STOCKHOLM SCHOOL OF ECONOMICS
1351 Master's thesis in Business Management
Academic year 2025–2026

Organizational Capabilities for Deploying AI in Corporate Environmental Sustainability

Jannis Heidemann (42790) and Anna List (42808)

Abstract

Organizations increasingly explore artificial intelligence (AI) to advance corporate environmental sustainability, yet research offers limited insight into the organizational capabilities required to do so effectively. This thesis addresses this research gap by examining the organizational capabilities that enable firms to deploy AI for corporate environmental sustainability. In order to answer the research question, an exploratory qualitative study was conducted, using semi-structured interviews with European professionals working in sustainability and AI. The data was analyzed through thematic analysis to uncover patterns across interviews.

Our findings show that organizations require Ordinary Capabilities for general AI adoption (covering Technological, Organizational, and Environmental dimensions). Crucially, these foundational capabilities must be complemented by four distinct Environmental Sustainability Capabilities: Environmental Sustainability Strategy, Environmental Sustainability Data, Environmental Sustainability KPIs, and Collaboration. These specific capabilities, which function as an integrated system, help companies identify a broader range of AI initiatives that benefit environmental sustainability not only as a by-product of efficiency projects but as strategically aligned tools for achieving long-term environmental objectives.

Practically, managers should embed these structural conditions by establishing a holistic environmental sustainability strategy, building robust environmental sustainability data capabilities, translating goals into measurable Environmental Sustainability KPIs across departments, and enhancing strong cross-functional Collaboration between sustainability, IT, and operational units. Thereby ensuring that AI is intentionally and effectively used for environmental sustainability.

Keywords

Artificial Intelligence (AI), Environmental Sustainability, Dynamic Capabilities, TOE Framework, Organizational Capabilities

Supervisor:	Korinzia Toniolo
Date examined:	15.12.2025
Discussant(s):	Himanshi Bansal, Yingchi Xu
Examiners:	Per Andersson, Henrik Glimstedt

Table of Contents

1. Introduction 1

1.1. Background 1

1.2. Purpose & Expected Contribution 1

1.3. Delimitations 2

2. Literature Review 4

2.1. Artificial Intelligence (AI) 4

2.1.1. Definition 4
2.1.2. AI in Organizations 4
2.1.3. Capabilities for AI Implementation 5

2.2. Sustainability 8

2.2.1. Definition 8
2.2.2. Corporate Environmental Sustainability 9

2.3. Artificial Intelligence for Corporate Environmental Sustainability 9

2.3.1. AI Applications for Corporate Environmental Sustainability 10
2.3.2. Capabilities for AI Implementation in Corporate Environmental Sustainability 10

2.4. Theoretical Framework 11

2.4.1. Organizational Capabilities 11
2.4.2. Strategic Management Frameworks for Organizational Capabilities 12
2.4.2.1. The Resource-Based View (RBV) 12
2.4.2.2. Dynamic Capabilities 13
2.4.3. Information System Frameworks for Organizational Capabilities 13
2.4.3.1. Technology-Organization-Environment (TOE) Framework 13
2.4.3.2. Capability Maturity Models 14

2.5. Integration of the Theoretical Frameworks 14

3. Methodology 15

3.1. Research Design 15

3.2. Data Collection 15

3.3. Data Analysis 18

3.4. Data Quality 19

4. Results 21

4.1. Ordinary Capabilities 21

4.1.1. T - Technological Capabilities 21
4.1.2. O - Organizational Capabilities 22
4.1.3. E - Environmental Capabilities 24

4.2. Environmental Sustainability Drivers and Use Cases 24

4.3. Environmental Sustainability Capabilities 26

5. Discussion 30

5.1. Ordinary Capabilities 30

5.1.1. Technological Dimension 30
5.1.2. Organizational Dimension 31

5.1.3. Environmental Dimension 32

5.2. Environmental Sustainability Capabilities 34

5.2.1. Relation to RBV and Dynamic Capabilities 36

5.3. Adapted Theoretical Framework 37

5.4. Theoretical and Empirical Contributions 38

5.5. Practical Implications 39

5.6. Limitations of the Study & Future Research 40

6. Conclusion 41

7. References 42

8. Appendix 49

8.1. Appendix A: Interview Guide 49

8.2. Appendix B: Initial Thematic Map (Braun & Clarke, 2006) 50

8.3. Appendix C: Declaration of AI Use in this thesis 51

List of Tables

Table 1: Overview of Capabilities for General AI Implementation in Literature 7
Table 2: Overview of Interviewees 17
Table 3: Overview of Ordinary Capabilities 21
Table 4: Overview of Environmental Sustainability Capabilities 26
Table 5: Overview of Literature and Interview Findings 33

List of Figures

Figure 1: Data Analysis Process 18
Figure 2: Final Thematic Map 19
Figure 3: Interrelation of Environmental Sustainability Capabilities 36
Figure 4: Adapted Theoretical Framework 38

Abbreviations

Abbreviation	Description
AI	Artificial Intelligence
AWS	Amazon Web Services
CSRD	Corporate Sustainability Reporting Directive
ESG	Environmental, Social, Governance
GPU	Graphics Processing Unit
KPI	Key Performance Indicator
LLM	Large Language Model
RBV	Resource-Based View
SDGs	Sustainable Development Goals

1. Introduction

1.1. Background

In 2025, more than 85% of organizations are already using artificial intelligence (AI) in their business operations, yet the majority remain in the early stages of scaling AI across the organization (McKinsey, 2025). Companies face diverse challenges in a rapidly evolving technological landscape and do not want to fall behind their competitors. Thus, AI has become a top strategic priority, with strong momentum reflected in recent industry reports (BCG, 2025; McKinsey, 2025).
Another study shows that European firms remain significantly behind their US counterparts in adopting generative AI, with a gap estimated at roughly 45 to 70 percent (McKinsey, 2024a).
However, when it comes to using AI specifically for decarbonization, European companies are already ahead, with an adoption rate of about 20 percent, compared to only 14 percent in the Asia-Pacific region and just 10 percent in North America (Accenture, 2024).

In this context, environmental sustainability has become an equally urgent organizational priority. Firms face growing regulatory demands, including the EU Corporate Sustainability Reporting Directive (CSRD), alongside rising stakeholder expectations and the broader societal imperative to address climate change (European Commission, n.d.-b; KPMG, n.d.). Yet, despite these pressures, progress remains limited. While 64 percent of European businesses have announced full Scope 1-3 net-zero ambitions, only 16 percent are currently on track to meet them, and nearly half have even reported increasing emissions (Accenture, 2024). As companies seek to close this performance gap, AI is increasingly regarded as a promising enabler of environmental sustainability, for example, through more accurate emissions forecasting, resource-efficiency analytics, or sustainability-related automation (Accenture et al., 2024). But, despite this potential, most organizations struggle to operationalize AI for environmental sustainability, revealing a persistent gap between technological opportunity and organizational reality (Accenture, 2024).

1.2. Purpose & Expected Contribution

Although academic interest in artificial intelligence has expanded significantly in recent years, research on AI in the business context has predominantly concentrated on two areas. One stream examines the wide range of AI applications, illustrating how AI can enhance operational efficiency, decision-making, and, more recently, sustainability performance. The second stream focuses on the organizational capabilities required for AI adoption more broadly, with particular emphasis on technological readiness, data infrastructure, human expertise, and managerial support (e.g. Enholm et al., 2022; Gama & Magistretti, 2025).

In the context of environmental sustainability, however, existing literature remains primarily oriented toward identifying potential AI use cases, benefits, and challenges rather than exploring the organizational foundations that enable their realization (e.g. Feng et al., 2024; Kar et al., 2022; Nishant et al., 2020; Toniolo et al., 2020). As a result, research has advanced the understanding of what AI could contribute to environmental sustainability, but it has not sufficiently addressed how firms can translate these possibilities into practice. This disconnect reveals a clear academic gap:

despite a growing body of literature on organizational capabilities for AI adoption and a parallel stream on AI-enabled sustainability applications, we still lack a systematic understanding of the specific organizational capabilities required to deploy AI for environmental sustainability.

Given accelerating regulatory pressure, increasing expectations from stakeholders, and the growing availability of AI technologies, this gap is both theoretically and practically relevant (KPMG, n.d.). The purpose of this thesis is to address this gap by developing a deeper understanding of the organizational capabilities that enable companies to effectively deploy artificial intelligence for environmental sustainability. By doing so, the study contributes by connecting the largely application-oriented research on AI for environmental sustainability (e.g. Feng et al., 2024; Kar et al., 2022; Nishant et al., 2020; Toniolo et al., 2020) with the broader literature on organizational capabilities (e.g. Enholm et al., 2022; Gama & Magistretti, 2025), thereby clarifying which capabilities enable firms to move from promising use cases to effective implementation.

This motivation leads to the central research question guiding this thesis:

> ***What organizational capabilities are required to effectively deploy AI for corporate environmental sustainability?***

To investigate this question, the research applies a qualitative design using semi-structured interviews, which allows for a detailed examination of the organizational capabilities required for deploying AI for corporate environmental sustainability.

1.3. Delimitations

We applied several delimitations to the scope of this study in order to address the research question effectively. First, due to the limited existing research at the intersection of AI and sustainability, the thesis focuses specifically on the capabilities required for using AI to advance environmental sustainability, understood as the E dimension of the Environmental, Social, and Governance (ESG) framework. Broader ESG aspects, such as social or governance considerations, fall outside the scope of this research.

