STOCKHOLM SCHOOL OF ECONOMICS
1351 Master's thesis in Business Management
Academic year 2023–2025

AI-Related Carbon Emissions in Corporate Sustainability Reporting: Extent, Challenges, and Legitimacy Strategies

Sahil Sharma (42374)

Abstract: Artificial intelligence (AI) is transforming industries and driving innovation, yet its significant environmental impacts related to carbon emissions from energy intensive computational processes remain largely hidden in corporate sustainability disclosures. This thesis investigates why companies rarely report AI-related carbon emissions explicitly and how legitimacy considerations shape their disclosure decisions. Guided by Legitimacy Theory, the study employs qualitative analysis of seventeen expert interviews with sustainability specialists, IT professionals, and strategy executives. Findings reveal a notable transparency gap - Organisations typically aggregate AI emissions within broader IT categories or omit them entirely. Practical challenges, such as difficulties in attributing energy use in shared infrastructures and the lack of standardised measurement methods, reinforce non-disclosure. However, these obstacles also conveniently serve corporate legitimacy strategies. Firms selectively frame AI in sustainability reports, emphasising its environmental benefits while downplaying or omitting its direct carbon costs, reflecting impression management practices aimed at preserving corporate legitimacy. Currently, external pressures from regulations, investors, and societal stakeholders remain limited, enabling continued opacity. Nonetheless, increasing internal awareness and evolving norms suggest that AI-specific emissions reporting could become essential in the near future. This research contributes to sustainability disclosure literature by extending Legitimacy Theory to digital sustainability contexts and offers practical recommendations for businesses and policymakers seeking improved transparency and accountability in AI's environmental impacts.

Keywords: Sustainability, Artificial Intelligence (AI), Emissions, Legitimacy

Supervisor:	Sven-Anders Stegare
Date examined:	20^{th} May 2025
Discussant(s):	Jonas Fagerlund and Elin Roslund
Examiners:	Henrik Glimstedt and Stefan Haefliger

Acknowledgement

It is not my intention for this study to be an indictment on the usage of AI. Rather I consider the conversation around AI's emissions as a tacit recognition of the fact that AI is here to stay. Through this study I hope to bring nuance to the broader AI discourse without denigrating its usage. Sustainability is not a stick to beat AI with as that would be unfair to both of these important phenomena of our times.

This thesis would not have been possible without the guidance of my advisor, Mr. Sven-Anders Stegare. His insights and feedback were invaluable for a novice like me with no prior experience with thesis or any academic style writing.

I would also like to thank all those interviewed for sparing the time out of their busy schedules and their expert insights.

I was the sole author for this thesis, but it did not feel as lonely. Thank you, Nicolò for our weekly chats – they made a world of difference in ensuring that I stay on track.

I would also like to thank my friend, Madhu for reading over my thesis and for her encouragement.

Thank you.

Table of Contents

1. Introduction

1.1 Background

Artificial Intelligence (AI) refers to technological systems capable of interpreting external data, autonomously learning from such data, and adaptively applying insights to achieve predefined goals (Haenlein & Kaplan, 2019). Over recent decades, AI technologies, particularly machine learning (ML) and deep learning (DL), have rapidly permeated business operations, reshaping industries by enhancing productivity, efficiency, and innovation capabilities (Dwivedi et al., 2021). The evolution of AI can be traced back to the mid-20th century, with early developments in symbolic AI and expert systems (Russell & Norvig, 2021). Advances in data availability, computing power, and neural network design in the 21st century have brought AI into mainstream use, with wide-reaching effects on industries and society (Russell & Norvig, 2021).

1.1.1 Historical Evolution of AI

The development of AI has not been steady but shaped by alternating periods of rapid progress and slowdown, often described as "AI winters" (Nilsson, 2009). In the early phases during the 1950s and 1960s, AI development focused on symbolic AI, where systems were designed to mimic human reasoning through rule-based algorithms (Russell & Norvig, 2021). However, the limitations of symbolic AI, such as its inability to manage ambiguity and learn from data, contributed to the first AI winter in the 1970s. In the 1980s, expert systems became popular as a way to replicate the decision-making of human specialists in specific fields (Nilsson, 2009). They did show early promise, but these systems depended heavily on manually coded rules and therefore struggled to adapt or scale. This contributed to a decline in interest and marked another AI winter by the end of the decade.

Developments beginning in the 2000s have been characterised by the rise of machine learning (ML) and deep learning (DL). Unlike earlier approaches, ML and DL systems learn patterns from large datasets, enabling them to perform tasks such as image recognition, natural language processing, and predictive analytics with unprecedented accuracy (LeCun et al., 2015). This wave has been driven by three key factors: (1) the availability of massive datasets, (2) the development of powerful computational hardware (e.g. GPUs), and (3) breakthroughs in algorithmic design, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) (Goodfellow et al., 2016). These advancements have enabled AI to move beyond academic research and into real-world applications, creating new opportunities for innovation across sectors.

1.1.2 AI Adoption Across Industries

AI technologies are increasingly embedded across diverse industries, where they enhance operational efficiency and decision-making but also raise concerns about environmental sustainability. In finance, AI supports fraud detection, credit scoring, and high-frequency trading by enabling rapid data analysis and predictive modelling (Bussmann et al., 2021; Chakraborty & Joseph, 2017). The retail sector leverages AI for personalised recommendations and demand forecasting, improving customer experience and inventory management (Wamba-Taguimdje et al., 2020). In manufacturing, AI-driven predictive maintenance and process optimisation reduce downtime and resource waste (Lee et al., 2018). Healthcare increasingly relies on AI for diagnostic imaging and personalised medicine, using large-scale models trained on complex medical data (Topol, 2019; Esteva et al., 2019). Telecommunications companies employ AI for network optimisation and automated customer service, enhancing reliability and responsiveness (Bega et al., 2019). While these applications deliver clear operational benefits, the substantial computational demands of AI systems contribute to growing energy consumption and associated emissions (Strubell et al., 2019).

1.2 Corporate Sustainability Reporting and AI Emissions

Firms traditionally disclose environmental impacts through structured sustainability reports guided by globally recognised standards, notably the Global Reporting Initiative (GRI), the Task Force on Climate-related Financial Disclosures (TCFD), and the Greenhouse Gas (GHG) Protocol (Depoers et al., 2016; Ascui & Lovell, 2011). Among these frameworks, the GHG Protocol developed by the World Resources Institute (WRI) and the World Business Council for Sustainable Development (WBCSD) is extensively adopted, providing explicit guidelines for categorising emissions (WRI & WBCSD, 2004). The Protocol classifies emissions into Scope 1 (direct emissions from owned sources), Scope 2 (indirect emissions from purchased energy), and Scope 3 (indirect emissions from upstream and downstream activities). Scope 3 emissions can encompass areas often overlooked in corporate disclosures, including cloud computing and outsourced data storage services integral to AI applications (Downie & Stubbs, 2013; Ascui & Lovell, 2011; Strubell et al., 2019).

However, explicit reporting on AI-specific emissions remains limited despite these comprehensive frameworks. Firms typically aggregate any AI-related energy use within broader categories (e.g. overall data centre operations or IT energy consumption), obscuring the contribution of AI and preventing stakeholders from accurately assessing AI's true environmental impact (Kaack et al., 2022). This lack of transparency is partly due to practical complexities: organisations face difficulties in isolating AI-related energy consumption within shared cloud infrastructure, challenges in quantifying indirect emissions attributable specifically to AI processes, and uncertainties in attributing emissions to discrete AI applications (Anthony et al., 2020; Kaack et al., 2022). In practice, measuring the carbon footprint of training a single AI model may involve tracing energy use across distributed servers and multiple data centres, which companies seldom do. As a result, AI's environmental impacts are often hidden within aggregate IT emissions figures.

1.3 Practical Urgency: Stakeholder Pressures and Regulatory Expectations

Stakeholders including investors, regulators, non-governmental organizations (NGOs), and customers are increasingly demanding greater corporate transparency regarding environmental impacts, especially those associated with emerging technologies such as AI (Michelon et al., 2015). Investors are progressively integrating sustainability considerations into decision-making, demanding explicit and comparable emissions data to manage financial and reputational risks (Hahn & Kühnen, 2013). Regulatory bodies, especially within Europe, have introduced stringent disclosure requirements (e.g. the EU Corporate Sustainability Reporting Directive), raising the standard for environmental reporting and encouraging more detailed emissions accounting (Bebbington & Unerman, 2018). Simultaneously, societal and consumer pressures have grown: companies touted as digital leaders face greater scrutiny from the public, who demand accountability for the environmental side-effects of innovation (Depoers et al., 2016). As awareness grows, being open and accurate about the environmental impact of AI is becoming essential for earning stakeholder trust, meeting legal obligations, and protecting a company's reputation.

Still, there is a clear gap between what people expect and what most companies actually report (Kaack et al., 2022). Many firms are still grappling with basic sustainability disclosures, so AI-specific reporting may be seen as a next step rather than an immediate priority. Yet as AI adoption accelerates and stakeholders become aware of its environmental costs, companies could soon face more pointed questions about how "green" their AI initiatives truly are.

1.4 Theoretical Justification: Legitimacy Theory

The lack of clear reporting on AI-related emissions can be seen through the perspective of **Legitimacy Theory** (Suchman, 1995; Deegan, 2019). This theory suggests that organisations shape what they share publicly in ways that reflect what society expects, aiming to maintain approval and trust from their stakeholders. In practice, firms may choose to highlight certain actions while downplaying others in order to appear socially and environmentally responsible (Cho & Patten, 2007; Michelon et al., 2015).

In the case of AI, companies might emphasise the technology's benefits such as its role in optimising resource use or enabling new climate solutions while omitting or obscuring its carbon costs. This selective reporting could be a deliberate strategy intended to preserve corporate legitimacy. By highlighting AI as a driver of innovation and sustainability and leaving out its less favourable aspects companies align themselves with what society wants to see. Legitimacy Theory helps explain why firms might hesitate to report emissions linked to AI as revealing these impacts could expose a gap between their stated sustainability commitments and the actual environmental costs of AI, which might put their legitimacy at risk.

Compared to alternative theoretical frameworks (such as Stakeholder Theory or Institutional Theory), Legitimacy Theory is especially useful here because it focuses on voluntary, strategic disclosure decisions aimed at shaping perceptions. It helps explain behaviours like *symbolic compliance* (providing sustainability information in principle but not in depth) and *impression management* (framing information to influence stakeholder perceptions). These concepts are directly relevant to analysing why companies might acknowledge AI in their sustainability narratives but stop short of detailing its carbon footprint. In summary, Legitimacy Theory is a fitting foundation to examine how AI-related emissions disclosures (or the lack thereof) function as part of corporate communication strategies in sustainability reporting.

1.5 Purpose and Research Questions

Given the increasing reliance on AI, its non-trivial environmental impacts, and notable gaps in explicit emissions reporting, this thesis critically investigates how legitimacy considerations shape corporate sustainability disclosures of AI-related carbon emissions. The primary research question is:

RQ: *How do companies approach the issue of AI-related carbon emissions in sustainability reporting, and what role does organizational legitimacy play in shaping their disclosure decisions?*

To address this broad question, the study is guided by four sub-questions:

- **RQ1:** How do companies perceive AI's environmental impact within their sustainability strategies?
- **RQ2:** Why are AI-related emissions not widely reported yet in corporate sustainability disclosures?
- **RQ3:** How do companies frame AI's role in sustainability, and do they present AI as a sustainability solution despite its footprint?
- **RQ4:** What pressures (regulatory, investor, or societal) could drive more explicit AI emissions reporting in the future?

