—*LVMH* and *Dior*—reported exclusively against TCFD, suggesting a more focused approach to climate-related disclosures, potentially due to their primary product offerings.

7.5.3 AI in Business Functions and DMAs

In 2023, all 25 analyzed companies actively leveraged AI technologies across various business functions. The Content Analysis compressed 16 identified into 12 categories of application in which AI was employed (Table 2). This widespread adoption of AI indicates a strong recognition among leading EU companies of the strategic importance of AI in driving innovation, efficiency, and competitive advantage. However, despite the broad use of AI, only 2 of the 25 companies—*SAP* and *Eaton*—leveraged AI specifically for conducting their DMAs. This represents a mere 8% of the largest EU companies utilizing AI in their materiality analysis for 2023. AI technologies like *NLP* enable companies to analyze stakeholder communications more effectively, identifying key concerns and sentiments that inform the DMA process. Companies already utilizing AI in different business functions should leverage AI for DMAs, as *Eaton* has leveraged AI to enhance its stakeholder analysis (Eaton, 2023, p. 39). The limited utilization of AI in DMAs suggests that although companies see AI's potential in various areas, its use in materiality assessments is still emerging among the largest EU companies.

These findings highlight a significant opportunity for companies to enhance their DMA processes through AI. Adopting AI in DMAs can lead to more efficient data processing, improved accuracy in identifying material issues, and enhanced compliance with regulatory requirements. However, the low adoption rate indicates potential barriers such as a lack of awareness, technical expertise, or concerns about integrating AI into existing processes.

Table 1 Content Analysis – Initial Results

	CSRD Preparation	Materiality Matrix	GRI	SASB	TCFD	WEF	AI Deployment	AI DMA Leverage
<i>Novo Nordisk</i>	✓	x			•	•	✓	x
<i>LVMH</i>	✓	x			•		✓	x
<i>ASML</i>	✓	✓	•		•		✓	x
<i>SAP</i>	✓	✓	•	•	•	•	✓	✓
<i>Hermès</i>	✓	x	•	•	•		✓	x
<i>L'Oréal</i>	✓	x	•	•	•		✓	x
<i>Accenture</i>	x	x	•	•	•	•	✓	x
<i>Prosus</i>	✓	✓	•	•	•	•	✓	x
<i>Inditex</i>	✓	✓	•	•	•		✓	x
<i>Siemens</i>	x	x	•	•	•	•	✓	x
<i>TotalEnergies</i>	✓	x		•		•	✓	x
<i>Schneider Electric</i>	✓	✓		•	•		✓	x
<i>Deutsche Telekom</i>	✓	x	•	•	•		✓	x
<i>Sanofi</i>	✓	x	•	•	•		✓	x
<i>Eaton</i>	✓	✓	•	•	•		✓	✓
<i>Anheuser-Busch</i>	✓	✓	•	•	•		✓	x
<i>Allianz</i>	✓	✓	•	•	•	•	✓	x
<i>Dior</i>	✓	x			•		✓	x
<i>Medtronic</i>	✓	x	•	•	•	•	✓	x
<i>Airbus</i>	x	✓	•	•	•		✓	x
<i>Air Liquide</i>	✓	✓	•	•	•		✓	x
<i>EssilorLuxottica</i>	✓	x	•		•		✓	x
<i>Iberdrola</i>	✓	x	•	•	•		✓	x
<i>Safran</i>	✓	✓	•	•	•		✓	x
<i>Investor AB</i>	✓	x	•	•	•		✓	x

Table 2 AI Deployment Categories of Largest EU Companies

	<i>Novo Nordisk</i>	<i>LVMH</i>	<i>ASML</i>	<i>SAP</i>	<i>Hermès</i>	<i>L' Oréal</i>	<i>Accenture</i>	<i>Prosus</i>	<i>Inditex</i>	<i>Siemens</i>	<i>TotalEnergies</i>	<i>Schneider Electric</i>	<i>Deutsche Telekom</i>	<i>Sanofi</i>	<i>Eaton</i>	<i>Anheuser-Busch</i>	<i>Allianz</i>	<i>Dior</i>	<i>Medtronic</i>	<i>Airbus</i>	<i>Air Liquide</i>	<i>EssilorLuxottica</i>	<i>Iberdrola</i>	<i>Safran</i>	<i>Investor AB</i>
Product Enhancement/ Improvement, R&D	•		•	•		•	•	•			•	•		•			•		•	•		•	•	•	
Transaction Automation		•						•		•	•		•	•						•	•	•	•	•	•
Training and Development	•					•	•	•			•	•	•						•		•		•	•	•
Cooperations and Partnerships		•					•					•		•				•	•		•	•			
Explore Opportunities		•	•					•	•		•												•	•	•
Customer Experience		•				•						•				•		•					•	•	
Optimize Operations																•		•		•		•	•	•	
Positive Impact							•					•							•	•		•			
Risk Management and Cyber Security										•			•		•		•			•					
Energy Efficiency					•								•		•								•		
Cost Reduction				•				•														•			
Double Materiality Assessment				•											•										