Second, the empirical investigation concentrates on organizations located in Germany, Austria, and Sweden. These countries were selected because they operate under comparable European regulatory frameworks, such as the CSRD, which was introduced in 2021 by the European Commission, and the EU AI Act, which was issued in August 2024, and they face similar pressures to adopt digital technologies, including AI (European Commission, n.d.-b, 2025). They also represent advanced economies in which AI adoption is already widespread, providing a shared institutional and technological context that supports comparability and interpretability across interviews (Eurostat, 2025).

Third, given that AI implementation remains relatively new in most organizations, this study primarily examines which capabilities are required to deploy AI for environmental sustainability. While the interviews provided initial insights into how some of these capabilities develop, analyzing capability-building processes in detail was not the main focus of this study. Similarly, it was beyond the scope of this research to investigate the relationships between different capabilities or their direct influence on implementation success.

Finally, while we acknowledge that AI also has broader environmental impacts, such as substantial energy and water consumption during model training and operation (van Wynsberghe, 2021), this thesis focuses exclusively on the contributions AI can make to corporate environmental sustainability. Other environmental effects and consumer-facing AI applications were not included in the analysis.

2. Literature Review

2.1. Artificial Intelligence (AI)

AI is not a new concept; its origins in academic literature can be traced back to the 1950s (Haenlein & Kaplan, 2019). However, in recent years, AI has attracted renewed attention, particularly in the context of organizations seeking to generate business value from its application (Ransbotham et al., 2018). Today, AI is widely used across industries, often at the individual level - for instance, through the use of generative models such as ChatGPT to increase efficiency. Despite some notable success stories, many organizations continue to struggle with realizing tangible value from AI initiatives (Winsor, 2024).

2.1.1. Definition

The OECD defines Artificial Intelligence as follows:

> "An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment." (OECD, 2024).

Although the literature offers a variety of definitions of AI, there is a general consensus that AI refers to computer systems capable of performing tasks that require intelligence and are typically carried out by humans, thus exhibiting human-like skills (Dwivedi et al., 2021; Enholm et al., 2022). Furthermore, AI can be classified according to its evolutionary stages: Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Superintelligence (ASI) (Haenlein & Kaplan, 2019). In addition to these broad categorizations, more technical definitions focus on the underlying technologies, such as machine learning and deep learning (Enholm et al., 2022).

For the purpose of this research, we adopt a broad definition of AI and do not limit ourselves to one specific type of AI, defining it as a machine-based system with human-like skills that can perform tasks requiring intelligence and are currently performed by humans. In regard to the evolutionary stage, our focus will be on Artificial Narrow Intelligence (ANI), i.e., AI systems that can perform dedicated tasks as well as, or better than, humans, but without general intelligence (Russel & Norvig, 2010; Toniolo et al., 2020).

2.1.2. AI in Organizations

Reflecting the growing interest, an expanding body of research has emerged on how companies can implement AI to create business value. This literature primarily addresses the capabilities organizations require for AI adoption and the potential applications of AI. For example, Gama and Magistretti (2025) differentiate between enabling capabilities, those that facilitate the adoption of

AI, and enhancing capabilities, which are created or strengthened as a result of AI implementation. Similarly, other researchers identify both enabling capabilities and inhibitors of AI adoption, as well as the first- and second-order effects of two primary types of applications: **automation**, where AI replaces human activities, and **augmentation**, where AI enhances human intelligence by supporting decision-making processes (Enholm et al., 2022; Raisch & Krakowski, 2021).

Automation refers to the replacement of human activities by intelligent systems that execute well-defined, routine, or repetitive tasks. Typical examples include knowledge and service work such as automated email handling or invoice processing, where algorithms execute predefined rules and eliminate manual intervention (Wamba-Taguimdje et al., 2020). Similarly, chatbots and conversational agents automate communication processes in customer service by responding to inquiries through natural language processing and machine learning (Nuruzzaman & Hussain, 2018). In industrial settings, automation has transformed manufacturing processes, enabling robotic systems to manage assembly lines and quality control with minimal human input (Demlehner & Laumer, 2020).

In contrast, **augmentation** denotes the use of AI to complement and enhance human intelligence rather than replace it (Schmidt et al., 2020). Augmentation applications support human experts by processing vast quantities of data, identifying patterns that are too complex or voluminous for manual analysis, and providing insights for more informed and timely decisions (Borges et al., 2021; Lichtenthaler, 2019). In this role, AI functions as a decision-support system that strengthens analytical, predictive, and strategic capabilities. One example is the use of AI to classify and segment customers in marketing analytics, enabling more personalized and targeted campaigns (Mishra & Pani, 2021).

While automation and augmentation are often treated as distinct categories, recent management research emphasizes their interdependence. Raisch and Krakowski (2021) describe this relationship as an automation–augmentation paradox: organizations need both approaches and must balance the efficiency gains of automation with the innovation potential of augmentation. The most advanced organizations integrate both approaches, viewing AI as a general-purpose technology that transforms how value is created and decisions are made across the enterprise (Raisch & Krakowski, 2021).
In this thesis, both automation and augmentation applications are considered.

2.1.3. Capabilities for AI Implementation

The growing body of literature examining the organizational capabilities for AI implementation emphasizes that organizations need to develop and coordinate a distinct set of capabilities, which determine whether technologies can effectively translate into business value. The literature consistently emphasizes that technological systems alone are insufficient; organizations must build complementary resources, processes, and managerial routines that enable effective data use, algorithm development, deployment, and continuous organizational learning (Enholm et al., 2022; Gama & Magistretti, 2025). Across studies (see Table 1), ten capability categories emerge as particularly critical for AI adoption.

A fundamental prerequisite concerns access to and quality of **Data**. Many researchers emphasize that reliable, comprehensive, and well-governed data assets constitute the foundation for all AI-related activities. Additionally, there is a need for systematic processes to ensure data accuracy and integration across functional boundaries, supported by standards that safeguard data quality over time (AlSheibani et al., 2018; Baier et al., 2019; Ghosh, 2025; Schmidt et al., 2020; Weber et al., 2023). Closely related is the development of suitable **Technological Infrastructure,** e.g., computing capacity, storage solutions, and algorithmic environments, that enable scalable experimentation and continuous model training. The ability to maintain and evolve machine learning models, monitor their performance, and manage deployment pipelines has been identified as a key differentiator for achieving AI-driven efficiency and innovation gains (Enholm et al., 2022; Ghosh, 2025; Kinkel et al., 2022; Wamba-Taguimdje et al., 2020; Weber et al., 2023).

As data and algorithmic complexity increase, Sjödin (2021) highlights **Cybersecurity Management** as another core capability. Safeguarding sensitive data, ensuring secure model deployment, and mitigating adversarial threats are essential to preserve reliability and trust in AI-enabled systems (Sjödin et al., 2021).

Beyond technical foundations, researchers identify that **Cultural and Organizational readiness** determines the extent to which AI can be embedded in everyday operations. Firms must foster openness to change, cross-functional collaboration, and a learning-oriented culture that empowers employees to experiment and adapt. Readiness thus encompasses both skill development and managerial practices that legitimize iterative learning (Ghosh, 2025; Pumplun et al., 2019; Weber et al., 2023). **Leadership and Governance** are seen as equally crucial in the literature: executive sponsorship, clear strategic direction, and well-defined decision rights ensure that AI initiatives receive sustained commitment and that insights from pilot projects are institutionalized rather than remaining isolated efforts (AlSheibani et al., 2018; Ghosh, 2025; Warner & Wäger, 2019).

According to Keding (2021), a coherent **AI Strategy** integrates these dimensions by aligning AI initiatives with organizational goals. It defines the areas where AI can create value, prioritizes investments, and connects data, technology, and talent decisions with business objectives. Strategic alignment helps prevent fragmented experimentation and supports long-term value creation beyond immediate efficiency gains (Keding, 2021).

Correani et al. (2020) and Weber (2023) emphasize that translating strategic intent into results requires strong **AI Project Management** capabilities. These integrate agile methodologies, data governance, and value tracking to address the inherent uncertainty of AI experimentation. Continuous evaluation, retraining, and model iteration enable organizations to refine their processes and sustain performance improvements over time (Correani et al., 2020; Weber et al., 2023).

Moreover, researchers highlight that in the interdependent nature of AI ecosystems, external collaboration capabilities and **Partnerships** also play a vital role. Partnerships with technology vendors, startups, and research institutions provide access to complementary data, expertise, and innovation potential. The ability to identify suitable partners, coordinate joint development efforts, and manage intellectual property and data-sharing agreements is essential for capturing network-level value (D. Teece et al., 2016; Warner & Wäger, 2019).

Furthermore, the literature mentions **Regulation** capabilities to navigate evolving AI governance frameworks. Mechanisms for documentation, transparency, and human oversight ensure accountability and audit readiness (Baier et al., 2019; Pumplun et al., 2019; von Hippel & Kaulartz, 2021). Similar, **Ethics & Moral** considerations have gained prominence in the literature. Organizations must establish structures to identify bias, ensure fairness and transparency, and manage the broader social implications of algorithmic decisions responsibly. Such mechanisms not only protect the reputation but also foster sustainable trust among stakeholders (AlSheibani et al., 2018; Baier et al., 2019).

Some authors apply the Technology-Organization-Environment (TOE) framework to categorize these capabilities into technological, organizational, and environmental dimensions (Enholm et al., 2022; Gama & Magistretti, 2025). Others, e.g., Ghosh (2025) and Weber et al. (2023), developed alternative, less established frameworks derived from qualitative research to identify key enablers of successful AI adoption.