These questions collectively help probe the extent of AI emissions transparency, the challenges and motivations behind current reporting practices, and the external forces that might influence change. They also connect empirical observations (what companies are doing) with theory (why they might be doing it that way), particularly regarding legitimacy management.

1.6 Contributions

This thesis offers several theoretical and practical contributions. The thesis contributes to corporate sustainability research by clarifying how companies are addressing artificial intelligence's environmental impacts. By focusing on AI-related emissions reporting, the study expands current knowledge on transparency and accountability in sustainability practices. From a theoretical perspective, it extends Legitimacy Theory to the context of AI in sustainability reporting. While Legitimacy Theory has been widely applied to traditional environmental reporting, applying it to AI emissions disclosures provides novel insights into strategic corporate behaviour in the digital age. The research uncovers how legitimacy seeking strategies manifest in a cutting-edge domain, potentially expanding the theory's applicability.

Speaking of practical relevance, for policymakers, the findings identify gaps in current reporting standards (like the GHG Protocol and EU directives) regarding AI, suggesting areas where guidelines could evolve. For corporate managers and sustainability officers, the study highlights factors influencing AI emissions disclosure. Understanding these factors can help managers improve transparency and perhaps proactively address stakeholder concerns about AI's environmental impact, aligning corporate practice with emerging societal expectations.

In sum, the thesis contributes to academic discourse by bridging AI technology and sustainability reporting research, and it offers actionable insights to those shaping sustainability communication and policy in an era of rapid AI adoption.

1.7 Delimitations

This study focuses explicitly on strategic sustainability disclosures around AI-associated emissions, rather than performing technical quantifications of those emissions. It does not attempt to measure the carbon footprint of specific AI systems or to develop new methodologies for doing so. Instead, the emphasis is on *reporting practices and organisational behaviour*. The research is geographically centred on European and more specifically Swedish context and experts. This focus means that findings may not fully generalise to regions with less stringent sustainability norms or different cultural expectations around corporate transparency. Additionally, the study is bounded to the perspective of corporate actors and closely related stakeholders (like sustainability professionals, and AI experts). It does not analyse consumer perspectives or broader societal debates about AI's environmental impact beyond how this manifests as pressures on companies. By defining these boundaries, the research hones in on its core inquiry: corporate disclosure behaviour in the face of an emerging sustainability issue.

1.8 Thesis Outline

The thesis is structured into seven chapters:

- **Chapter 2 (Literature Review):** Reviews the existing literature on AI's environmental impacts, corporate sustainability reporting practices, and Legitimacy theory. This chapter identifies gaps in knowledge regarding AI-related carbon disclosures, and sets the foundation for the theoretical framework.

- **Chapter 3 (Theoretical Framework):** Presents Legitimacy Theory as the primary theoretical lens guiding the study. It defines key concepts and explains why this theory is suitable for analysing AI emissions reporting, in comparison to alternative perspectives.

- **Chapter 4 (Methodology):** Outlines the qualitative research design, including the use of semi-structured expert interviews. It details the participant selection, data collection procedures, and the thematic analysis approach used to interpret the data. Methodological considerations and limitations are also discussed.

- **Chapter 5 (Empirical Findings and Analysis):** Details the empirical results from the expert interviews. The findings are organised into thematic categories (current practices, measurement challenges, legitimacy-seeking strategies, and external pressures) and are analysed in light of the literature and theory.

- **Chapter 6 (Discussion):** Interprets the findings in relation to the research questions and theoretical framework. It examines how the empirical results align with or diverge from expectations in the literature, and it discusses the implications for legitimacy theory and corporate practice.

- **Chapter 7 (Conclusion):** Summarises the key findings of the research and reflects on their significance. It outlines the study's limitations and offers recommendations for future research. This chapter also provides closing thoughts on the evolving intersection of AI innovation and sustainability accountability.

By following this structure, the thesis builds from broad context and theory to focused empirical insights and then to broader implications, mirroring the research process itself.

2. Literature Review

This chapter provides a comprehensive overview of academic literature related to the environmental implications of AI, sustainability reporting practices, and corporate legitimacy in reporting. It identifies the research gaps that the present study addresses and sets the stage for the theoretical framework in Chapter 3.

2.1 Artificial Intelligence and Its Environmental Impact

The rapid adoption of AI technologies by businesses worldwide has significantly transformed organisational practices (Dwivedi et al., 2021). AI applications promise improved operational efficiency, productivity, and competitiveness. However, emerging research highlights the environmental impact of AI, with a focus on carbon emissions caused by energy intensive computation (Brevini, 2022; Strubell et al., 2019).

2.1.1 The Energy Intensity of AI Systems

AI systems such as those based on deep learning require substantial computational resources for training, inference, and ongoing maintenance (Anthony et al., 2020). Training a state-of-the-art deep learning model involves running vast neural networks on specialised hardware (GPUs or TPUs) for days or weeks, consuming large amounts of electricity. For example, an NLP model training run can emit as much carbon as several passenger cars do in a year (Strubell et al., 2019). These energy demands translate into a sizeable carbon footprint if the electricity is generated from fossil fuels.

Research has begun quantifying this footprint. Strubell et al. (2019) famously estimated the CO2 emissions of training a big NLP model (with hyperparameter tuning) at around 300 tons. Similarly, Anthony et al. (2020) introduced tools like CarbonTracker to monitor and predict emissions from model training. Such efforts highlight that AI's environmental cost is not negligible, especially as models grow larger and more ubiquitous.

Importantly, AI's energy intensity spans the entire lifecycle of AI systems, not just training. Continuous deployment, frequent model updates, and billions of inferencing operations (such as daily user queries to AI services) cumulatively draw significant power. The environmental impact therefore includes operational phases, and even extends to manufacturing and disposing of hardware (Brevini, 2022). Nonetheless, the most direct and measurable component remains electricity usage and its associated emissions during computation.

2.2 Corporate Sustainability Reporting Practices

Corporate sustainability reporting has evolved into a standardised practice for disclosing environmental, social, and governance (ESG) performance. Firms use sustainability reports and related disclosures to communicate their impacts and commitments to stakeholders. This section reviews general sustainability reporting practices and the typical treatment of IT-related emissions within them.

2.2.1 Evolution of Sustainability Disclosure

Over the past two decades, sustainability reporting has shifted from a voluntary, niche practice to a more regulated and expected corporate activity. Many large companies now produce annual sustainability reports alongside financial reports (Hahn & Kühnen, 2013).

Despite increased reporting, quality and transparency vary. Research finds that companies sometimes engage in selective disclosure highlighting favourable information (e.g., emission reductions, renewable energy use) while omitting less favourable aspects (Cho et al., 2015). Assurance of reports by third parties is one mechanism to improve credibility, but it is not universally practiced.

Additionally, *what* gets reported is influenced by materiality assessments that identify issues deemed material to stakeholders. Historically, energy use and greenhouse gas emissions have been material for many industries, leading to fairly robust disclosure of Scope 1 and Scope 2 emissions (Kolk, Levy, & Pinkse, 2008). However, newer or less understood categories like emissions from digital services may not be identified as material, and thus may be absent from reports.

2.2.2 IT and Digital Emissions in Reporting

Prior to concerns about AI, companies have grappled with how to report environmental impacts of IT operations. Initially, the focus was on hardware (e.g., data centre electricity, e-waste from devices). Many firms report data centre energy efficiency improvements or total energy consumption, often consolidating all IT-related emissions under a single category in their carbon footprint. Scope 2 emissions from purchased electricity for data centres are typically counted, but Scope 3 emissions from outsourced computing (like cloud services) are less consistently reported (Downie & Stubbs, 2013).

As digitalisation accelerates, new challenges have emerged around what has come to be conceptualised as digital sustainability which includes the environmental implications of digital infrastructure and services. Research shows that while firms are beginning to acknowledge topics such as the carbon footprint of cloud computing, videoconferencing, and big data analytics, these discussions often remain abstract and unquantified (Loeser et al., 2017). AI, as a subset of IT, inherits this context. If companies have not been in the practice of separately quantifying IT service emissions, they are unlikely to single out AI emissions. Instead, they may mention AI under qualitative sections to describe how AI contributes positively (for instance, by optimising energy use elsewhere), without providing numbers on AI's own footprint. This practice aligns with the notion of symbolic rather than substantive disclosure on the topic of digital emissions.

2.3 AI in Sustainability Narratives

Given AI's transformative promise, it has started to feature in corporate sustainability narratives. Companies often portray AI as an enabler of sustainability solutions. For example, using AI for smarter resource management, reducing waste, or advancing clean technology. This section examines how AI is framed in sustainability communications and whether its downsides are acknowledged.

2.3.1 Framing AI as a Sustainability Enabler

Corporations commonly highlight instances where AI contributes to environmental goals, a form of positive framing (Vinuesa et al, 2019). For instance, a manufacturing firm might report how AI algorithms reduced energy consumption in its factories by optimising machine usage, or a tech company might describe AI tools that help customers track and cut their carbon emissions. This narrative positions AI as part of the *solution* to sustainability challenges, aligning it with the company's broader CSR message.

Such framing serves a dual purpose. It justifies the company's investments in AI (as not only economically beneficial but also socially responsible), and it pre-empts criticism by showing a proactive stance. Michelon et al. (2015) note that emphasising good news is a common impression management tactic in CSR disclosures. AI provides fresh material for such good news stories.

2.3.2 Omission of AI's Direct Impacts

While the benefits of AI are touted, its direct environmental impacts are often omitted. This omission can be seen as a *strategic silence* (Pang et al., 2022). Companies might refrain from discussing the energy needed to train their AI models or the emissions from data centres running AI services. The rationale may be that these details could raise difficult questions or cast the innovative efforts in a less favourable light.

The absence of AI specific impact data in reports suggests either a lack of information or a deliberate choice. Given that many organisations do track overall IT energy costs (for operational reasons), the data likely exists internally, but disaggregating it and disclosing it publicly is another step one that firms appear reluctant to take unless demanded by stakeholders.

2.4 Legitimacy and Impression Management in Sustainability Reporting

The literature on corporate legitimacy and impression management provides insight into why companies disclose (or withhold) certain information. Key concepts include *symbolic vs. substantive actions* and the construction of organisational façades to satisfy external observers (Suchman, 1995; Cho et al., 2015).

In sustainability reporting, symbolic actions might involve creating a narrative of commitment to the environment through policies, goals, success stories without fully integrating these values into all operations. Substantive action, by contrast, would mean actually reducing emissions and transparently reporting all impacts, even negative ones (Cho & Patten, 2007).

Studies have found that companies often engage in *organised hypocrisy* where talk, decisions, and actions diverge in order to maintain legitimacy (Cho et al., 2015). In disclosures, this can manifest as *talking green, while operating less green in practice*, under the assumption that stakeholders (aside from expert analysts) may not scrutinise the gaps closely.

Impression management techniques identified in sustainability reports include thematic manipulation (focusing on positive themes), selective omission (as discussed), and even visual and structural presentation tactics to downplay bad performance (Cho & Patten, 2007; Michelon et al., 2015). The underlying driver is often to meet societal expectations sufficiently to avoid legitimacy threats, such as public criticism, activist pressure, or investor divestment.

Applying this lens to AI emissions, if revealing that a company's AI initiatives come with significant emissions could threaten its image as a sustainability leader, the company has a legitimacy-based incentive to withhold or soften that information. On the other hand, completely ignoring AI in sustainability discourse could also be risky if stakeholders start asking questions. Thus, companies are expected to acknowledge AI in sustainability contexts to show they are aware and responsible but in a carefully managed way that maintains a positive legitimacy image.