8 Discussion

The findings address the research objectives by demonstrating how AI technologies are used in DMAs, mitigating specific challenges, and assessing their benefits and limitations. The Market Scan identified key AI tools and providers in the DMA space, detailing their functionalities and value propositions, thus achieving the first objective. The investigation into how AI addresses challenges in DMAs shows that AI mitigates inconsistencies, enhances operational efficiency, and improves stakeholder engagement, aligning with the second objective. The critical analysis highlights the potential benefits of AI, such as data processing capabilities and efficiency gains, while also acknowledging limitations like transparency issues and ethical concerns, fulfilling the third objective.

This paper links AI tools to specific challenges in the DMA process identified in the literature. AI enhances each DMA step at different levels. In context analysis, it aggregates and structures data efficiently. In identifying IROs, it broadens potential issues through insights. In materiality assessments, it automates the process, reducing manual work and increasing consistency. AI further supports reporting by generating summaries, ensuring compliance, and enhancing transparency through traceability. Inconsistencies in materiality assessments, as highlighted by *Fiandrino et al.*, stem from varying methodologies and applications across companies, leading to different prioritizations of sustainability issues and a lack of transparency in materiality processes (2022, pp. 670–671).

AI tools can address these inconsistencies by providing a more standardized and data-driven approach to materiality assessments. For instance, AI-powered platforms can systematically collect and analyze large volumes of data from diverse sources—including regulatory documents, industry standards, and stakeholder inputs—to generate a comprehensive list of potentially material topics. By mapping collected data to relevant guidelines such as the ESRS, AI facilitates quantitative and qualitative assessments of sustainability issues, promoting consistency in identifying and prioritizing material topics across different organizations (Louis, 2024; Moran et al., 2024).

AI can enhance understanding of results' sources in the materiality assessment process, which is crucial since companies often fail to provide detailed reporting on their materiality assessments, leading to stakeholder skepticism (Beske et al., 2020; Machado et al., 2021). Companies can provide verifiable information that increases stakeholder trust by utilizing AI technologies that trace each generated insight back to its retrieval sources, such as *KAROMIA*'s approach of linking insights to specific documents and pages (Hiel, 2024). This aligns with EFRAG's prescribed need for transparent methodologies in the DMAs (EFRAG, 2024a, pp. 24–25).

The issue of biases in traditional DMAs, as noted by *Klein et al.*, arises from human subjectivity and the tendency to focus on issues aligned with current strategies rather than assessing all relevant material issues (2023). AI can mitigate these biases by leveraging objective data analysis. AI algorithms can process vast amounts of information without preconceived notions, reducing the influence of individual biases in the materiality assessment process. For example, AI-based scans support objective data scanning for relevance and bias minimization, considering a wider array of stakeholder perspectives. This helps in enriching decision-making processes in DMAs by reducing human biases in data collection and analysis (EFRAG, 2021c, p. 93).

AI can facilitate a more comprehensive stakeholder engagement process, which is essential since DMAs require evaluating sustainability issues from multiple stakeholder perspectives (Latos et al., 2024). AI tools can analyze stakeholder communications, social media, and public reports to capture a wide array of stakeholder perspectives, minimizing the risk of selective consideration of stakeholder views. For instance, AI can perform sentiment analysis to understand stakeholder opinions on material issues, as utilized by *MORNINGSTAR SUSTAINALYTICS* (Theil & Brutian, 2024). Challenges identified by *Gleissner* regarding the implementation of the CSRD—such as difficulties in systematically comparing different topics and the need for a focused and methodically correct materiality analysis (2024)—can be partially addressed by AI applications. AI tools can standardize various non-financial indicators by converting them into standard units or indices, facilitating systematic comparisons. By automating the prioritization process, AI reduces the manual workload and potential for human error, addressing the challenge of high review and updating costs (Gleissner, 2024, p. 32). For instance, AI can continuously monitor and update materiality assessments based on real-time data, ensuring that companies remain responsive to emerging sustainability issues and regulatory changes (C3.ai, 2023).