Table 1: *Overview of Capabilities for General AI Implementation in Literature*

Capabilities Literature	
Data	Schmidt, 2020; Baier, 2019; Alsheibani, 2018; Ghosh, 2025; Weber, 2023
Technology Infrastructure	Enholm et al., 2022; Wamba-Taguimdje et al., 2020; Kinkel et al., 2022; Ghosh, 2025; Weber, 2023
Cybersecurity Management	Sjödin, 2021
Culture & Organizational Readiness	Pumplun, 2019; Ghosh, 2025; Weber, 2023
Leadership & Governance	Alsheibani, 2020; Warner & Wäger, 2019; Ghosh, 2025
AI Strategy	Keding, 2021
AI Project Management	Correani et al., 2020; Weber, 2023
Regulation	von Hippel & Kaulartz, 2021; Pumplun, 2019; Baier, 2019
Partnerships	Teece, 2016; Warner & Wäger, 2019
Ethics & Moral	Baier, 2019; Alsheibani, 2020

2.2. Sustainability

Sustainability comes from the concept of sustainable development, which was first mentioned in the Brundtland report by the United Nations World Commission on Environment and Development and is described as "development that meets the needs of the of the present without compromising the ability of future generations to meet their own needs" (Brundtland, 1987; Toniolo et al., 2020). In order to monitor sustainable development, the UN formulated the 17 Sustainable Development Goals (SDGs) to guide countries and organizations in promoting economic, social, and environmental sustainability (United Nations, 2015). The ESG (Environmental, Social, Governance) framework has emerged as a central framework for assessing how responsibly firms operate across environmental, social, and governance dimensions. Although it is commonly linked to investment decisions, its relevance now extends to customers, suppliers, and employees, who increasingly evaluate organizations based on the sustainability of their practices (European Commission, n.d.-a).

2.2.1. Definition

Today, when referring to sustainability in a corporate context, it typically aligns with the term of corporate sustainability, which the OECD defines as:

> "[…] integrating environmental and social considerations into a company's business strategy and operations. It fosters sound governance and decision-making and helps investors better understand a company's long-term risks and opportunities" (OECD, n.d.)

Within management literature, terms such as Corporate Social Responsibility (CSR), Corporate Sustainability (CS), Sustainable Development, and Environmental Management (EM) are often used interchangeably, despite lacking a clear conceptual distinction (Dyllick & Muff, 2016; Montiel & Delgado-Ceballos, 2014).
To make the concept analytically manageable at the organizational level, scholars commonly focus on Corporate Sustainability or Business Sustainability, which refers to how firms manage their financial, economic, social, and environmental risks, obligations, and opportunities (Branco & Rodrigues, 2006; Dyllick & Muff, 2016; Montiel, 2008).
Additionally, research on corporate sustainability commonly distinguishes, in line with the Greenhouse Gas (GHG) Protocol, between Scope 1 and Scope 2 emissions, which include direct emissions from company-owned or controlled sources and indirect emissions from purchased energy, and Scope 3 emissions, which stem from upstream and downstream activities across the value chain (McKinsey, 2024b).

In line with the purpose of this research, this thesis refers to corporate sustainability when talking about sustainability and focuses explicitly on the environmental dimension of corporate sustainability within the ESG framework. Moreover, this thesis concentrates primarily on Scope 1 and Scope 2 emissions, as these are within the direct control of organizations and therefore constitute the central focus of the analysis.

2.2.2. Corporate Environmental Sustainability

Corporate environmental sustainability refers to the measures companies take to reduce the ecological footprint created by their operations. Since every firm affects the environment in some way, the goal is to minimize these negative impacts through more responsible use of resources, lower emissions, and improved environmental practices (Bansal, 2005).

Firms implement the environmental perspective in their business operations for a complex blend of reasons. Investing in more environmentally sustainable processes and product innovations enables firms to conserve resources while improving return on investment and sales (Dangelico & Pujari, 2010). Better environmental performance generates savings through reduced energy and material consumption and lower pollution-related costs (Dangelico & Pujari, 2010; Russo & Fouts, 1997). Regulations (e.g. CSRD) can further stimulate innovation, open new market opportunities, and strengthen competitive advantage (Bansal & Song, 2017; Dangelico & Pujari, 2010). In addition, environmentally responsible firms benefit from an enhanced corporate image and face fewer capital constraints. A strong environmental orientation also becomes part of the organization's identity, shaping its reputation and also attracting talented employees (Branco & Rodrigues, 2006). This pro-environment reputation constitutes a valuable and difficult-to-imitate resource (Branco & Rodrigues, 2006; Russo & Fouts, 1997).

However, environmental sustainability efforts can also create potential risks for firms. First, they can impact financials because sustainable technologies, programs, and reporting systems require upfront investment, which may reduce short-term profitability and divert managerial attention from core activities (Branco & Rodrigues, 2006; Russo & Fouts, 1997). Second, companies that commit publicly to sustainability face higher scrutiny and reputational vulnerability; any inconsistency, failed partnerships, or eco-harmful incidents can rapidly damage trust and financial performance (Flammer, 2013; Russo & Fouts, 1997). Finally, when sustainability is justified solely through financial benefits, managers may act only when profits are at stake, causing initiatives to be abandoned quickly and undermining the long-term moral purpose of environmental responsibility (Bansal & Song, 2017; Dyllick & Muff, 2016).

2.3. Artificial Intelligence for Corporate Environmental Sustainability

Prior research on AI and sustainability has expanded considerably in recent years, although the thematic focus remains uneven. Earlier studies primarily examined how AI can support sustainability goals and what impacts it can have (Kar et al., 2022; Nishant et al., 2020; Vinuesa et al., 2020). More recent work has begun to address the organizational requirements and capabilities needed to use AI for sustainability, yet these contributions remain comparatively limited in scope and depth when contrasted with the broader literature on general AI adoption (Kulkov et al., 2024; Schwaeke et al., 2025). Moreover, this emerging stream of research typically examines sustainability in a broad ESG context, rather than focusing specifically on environmental sustainability (Kar et al., 2022; Kulkov et al., 2024; Nishant et al., 2020; Schwaeke et al., 2025; Vinuesa et al., 2020).
The following chapters will unpack the literature relevant to corporate environmental sustainability by first outlining the existing research on AI applications for environmental sustainability.

Thereafter, the chapter introduces the literature on organizational capabilities for AI adoption in this context.

2.3.1. AI Applications for Corporate Environmental Sustainability

On a top level, Kar et al. (2022), based on a review of 287 papers, demonstrate that AI is already used to achieve environmental sustainability across multiple sectors such as transportation, energy, medical, IT, education, food, services, construction, and manufacturing. Their work highlights that, across these industries, AI applications primarily rely on quantitative analysis and prediction, which serve as core inputs for sustainability-related decisions (Kar et al., 2022). In line with the SDGs prior quantitative research found that AI is a positive enabler to achieve the 3 environmental SDGs (13 climate action, 14 life below water, 15 life on land) (Vinuesa et al., 2020).
On an organizational level, Toniolo et al. (2020) extend this understanding by examining how companies integrate AI into their sustainability ambitions in all dimensions of ESG. Their findings illustrate that AI not only improves environmental performance but also influences business model configurations. The study highlights concrete applications in areas such as energy efficiency, emissions reduction, waste minimization, and logistics optimization. Nishant et al. (2020) provide additional evidence on how AI-driven technologies can support sustainability-enhancing decisions across different organizational functions.

Specific use cases are identified for **energy management and efficiency.** AI-driven systems analyze combustion data to minimize emissions and enhance plant efficiency, achieving significant CO_2 reductions. Moreover, AI supports building energy optimization by analyzing consumption patterns and promoting the design of smarter, energy-efficient infrastructures (Feng et al., 2024; Kar et al., 2022; Nishant et al., 2020; Schwaeke et al., 2025; Toniolo et al., 2020; Vinuesa et al., 2020).
Further research also identified that AI contributes **significantly to resource and production optimization** by enabling smarter, data-driven decision-making across industries. Through advanced analytics, AI identifies patterns in material and energy use, allowing companies to allocate resources more efficiently and minimize waste. Within manufacturing, AI technologies detect anomalies to reduce material consumption and energy waste (Feng et al., 2024; Kar et al., 2022; Kulkov et al., 2024; Leuthe et al., 2024).
Another use case for AI can be identified within **supply chain and logistics**, where it helps organizations reduce waste, emissions, and inefficiencies across operations. By analyzing data from every stage of the supply chain, AI identifies opportunities to improve sustainability and resource use (Feng et al., 2024; Kulkov et al., 2024). Intelligent logistics systems equipped with sensors and communication technologies can monitor cargo conditions and enable smart rerouting decisions that save both time and energy (Toniolo et al., 2020). Moreover, AI's predictive power optimizes inventory management, which not only reduces costs but also significantly lowers carbon emissions throughout production and transportation processes (Schwaeke et al., 2025).

2.3.2. Capabilities for AI Implementation in Corporate Environmental Sustainability

In the literature related to organizational capabilities required to deploy AI for sustainability, Kulkov et al. (2024) and Schwaeke et al. (2025) deliver the most comprehensive contributions.