2.5 Regulatory and Market Drivers for Disclosure

Literature on sustainability accounting shows that external pressures such as regulation and investor demands play an important role in shaping what companies report (Hahn & Kühnen, 2013; Bebbington & Unerman, 2018).

When laws or standards mandate certain disclosures, companies typically comply, at least minimally. For example, mandatory GHG reporting schemes have significantly increased the transparency of carbon emissions for many firms (Kolk, Levy, & Pinkse, 2008). In the context of AI emissions, as of the literature to date, there are *no AI-specific disclosure requirements*. However, broader regulations like the EU's Corporate Sustainability Reporting Directive (CSRD) might implicitly cover AI under categories like energy use or Scope 3 emissions. Researchers argue that clear regulatory guidance could force companies to measure and report AI impacts (Kaack et al., 2022).

Institutional investors and ESG rating agencies influence disclosure by asking for data. If major investors were to inquire about AI's carbon footprint (for instance, questioning whether a tech company's rising emissions are due to AI expansion), it could prompt more transparency. So far, AI hasn't been a focal point in ESG criteria, but as climate concerns deepen, this could change. Hahn & Kühnen (2013) suggest that when new sustainability issues become financially material or tied to risk, markets will compel firms to act. Another driver is normative pressure. If industry leaders start reporting something, others may follow to avoid looking laggards. This has happened with things like reporting Scope 3 emissions categories. If a few prominent companies began highlighting AI emissions, it could set a precedent.

At present, the literature implies that we are in an early stage where these drivers are just beginning to converge on AI. As one author put it, AI's carbon footprint is an "emerging risk" for corporate climate accountability, and how quickly it becomes a standard part of reporting will depend on both policy developments and stakeholder awareness (Brevini, 2022).

2.6 Chapter Summary

This literature review has synthesised existing knowledge on AI's environmental impact, corporate sustainability reporting practices, and theories of legitimacy in disclosure. It reveals a clear gap: AI-related emissions reporting is largely absent in current practice, even though AI can significantly contribute to a company's carbon footprint. Companies tend to showcase AI's positive contributions to sustainability while leaving its direct impacts unquantified and unreported. Legitimacy theory and prior studies on impression management provide a framework for understanding this behaviour as a strategic response to external expectations.

Moreover, the review highlights that no regulatory requirements or strong stakeholder pressures specifically target AI emissions yet, giving companies latitude in how to handle or ignore this issue. This gap between AI's growing footprint and its invisibility in reports forms the basis of this research. Building on these insights, Chapter 3 will present the detailed theoretical framework that guides the inquiry into why companies might be underreporting AI-related emissions and how they justify their approaches. This theoretical grounding will then inform the research design and analysis of expert interviews in subsequent chapters.

3. Theoretical Framework

This chapter presents Legitimacy Theory as the primary lens for analysing corporate behaviour in AI emissions reporting. It defines key concepts and explains how the theory applies to the context of sustainability disclosures. Competing or complementary theories (such as Stakeholder Theory or Institutional Theory) are also briefly considered, with justification for the choice of Legitimacy Theory.

3.1 Legitimacy Theory in Corporate Disclosure

Legitimacy Theory posits that organisations are continually seeking to ensure their actions are perceived as desirable, proper, or appropriate within the socially constructed system of norms, values, beliefs, and definitions (Suchman, 1995). In essence, firms need to maintain legitimacy, which is like a reservoir of goodwill or social license to operate. One key way organisations manage legitimacy is through communication and disclosure. By disclosing information about their activities, companies can shape stakeholder perceptions of their adherence to social norms and expectations.

In corporate sustainability disclosure, Legitimacy Theory has been extensively used to explain why firms might report environmental information even when not required to do so. It suggests that companies disclose positive environmental performance to bolster legitimacy, and may also disclose negative information in a controlled manner to show transparency and retain trust (Deegan, 2019). However, if certain information could threaten legitimacy and isn't explicitly required, companies might choose not to disclose it.

Key concepts in Legitimacy Theory are relevant to understanding how companies disclose information related to AI and environmental impact. A central idea is the legitimacy gap, which refers to the difference between what society expects and what a company is perceived to be doing. For example, if stakeholders expect climate neutrality while the company's AI initiatives are energy-intensive, the resulting gap may create pressure to respond either through action or communication.

According to Suchman (1995), organisations can adopt various legitimacy strategies such as conforming to expectations through actual changes, informing and educating stakeholders through disclosure, or manipulating perceptions via symbolic actions or framing. Legitimacy itself can be categorised into pragmatic, moral, and cognitive forms. Pragmatic legitimacy is based on the self-interest of stakeholders, moral legitimacy on normative approval, and cognitive legitimacy on whether an organisation's actions are perceived as understandable and naturally appropriate within existing norms. In the case of AI, portraying the technology as environmentally beneficial may be seen as a moral legitimacy issue that is, whether the company is doing the "right" thing for the environment.

Accordingly, companies may choose to disclose information that affirms their alignment with sustainability values, while avoiding details such as emissions data that could reveal a misalignment. This theoretical framing will guide the interpretation of corporate interviewees' explanations.

3.2 Relevance of Legitimacy Theory to AI Emissions Reporting

AI emissions reporting is a new subject, but the dynamics around it fit classic legitimacy considerations. Society increasingly values climate responsibility and thus, for any large company, being seen as contributing to climate change could pose a legitimacy risk. AI projects, despite their innovative halo, could tarnish a company's green image if their energy hunger is highlighted.

Legitimacy Theory helps frame several hypotheses or expectations:

- Firms will be reluctant to voluntarily disclose AI-related emissions if they perceive that doing so might create a legitimacy gap (e.g., reveal inconsistency with climate commitments).
- Firms might instead emphasise narratives that *legitimise AI* by aligning it with sustainability (for example, "AI is helping us and our customers save energy"), thus reinforcing legitimacy.
- If firms do face direct questions or pressures about AI's footprint, they might respond with symbolic actions or partial disclosure to demonstrate responsiveness without fully compromising their legitimacy.

These expectations align with observed patterns in analogous areas. For instance, when data privacy became a hot societal issue, many tech companies increased transparency about privacy practices, but often in ways that were more symbolic than deeply informative, aiming to maintain user trust (an aspect of legitimacy) without necessarily changing data-heavy business models. Similarly, for AI emissions, companies might adopt surface-level legitimacy tactics such as publishing a one-time figure or a vague acknowledgement rather than a comprehensive accounting, unless compelled.

3.3 Comparison with Alternative Theories

While Legitimacy Theory is central to this analysis, it is worth noting other theoretical perspectives. *Stakeholder Theory* emphasises that companies manage disclosures to meet the needs of various stakeholder groups, which overlaps with legitimacy but focuses more on balancing specific interests (Roberts, 1992). Stakeholder Theory would prompt look at which stakeholder (investors, customers, regulators, employees) is most influential in demanding or suppressing AI emissions information. *Institutional Theory* suggests that organisations conform to institutionalised norms and practices to gain legitimacy (mimetic, coercive, and normative isomorphism). If, for instance, no peer companies report AI emissions, a company might also not report (mimetic), or if industry standards evolve to require it, companies will follow (coercive). Institutional theory underscores the role of industry norms and regulations, which we also discuss in the context of external pressures (DiMaggio & Powell, 1983). The reason for prioritising Legitimacy Theory is that AI emissions reporting currently largely falls in a voluntary, normative realm rather than a regulated one. It is precisely in such areas that legitimacy-seeking behaviour is most observable.

3.4 Analytical Framework

Bringing together insights from the literature and Legitimacy Theory, the study uses the following analytical framework:

- **Organisational Actions:** Companies’ approaches to AI emissions encompassing from not measuring emissions at all, to measuring internally but not disclosing, to partial or full disclosure.

- **Drivers of Action:** Interpreted through legitimacy (the need to appear responsible), stakeholder influences (specific demands or lack thereof), and institutional context (regulatory environment, industry benchmarks).

- **Legitimacy Outcomes:** How each approach potentially affects or protects the company's legitimacy. For example, not disclosing might protect legitimacy in the short term by hiding negative info but could risk legitimacy if stakeholders later discover omission. Conversely, disclosing might bolster legitimacy among certain stakeholders (for transparency) but harm it among others (for revealing high emissions).

Using this framework, the empirical research (expert interviews) will explore both *what companies are doing about AI emissions* and *why*. The "why" will be explored in interviews by asking about perceived challenges and motivations. The analysis in Chapters 5 and 6 will map these responses to the theoretical expectations thereby testing the applicability of Legitimacy Theory in this new context.

3.5 Chapter Summary

This chapter presented Legitimacy Theory as the guiding framework for the study, explaining how it provides a lens to understand corporate reluctance or willingness to report AI-related emissions. Legitimacy Theory suggests that the decision to disclose or withhold information is strategic and aimed at aligning with stakeholder expectations to preserve the organisation's social license. In the context of AI emissions, this implies companies will carefully manage the narrative to stay in society's good graces, perhaps at the expense of full transparency.

The framework outlined will inform the design of interview questions and the subsequent analysis. By anticipating patterns of selective disclosure and legitimacy-seeking behaviour, the research is well-positioned to interpret expert insights critically. The next chapter, Chapter 4 (Methodology), will detail how the study is conducted, including how the theoretical framework shaped the research approach, and ensure that the data collected can effectively address the research questions through the lens of legitimacy and related theories.

4. Methodology

This chapter outlines the research design and methods used to investigate the research questions. It describes the qualitative approach, the process of data collection via expert interviews, the criteria for selecting participants, and the thematic analysis employed to derive findings. It also addresses ethical considerations and methodological limitations.

4.1 Research Approach and Design

This study adopts a qualitative research approach to investigate how AI-related emissions are reported in corporate sustainability disclosures and whether firms engage in selective transparency and legitimacy-seeking behaviours. A qualitative approach is appropriate because AI emissions reporting is an emerging issue with limited prior empirical research, requiring exploratory insight (Yin, 2018). Given the absence of standardised AI-specific disclosure frameworks (Kaack et al., 2022), engaging directly with experts allows me to capture nuanced understandings of how companies navigate this gap.

The research is designed as a theory-driven qualitative study, using semi-structured interviews to explore stakeholder perspectives on:

- Current corporate practices in AI emissions reporting.
- Challenges in quantifying AI-related carbon footprints.
- Legitimacy-seeking behaviours in sustainability disclosures.
- External pressures (regulatory, investor, etc.) influencing AI disclosure.

By structuring the inquiry around these thematic pillars derived from literature and theory, the study ensures that the findings will contribute to both empirical and theoretical discussions, directly linking back to Legitimacy Theory and the research questions.

4.2 Data Collection: Expert Interviews

Because corporate sustainability reports currently provide limited disclosure on AI emissions (Kaack et al., 2022), expert interviews serve as the primary empirical data source. These interviews tap into the insights of professionals who are knowledgeable about either sustainability reporting or AI operations (or both), thereby illuminating corporate practices and rationales that are not apparent in published reports.

Engaging directly with professionals involved in sustainability reporting, AI governance, and ESG policy development enables the research to:

- Uncover industry-wide trends in AI transparency practices.
- Identify corporate motivations behind selective disclosure (or non-disclosure) of AI impacts.
- Assess how existing regulatory frameworks (or lack thereof) influence AI emissions reporting decisions.