This thesis contributes to the emerging field of AI applications in integrated reporting, specifically in conducting a DMA. It highlights the potential of AI technologies to enhance the DMA process by addressing key challenges identified in the literature. However, it also acknowledges the challenges, limitations, and potential risks associated with AI implementation, such as data bias, privacy concerns, and the need for transparency.

Despite AI benefits to DMAs, limitations include the AI algorithm's opaque nature, dependence on data quality, and potential ethical concerns, highlighting the need for human oversight in AI-driven DMAs. AI DMA providers often address the process's more straightforward or easily achievable aspects—commonly referred to as 'low-hanging fruit.' This typically involves focusing on automating routine processes such as data collection, aggregation, and basic reporting tasks like text enhancement. However, they tend to fall short of offering genuinely independent and innovative in-depth assessments of material IROs.

Instead of harnessing AI's potential for deeper analysis and insights into complex, multifaceted ESG issues, many providers remain confined to basic automation, thus limiting the overall effectiveness of the DMA process. This highlights a gap between the potential for AI to drive transformative insights in sustainability reporting and its current application within the field. Furthermore, AI DMA providers fall short of addressing the critical connection between financial and impact materiality and miss thus the essential idea of dynamic materiality.

Integrating AI into the DMA process introduces challenges that companies must navigate carefully to ensure compliant DMAs. Regulatory requirements emphasize the need for transparency in the materiality assessment process. The black-box nature of AI thus can hinder transparency, making it challenging to understand how decisions are made and to maintain confidence in the reported data. AI algorithms can make it hard for stakeholders to understand how metrics are calculated, undermining transparency and accountability. This concern highlights the need for clear explainability and visibility into AI-driven processes to ensure trust and auditability (EY, 2023). AI models are dependent on the data on which they are trained. Poor-quality or biased data can lead to flawed assessments, which may result in overlooking significant IROs. Ensure diverse and high-quality data sources and regularly audit AI outputs to maintain the integrity of the DMA.

The use of AI in DMAs raises ethical concerns related to privacy, data security, and the potential for AI to amplify existing social inequalities if not carefully managed (Babashahi et al., 2024; Cows et al., 2023). Ethical AI practices and inclusive approaches are key to ensuring that AI implementation does not introduce new biases or exacerbate existing ones (Ametepey et al., 2024). As *van Wynsberghe* suggested, there is a need for a policy framework to assess AI applications, particularly concerning their environmental impact and ethical considerations (2021). There is a risk that companies might rely too heavily on AI-generated outputs without sufficient human validation. This over-reliance could lead to inaccuracies, especially if the AI models are not regularly updated or if they fail to capture the dynamic nature of materiality and evolving stakeholder expectations (De Cristofaro & Gulluscio, 2023, p. 21).

The lack of transparency can conflict with the CSRD's requirements for transparency and documentation of the materiality assessment process (Gleissner, 2024) and undermine stakeholder trust, and fail to meet regulatory expectations. If companies cannot explain how AI algorithms arrived at specific materiality determinations, it may undermine stakeholder trust and fail to meet regulatory expectations (EFRAG, 2024a, pp. 24–25). To address this, AI DMA providers should incorporate *XAI* techniques to ensure the decision-making processes are transparent and understandable (Theil & Brutian, 2024). DMA AI providers seem to recognize the utter importance of *XAI* for leveraging AI advantages while maintaining transparency and traceability in decision-making. In the same vein, it is important to state that non-AI conducted DMAs might also be subject to a lack of transparency by not being able to communicate methodologies and criteria used in the process (Klein et al., 2023).

In light of the new DMA regulations, companies are encouraged to re-evaluate their core activities and impacts extensively (Nielsen, 2023). AI DMA providers are marketing solutions for novel and legally mandatory integrated reporting directives. Many ESG software providers already adapted AI technologies to their products and integrated them into products to offer companies value via facilitation, simplification, and add-on services. AI can identify emerging risks not captured in static approaches by continuously tracking metrics. This dynamic element of AI allows early intervention and timely adaptability. Businesses are encouraged not to ignore AI to avoid falling behind competitors (A. McAfee et al., 2023). DMAs conducted with AI can serve as verification mechanisms against manually extracted results which might enhance trust and reliability of represented results (Moran et al., 2024).