In a comprehensive literature review, Kulkov et al. (2024) examined organizational, technical, and processing approaches to achieving global sustainability goals. Across these domains, three requirements are identified, which are particularly relevant for environmental sustainability. **Strategic Alignment and Commitment** is important, requiring organizations to align their strategies, goals, and objectives specifically with the principles of sustainability and the broader UN SDGs. This alignment must be supported by top management commitment and the development of performance metrics related to sustainability. **Stakeholder Engagement and Partnership Building** is also critical, as organizations must actively collaborate with customers, suppliers, regulators, and academia to co-create innovative solutions and accelerate the adoption of AI technologies specifically for sustainable development. Finally, **AI Ethics and Responsible Innovation** ensure that AI development is guided by ethical principles, necessitating that organizations consider the potential social, environmental, and economic impacts of their AI initiatives and work to minimize negative consequences while maximizing positive outcomes to meet SDGs (Kulkov et al., 2024). Furthermore, the capabilities Human Capital Development and Talent Management, AI Technology Selection and Implementation, Data Management and Analytics, Business Process Transformation and Integration, Change Management and Organizational Adaptation, and Continuous Improvement and Innovation are mentioned which align with the previously presented capabilities required for general AI adoption in the literature and are not relevant specifically for environmental sustainability (Kulkov et al., 2024).
Schwaeke et al. (2025), who conducted a qualitative study based on interviews with 24 experts and executives, describe two main types of capabilities that organizations need to use AI effectively for sustainability (including environmental sustainability): **operational enablement** and **technical capacity**. Operational enablement includes the organizational side, such as supporting Leadership, Stakeholder Management, and Impact Measurement by tracking how AI actually improves sustainability outcomes. Technical capacity refers to the technological basics needed for AI, such as the right IT Infrastructure, Data Management, and System Integration (Schwaeke et al., 2025). Overall, their work shows that using AI for sustainability depends on both organizational factors and solid technical foundations (Kulkov et al., 2024; Schwaeke et al., 2025)

The emerging literature on AI and sustainability offers only fragmented evidence and insufficient conceptual clarity on environmental sustainability in particular. What is not sufficiently explored yet is an understanding of which organizational capabilities firms need to deploy AI specifically for corporate environmental sustainability.

2.4. Theoretical Framework

2.4.1. Organizational Capabilities

Although the strategic management literature extensively discusses organizational capabilities, there is still no universally accepted definition. Broadly, organizational capabilities are described as the combination and coordination of resources that enable a firm to perform specific activities. These capabilities allow firms to achieve and sustain competitive advantages over their rivals. Put more simply, organizational capabilities represent the skills and competencies that enable an organization to carry out activities in ways that strengthen its competitive position. Examples include the ability to innovate, to adapt effectively to environmental changes, or to manage the production of complex products (Collis, 1994; Helfat & Winter, 2011; Schreyögg & Kliesch-Eberl, 2007).

The literature commonly distinguishes between **operational** capabilities and **dynamic capabilities**, which are differentiated by their relationship to change. **Operational capabilities** are associated with conditions of stability and the execution of established routines. They enable firms to perform standard activities and processes that maintain the status quo. This includes, for instance, producing established products for existing customer segments. Such capabilities are essential for conducting the core business of an organization, but do not contribute to managing change or enhancing future competitiveness (Helfat & Winter, 2011; Winter, 2003).
By contrast, **dynamic capabilities** equip firms to adapt to change and reconfigure their existing resource base. They allow organizations to improve, transform, and adjust their activities in response to evolving environments, thereby ensuring long-term viability and competitiveness. In this sense, dynamic capabilities are central to innovation, strategic renewal, and the continuous development of the business (D. J. Teece et al., 1997).

Building on the foundational concept of organizational capabilities, the literature offers several related frameworks. For this research, we focus on two domains. First, we draw on strategic management frameworks that provide a conceptual lens for analyzing capabilities and their role in creating and sustaining competitive advantage. Second, we incorporate information systems frameworks, which take a more practice-oriented perspective and are well suited to examining and structuring the capabilities required for the effective implementation of AI in environmental sustainability contexts.

2.4.2. Strategic Management Frameworks for Organizational Capabilities

Similar to the definition of organizational capabilities, there exists a wide range of strategic management frameworks concerned with organizational capabilities. These frameworks differ, for example, in the perspectives they adopt. For the purpose of this thesis, we will focus on those that emphasize the internal perspective and organization of the firm, rather than those primarily concerned with industry structure, market positioning, or competitive dynamics (e.g. Porter's Five Forces (Porter, 2008)). Within this scope, two frameworks are particularly relevant to our research as they provide a fundamental understanding of organizational capabilities: the Resource-Based View (RBV) and the Dynamic Capabilities framework.

2.4.2.1. The Resource-Based View (RBV)

The Resource-Based View (RBV) is one of the most influential theoretical frameworks in strategic management, originally developed by Wernerfelt (1984) and later extended by Barney (1991). The RBV explains how firms can achieve and sustain a competitive advantage by focusing on and combining their internal resources, in contrast to traditional frameworks that emphasize products, industry structure, or strategic positioning. In the RBV, capabilities are a type of resource (Barney, 1991; Eisenhardt & Martin, 2000; Helfat et al., 2023; Wernerfelt, 1984). Wernerfelt (1984) broadly defines a resource as "anything which could be thought of as a strength or weakness of a given firm". To generate a sustained competitive advantage, resources must fulfil the VRIN criteria: they must be valuable, rare, imperfectly imitable, and non-substitutable (Barney, 1991).

2.4.2.2. Dynamic Capabilities

Building on the RBV, Teece developed the Dynamic Capabilities framework, which extends the analysis to how firms achieve and sustain a competitive advantage in environments characterized by rapid technological change. Dynamic capabilities are defined as "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (D. J. Teece et al., 1997). The framework highlights that long-term success depends less on static market positioning strategies and more on developing internal capabilities that enable firms to identify and seize emerging opportunities. To operationalize this concept, Teece (2007) further distinguishes three core capacities: sensing new opportunities and threats, seizing opportunities through effective resource mobilization, and transforming the firm's assets to sustain competitiveness over time (D. J. Teece, 2007).

Together, both frameworks provide complementary insights. The RBV explains what resources and capabilities firms need to sustain competitiveness, while Dynamic Capabilities explain how these can be transformed to respond to a shifting technological environment. These combined frameworks are foundational for our research to understand the capabilities needed and help organizations to continuously adapt in an environment of evolving sustainability challenges and technological development.

2.4.3. Information System Frameworks for Organizational Capabilities

The Information Systems literature offers a wide range of frameworks for analyzing technology adoption. Among these, the Technology-Organization-Environment (TOE) framework and Capability Maturity Models are particularly relevant for investigating the capabilities required for AI adoption. The TOE framework provides an overarching structure by categorizing capabilities into technological, organizational, and environmental dimensions, while maturity models introduce a developmental perspective by capturing how these capabilities evolve and progress over time.

2.4.3.1. Technology-Organization-Environment (TOE) Framework

The Technology-Organization-Environment (TOE) framework is one of the most widely applied models in the information systems field for analyzing the factors that influence technology adoption. Consequently, it has been extensively employed in studies on AI adoption within organizations (Enholm et al., 2022; Gama & Magistretti, 2025). Originally introduced by Tornatzky et al. (1990), the framework distinguishes three contextual dimensions: the technological dimension (e.g. characteristics of the technology), the organizational dimension (e.g. processes, resources, and structure of the firm), and the environmental dimension (e.g. regulations, competitive pressure, and industry characteristics) (Baker, 2011; Tornatzky et al., 1990). When applied to the study of organizational capabilities for AI adoption, these dimensions provide a useful basis for identifying the technological, organizational, and environmental capabilities required (Gama & Magistretti, 2025; Schwaeke et al., 2025). This framework recognizes the importance of internal and external factors when it comes to technology implementation. However, using this framework as a baseline can also have some downsides, as it does not take individual or behavioral criteria into account (Oliveira & Martins, 2011).

2.4.3.2. Capability Maturity Models

Capability maturity models in information system literature offer a structured way to describe and assess the complex process of AI implementation. Because AI is still relatively new in practice, these models are not yet widely applied, but they provide a useful conceptual foundation. The AI Capability Maturity Model (AICMM) is one example. It outlines the developmental stages of AI-related capabilities and highlights where improvement is needed during implementation. Its structure aligns with the Technological, Organizational, and Environmental dimensions of the TOE framework and is organized into five maturity levels (Hansen et al., 2024).

Another relevant model is the Twin Transformation Capability Maturity Model (TTCMM). This framework evaluates how far organizations have progressed in integrating their digital transformation and sustainability transformation. It defines stages based on the capabilities required in each phase and helps identify where gaps remain and where further development is necessary (Breiter et al., 2024)

Overall, maturity models help companies assess their technological development and locate themselves along a transformation journey. However, this thesis does not examine the maturity level of capabilities as it only focuses on identifying which capabilities are required for deploying AI in environmental sustainability contexts, without classifying the process into maturity stages.

2.5. Integration of the Theoretical Frameworks

The strategic management literature on organizational capabilities provides the conceptual foundation for this research by offering an understanding of what capabilities are and how they function within organizations. Within this body of theory, the Resource-Based View (RBV) and Dynamic Capabilities perspectives are the most relevant and widely applied and are therefore used in this thesis to establish the foundational understanding of capabilities (Barney, 1991; D. J. Teece, 2007; D. J. Teece et al., 1997).

The Information Systems literature complements these perspectives by providing a more practice-oriented view on the adoption and implementation of new technologies. The Technology-Organization-Environment (TOE) framework structures capabilities into domains relevant for technology adoption (Tornatzky et al., 1990).

Combining the RBV and dynamic capability framework with the TOE enables a comprehensive analysis of the research question by providing a structured understanding of which capabilities firms require to deploy AI for environmental sustainability and how these capabilities can support firms in becoming more environmentally sustainable by leveraging AI.