4.2.1 Participant Selection Criteria

A *purposive sampling* strategy was used to ensure participants have relevant expertise in corporate sustainability, emissions accounting, and/or AI infrastructure. The study targeted three broad categories of experts:

- **Sustainability Reporting Professionals:** Individuals responsible for preparing ESG and sustainability disclosures in companies. This includes experts working within corporate sustainability or CSR teams who would directly face the question of reporting AI emissions.
- **AI and IT Industry Experts:** Professionals with deep knowledge of AI infrastructure, cloud computing, or energy consumption modelling in IT. This could include data centre operations managers, AI project leads, or consultants in green IT, who understand the technical side of AI's resource usage and can comment on measurability and data availability.

By ensuring diversity in participant expertise, the research aims to provide a holistic perspective on AI emissions transparency including the internal corporate viewpoint to the external policy outlook. The final sample comprised employees primarily from the IT and Sustainability departments at a Swedish manufacturing company with global operations, as well as sustainability and carbon accounting consultants based across Europe.

The study conducted a total of seventeen semi-structured interviews. This number was deemed sufficient as thematic saturation was achieved. Later interviews were largely reinforcing insights that had already emerged in earlier ones, indicating a comprehensive capture of major themes.

4.2.2 Interview Structure and Key Themes

The semi-structured interview format was chosen for flexibility and depth. An interview guide with predefined themes ensured comparability, while open-ended questions allowed experts to introduce new insights beyond the initial scope.

The interview guide was organised around the key themes identified in the literature and theoretical framework:

- **AI's Role in Sustainability Reporting:** Questions explored how companies are currently addressing AI-related emissions (if at all) in their sustainability reports. For example: *"Does your organisation explicitly report any environmental impacts related to AI or data centre usage?"* and *"If not, how are such impacts accounted for or discussed internally?"*.

- **Challenges in AI Emissions Quantification:** We asked about difficulties in measuring AI's energy use and carbon footprint. E.g.: *"What challenges do you see in isolating and calculating emissions from AI workloads?"* and *"How are emissions from cloud-based AI services categorised (Scope 1, 2, or 3) under frameworks like the GHG Protocol?"*.

- **Legitimacy-seeking strategies in reporting:** Questions probed whether companies might be framing AI in certain ways. E.g.: *"Do you think companies tend to highlight AI's benefits to sustainability while not discussing its own footprint? Why might that be?"* and *"Have you observed any instances of selective disclosure or omission regarding IT or AI environmental impacts?"*. These questions draw directly on concepts of impression management and symbolic compliance.

- **Regulatory and market pressures:** Here the questions centred around the potential influence of external pressures. Sample questions: *"Are there any regulations or guidelines pushing companies to disclose digital or AI-related emissions?"*; *"How are* *investor or customer expectations evolving regarding the environmental impact of AI or IT?".*

Each interview lasted between 45 minutes to 1 hour. Interviewees were assured that the conversation would focus on general practices and insights. They were not expected to reveal any confidential company data. This was important to make them comfortable discussing potentially sensitive topics like non-disclosure of information.

The interviews were conducted via video call using the Microsoft Teams platform. None of the interview meetings were recorded but appropriate and detailed notes were taken during each interview to capture relevant insights.

4.3 Data Analysis Approach

Given the qualitative nature of the data, the study employed thematic analysis (Braun & Clarke, 2006) to identify recurring patterns and insights across the interviews. The analysis was both deductive (guided by the initial themes from the literature and theory) and inductive (open to new themes emerging from the data).

4.3.1 Thematic Coding Process

Interview transcripts were analysed manually, following Braun & Clarke’s six-step approach:

1. **Familiarisation:** The researcher transcribed the interviews and read through transcripts multiple times to become deeply familiar with the content.

2. **Generating Initial Codes:** Using the research questions and theoretical framework as a guide, segments of text were coded. Initial codes included, for example, "No AI in report", "Internal tracking only", "Lack of methodology", "Frame as benefit", "Fear of misinterpretation", "Regulation absent", "Employee awareness", etc. Each meaningful piece of data related to the research focus was given a label.

3. **Searching for Themes:** Codes were then grouped into broader themes. Based on the design, expected themes corresponded roughly to:

    - **Current Practices in AI Emissions Reporting** (what companies do or don't do).

- **Challenges in Measurement** (technical and organisational hurdles).
- **Legitimacy/Transparency Strategies** (how companies talk about or obscure AI impacts).
- **External Pressures** (regulatory, investor, societal influences).

The coding confirmed these, but also allowed for sub-themes or unexpected themes to surface.

4. **Reviewing Themes:** I checked that the collated data for each theme coherently fitted together, and that distinct themes were indeed distinct. For instance, ensuring that "Challenges in Measurement" was separate from "External Pressures," even though a lack of methodology could be seen as a challenge that might also become an explanation companies give (which might relate to legitimacy strategy).
5. **Defining and Naming Themes:** I refined the specifics of each theme, how it helps answer the research questions, and came up with clear definitions. The final themes aligned closely with the sections used to present findings in Chapter 5 (as listed above in 4.3.1).
6. **Writing the Findings:** Finally, I integrated the thematic insights into a narrative (see Chapter 5), interweaving quotes from the interviews with interpretation and connections to theory and prior research.

Thematic coding enabled comparison of expert perspectives, revealing common trends and divergences. For example, if multiple interviewees mentioned that “AI emissions are hard to isolate because of shared cloud infrastructure,” this became a strong shared theme (a measurement challenge). If only one interviewee raised a point, it might be treated as a unique insight or counterpoint.

4.3.2 Triangulation and Validity

To enhance the validity of the findings, I engaged in a form of *triangulation* by comparing interview insights with existing literature and, where possible, with any publicly available evidence (Bebbington & Unerman, 2018). For instance, if an interviewee claimed, “No one is asking for AI emissions data," I cross-checked whether there are any signs of investor queries or media questions on this topic. If another said, "Our company considers AI emissions as part of Scope 3," I could verify if anything about that was mentioned in their latest report.

This cross-referencing ensures a convergence of evidence. That is to say where interview claims aligned with known trends or documents, my confidence in those findings increased. Conversely, if discrepancies it indicated either a miscommunication or an interesting nuance to explore (perhaps the disclosure was minimal, or the expert was not aware).

Consistency between what was said and what is documented in policies or reports (where such documentation exists) adds credibility. Moreover, aligning interview findings with theoretical expectations (or noting where they diverge) provided a check on whether I was interpreting data in a theoretically sensible way. Any major discrepancy prompted a revisit to the data to ensure it weren't being forced into preconceived themes incorrectly.

4.4 Ethical Considerations

The research adhered to strict ethical guidelines. All interviewees received an explanation of the study’s purpose and how their data would be used before the interview. They consented over email to participate and to permit the interviewer (the author) to take notes for research purposes. Interviewees were assured that any quotations or insights used in the thesis would be anonymised. The study does not attribute statements to individuals by name or to their organisations. Instead, the text refers to "an interviewee" or by a generic role descriptor (e.g., "a sustainability manager noted that..."). Interviews were not recorded but detailed notes were taken. Only the author had access to the full data. Interview transcripts were retained for reference in case of any need to verify quotes during writing. Participants were informed that they could decline to answer any question or terminate the interview at any time. They were also given the opportunity to review their quotes if desired. One participant chose to clarify a point via email after the interview, which was incorporated accordingly.

Throughout the study, sensitivity was maintained regarding the fact that some topics could reflect critically on organisations or individuals. The goal was to understand practices, not to cast judgment on any single entity. This was communicated to participants to avoid defensiveness and encourage honest reflection.

INTERVIEWEE	TITLE	INDUSTRY
1	Head of Research and Sustainability	Carbon Accounting Consultancy
2	Sustainability consultant	Consulting
3	IT Sustainability lead	Manufacturing
4	“Sustainable” Software Developer	Manufacturing
5	Head of Digitalisation and Data Management	Manufacturing
6	Business Developer	Manufacturing
7	Brand Executive (Strategy and Business opportunities)	Manufacturing
8	Software Developer	Manufacturing
9	Software Developer	Manufacturing
10	Business Analytics Manager	Manufacturing
11	Software Developer	Manufacturing
12	Cloud Migration Lead	Manufacturing
13	Cloud Engineer	Manufacturing
14	Head of Business Development	Manufacturing
15	Former founder and engineer	Sustainable Startup
16	Communications Lead	Manufacturing
17	Software Engineer	Manufacturing

Table 1: List of interviewees (anonymised)

4.5 Limitations of the Methodology

While the chosen methods are suitable for the exploratory nature of the research, there are some limitations to acknowledge.

The study relies on a relatively small sample of experts (n=17) primarily from European (Swedish) context. While qualitative research does not seek statistical generalisability, the insights may not capture all possible perspectives, especially from other regions or industries not represented. The findings should be viewed as analytical insights rather than universal conclusions. Then there is the issue of organisational diversity as most interviewees, with the exception of external sustainability reporting professionals, were affiliated with the same company. Although it is pertinent to note that they held different roles, were part of different teams, and also had diverse professional backgrounds. Nevertheless, their shared organisational environment may have shaped their perspectives in similar ways. Moreover, the data collected from these participants is based on their perceptions and recollections. These are inherently subjective and there is a risk of bias. For example, interviewees might portray their company in a more favourable light, or conversely, external experts might be more critical of industry practices. By crosschecking and ensuring anonymity, attempts were made to mitigate these biases, but they cannot be eliminated entirely.

Another potential limitation is related to the nature and scope of the study. The study does not measure AI's actual energy consumption or emissions. Thus, it cannot quantitatively correlate what companies report with what the emissions actually are. The research focuses on disclosure behaviour and motivations and not on calculating the carbon footprint of AI. This means the study cannot tell us the magnitude of the "hidden" AI emissions but only that they are likely to be underreported and why.

Finally, AI technology and sustainability reporting standards are both rapidly evolving. The insights represent a snapshot as of 2024. It is possible that within a short time, new regulations or industry initiatives could change the landscape. The thesis findings might age faster than in more stable research domains. To counter this, participants who are at the forefront of policy discussions to capturing where things are heading, not just where they have been.

Despite these limitations, the methodology provides a solid foundation to explore the novel intersection of AI and sustainability disclosure. The combination of targeted expert input and theory-driven analysis is suitable to uncover the key themes and lay groundwork for further research. With the methodology now described, the thesis turns to presenting the findings in the next chapter.

5. Findings and Analysis

This chapter presents the empirical findings from the expert interviews. The analysis is organised according to four central themes derived from the research questions and literature: (1) current corporate practices in AI emissions reporting, (2) challenges in measuring AI's carbon footprint, (3) legitimacy-seeking disclosure behaviours, and (4) the influence of regulatory and market pressures. A total of 17 expert interviews were conducted, encompassing sustainability managers, AI/IT specialists, and policy advisors. The findings below synthesise these experts' insights, illustrated with representative quotes), and interpret them through the lens of the study's framework.

5.1 Overview of Key Themes in AI Sustainability Reporting

Across the interviews, four major thematic categories were identified. The first theme, *Current corporate practices in AI emissions reporting*, explores how companies are currently disclosing, or not disclosing, AI-related emissions in their sustainability reports. The second theme, *Challenges in AI carbon footprint measurement*, addresses the practical difficulties and uncertainties that organisations face in quantifying AI's energy use and emissions. The third theme, *Legitimacy-seeking strategies in AI disclosure*, examines how companies shape the narrative around AI within their sustainability communications, including through selective disclosure and strategic framing, in efforts to maintain legitimacy. The final theme, *Regulatory and market influences on AI transparency*, considers the extent to which external pressures, both regulatory and market-driven, are encouraging greater transparency or permitting continued opacity in relation to AI emissions.

Each of these themes is discussed in detail in sections 5.2 through 5.5, with a summary of findings provided in section 5.6.