Companies should implement AI through pilot projects to test applications on a smaller scale, assess effectiveness, and address issues before full integration (Enholm et al., 2022). This approach helps build internal capabilities and ensures that AI tools are tailored to the company's specific context and needs. Furthermore, policymakers and companies should consider guidelines for the ethical use of AI in sustainability reporting. Addressing potential risks such as data privacy concerns and lack of transparency in algorithms is essential (Mariani et al., 2022; van Wynsberghe, 2021). Establishing clear regulatory frameworks promotes responsible AI adoption, including adherence to data protection regulations and the incorporation of explainable AI techniques (Theil & Brutian, 2024).

The integration of AI into DMAs does not eliminate the need for human expertise and judgment. Overreliance on AI could result in companies overlooking the nuanced understanding of their unique contexts, cultures, and strategic objectives that human analysts provide (Grebe et al., 2023). Human analysts play a crucial role in interpreting AI-generated insights, validating findings, and making strategic decisions based on the materiality assessment. This collaboration ensures that DMAs are not only data-driven but also aligned with the company's values and stakeholder expectations (Moran et al., 2024). Companies increasingly recognize the importance of human supervision in the use of AI and are committing to responsible AI practices in their business activities. This need for human oversight becomes even more critical when employing generative AI solutions, which can introduce additional complexities and risks. For example, *Allianz* has integrated robust human-centric controls into its AI governance framework. Their strategy ensures that AI is used responsibly and ethically across the organization, particularly in areas where generative AI is applied (Allianz, 2023, p. 127).

Experts advocate not to use *LLMs* for tasks where errors could have severe consequences to avoid high risks. Human supervision over AI outputs ensures quality, especially in critical applications (A. McAfee et al., 2023). Collaboration between humans and AI is key since human judgment is still required to undergo the CSRD journey and ensure the quality of DMAs (Moran, D'Antoni, and Jonas 2024). Such a human-AI interplay hybrid approach might reap the advantages of both realms without compromising DMAs' results since successful AI adoption requires seamless integration of human judgment with AI capabilities (Grebe et al., 2023). *GenAI* can handle ambiguity and facilitate human-AI collaboration, surpassing traditional AI in handling ambiguity and uncertainty, fostering human-AI collaboration (Feiner et al., 2024).

While AI enhances the DMA process, it cannot replace human expertise. The complexities of sustainability issues often require nuanced understanding and strategic judgment that AI alone cannot provide. Human judgment is essential for interpreting AI outputs, making strategic decisions, and ensuring that the company's values and context are appropriately considered. For instance, understanding the implications of a particular environmental risk may require industry-specific knowledge and an appreciation of local community concerns.

Self-control mechanisms are key for companies to address AI's ethical concerns when integrating into products. For example, in its governance efforts, *SAP* deploys internal and external AI committees to discuss ethical AI considerations in its products and supervise and ensure upholding the company's principles, policies, and standards when integrating AI into its products (*SAP*, 2023, pp. 122, 264). Companies are aware of the ever-increasing social demand for transparency and ethical considerations when deploying AI (*L'Oréal*, 2023a, p. 159).

9 Conclusion

This thesis explored how AI and DMAs intersect within the EU's CSRD framework. The main findings indicate that AI has the potential to enhance each step of the DMA process. AI tools can address inconsistencies in materiality assessments (Fiandrino et al., 2022), mitigate human biases in traditional DMAs (Klein et al., 2023), and help overcome operational challenges associated with the implementation of the CSRD (Gleissner, 2024). The thesis's significance lies in its timely exploration of AI's role in addressing the complexities of DMAs, especially in light of the CSRD framework. By analyzing existing AI technologies and their applications in the DMA process, the paper provides valuable insights into the market of AI DMA providers. It also contributes to the broader discourse on the application of digitization in integrated reporting.

This thesis emphasizes the execution of DMAs, while the AI technologies discussed may assist in analyzing data received from third-party limited assurers and evaluating the process of addressing shortages in first submissions. Consequently, the implementation of AI technologies holds promise for integrated reporting, specifically following the DMA conducting process.

While this study provides valuable insights, it is important to acknowledge certain limitations. One significant limitation is the rapid evolution of AI technologies. The field of generative AI is rapidly evolving, with new use cases and models emerging constantly (McKinsey & Company, 2024a). This means that the findings of this study may quickly become outdated as newer AI tools and algorithms are developed. Scholars are keen to further enhance AI models e.g. by equipping them with advanced problem-solving and efficiency capabilities (Lingo et al., 2024), and by developing new frameworks to circumvent complexity (Zhu et al., 2024a).

One recent example of the rapid advancements in the AI landscape is OpenAI's latest LLM 'OpenAI o1', which potentially exhibits characteristics of consciousness during its training and inference phases. OpenAI o1's capability of self-correction and internal feedback mechanisms is to be interpreted as evidence of a rudimentary form of self-awareness and the existence of an internal value system (Zhu et al., 2024b). This development may have substantial implications for DMAs, as advanced AI models could provide improved capabilities in the understanding and processing of complex sustainability data.