3. Methodology

3.1. Research Design

Given the exploratory nature of the research and the limited empirical understanding of how organizations develop and orchestrate AI capabilities for environmental sustainability, a qualitative approach was adopted. The topic is characterized by high contextual complexity and limited prior empirical evidence, making qualitative inquiry appropriate for generating a rich, process-oriented understanding rather than testing predefined hypotheses. From an ontological perspective, this thesis adopts a constructionist view of reality, assuming that organizational phenomena are created and continuously shaped through the interactions and meanings that social actors attribute to them (Bell, 2019; Saunders, 2009). Epistemologically, the study follows an interpretivist stance, which holds that such socially constructed realities are best understood by exploring the subjective experiences, interpretations, and sense-making of individuals involved in AI, sustainability, and transformation (Bell, 2019; Saunders, 2009).

We adopted an abductive research approach, alternating iteratively between theory development, research design, data collection, and analysis (Bell, 2019). As the research topic is not sufficiently explored, an abductive approach allowed us to use empirical findings to refine and extend already existing theoretical assumptions. Additionally, we were able to explore our topic in the early stages and continuously refine our conceptual framework by iterating between empirical insights and theoretical understanding.

Initially, we began with an inductive orientation by conducting a preliminary literature review to identify relevant research fields and gain a broad understanding of the topic. This included reviewing studies on organizational capabilities within the management literature, research on AI implementation in organizations within both the management and information systems domains, and literature related to corporate sustainability (Bell, 2019). While this initial exploration was essential for contextual understanding, we intentionally refrained from examining specific frameworks in excessive detail to avoid a confirmation bias in the beginning (Gioia et al., 2013). Consequently, we adopted an abductive logic, iteratively developing our theoretical framework based on insights emerging from the empirical data and theory (Bell, 2019; Charmaz, 2009).

Semi-structured interviews were chosen as the primary data collection method to balance structure and flexibility. This approach allows the collection of relevant information while providing sufficient openness to explore emerging themes and unexpected insights. It enables respondents to articulate how AI is used to advance environmental sustainability and what organizational capabilities are required to support this process, and therefore answer our research question (Bell, 2019). Furthermore, this qualitative approach aligns with prior research in the field, where similar studies have successfully employed qualitative designs to explore capability development and digital transformation processes (Ghosh, 2025; Schwaeke et al., 2025; Weber et al., 2023).

3.2. Data Collection

To identify suitable interview partners, we focused on companies in transportation, food, services, construction, production, and IT, as these sectors already explore AI for sustainable development (Kar et al., 2022). We then reviewed company websites and reports to ensure that the firms approached had already started experimenting with AI for environmental sustainability. Companies from Sweden, Germany, and Austria were included, since they operate under the same European regulations (such as the CSRD and the EU AI Act) and are at similar stages of AI implementation. In Austria and Germany, around 20% of businesses already use AI, while in Sweden, the share is approximately 25% (Eurostat, 2025). In addition to experts from large organizations, six sustainability consultants with experience across multiple sustainability and AI projects were interviewed, providing broader insights and contributing to a more comprehensive understanding of the topic. Participants who were not working in consulting were employed in large companies (250+ employees), where AI adoption rates tend to be higher due to greater resource availability (Eurostat, 2025).

To identify and recruit suitable interview participants for the semi-structured interviews, we employed an outreach strategy combining three complementary approaches.
First, we leveraged our existing professional and academic networks, developed during our studies and previous work experiences. Through these contacts, we were able to connect with individuals engaged in AI transformation and sustainability initiatives within their organizations.
Second, we conducted direct outreach to relevant companies and professionals in the field via email and LinkedIn, inviting them to participate in the interviews or to forward our request to colleagues with expertise in AI or sustainability. Additionally, we reached out in an alumni LinkedIn group with over 500 members.
Third, we attended events and conferences related to AI and sustainability to establish new connections and engage directly with experts and practitioners active in these domains.

Within our personal and professional networks, we were able to secure seven interviews. It is important to note that although these contacts were accessed through our networks, we did not personally know the interviewees beforehand.
Through LinkedIn, we contacted approximately 60 professionals directly and received four positive responses. Through the LinkedIn alumni group, we were not able to get any interview participants. Via email outreach, we approached around 150 companies, resulting in three confirmed interviews, and additionally contacted approximately 200 experts and employees working in the field, which led to two further interviews.
Lastly, during networking events related to AI and sustainability, we engaged with three professionals but were unable to arrange any interviews from these interactions.

Before conducting the main interviews, we carried out a pilot interview with a Swedish sustainability manager at a Technology & Digital Services company to test the initial version of our interview guide. Insights from this pilot were used to refine both the structure and wording of the questions. Specifically, we reduced the number of questions to allow for a more open and natural conversation flow and removed several overly detailed or complex items that could interrupt the dynamics of the interview. The final interview guide comprised five main topics, each structured by two to five open-ended questions designed to explore specific aspects in greater depth while maintaining flexibility to adapt to the flow of discussion (see Appendix A: Interview Guide).

The five main topics in the final interview guide addressed key thematic areas central to our research. These included an introduction, the applications of AI, including motivation for

implementation, the resources and capabilities required for successful implementation, the adoption process, and the main obstacles encountered (see Appendix A: Interview Guide). The questions were asked in the specific context of environmental sustainability. To avoid steering participants toward a specific technical understanding or narrowing the scope of their responses, we deliberately refrained from providing a predefined definition of artificial intelligence during the interviews.
Based on each interview, we asked context-specific follow-up questions within these areas to explore emerging themes in greater depth and to capture the nuances of each organization's experience. At the end of each interview, we deliberately allowed space for additional remarks by the interviewee to capture insights on aspects that were not explicitly addressed by our questions.

All 16 interviews were conducted online via Microsoft Teams and in English. Before each session, participants were informed about the purpose of the study and the main questions. Furthermore, all interviewees agreed to record and automatically transcribe the interviews by Microsoft Teams, which made it possible to later listen to and read the interviews again for the analysis. The duration of the interviews ranged from 20 to 45 minutes, with an average length of approximately 30 minutes per interview.

Table 2: *Overview of Interviewees*

Respondent No.	Position	No. of Employees	Industry	Country	Interview Duration
R1	Sustainability Manager	>50k	Technology & Digital Services	Sweden	29 min
R2	Sustainability Manager	>10k	Industrial & Production	Sweden	31 min
R3	Sustainability Manager	>10k	Industrial & Production	Austria	42 min
R4	Data & AI Manager	>10k	Technology & Digital Services	Germany	22 min
R5	Business Developer	1-5k	Infrastructure	Sweden	33 min
R6	Manager	2-10	Consulting	Sweden	34 min
R7	Manager	>10k	Consulting	Sweden	31 min
R8	Digitalization Leader	>10k	Industrial & Production	Sweden	38 min
R9	Data Manager	>10k	Industrial & Production	Germany	22 min
R10	Consultant	2-10	Consulting	Austria	20 min
R11	Sustainability Manager	1-5k	Transport & Mobility	Germany	45 min
R12	Senior Consultant	<50	Consulting	Germany	21 min
R13	Sustainability Manager	>10k	FMCG	Germany	35 min
R14	Sustainability Manager	>10k	Industrial & Production	Sweden	31 min
R15	Senior Consultant	>10k	Consulting	Sweden	20 min
R16	Founder/Consultant	2-10	Consulting	Sweden	27 min

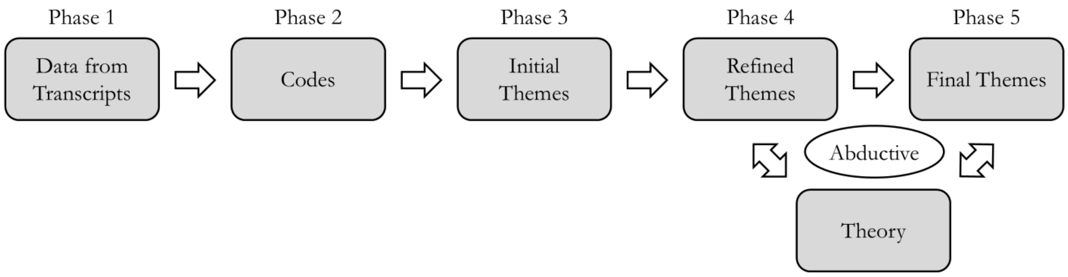
3.3. Data Analysis

To analyze the data collected from the semi-structured interviews, we applied Thematic Analysis (TA) following the approach developed by Braun and Clarke (2006). Thematic Analysis was chosen because it offers a systematic yet flexible method for identifying, analyzing, and interpreting patterns of meaning (themes) within qualitative data. It is particularly well-suited to exploratory research, as it allows for both theory-informed and data-driven insights to emerge while maintaining transparency and rigor in the analytic process (Braun & Clarke, 2006).

Given the abductive and interpretivist nature of this study, Thematic Analysis was applied in a way that combined theoretical and inductive elements. The theoretical perspective was guided by existing research on organizational capabilities and AI adoption, while the inductive component allowed new insights to emerge directly from the data. This approach enabled us to remain grounded in participants' lived experiences and meanings while connecting them to the broader conceptual frameworks of the study (Bell, 2019; Braun & Clarke, 2006). In regard to the level of analysis, we decided to identify themes on a latent level, looking beyond the surface meaning of the data and making conclusions from the interviewee's answers (Braun & Clarke, 2006).

Following Braun and Clarke's (2006) six-phase process, the analysis involved: (1) familiarizing ourselves with the data through repeated reading of the transcripts; (2) generating initial codes by identifying meaningful segments; (3) searching for preliminary themes by clustering related codes; (4) reviewing and refining these themes to ensure internal coherence and distinction; (5) defining and naming final themes; and (6) producing a coherent analytic narrative that integrates empirical findings with theoretical insights. Figure 1 illustrates this thematic analysis process.