5.2 Current corporate practices in AI emissions reporting

5.2.1 Corporate Sustainability Reporting - Status Quo of AI Disclosures

All experts concurred that at present, AI-related emissions are rarely reported explicitly in corporate sustainability disclosures. Typically, and if at all, any emissions from AI workloads are bundled into broader IT or cloud computing categories without special mention. For example, a sustainability report might have a line for "Data Centre Electricity Use" but make no reference to how much of that is driven by AI.

One interviewee, *Interviewee 1* explained that organisations "*often do not have access to granular data due to reliance on third-party service providers. Even if they want to be truthful, it is hard for them to be accurate.*" He noted that when a company uses cloud AI services, it receives an overall energy or carbon estimate from the provider (if anything at all), which isn't broken down by application. Thus, lack of detailed data is one immediate reason AI gets hidden under aggregate figures. *Interviewee 1's* remark - "*hard for them to be accurate*" also reflects a sense that companies hesitate to report anything they can't substantiate with hard numbers, and currently AI's footprint tends to fall in that ambiguous zone.

A sustainability consultant, *Interviewee 2* reinforced this, saying: "*presently in sustainability reports, organisations talk about digital transformation initiatives, but there's no line item for the carbon cost of AI. It's all just assumed to be a part of IT*." She indicated this is not because the company is unconcerned, but "*that level of detail just isn't required or expected in reports right now*." This highlights that norms and expectations play a role

A common practice mentioned is to attribute AI-related emissions to Scope 3 (indirect emissions) when AI is run on external cloud platforms. For instance, if a bank uses an AI service from a cloud provider, any emissions might be counted under "outsourced IT services" in Scope 3, if counted at all. But as *Interviewee 2* noted, "*Scope 3 is a black box where a lot of things can be tucked away.*" In other words, even if AI emissions are conceptually in Scope 3, companies often report Scope 3 in aggregate (or only selected categories like business travel, supply chain, etc.) and not the portion from AI specifically.

Overall, the status quo is that AI's carbon footprint remains largely invisible in public reports. Companies adhere to existing frameworks that don't explicitly call it out, and in doing so, they neither lie nor fully inform. This finding confirms the literature's indication (Kaack et al., 2022) that there is a transparency gap. Importantly, experts suggested this gap is partly due to inertia and complexity and not simply deliberate hiding. Nonetheless, as the next section shows, some deliberate choices are indeed at play.

5.2.2 Variations and Emerging Trends in Transparency

While no company was identified by the interviewees as *fully* disclosing AI emissions, interviews did reveal some variations across industries and companies in approaching the issue:

Industry maturity in sustainability featured prominently in interviewees' accounts. Most of the interviewees belong to a sector with a very mature sustainability reporting tradition, at least in Sweden, and indicated that they are beginning to internally discuss the emissions impact of software and AI. For instance, a Sustainability lead, *Interviewee 3,* reflecting on her role, said: "*Discussions around AI emissions are in an early stage. We've tracked hardware impacts like e-waste for years, but software tools like our use of ChatGPT or machine learning models haven't made it into formal assessments yet.*"

Another theme that surfaced was employee-driven transparency initiatives. In some companies, employees have started asking questions about digital sustainability. *Interviewee 12*, who works in a cloud services team, mentioned the rise of "Green IT ambassadors" in his company. These are employees advocating for reducing the carbon footprint of IT operations. He said: "*We have a Cloud Emissions Tracker tool internally, and interestingly, a lot of people requested access to it when they heard about it. There's clearly interest.*" Such internal tracking tools, while not public, are a step towards quantifying AI and cloud impacts. The presence of such tools indicates that data might become more available over time. If internal culture values that data, it could eventually translate into external reporting. However, as of now, this particular company still does not publish AI emissions data. The interviewee implied the data from the tracker is mostly used for optimisation and awareness.

Company size and public exposure also appear to shape disclosure behaviour. Some experts who were interviewed noted that very large tech companies such as Google, Microsoft, and Amazon are under more scrutiny and thus publish extensive sustainability reports, yet they still aggregate AI impacts. In contrast, smaller firms or B2B companies might not even mention AI in a sustainability context at all. One expert, *Interviewee 16*, pointed out, *"If you look at non-tech, they might be using AI services heavily but their sustainability report won't say much about digital emissions. It's all about their manufacturing or their fleet or whatever their core business is. IT is just considered overhead"*.

Another insight relates to leading versus following peers. *Interviewee 15* suggested that if one prominent company were to start highlighting AI emissions in their report, it could influence others. "*We saw it with plastic or with water usage; once one big player adds a section, others don't want to look like they're ignoring it.*" However, he then noted: "*So far, I haven't seen a big company break ranks on AI emissions transparency. Everyone's sort of waiting.*" This indicates a herd behaviour dynamic, where no one wants to be first which could draw attention to their possibly high AI footprint. However, if transparency becomes a trend, companies would likely follow to avoid looking laggard.

In summary, while the general practice is non-disclosure of AI emissions, there are early signals of change viz., internal tracking tools, differences based on how AI is used in products, and grassroots interest in digital sustainability.

5.3 Challenges in Measuring AI's Carbon Footprint

A strong theme from almost all interviewees was that methodological and data challenges significantly impede the reporting of AI-related emissions. It became clear that even if a company were willing to be transparent, they face non-trivial hurdles in actually calculating and substantiating the numbers.

A key challenge identified is the lack of standard emission factors. Traditional carbon accounting relies on established emission factors, such as kilograms of carbon dioxide per kilowatt hour of electricity or per unit of activity (World Resources Institute and World Business Council for Sustainable Development, 2004). For artificial intelligence, however, there is no universally accepted set of emission factors. *Interviewee 4* noted, "*We don't have something like an agreed upon 'emissions per GPU hour' or per training hour metric universally applied. Every data centre and every model is different.*" Although academic efforts have proposed such metrics, such as those from Strubell et al. (2019), these have not yet been codified into frameworks like the Greenhouse Gas Protocol. In the absence of such standards, companies fear that any figures they publish could be misinterpreted or criticised, creating a disincentive to report.

Attribution within shared environments presents another major obstacle. Many artificial intelligence workloads are hosted on shared cloud infrastructure, making it difficult to disaggregate energy use. Interviewees highlighted this problem. "*If you run an AI model on OpenAI, how do you isolate the energy for just your usage? Quite possibly OpenAI would give some high level data but doesn't reveal everything.*" Companies are largely dependent on whatever information their service providers choose to disclose. *Interviewee 14* remarked, "*We attempted to ask our cloud provider for more detailed emissions data for specific services. The answer was essentially that it's not straightforward to provide.*" This opacity within the supply chain means that corporate sustainability teams often cannot trace the carbon footprint of outsourced artificial intelligence processing with confidence. Although rough estimates can be made based on usage hours and average data centre emission intensities, these are perceived as unreliable. As one expert noted, "*It's a lot of guesswork, which doesn't inspire putting it in a polished report.*"

The early stage of internal discussions further limits progress. Most interviewees from the case company emphasised that their organisations had only recently begun internal discussions on how to classify software related emissions. This indicates that, for some firms, the issue is still seen as relatively minor. Artificial intelligence may still be viewed as a small subset of broader information technology operations and thus not separated out in reporting frameworks. One interviewee underscored this early stage of maturity, stating, "*It's not that we calculated it and chose to hide it; it's that we haven't figured out how to calculate it properly. We're engineers, and if we report something, we want it to be precise.*"

There is also widespread confusion around scope classification. Several interviewees raised the issue of where artificial intelligence emissions should be placed within the Scope 1, Scope 2, and Scope 3 categories of greenhouse gas reporting. The general consensus was that if artificial intelligence runs on a cloud platform not owned by the company, it should fall under Scope 3 as an outsourced service. If it runs on in house servers, it could be classified as Scope 2 when based on purchased electricity or Scope 1 if emissions are directly generated on site. This classification matters because companies traditionally have more control over, and better data for, Scope 1 and Scope 2. Scope 3 is notoriously difficult to quantify and is often reported only partially. As one interviewee explained, "*Artificial intelligence emissions likely fall under Scope 3 for most companies using AI. And we know Scope 3 is where the data quality drops and many companies disclose only partial info.*" As a result, artificial intelligence is frequently relegated to the least visible and least reliable part of sustainability reporting.

In sum, measurement difficulty represents a genuine and persistent barrier to artificial intelligence emissions reporting. It provides companies with a convenient and often justifiable reason for non-disclosure. As one interviewee implied, reporting flawed data can be more damaging than not reporting at all. The findings suggest that many companies are currently hiding behind these measurement challenges. Unless they can report with accuracy and confidence, they prefer to remain silent on artificial intelligence related emissions. Nonetheless, some experts predict that this situation will evolve as carbon accounting methodologies improve and external pressure to disclose increases.

5.4 Legitimacy Strategies in AI Emissions Disclosure

While practical difficulties are significant, the interviews also uncovered clear signs of strategic non-disclosure and framing i.e., behaviour consistent with legitimacy management.

Strategic omission was a common theme across several interviews. Interviewees described an intentional bias in what is communicated about artificial intelligence. *Interviewee 11* observed, "*Across companies, there's definitely a pattern of talking up how AI helps sustainability (like efficiency) and not talking about the energy it consumes.*" This aligns with what Legitimacy Theory would predict, namely that companies highlight beneficial narratives and omit the troublesome ones. *Interviewee 2* termed it a pattern of strategic omission. He shared an example from one of his consultancy projects in which a client decided to publish a case study on how AI optimises their logistics to save fuel. When he suggested also mentioning the footprint of running that AI, the idea was quickly dropped by the communications team. "*It was not that they denied the footprint existed, but rather that they saw no need to muddy a good story with that detail".*

Attempts at framing AI as a sustainability enabler was another recurring narrative. *Interviewee 14* shared that "*AI is mostly publicly framed as part of digital innovation that will help the company's sustainability in indirect ways, such as improved product design or operational efficiency*". *Interviewee 3* mentioned that employee concerns about information technology sustainability are starting to surface. He noted that "currently employee concerns are largely related to IT hardware and its disposal, but as the use of AI becomes widespread, aware employees will take notice". This internal awareness is gradually prompting companies to at least acknowledge the issue in principle. However, externally, companies continue to remain silent on the negative impacts. *Interviewee 7* pointed out that in sustainability reports, "*Tech giants emphasise our data centres are getting more efficient, running on renewable energy, etc., but you won't see them specifying how much of that is because of AI projects.*"

Selective reporting and impression management were also identified by some interviewees. They confirmed that companies selectively report what casts them in a favourable light. They highlight positive narratives, such as AI cutting emissions in other domains or enabling green solutions, and omit hard to measure or potentially critical information, including AI's direct footprint. *Interviewee 4* stated, "*Of course they're not going to volunteer information that makes them look bad unless they have to. That's PR 101.*" This comment highlights that there is a deliberate element of omission as a means of reputation management.

Emerging internal legitimacy concerns also appear to be influencing corporate communication strategies. A few interviewees noted that internal legitimacy with employees is becoming a relevant issue. Younger employees or those in technology-related roles are increasingly aware of, and sometimes critical of, unsustainable practices. A software developer, *Interviewee 9*, expressed personal cynicism about the commonly touted benefits of AI, calling the AI community "*brainwashed*" to ignore issues like energy use. Although this is one individual's opinion, it suggests that if internal stakeholder pressure continues to grow companies may need to revise their stance to preserve legitimacy not only among external audiences but also within their own workforce.