The Market Analysis shows that AI DMA providers can deliver on the four steps of DMA advocated by EFRAG. However, vague statements and insufficient information about the process used were evident. For example, *DATAMARAN* states that it aims to help companies identify material issues and assess IROs for CSRD and advocates data-backed decisions in order to allow companies to focus their resources on material matters (Datamaran, 2024). Such general statements do not account for the high stakes of new regulations. Also, AI DMA providers lack specific information on how to undergo the process. For example, C3 promises to perform materiality assessments to help determine focus areas and topics, combining financial and stakeholder impact data to determine material topics to be disclosed (C3.ai, 2023). Nonetheless, the means by which this can be accomplished remains ambiguous.

The conducted Market Analysis reveals that product descriptions of DMA AI providers tend to be positively connotated, as vendors are primarily focused on marketing their products. The term 'AI' appears to be overstated among most providers, resembling a bubble that might disregard the complexity associated with DMAs and their corresponding IROs. This undermines the validity of the Market Scan and increases vulnerability to subjective evaluation and biased results. To address this challenge, the rigorous desktop academic Literature Research was conducted to mitigate positive marketing sentiments and ensure a thorough analysis of the potential and constraints of AI in conducting a DMA. The Content Analysis reveals a proactive stance among leading EU companies in embracing sustainability reporting and AI technologies. However, the application of AI in DMAs requires further enhancement.

There is a clear avenue for companies to leverage AI more extensively in their materiality assessments, which could enhance the effectiveness of sustainability reporting and compliance with evolving regulations like the CSRD. The potential risks of overreliance on AI include possible data privacy concerns. As AI systems process vast amounts of data, including, there is an increased risk of violating data protection regulations. AI DMA providers must implement robust data governance frameworks to safeguard personal data and maintain stakeholder trust (Mariani et al., 2022). AI systems trained on historical data may perpetuate existing biases (De Villiers et al., 2024; A. McAfee et al., 2023). The AI model may overlook or undervalue issues pertinent to underrepresented stakeholders, leading to skewed materiality assessments. Companies must ensure that their AI tools are developed and used responsibly, adhering to ethical guidelines and regulatory requirements (Babashahi et al., 2024; van Wynsberghe, 2021).

This study focuses primarily on the application of AI in DMAs within the context of EU regulations, specifically the CSRD framework. While the findings offer valuable insights, they may not directly apply to other regulatory contexts or industries. While the requirements of different frameworks might be similar, the Eurocentric approach may limit the generalizability of the findings. Therefore, additional research is needed to explore the potential of AI in DMAs across different regulatory contexts and industries. Future studies could explore AI applications in DMAs under different regulatory environments, examining how AI tools can be adapted to comply with various international sustainability reporting standards. Longitudinal research could evaluate the long-term impacts of AI integration into DMAs, evaluating how AI adoption influences sustainability reporting practices over time

As AI models become more sophisticated, they may provide improved accuracy and efficiency in conducting DMAs. However, these advancements also raise new ethical and regulatory considerations, particularly regarding transparency, accountability, and the potential for AI systems to operate beyond human oversight. Companies and policymakers must remain vigilant in monitoring these developments to ensure that the integration of AI into DMAs aligns with ethical standards and regulatory requirements.

AI has the potential to enhance the DMA process under the CSRD framework by improving consistency, reducing biases, and addressing operational challenges. However, companies must balance the benefits of AI with careful consideration of its limitations. Companies must invest in training employees to work effectively with AI tools. This includes developing skills in data interpretation, critical thinking, and ethical considerations. The human-AI partnership is crucial in achieving a balanced and effective DMA. Organizations can enhance their sustainability reporting practices by combining AI capabilities with human expertise and starting with pilot projects. Adhering to ethical guidelines further ensures they meet regulatory requirements and contribute to more sustainable business practices. Future research and attention to recent developments in AI will be essential in maximizing the benefits and minimizing the risks associated with AI integration into DMAs.

The author acknowledges the use of AI tools, specifically ChatGPT, QuillBot and Grammarly, in various aspects of this thesis, including proofreading and streamlining text. These tools were utilized as supplementary resources to support the research process. All interpretations, conclusions, and original contributions presented in this work are the responsibility of the author. The use of AI tools was conducted following most current European recommendations ethical guidelines and policies for AI deployment in research (European Commission, 2024)

10 References

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