Figure 1: *Data Analysis Process*

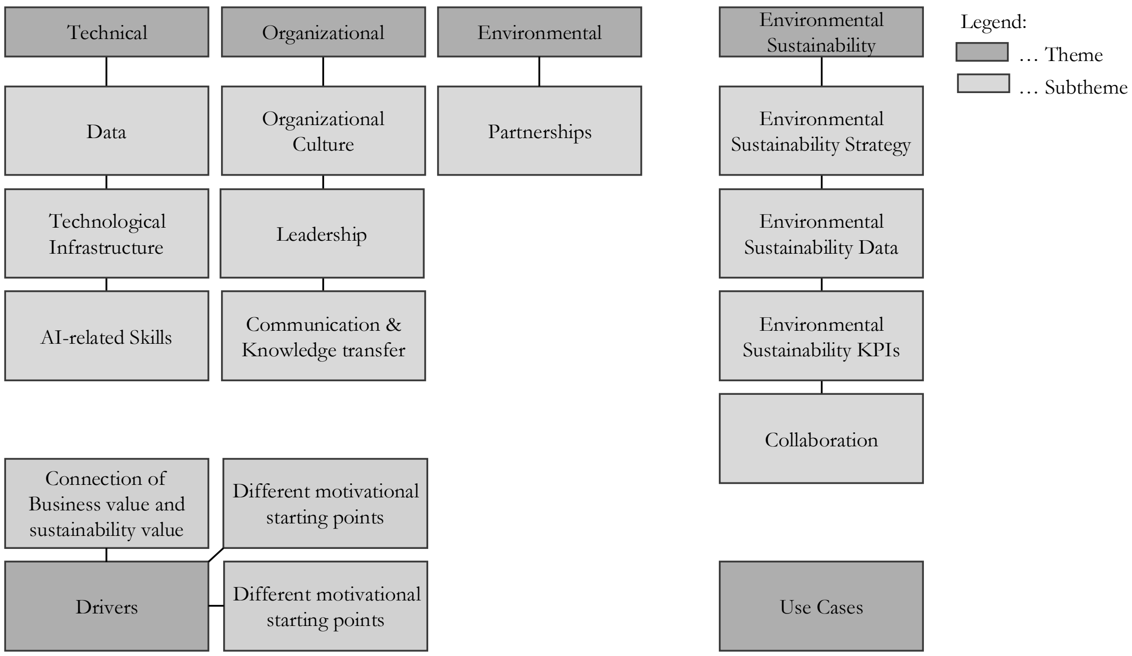


The first phase began already during the interview process. After each interview, we summarized and discussed the main findings and emerging ideas, which allowed us to continuously reflect on the data and begin identifying preliminary concepts. These insights were documented and later complemented by detailed summaries prepared for every interview. This iterative process supported early familiarization with the material. In addition, the full interview transcripts were read at least once by each of us before the formal coding phase to deepen our understanding of the data.

In the second phase, each researcher independently coded all interviews, identifying meaningful data segments and emerging ideas. We then compared and discussed our coding results to reach a

shared understanding. The identified codes were systematically documented in an Excel sheet to maintain transparency and traceability.
In the third phase, we reviewed and compared the initial codes to identify emerging patterns and potential themes. Similar codes were clustered into overarching thematic categories (see Appendix B: Initial Thematic Map).
During the fourth phase, these themes were refined and restructured, with some codes being reassigned, merged, or split into subthemes to enhance coherence and analytical precision.
After reviewing and finalizing the thematic structure, in the fifth phase we defined and named the themes to capture their core meaning (see Figure 2). Throughout phases four and five, we iterated between our empirical findings and theoretical literature, refining our themes in light of existing research while allowing new, data-driven insights to emerge. Finally, we conducted a detailed analysis integrating our empirical results with theoretical insights.

Figure 2: *Final Thematic Map*



3.4. Data Quality

To ensure high-quality data, this study follows the main evaluation criteria proposed by Guba and Lincoln (1994), who argue that qualitative research requires different assessment standards than quantitative approaches (Bell, 2019). According to Guba and Lincoln, trustworthiness in qualitative research is established through five key factors: credibility, transferability, dependability, confirmability, and authenticity (Guba & Lincoln, 1994).

Credibility was addressed by interviewing sustainability experts from various companies and expanding their insight with perspectives of sustainability consultants who have worked across multiple organizations on AI for environmental sustainability. Although methods such as

respondent validation or triangulation were not feasible due to time constraints, credibility was further supported through the inclusion of direct quotes in the analysis section.
Achieving transferability in qualitative research is inherently challenging, as findings are shaped by individual experiences and social contexts (Bell et al., 2019). To enhance the transparency and comprehensiveness of our dataset, the data collection section provides detailed descriptions of the interviewees, their professional backgrounds, and the interview guide used.
Dependability and Confirmability were ensured by refining the interview guide following a pilot interview and by following a structured coding process based on Braun and Clarke (2006) which also includes a thorough description of the coding themes used during data analysis (see Appendix B: Initial Thematic Map). Finally, authenticity was strengthened by selecting interview participants from diverse sectors and by abstracting the findings to a more general level to ensure broader applicability.
Recognizing that complete objectivity cannot be achieved in qualitative research, the data analysis was conducted in very close collaboration with daily check-ins by both researchers to ensure coherence in interpretation and to mitigate personal bias.

4. Results

The analysis of the interviews revealed several relevant themes, which will be presented in the following chapter. First, these include what we refer to as **Ordinary Capabilities**, which are comparable with those identified in the existing literature on AI implementation and are typically applied without a direct connection to environmental sustainability. Second, the interviews uncovered **drivers and use cases** for applying AI to environmental sustainability, which provide important contextual foundations for understanding how organizations engage with this domain. Third, we identified **Environmental Sustainability Capabilities**, which are particularly relevant in the context of implementing AI for environmental sustainability.

4.1. Ordinary Capabilities

During the interviews, a distinct theme emerged concerning capabilities that are essential for implementing AI in general but not specifically related to environmental sustainability. Participants referred to these capabilities when discussing AI initiatives without a sustainability focus or by emphasizing that such capabilities do not differ between environmental and other business contexts.

Furthermore, these **Ordinary Capabilities** were found to cluster across three main dimensions: **Technological**, **Organizational**, and **Environmental**. This differentiation evolved through an iterative process of engaging with the literature and analyzing the interview data. Accordingly, the following section structures the identified Ordinary Capabilities in alignment with the Technology-Organization-Environment (TOE) framework (Tornatzky et al., 1990).

Table 3: *Overview of Ordinary Capabilities*

Ordinary Capabilities		
Technological	**Organizational**	**Environmental**
Data Technological Infrastructure AI-related Skills	Organizational Culture Leadership Communication & Knowledge transfer	Partnerships

4.1.1. T - Technological Capabilities

Technological Capabilities refer to the technical requirements and competencies necessary for organizations to implement AI successfully. Within this domain, three capabilities emerged as particularly fundamental: **Data**, **Technological Infrastructure**, and **AI-related Skills**.

Across nearly all interviews, available **Data** was identified as one of the most critical capabilities and as the foundation for any AI implementation (e.g. R1, R4, R5, R14). Participants emphasized that it is not sufficient for data merely to exist; it must also be interconnected, accessible, and well-integrated across systems.

In addition, several participants emphasized the importance of data quality and structure, noting that reliable, accurate, and well-organized data are essential prerequisites for developing and deploying effective AI solutions. A common view across interviews was that data serves as the starting point for AI integration, with many organizations initially focusing their efforts on creating and structuring datasets within centralized databases before progressing to more advanced stages of AI implementation. As one interviewee explained:

> "Probably it starts with a very simple thing, building a shared data pool […]. We are still having a lot of data silos in the company, so systems that are not talking to each other […]." – R11

Furthermore, some interviewees highlighted the importance of the **Technological Infrastructure** as an important capability to implement AI (e.g. R3, R5). In this context, many organizations use cloud providers for the necessary computing power to run different AI models or algorithms.

> "Second thing to run this data or to build an AI-based application, we need GPU-based devices because it requires high computation. […] [So we] purchase cloud based services such as Azure or AWS." – R2

Lastly, half of the participants emphasized the importance of **AI-related Skills** within the organization (e.g. R9, R10, R12). This encompasses both technical expertise in developing AI systems on the IT side and business-oriented knowledge of how AI functions and where it can be effectively applied. Several interviewees emphasized that organizations cannot rely solely on external expertise, as it is essential to have in-house personnel who understand both the technological aspects of AI and the organization's specific context, processes, and goals. The combination of deep technical proficiency within IT and AI knowledge on the business side was seen as crucial for identifying appropriate use cases and ensuring that AI solutions are developed and implemented in alignment with organizational needs.

> "You need very good AI and ML engineers. […]. If you don't have the resources and the skills, you will never succeed. […]. You can have a good partner like Google, which can have AI products, but you need people on-site implementing this. People who have knowledge about the local environment as well. So, I highly recommend having internals […]." – R4

4.1.2. O - Organizational Capabilities

In terms of organizational capabilities, the analysis revealed that **Organizational Culture**, **Leadership**, and **Communication & Knowledge transfer** are the most critical factors for the effective implementation of AI. Among the three TOE dimensions, the organizational aspect received the greatest emphasis from participants, as it encompasses a wide range of interrelated factors influencing AI adoption.

Regarding **Organizational Culture**, several interviewees highlighted that a culture that encourages openness to change, active participation, and collaboration is a key enabler of AI adoption, as

higher employee involvement facilitates both the implementation process and the identification of new AI use cases. R9 and R10 further noted that flat hierarchies support the diffusion of AI by enabling faster decision-making and experimentation across organizational levels. Several interviewees (e.g. R9, R11, R12, R16) emphasized that this agile or lean organizational culture significantly supports digital transformation processes, which in turn form the foundation for successful AI implementation. In general, a mindset of curiosity, openness, and trust in AI technologies was seen as essential for enhancing adoption.
Creating positive momentum was considered another important cultural factor. As an industry expert described, initiating successful pilot projects helps convince employees of AI's potential, thereby increasing acceptance and motivation across the organization.