In conclusion, the qualitative evidence strongly indicates that companies are employing legitimacy-protecting strategies in their treatment of AI and sustainability. They engage in selective transparency by promoting the positive dimensions of AI while concealing its direct environmental costs. This aligns closely with theoretical expectations that firms manage disclosures to protect their image (Suchman, 1995; Cho et al., 2015). The issue is not merely the difficulty of measuring AI emissions. Even when companies have some awareness of the environmental impact, they see limited benefit in publicly acknowledging it. In the absence of external pressure, omission or neutralisation remains the preferred strategy. However, as the next theme will demonstrate, these disclosure practices take place within a broader context defined by currently weak external pressure. If that context were to change, it is likely that corporate strategies would evolve accordingly.

5.5 Regulatory and Market Pressures Shaping AI Sustainability Reporting

A key part of the discussion with experts was whether the external environment is forcing companies to be more transparent about AI's footprint, or if it's likely to do so soon. The consensus here was that current external pressures are limited, but growing.

Interviewee 1 and *Interviewee 7* both emphasised that no existing regulation explicitly mandates AI-related emissions disclosure. *Interviewee 11* stated, "*Standards like the GHG Protocol are likely to classify AI under Scope 3, but no detailed guidance or tools exist.*" He added that the EU's focus with AI has been on governance and ethics, for example the AI Act regarding bias and safety, rather than environmental impact. *Interviewee 14*, agreed, noting that sustainability regulations like the CSRD are broad and principle-based. They require reporting of significant impacts, but since AI's impact is not yet widely recognised as significant, companies are not being flagged for omitting it. One could interpret this as a regulatory blind spot as policymakers haven't caught up to the idea that AI operations might need a spotlight in environmental reporting. That said, interviewees mentioned that the broader push for carbon transparency could indirectly compel companies to look at all sources of emissions, including digital ones, in the future. On the investor side, none of the experts were aware of investors directly asking about AI emissions.

Interviewee 15 noted that in her experience, company's discussions with investors or ESG ratings agencies, "*the questions are about overall carbon targets, Scope 1-3 totals, etc. Nobody's asking, 'and how much of that is from AI?*" She then speculated, "*Maybe because even the investors don't know to ask that yet. It's a bit too granular or technical for them at this stage.*" However, *Interviewee 17* did note a shift: "*General awareness of IT sustainability is rising driven partly by employee concern over electronic waste but AI-specific carbon accounting frameworks have yet to be established.*" This suggests that while investors aren't knocking on the door about AI, the general trajectory towards scrutinising digital operations is upward. She also mentioned that in their internal priority triangle of sustainability, cost, and performance, sustainability is increasingly taking precedence over cost in IT decisions, which is a notable cultural shift. However, the caveat is that this is true more for hardware assets rather than AI and software assets where functionality supersedes any other concerns. Because neither regulators nor investors nor consumers, who mostly see the benefits of AI in products, are currently pressuring companies for this information, companies face little short-term risk in not disclosing it. As one interviewee put it, "*No one's losing sleep over not reporting AI emissions… yet*." This lack of immediate incentive reinforces the legitimacy strategies noted earlier that it's easy to justify not volunteering information that no outside party has demanded.

The interviews also touched upon future scenarios. Interviewee 13 said, "I wouldn't be surprised if in a few years, CSRD guidelines or some standard comes out for digital carbon footprints. Once that happens, companies will have to follow." Meanwhile, Interviewee 17 remarked that "if a major climate-related scandal or exposé occurred, public pressure could spike suddenly". So, while not much is forcing companies' hands today it is likely that it will not be the case indefinitely. The interviewees generally believed that external pressure will incrementally increase. One said, "It's a bit like data privacy before GDPR which was an issue hiding in plain sight until regulation crystallised it. With AI emissions, I think we're in that pre-GDPR phase where everyone knows it's out there, but no one's compelled to act yet." If he's right, a combination of regulatory evolution and stakeholder awakening could change the game.

5.6 Summary of Findings and Theoretical Reflections

AI emissions are currently underreported, and in fact, mostly not reported at all, which confirms the initial observation of a transparency gap. Companies tend to aggregate or omit AI-related carbon data in their public disclosures. Attribution challenges and data limitations play a significant role in this pattern of non-reporting. Many companies do not have precise figures due to their reliance on third-party cloud providers and the absence of standardised metrics, which offers a practical justification for withholding such information. In addition, companies actively engage in selective disclosure when it comes to AI's environmental impact. They emphasise the benefits of AI while rarely acknowledging its costs, a practice that aligns with legitimacy theory's expectations around impression management. Decisions about what to communicate in sustainability reports are often influenced by the desire to preserve a positive and innovative image. At present, external pressures such as regulatory, investor, and societal remain weak in relation to this specific issue, allowing companies to maintain their current practices without facing immediate consequences. However, there are signs that this may not remain the case indefinitely, as internal awareness and evolving regulatory frameworks suggest a possible shift in the external landscape.

From a legitimacy theory standpoint, these findings reinforce the idea that companies manage their sustainability narratives carefully. The *symbolic compliance* is evident as companies can claim they are following all required reporting standards (which do not explicitly ask for AI emissions) and thus appearing compliant. While in substance they avoid disclosing a potentially significant impact area. This is a form of *organised hypocrisy* (to borrow the term from Cho et al., 2015) where the talk (commitment to sustainability) and the walk (fully transparent reporting) are misaligned but done in a way that is not overtly confrontational to stakeholder expectations.

The findings also suggest that unless stakeholder expectations shift, companies will likely continue this pattern. However, the experts believed that expectations are indeed shifting slowly. In the long run, legitimacy may demand transparency even in this area, especially if sustainability metrics become more granular or if AI's share of carbon footprint grows to a point where omission would be glaring.

In conclusion, the initial insights from these expert interviews depict a corporate world that is aware of AI's environmental impact but is cautiously navigating it. Organisations are hesitating to publicly acknowledge the issue and will possibly continue to do so until forced by necessity. This behaviour is highly consistent with legitimacy-seeking as described in literature. Companies are essentially enjoying the legitimacy gains of AI adoption and innovation, while not yet paying a legitimacy price for the associated emissions, thanks to the current gap in scrutiny.

The next chapter will delve deeper into these findings and discuss their implications in a broader context.

6. Discussion

This chapter integrates the findings from the expert interviews (Chapter 5) with the academic literature and theoretical framework (Chapters 2 and 3). It interprets how companies approach AI-related emissions in sustainability reporting, why AI remains underreported, and what role various pressures play. The discussion highlights the alignment (and misalignment) between empirical practices and theoretical expectations. It considers what these insights mean for the future of corporate transparency and legitimacy management of AI.

6.1 AI Transparency in Sustainability Reporting: Empirical Reality vs. Theoretical Expectations

The findings indicate that AI-related carbon emissions are rarely disclosed explicitly, which aligns with prior research on corporate transparency gaps for emerging issues (Kaack et al., 2022).

Theoretically, this empirical behaviour resonates with Legitimacy Theory's notion of *symbolic compliance* (Suchman, 1995). Companies appear to comply with sustainability reporting norms by disclosing their overall IT emissions or energy usage, but this compliance is symbolic in that it doesn't offer complete transparency. They fulfil the letter of current guidelines (since no guideline specifically asks for AI emissions) while sidestepping the spirit of comprehensive disclosure. This creates a kind of legitimacy façade where stakeholders see that the company is reporting its emissions and might assume it's thorough, while the company internally knows a portion is unaccounted for or lumped together opaquely.

In practice, this results in two distinct reporting strategies that emerged from the analysis:

- **Omission framed as Compliance:** Firms report nothing specific about AI, effectively treating it as non-material. Because reporting standards haven't demanded it, this omission doesn't blatantly violate any norms.

- **Aggregation with Positive Spin:** Firms mention AI in contexts that make them look proactive, but when it comes to emissions data, they aggregate it under broader categories or more commonly do not report. This way, AI is acknowledged as part of the company's operations (fulfilling any expectation that they talk about new tech in sustainability terms), but its downside is masked.

These strategies mirror what the literature describes as *frontstage and backstage behaviour* in sustainability reporting (Cho et al., 2015). Frontstage, companies speak about AI as an innovation and sometimes even as an environmental solution; backstage, the actual data about AI's footprint is kept internal or unexamined. This dual approach is essentially an exercise in *impression management*, ensure the impression given is that nothing is amiss with AI's role in their sustainability profile.

A conversation with a communication consultant supported this dynamic. She noted that at most companies, AI's role in sustainability is externally framed in terms of benefits with no discussion of its own resource use. This selective framing corroborates that what is publicly seen is closer to a curated narrative than the complete truth.

Theoretically, this empirical pattern is a textbook case of what Deegan (2019) and others' assertion that companies often prioritise maintaining legitimacy over complete transparency. Since AI emissions reporting is not yet a norm, omitting it does not threaten legitimacy among most stakeholders. Instead, talking about it might threaten legitimacy by revealing something potentially negative that stakeholders are not already concerned with. Hence, companies find it rational to stay quiet.

6.2 Why AI Emissions Remain Underreported: Legitimacy and Practical Factors

The question of *why* AI-related emissions are not widely reported involves a combination of practical challenges and legitimacy-driven motives. Practical challenges serve as a cover for legitimacy-driven non-disclosure.

Practical Factors: As discussed in 5.3, companies face genuine hurdles in accurately measuring AI's carbon footprint. The absence of standard metrics or mandates means uncertainty over how to do it. From a rationalist perspective, one could argue companies behave cautiously and don't want to release bad data. This ties into everyday business concerns about data reliability and not confusing or alarming investors with estimates that might later change.

However, bringing legitimacy back into the picture, it's notable that companies are not making a significant effort to overcome these challenges quickly. Instead, many are taking a *wait-and-see approach*. Legitimacy Theory would suggest that because there's no legitimacy reward yet for solving the measurement problem as no one is praising or demanding companies for an AI carbon number. There is a potential legitimacy risk in quantifying something that could look large or problematic, companies are content to let the measurement challenges remain unresolved for external reporting purposes. In short, the inertia in developing reporting methods for AI emissions can be seen as a legitimacy-protecting stance

Legitimacy Motives: There is a clear desire not to cast AI in a negative light. Publicly acknowledging a significant carbon cost of AI could conflict with the image companies wish to project as sustainable innovators. This is the crux of the legitimacy issue. A company's adoption of AI is usually narrated as a forward-looking, savvy move which stakeholders like investors and customers generally applaud. Attaching a big "but it's costly for the environment" asterisk to that story complicates the narrative.

Legitimacy theory tells us companies will avoid such complications unless failing to mention them becomes costlier than mentioning them. Right now, failing to mention AI's emissions has almost no cost because of low awareness but mentioning them has an uncertain but possibly negative cost. Stakeholders might start questioning the net benefit of these tech investments, NGOs might criticise, regulators might get ideas to clamp down, etc.

Interestingly, one might think internal corporate sustainability champions would push for transparency anyway, out of principle. The interviews suggest that even among internal teams, there is caution. Sustainability professionals are juggling their own legitimacy and want to show their company in the best light and focus on the areas where they can demonstrate progress. AI emissions are, at present, a blurry area with no clear success story to tell, as no company can claim "we have carbon-neutral AI" yet in a credible way. Therefore, even internal advocates might prioritise issues where they can drive improvements and report wins like renewable energy procurement, reducing waste, etc., rather than tackling AI emissions reporting, which could just expose a problem they can't easily fix. This perspective aligns with the idea of organisational self-interest moderated by norms. Tackling AI emissions might be the right thing in the long run, but currently it's not incentivised by any norm or pressure, so it falls by the wayside.

In summary, AI emissions remain underreported because reporting them is hard and unrewarding. Companies can plausibly say, “We’re not reporting that because there’s no standard or, it’s too hard to calculate,” and stakeholders accept that or more commonly, haven’t asked. Underneath that plausible deniability, companies also have the comfort of not having to publicise something that could raise awkward questions. This combination of reasons, a mix of “can’t do” and “don’t want to do,” has proven to be a durable barrier to transparency so far.

6.3 The Role of External Pressures in Shaping AI Disclosure

External stakeholder expectations play a mixed role in the current state of AI emissions reporting. This study finds that stakeholders have not yet forced transparency.

Regulatory Influence: Despite strong environmental reporting frameworks (like the CSRD in the EU) that demand comprehensive carbon disclosures, none currently mandate anything AI-specific. *Interviewee 1* pointed out that AI emissions “*likely fall under Scope 3*,” which means that if a company’s AI emissions were significant, they could be captured in its Scope 3 inventory. But the catch is that because there’s no detailed guidance, companies can incorporate them without disaggregating or simply omit them. Regulatory focus has been elsewhere (safety, bias in AI according to one interviewee). This indicates that regulators have inadvertently left a gap. Companies, of course, exploit such gaps to maximise their perceived compliance. They can say “we follow GHG Protocol” truthfully, without having to mention AI separately.

Thus, current regulation indirectly enables omission. However, as experts noted, regulators could fill this gap if they recognised it. There is a historical pattern in sustainability reporting where novel issues eventually get codified. For example, decades ago, companies didn’t report much on supply chain emissions but now many are compelled to follow Scope 3 rules because stakeholders pushed and frameworks were adapted. A similar trajectory can be anticipated if data centre emissions become recognised as a material issue, regulators might add requirements.

Investor and Market Expectations: As *Interviewee 14* mentioned that investor pressure for granular breakdowns like “AI emissions” is minimal to non-existent. Investors care about climate risk, but they look at the big picture (Is the company’s overall carbon footprint aligned with net-zero pathways? Is it exposed to carbon pricing risk? etc.). Unless AI's footprint threatens those big-picture goals, investors won't zoom in on it. Right now, AI's footprint might be relatively small in many companies compared to their total footprint, except for cloud and tech companies themselves, where IT is the core business. If AI's energy use grows, then investor concern could grow in tandem, or if investors get signals that "hidden" carbon could later become a liability.

Consumer/Societal Influence: Currently, consumers admire AI as a feature and think of AI in products like voice assistants, recommendation engines, etc. They are mostly oblivious to its environmental impact. A potential indirect effect is that if society at large grows more carbon-conscious about digital activities (like how some are now aware streaming video has a footprint, etc.), there could be reputational risk in being seen as an unecological tech user. The mention in interviews of employee awareness and employees being, in some ways, a subset of society suggests that a grassroots shift can happen.

However, such a narrative is nascent. There was a minor flurry of media coverage around the energy use of training models like OpenAI Chat GPT (Baraniuk, 2024), but it hasn't become a mainstream public concern. If climate change continues to worsen and every emission source comes under scrutiny, AI could eventually get its turn in the spotlight of public opinion.

In the current equilibrium, external pressures allow companies to maintain substantive opacity with little backlash. The legitimacy gap of non-disclosure of AI emissions hasn't become a legitimacy crisis because stakeholders haven't made it one. But legitimacy is a dynamic construct. If stakeholder norms shift to a point where omitting AI emissions is viewed as deceptive or irresponsible, then companies must adapt to preserve legitimacy. Legitimacy Theory would suggest companies will do exactly that – they'll change their disclosure practices once not changing them poses a threat to their social license.

Not all legitimacy challenges arise from external scrutiny. Several interviews suggested growing internal awareness of the contradictions in corporate sustainability narratives. One interviewee invoked *Jevons Paradox*, observing that "*making systems more efficient doesn't mean we consume less but it usually means we end up using more.*" Jevons Paradox challenges the often-repeated narrative of AI being good for the environment through improving operational efficiency (Jevons, 1865). The fact that this narrative is being challenged internally might have an impact on internal reporting cultures and disclosure practices. Right now, some companies, as a precaution, are starting to prepare for that future by measuring internally (so that if asked, they won't be caught completely off guard). The example of internal "*Cloud Emissions Tracker*" tools and discussions about categorising software emissions show that organisations are at least bracing for more scrutiny.

6.4 Broader Implications: Corporate Legitimacy in the Age of AI

The relationship between AI adoption and sustainability reporting reflects a broader corporate challenge of how companies can integrate advanced but resource-intensive technologies into a world increasingly committed to environmental responsibility. The study's findings, interpreted through legitimacy theory, suggest several wider implications.

At present, legitimacy in this area is relatively easy to maintain. Because awareness of AI's environmental impact is still emerging, companies have benefitted from what can be described as a legitimacy lag. This refers to a period during which firms enjoy reputational gains from AI related innovation without facing corresponding demands for environmental accountability. Such lags are not unique to AI. Historical examples include the initial public enthusiasm for plastics, later tempered by concerns over pollution, and the early exploitation of personal data before data privacy norms were established. While the legitimacy lag offers a strategic advantage in the short term, it may evolve into a legitimacy trap for unprepared companies when public expectations eventually rise.

There is also a significant risk of legitimacy crises A triggering event could lead to public backlash if the gap between corporate rhetoric and actual practices persists. According to Suchman, a legitimacy threat arises when stakeholders perceive that an organisation's behaviour fails to meet societal expectations. Although public concern over AI's carbon footprint remains limited, it could grow rapidly. If that occurs, current practices of omitting or generalising AI emissions could come to be viewed as deceptive or insincere.

At the same time, companies can strengthen by leading in this space. A firm that transparently reports AI emissions and demonstrates steps to reduce them could gain a competitive advantage in responsible technology leadership. Although such actions may only resonate with a small segment of stakeholders, the potential for long-term reputational benefits exists. The strategic timing of such leadership is important. Acting too early may result in little recognition. Acting at the right moment may bring acclaim. Acting too late means its routine compliance.

As new industry norms are established, companies may be compelled to improve their disclosure practices. Not falling in line with these norms means that companies risk non-compliance. For instance, updates to widely adopted sustainability frameworks such as the Greenhouse Gas Protocol or coordinated efforts by industry associations could result in the emergence of sector-specific guidance. Once such norms become widely accepted, conformity will be necessary to maintain organisational legitimacy.

Finally, companies will increasingly need to present a balanced narrative. AI should be communicated to stakeholders as both a source of innovation and environmental cost. Organisations that acknowledge this duality and demonstrate how they manage it will be better positioned to meet rising demands for corporate accountability. At present, many firms behave rationally within the current legitimacy context. They provide enough information to meet basic expectations without attracting excessive scrutiny. However, the findings of this study suggest that this equilibrium is likely to shift. Companies that recognise legitimacy as involving the fulfilment of rising stakeholder expectations and not merely the avoidance of criticism will be better prepared for this transition.

In conclusion, AI emissions reporting is a clear example of how corporate legitimacy is negotiated in response to both technological and societal change. Although these negotiations are currently taking place within organisations, they will likely become a more visible part of corporate sustainability communication soon.

7. Conclusion

7.1 Summary of Key Findings

This thesis examined the extent, challenges, and strategic motivations behind AI-related emissions reporting in corporate sustainability disclosures. The research found that AI-related carbon emissions remain underreported in corporate sustainability communications. As was revealed from expert interviews, companies do not typically disclose the carbon footprint of their AI activities separately, often subsuming it under general IT or cloud emissions, or omitting it entirely. Furthermore, firms use selective transparency and legitimacy-seeking strategies regarding AI's environmental impact. That is to say, firms tend to highlight AI's benefits, such as efficiency gains enabled by AI, while avoiding detailed disclosure of AI's direct carbon costs.

In addition, practical and organisational challenges contribute to non-disclosure. Difficulties in accurately measuring AI's energy consumption and attributing emissions within shared IT infrastructure make reporting AI emissions cumbersome. There are neither established reporting standards nor explicit stakeholder demands for reporting AI-specific emissions. Popular and widely accepted frameworks, such as the GHG Protocol, do not provide guidance related to AI-emissions reporting. However, academia and some industry practitioners increasingly highlight that this gap may need to be addressed as AI's role in business expands.

These findings confirm prior research observations about transparency gaps in corporate sustainability reporting, especially for emerging issues, and extend legitimacy theory into the novel context of AI emissions. Companies are shown to manage their sustainability image by controlling the narrative around AI, which is simultaneously a driver of innovation and a source of unacknowledged environmental impact.

7.2 Implications and Recommendations

The insights from this study carry several implications for industry, policymakers, and academic research.

7.2.1 Implications for Industry

Companies should consider adopting explicit AI carbon accounting practices. This involves internally tracking the energy use and emissions of significant AI workloads or services. Early development of this capacity can help firms be future-ready, as they would be able to integrate AI emissions into their sustainability strategies. For example, a company could expand its existing sustainability data collection to include metrics such as energy consumed by data analytics and AI as a category.

Where AI contributes meaningfully to a company's energy usage, integrating that information into sustainability disclosures would enhance transparency. Rather than aggregating everything under general IT, firms could provide a brief discussion or data point on AI. This could be qualitative initially, acknowledging that AI training is energy intensive, the company is monitoring and seeking to improve its efficiency, and progress to quantitative methods as methods improve. Doing so voluntarily could strengthen a company's credibility and demonstrate leadership in sustainable technology adoption.

Additionally, communications teams should craft narratives that reflect both the opportunities, and the responsibilities associated with carbon emissions of AI. This pre-empts potential criticism and shows a holistic understanding of innovation. It aligns with growing stakeholder interest in genuine corporate responsibility, potentially turning a risk into an opportunity for reputational gain.

7.2.2 Implications for Policymakers

Regulatory bodies and standard setters should consider updating sustainability reporting standards to explicitly include digital technology impacts. For instance, the GHG Protocol could provide guidance on how to account for emissions from cloud computing and AI services under Scope 3. The EU's CSRD framework, or its implementing standards, could mention disclosure of significant IT related emissions or data centre emissions, which would naturally encompass AI. By clarifying expectations, policymakers would level the playing field and ensure companies address this area consistently.

In the near term, policymakers and industry regulators could encourage voluntary transparency without the usage of hard mandates. This might be done via reporting awards, pilot programs, or inclusion of AI emission metrics in public sustainability indices or ratings.

If a few leading companies start reporting this information, it creates a benchmark that can spread through peer influence, a form of soft regulation via norms.

Governments and international bodies can also fund or facilitate the development of better measurement tools for AI’s energy and carbon impact. For example, an initiative to work with AI providers on providing clients with standardised emissions data for their usage would tackle a key barrier. Policymakers could convene dialogues between Tech providers companies, large corporate users, and sustainability experts to create practical solutions, similar to how the financial industry collaborated on TCFD reporting methodologies. When measurement is easier, reporting will naturally improve.

7.2.3 Implications for Academic Research

This study highlights the need for further empirical and methodological research on AI’s carbon footprint. Academics can contribute by developing and refining models to estimate emissions for different types of AI workloads leading to widely accepted coefficients or benchmarks. Additionally, case studies of organisations that attempt AI emissions reporting can yield insights and best practices for others to follow.

Future research could also survey sustainability reports across various industries to quantify how many mention AI or digital emissions, and correlate that with factors like industry type, company size, or region. This would track progress or lack thereof in transparency and help identify what drives some firms to be more open. It could also be interesting to explore whether companies in tech versus non tech sectors differ in their approach to this issue.

The application of legitimacy theory in this thesis could be broadened. Researchers might examine other emerging technologies, such as blockchain or the Internet of Things, to see if similar patterns occur in disclosure of environmental impacts. Comparative studies could enrich the theoretical understanding of how companies navigate new challenges to their legitimacy.