> "[…] This is my general answer how you would tackle such a big change with my start-up experience is in an agile way, that you're working on smaller pieces and continuously iterate them into a bigger something or in a bigger total, which means you should not plan something like a full AI transformation. You can't say this we're doing now, this we're doing in two years. This we're doing in five years because in two years everything is different." – R3

Supportive and engaged **Leadership** was also mentioned as important, by the majority of interviewees, for creating a culture in which AI can thrive (e.g. R4, R6, R8, R12). Leaders play a crucial role in enabling experimentation, providing time and resources for employees to explore AI, and leading by example. Several interviewees noted that top-down encouragement and visible commitment from management strongly influence employees' willingness to adopt AI. R5 and R12 highlighted that young, open-minded leaders often make the process easier, while R12 additionally emphasized that leaders face the challenge of motivating teams in areas where they may not be experts themselves.

> "[…] also from their management to actually encourage [the employees] to take a few hours to actually sit down and understand how it's working." - R9

The third critical factor concerns **Communication & Knowledge transfer**, which facilitates the distribution of AI-related understanding across the organization. Interviewees (e.g. R2, R4) stressed that effective internal communication, along with training initiatives and knowledge exchange forums, helps employees without prior AI or sustainability expertise build confidence and trust in using AI tools.

> "And I think you need to communicate a lot. You need to take away the fear. You need to give a lot of, like, context, reassurance around the topic." - R12

> "Let's call it training on a job, meaning let people feel it, use it, do it, create experience groups, create communities where spearheads are exchanging, where they are sharing knowledge, where they are providing joint experiences to each other, whatever else. So that's kind of not an education or training itself, but it's kind of a group and community building of people who are willing and wanting to adapt to AI quickly [...]." - R3

4.1.3. E - Environmental Capabilities

The third theme that emerged within the Ordinary Capabilities is related to the environmental dimension of the TOE. In this context, especially **Partnerships** with external partners play a crucial role (e.g. R3, R5).

Partnerships were fundamentally divided into two different types of partnerships. First, with big tech companies, which provide cloud computing power and foundational Large Language Models (LLMs) such as ChatGPT or Google Gemini, on which the companies can build their own applications. Second, several organizations had partnerships with smaller companies or startups that provided different, individually tailored types of AI Software.

> "You want to exponentially scale these applications, and this doesn't work without knowledge, know-how, and technology related to cloud applications, because it's so compute-intensive and data-intensive, so we also work strongly with partners." – R3

> "We have an AI company that is in charge of [our] model." – R5

4.2. Environmental Sustainability Drivers and Use Cases

The theme of **drivers** concerns the motivations as well as the connections and distinctions between applying AI for general business purposes and applying it for environmental sustainability-related objectives. **Use cases** in our context refer to AI applications for environmental sustainability that emerged in the interviews. To provide the necessary contextual foundation, the findings related to these drivers are presented first, followed by the description of use cases and the Environmental Sustainability Capabilities.

The majority of interviewees emphasized a strong interconnection between AI use for environmental sustainability and for business value creation (e.g. R3, R7, R16). They explained that environmental and economic objectives are often mutually reinforcing rather than contradictory. A consultant explained this as follows:

> "[For one project] it was very much about helping them to see how this had the parallel benefit then in terms of the CO2 reduction, but that initial KPI was looking at inventory cost. For another client […], it would be primarily driven by the sustainability benefit. So I worked, for example, with a global logistics transformation, which [had the intention] to reduce the CO2 impact of the global logistics, but that also had a financial benefit." – R7

Building on this understanding, the findings revealed that organizations apply AI to environmental sustainability from different motivational starting points. In some cases, AI projects are primarily driven by business objectives, with environmental benefits emerging as a positive side effect, for example, optimizing energy consumption in office buildings to reduce costs, which simultaneously lowers emissions (R7). In contrast, other organizations pursue AI use cases with an explicit sustainability orientation or through a combined business-sustainability perspective. Here, environmental goals such as reducing emissions or energy consumption are the primary motivation, with economic benefits realized secondarily. As a consultant noted:

> "I think that depends a lot on the maturity of the client in the sustainability space. Some companies focus on cost, for example, reducing inventory costs and then recognizing the parallel benefit in terms of CO_2 reduction. For another company, the initiative is primarily driven by the sustainability benefit, […] which also had financial and quality benefits." – R7

Other participants mentioned that compliance with the CSRD has recently become a more tangible driver for AI use, particularly in the context of data management and reporting (e.g. R4, R13, R15).

> "The first one is coming out of the context of the CSRD, so the new sustainability reporting directive on EU level. […] And here we are using software that supports consolidating and analyzing the quantitative data and especially on the qualitative side where you need to translate those billions of inputs into a comprehensive, nice-to-read report […]. " – R11

This regulatory requirement appears to be one of the few external pressures prompting firms to consider AI from a sustainability perspective.

Several participants stressed that environmental sustainability initiatives should not be viewed as isolated from business goals but rather as complementary drivers of long-term value creation. As one interviewee expressed:

> "So it's neither, nor or both - coming back to the harmony that I've mentioned in the beginning. So to us, sustainability doesn't mean we want to be just environmentally friendly and therefore reduce our carbon footprint. We truly believe and strongly believe if we do that, it also brings economic value. Giving you an easy example: reducing CO_2 most of the time means also reducing the energy consumption and therefore at lower cost." – R3

The **use cases** of most interviewed companies typically originated in isolated departments or individual functions, indicating a fragmented rather than integrated organizational approach. In many cases, organizations use LLMs and predictive AI to analyze data, generate forecasts, and identify opportunities to save resources. Some interviewees also mentioned the use of algorithmic AI or multi-agent systems to automate manual work and improve process efficiency.
In the context of environmental sustainability, several interviewees reported that their sustainability departments had begun experimenting with AI through small-scale pilot projects (e.g. R2, R5, R11, R16). These initiatives were primarily exploratory and served as proof of concept rather than fully scaled implementations. As one interviewee stated:

> "So you need to start with things. You need to create momentum on some lighthouse projects. You need to create momentum on obvious things. You get to build knowledge on things that you can already do because of the data availability. And then culture is already there. And out of those exemplary initiatives, you then start creating something more holistic again." – R3

Examples of use cases include using AI to calculate product carbon footprints, match operational data with emission factors, for route optimization for vehicles, and to optimize energy use or reduce waste in production processes. These efforts demonstrate that while many companies see the potential of AI for environmental sustainability, their current applications remain at an early and exploratory stage.

4.3. Environmental Sustainability Capabilities

As discussed in the previous sections, we first identified a set of Ordinary Capabilities that serve as fundamental requirements for AI implementation in general. The interviews further revealed that there are different drivers to apply AI for environmental sustainability, and that some organizations achieve environmentally beneficial outcomes without explicitly aiming to do so, relying solely on these Ordinary Capabilities. However, the findings further indicate that organizations possessing additional environmental sustainability-oriented capabilities are better equipped to identify, prioritize, and implement a broader range of AI use cases that advance environmental sustainability.

During the analysis, four **Environmental Sustainability Capabilities** were identified. These include an **Environmental Sustainability Strategy**, **Environmental Sustainability KPIs**, **Collaboration and Environmental Sustainability Data.**

Table 4: *Overview of Environmental Sustainability Capabilities*

Environmental Sustainability Capabilities
Environmental Sustainability Strategy
Environmental Sustainability Data
Environmental Sustainability KPIs
Collaboration

Some interviewees identified the presence of a mature **Environmental Sustainability Strategy**, which needs to be embedded in a holistic sustainability strategy (including environmental, social and governance) as essential for implementing AI for environmental sustainability (e.g. R3, R7). In this context, this strategy must incorporate detailed environmental objectives and be fully integrated into the overall corporate strategy, reflecting the understanding that environmental and economic goals are mutually reinforcing rather than competing. Such strategies extend beyond high-level commitments and are embedded across all organizational levels, supported by science-based targets and measurable KPIs that guide decision-making and operational priorities. One interviewee described this relationship as follows:

> "We'll be looking at how mature is the strategy, but we have a separate organizational section where we're looking at how is this being translated into the organizational culture. […] Is it mainly within a sustainability [department] or are you also seeing this actually broadly within the organization, a certain minimum level of sustainability awareness and that you're also looking at how are you actually driving action." – R7

As discussed earlier, data is a fundamental capability for AI implementation in general. However, in the context of environmental sustainability, the analysis revealed that environmental sustainability-related data must be viewed differently from conventional business data. Therefore, the capability **Environmental Sustainability Data** is introduced as a distinct capability.