7.3 Limitations and Future Research

7.3.1 Limitations

This research was qualitative in nature, drawing on a limited number of expert interviews and focusing on depth over breadth. Moreover, most of the experts belonged to the same organisation. As such, the findings are exploratory. They illustrate key issues and perceptions but are not statistically generalisable. Corporate practices likely vary widely and thus the study provides themes rather than exhaustive documentation of all behaviours in all companies.

The expert insights were primarily from a European, specifically Swedish, context, where sustainability reporting is relatively advanced. This may not reflect situations in regions with different regulatory pressures. Companies in regions with fewer sustainability regulations might be even less inclined to consider AI emissions, whereas companies in very tech centric markets might be slightly more aware. Future research could expand to a broader geographic sample.

Moreover, the state of AI adoption and sustainability norms is changing quickly. What holds true at the time of writing in 2025 may shift in the next few years. This thesis provides a snapshot and analysis based on current conditions. It does not capture future developments that could alter corporate behaviour, such as if energy costs surge or if a major climate pledge requires tackling all sources.

7.3.2 Future Research Directions

Future studies should aim to establish quantitative benchmarks for AI emissions reporting. This could involve experiments or measurements in controlled settings, such as monitoring the energy use of training specific models, to create reference points. Also, cross disciplinary work between computer science focusing on AI efficiency and environmental science focusing on carbon accounting could yield new tools or frameworks that companies can use.

As mentioned, broadening the scope to other regions such as Asia and the Americas and industries including finance, healthcare, and manufacturing would provide a more comprehensive picture. It would be valuable to see if, for example, a bank or an automotive firm in the United States or Asia has similar reporting gaps and motivations, or if there are unique factors in those contexts.

Tracking how a set of companies manage AI emissions over time as external pressures change could offer powerful evidence of legitimacy driven adaptation. If, for instance, a regulation comes into effect in 2026 requiring more disclosure, a study could analyse reports from 2024 through 2028 to see the before and after effect. This would empirically test some predictions made in this thesis about how companies might respond when pressures intensify.

On the stakeholder side, research could explore awareness and expectations. Surveys of investors or consumers could gauge whether they think companies should disclose AI's footprint, or if knowing a product's AI component is energy intensive would affect their opinions or decisions. Such research helps close the loop in understanding the stakeholder and company dynamic around this issue.

In closing, this thesis contributes to understanding a contemporary challenge in corporate sustainability reporting. As AI becomes ever more embedded in business operations, ensuring transparency about its environmental impact will be important for credibility and holistic accountability. The study underscores that legitimacy considerations significantly shape disclosure decisions, more so in areas not yet standardised or demanded by stakeholders. By shedding light on these dynamics, the hope is to inform both corporate practice and policy, steering them toward greater openness and sustainability in the digital age.

References:

Anthony, L. F. W., Kanding, B., & Selvan, R. (2020). *Carbontracker: Tracking and predicting the carbon footprint of training deep learning models.* arXiv preprint arXiv:2007.03051. https://arxiv.org/pdf/2007.03051

Ascui, F., & Lovell, H. (2011). As frames collide: Making sense of carbon accounting. *Accounting, Auditing & Accountability Journal*, *24*(8), 978–999. https://www.proquest.com/docview/940980850

Baraniuk, C. (2024, May 21). *Electricity grids creak as AI demands soar*. BBC News. https://www.bbc.com/news/articles/cj5ll89dy2mo

Bebbington, J., & Unerman, J. (2018). Achieving the United Nations Sustainable Development Goals: An enabling role for accounting research. *Accounting, Auditing & Accountability Journal*, *31*(1), 2–24. https://www.emerald.com/insight/content/doi/10.1108/aaaj-05-2017-2929/full/html

Bega, D., Gramaglia, M., Fiore, M., Banchs, A., & Costa-Perez, X. (2019). AI-based autonomous control, management, and orchestration in 5G. IEEE Network, 33(6), 44–51. https://www.it.uc3m.es/banchs/papers/ieeenet20.pdf

Brevini, B. (2022). *Is AI good for the planet?* Polity Press.

Bussmann, N., Giudici, P., & Marinelli, D. (2021). Explainable AI in credit risk management. *Journal of Financial Transformation*, *53*, 79–88. https://www.proquest.com/docview/2493262940?parentSessionId=cTQWe5KTvpe7YRiAQeqeVQhj77cnC1xK4o7lmNVX%2F2E%3D&pq-origsite=primo&accountid=39039&sourcetype=Scholarly%20Journals

Chakraborty, C., & Joseph, A. (2017). *Machine learning at central banks* (Bank of England Working Paper No. 674). Bank of England. https://www.bankofengland.co.uk/-/media/boe/files/working-paper/2017/machine-learning-at-central-banks.pdf

Cho, C. H., & Patten, D. M. (2007). The role of environmental disclosures as tools of legitimacy: A research note. *Accounting, Organizations and Society, 32*(7–8), 639–647. https://www.sciencedirect.com/science/article/pii/S0361368206001036

Cho, C. H., Laine, M., Roberts, R. W., & Rodrigue, M. (2015). Organized hypocrisy, organizational façades, and sustainability reporting. *Accounting, Organizations and Society*, *40*, 78–94. https://ore.exeter.ac.uk/repository/bitstream/handle/10871/17859/ORE_AAAJ_2015.pdf

Deegan, C. (2019). Legitimacy theory: Despite its enduring popularity and contribution, time is right for a necessary makeover. *Accounting, Auditing & Accountability Journal*, *32*(8), 2307–2329. https://www.proquest.com/docview/2315473225

Depoers, F., Jeanjean, T., & Jérôme, T. (2016). Voluntary disclosure of greenhouse gas emissions: Contrasting the Carbon Disclosure Project and corporate reports. *Journal of Business Ethics*, *134*(3), 445–461. https://www.proquest.com/docview/1778703306

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 48(2), 147–160. https://doi.org/10.2307/2095101

Downie, J., & Stubbs, W. (2013). Evaluation of Australian companies' scope 3 greenhouse gas emissions assessments. *Journal of Cleaner Production*, *56*, 156–163. https://www.sciencedirect.com/science/article/pii/S0959652611003416

Dwivedi, Y. K., Hughes, D. L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J. S., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., ... Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., Cui, C., Corrado, G. S., Thrun, S., & Dean, J. (2019). A guide to deep learning in healthcare. *Nature Medicine*, *25*(1), 24–29. https://doi.org/10.1038/s41591-018-0316-z

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, *61*(4), 5–14. https://doi.org/10.1177/0008125619864925

Hahn, R., & Kühnen, M. (2013). Determinants of sustainability reporting: A review of results, trends, theory, and opportunities in an expanding field of research. *Journal of Cleaner Production*, *59*, 5–21. https://www.sciencedirect.com/science/article/pii/S0959652613004654

Jevons, W. S. (1865). *The coal question: An inquiry concerning the progress of the nation, and the probable exhaustion of our coal-mines*. London: Macmillan.

Kaack, L. H., et al. (2022). Aligning artificial intelligence with climate change mitigation. *Nature Climate Change*, *12*(6), 518–527. https://par.nsf.gov/servlets/purl/10469824

Kolk, A., Levy, D., & Pinkse, J. (2008). Corporate responses in an emerging climate regime: The institutionalization and commensuration of carbon disclosure. *European Accounting Review*, *17(4), 719–745.* https://doi.org/10.1080/09638180802489121

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539

Lee, J., Davari, H., Singh, J., & Pandhare, V. (2018). Industrial Artificial Intelligence for industry 4.0-based manufacturing systems. *Manufacturing Letters*, *18*, 20–23. https://www.sciencedirect.com/science/article/pii/S2213846318301081

Loeser, F., Recker, J., Brocke, J. V., & Seidel, S. (2017). How IT executives create organizational benefits by translating environmental strategies into green IS initiatives. *Information Systems Journal*, *27*(4), 503–553. https://onlinelibrary.wiley.com/doi/full/10.1111/isj.12136

Michelon, G., Pilonato, S., & Ricceri, F. (2015). CSR reporting practices and the quality of disclosure: An empirical analysis. *Critical Perspectives on Accounting*, *33*, 59–78. https://www.sciencedirect.com/science/article/pii/S1045235414001051

Nilsson, N. J. (2009). *The quest for artificial intelligence: A history of ideas and achievements.* Cambridge University Press.

Pang, A., Jin, Y., Seo, Y., Choi, S. I., Teo, H. X., Le, P. D., & Reber, B. (2022). Breaking the sound of silence: Explication in the use of strategic silence in crisis communication. *International Journal of Business Communication*, 59(2), 219–241. https://doi.org/10.1177/23294884211046357

Roberts, R. W. (1992). Determinants of corporate social responsibility disclosure: An application of stakeholder theory. *Accounting, Organizations and Society*, 17(6), 595–612. https://doi.org/10.1016/0361-3682(92)90015-K

Russell, S. J., & Norvig, P. (2021). *Artificial intelligence: A modern approach* (4th ed.). Pearson.

Schwartz, J., et al. (2020). *Artificial intelligence and the future of humans.* Pew Research Center. https://research-ebsco-com.ez.hhs.se/c/ypcopz/viewer/pdf/cmnylkpx6v?route=details

Strubell, E., Ganesh, A., & McCallum, A. (2019). Energy and policy considerations for deep learning in NLP. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics* (pp. 3645–3650). https://aclanthology.org/P19-1355.pdf

Suchman, M. C. (1995). Managing legitimacy: Strategic and institutional approaches. *Academy of Management Review*, *20*(3), 571–610. https://www.proquest.com/docview/210941848

Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine*, *25*(1), 44–56. https://doi.org/10.1038/s41591-018-0300-7

Vinuesa, R., Azizpour, H., Leite, I. & Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S., Tegmark, M. & Nerini, F. (2019). The role of artificial intelligence in achieving the Sustainable Development Goals. *Nature Communications, 11*(1), Article 233. https://doi.org/10.1038/s41467-019-14108-y

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. *Business Process Management Journal*, *26*(7), 1893–1924. https://www.proquest.com/docview/2461009218

World Resources Institute, & World Business Council for Sustainable Development. (2004). *The greenhouse gas protocol: A corporate accounting and reporting standard* (Rev. ed.). http://pdf.wri.org/ghg_protocol_2004.pdf

Yin, R. K. (2018). Case study research and applications: Design and methods (6th ed.). *SAGE Publications.*

Appendix

Appendix A: On AI usage

This thesis acknowledges the usage of OpenAI's ChatGPT (GPT-4) and Grammarly in the writing process. However, it must be clearly noted that the analysis, arguments, interpretations, and conclusions reflect the author's own synthesis and judgement. The use of AI tools in this thesis was limited to writing support functions such as improving tone, clarity, and coherence. At no point did these tools contribute to the intellectual substance of the research.

Additionally, in the starting phase of the research, ChatGPT was used to summarise research articles and explain complex concepts. An important observation here was the notable differences in the quality of output between different GPT models. Regardless, oversight was necessary to ensure that the summaries and explanations provided by ChatGPT did not miss key findings (as was often the case).

Regarding the writing process, ChatGPT's (and also Grammarly's) suggestions for phrasing sometimes introduced unintended meanings or generic statements. Moreover, ChatGPT occasionally introduced factual inaccuracies or made confident claims that were not supported by the literature. Thus, the suggestions were treated simply as that – mere suggestions.

Irrespective of the aforementioned shortcomings, the AI tools have their utility if used with appropriate caution and in line with applicable guidelines.