Across interviews (e.g. R4, R5, R13, R14, R16) participants consistently emphasized that data plays a central yet challenging role in implementing AI for environmental sustainability purposes, this data includes for example water consumption, CO_2 emissions, waste, or energy usage from factories, office buildings, or fleet and differs from regular business data for two main reasons. First, for many firms, environmental sustainability remains a relatively new strategic area, and therefore, the necessary data often still needs to be created and collected. Second, the data required to assess environmental sustainability is often fragmented across multiple unconnected systems managed by different departments, which makes it difficult to access, aggregate, and standardize. Two industry experts explained this challenge as follows:

> "Our challenge right now is to know where the data is, how it is structured and how we can extract the data and bring it to one system where we can use the data. So in many cases we don't know yet where the data is, in which format and on top the data often does not have high quality. Because these [environmental] sustainability use cases were not important in the past and we are now, for the first time, really setting this up. [Additionally, sometimes] the data is simply not there yet or it's too scattered, let's say across systems and some data we simply don't have in any system." – R4

> "Let's take one example, water usage. So we would like to reduce our water usage in the plants, but currently we don't have any intelligent meters. […]. So there is simply one guy at the beginning of the year or 1st of January, [that is] walking to the water meter in the plant and looking how much water did we use? And then he compares it with what he was looking at one year before on the 1st of January and this is our water usage. That's how we track it. And of course this is in none of the systems, so in order to improve it in a way, from my perspective, we would need to have intelligent meters which are connected to a system […]. And then of course we could use AI in a way. Have a look, do we have on certain days, on certain lines, in certain production processes, a lot of water use and can we improve that?" – R13

To overcome these challenges, participants highlighted the importance of establishing shared data infrastructures, for instance, by creating a centralized sustainability data pool that consolidates environmental data across the organization (e.g. R11). Several interviewees also pointed to the growing significance of EU reporting regulations, which push companies to collect and standardize sustainability data, thereby acting as a catalyst for improving data availability and quality (e.g. R2, R4, R5, R11).

The third capability that emerged from the interviews is the implementation of **Environmental Sustainability KPIs**. Several participants emphasized that such KPIs (e.g. energy usage, over consumption, CO_2 emissions) are essential for translating the environmental sustainability strategy and overarching targets into actionable goals across the organization and, crucially, for identifying where AI can create environmental value (e.g. R1, R7, R11). Accordingly, Environmental Sustainability KPIs should not remain confined to top management but must be integrated into daily operations and applied throughout all organizational layers. One interviewee stressed that breaking down high-level sustainability targets into concrete operational objectives provides the necessary clarity to pinpoint relevant use cases and subsequently employ AI in a focused and measurable way. Further, this KPIs should be embedded across departments and incorporated into the performance measurement systems of managers to ensure organizational alignment and accountability:

> "What are the KPIs that are being used in the organization? Are the sustainability KPIs coming into those? [Are those in] Standard reports that are driving those daily and weekly meetings that are driving operations, or are they simply being rolled up into maybe quarterly or annual reporting. […] Managers need to have their own scorecards attached to sustainability outcomes, so that it is actually part of a bonus that will be driven by sustainability outcomes." – R7

> "I'm putting up targets for our carbon emission reduction and then those targets are translated in what fleet needs to contribute, what operations needs to contribute and then we have our own programs in place, we call that the OPS sustainability program, that then really comes up with different measures." – R11

The last capability identified throughout the interviews is **Collaboration**. This capability can be divided into two primary dimensions. First, the majority of interviewees emphasized that effective collaboration between different business departments is essential for implementing AI in the context of environmental sustainability. This includes, in particular, cooperation between the sustainability function and operational departments, as a significant share of some organization's environmental footprint, and the related data, originate in its operational activities and these departments are often separated from the sustainability function (e.g. R4, R11, R13). Second, close collaboration between business departments and the IT department is crucial for the technical development and deployment of AI solutions. This need is particularly pronounced in the sustainability domain, where dedicated AI developers or IT professionals are often not embedded within the department, and communication channels between business and technical units tend to be limited (e.g. R1, R8).

One participant noted that establishing a digitalization or innovation department with knowledge in both sustainability and AI can help bridge this gap and facilitate AI implementation for environmental sustainability:

> "And we have a digitalization team. So basically, I sit in the digitalization team with acting as a bridge between the global IT and the group sustainability in that case because I understand the language of the IT employees and at the same time, I understand the language of the sustainability employees. So I understand the IT landscape and then the business needs and how I can translate them into actionable projects and initiatives." – R8

Overall, developing the Collaboration capability requires building structures at the intersection of IT and business to close knowledge gaps and ensuring sustained cooperation between the sustainability department and operational units to jointly identify and develop AI initiatives for environmental sustainability.

5. Discussion

As outlined in the results chapter, two overarching themes of capabilities emerged from the interviews. The first includes what we refer to as Ordinary Capabilities, which are relevant for implementing AI in general and do not have a specific connection to the environmental sustainability domain. The second encompasses Environmental Sustainability Capabilities, which are particularly important for implementing AI aimed at advancing environmental sustainability.

The following chapter will compare and integrate these empirical findings with existing literature, while also analyzing the interconnections between Ordinary and Environmental Sustainability Capabilities and creating a connection to Dynamic Capabilities (D. J. Teece, 2007; D. J. Teece et al., 1997). Building on these insights, a comprehensive framework grounded in the Technology-Organization-Environment (TOE) model will be developed to address the research question and illustrate how organizations can effectively deploy AI for environmental sustainability.

5.1. Ordinary Capabilities

After analyzing the interviews, the identified Ordinary Capabilities were compared with the capabilities in the existing literature, which revealed several noteworthy similarities and differences. This comparison also reinforced the relevance of categorizing the capabilities according to the three domains of the TOE framework, which provides a clear structure for understanding them across different organizational contexts.

5.1.1. Technological Dimension

Within the **technological dimension**, literature identifies three primary capabilities: **Data**, **Technological Infrastructure**, and **Cybersecurity Management**. Consistent with our findings, the literature emphasizes that access to high-quality **Data** is fundamental for leveraging AI (AlSheibani et al., 2018; Baier et al., 2019; Ghosh, 2025; Schmidt et al., 2020; Weber et al., 2023). Closely related, the capability of establishing and maintaining an appropriate **Technological Infrastructure**, including elements such as computing capacity and scalable architectures, is highlighted as a critical enabler of AI initiatives (Enholm et al., 2022; Ghosh, 2025; Kinkel et al., 2022; Wamba-Taguimdje et al., 2020; Weber et al., 2023). These two technological capabilities align strongly with our interview results, which likewise identified Data and Technological Infrastructure as foundational prerequisites. Across both empirical and theoretical sources, there is a broad consensus that these capabilities form the essential technological basis for successful AI implementation.

In contrast, the literature identifies **Cybersecurity Management** as a third key capability in the technological domain. This capability underscores the importance of safeguarding data, ensuring secure system integration, and building trust in AI systems (Sjödin et al., 2021). However, this capability did not prominently emerge from our interviews. While interviewees acknowledged the importance of trust in AI systems, their comments focused primarily on the quality and reliability of AI outputs, rather than on cybersecurity measures specifically. A plausible explanation is that cybersecurity can be seen as a second type of concern that emerges once the overall data infrastructure and AI solutions is in place. Another assumption could be that most interviewees represented the business side, rather than IT experts or AI developers, and therefore may be less involved in the security-related aspects of AI implementation.

Finally, the interviews revealed a capability that receives comparatively less attention in the literature: technological **AI-related skills**. Although some studies mention the need for technical competencies or AI developers, our interviewees placed substantial emphasis on the importance of AI-specific technical expertise, both for developing appropriate AI models and for ensuring that solutions are effectively tailored to organizational use cases (Pumplun et al., 2019; Wamba-Taguimdje et al., 2020). This indicates that AI-related skills may constitute a more critical technological capability for organizations, especially in the context of environmental sustainability, than is reflected in the existing literature. A possible explanation is that sustainability functions are often still relatively small and emerging, and therefore possess less technical expertise. Compared to operational units, many of which have long-standing experience with digital transformation, sustainability departments tend to be more specialized and less technologically mature.

5.1.2. Organizational Dimension

In the organizational dimension, the literature commonly identifies four overarching capabilities: **Culture & Organizational Readiness**, **Leadership & Governance**, **AI Strategy**, and **AI Project Management**. These capabilities describe the internal conditions and organizational routines that enable firms to adopt and scale AI (Enholm et al., 2022; Ghosh, 2025; Weber et al., 2023).

Our findings show both substantial similarities with, and differences from, the existing literature. First, the literature emphasizes the role of **Culture & Organizational Readiness**, referring to an organizational climate that is open to experimentation, receptive to digital transformation, and characterized by cross-functional collaboration (Ghosh, 2025; Pumplun et al., 2019; Weber et al., 2023). This aligns strongly with our identified capability Organizational Culture, which was consistently highlighted by interviewees as a crucial enabler for successful AI adoption. Participants repeatedly stressed elements such as openness to change, curiosity, trust in AI systems, flat hierarchies, and agile ways of working, elements which closely align with factors described in prior studies.

Second, the literature highlights the importance of **Leadership and Governance** in providing clear strategic direction and sustained support for AI initiatives (AlSheibani et al., 2018; Ghosh, 2025; Warner & Wäger, 2019). This aligns closely with the interview findings. Participants emphasized that visible leadership commitment and top-down encouragement strongly influence employees' willingness to adopt AI. Moreover, interviewees noted that leaders play a crucial role in creating an open and supportive organizational culture in which employees are able to experiment with AI and are given the necessary time and resources to explore its potential.

Third, the literature positions **AI Strategy** as a key capability, referring to strategic alignment, prioritization of AI initiatives, and clarity on value creation (Keding, 2021). Interestingly, this capability did not explicitly emerge in our empirical findings as part of the Ordinary Capabilities. Instead, strategic aspects surfaced more prominently as part of the Environmental Sustainability Capabilities (e.g. Environmental Sustainability Strategy, Environmental Sustainability KPIs). A plausible explanation is that the interviewees, primarily representing sustainability business units rather than top management, experienced strategy less as a standalone capability for AI adoption, and more as an overarching sustainability requirement influencing AI project identification for environmental sustainability.

Finally, the literature highlights **AI Project Management**, referring to iterative development routines, agile governance, and the capacity to manage AI-specific projects (Correani et al., 2020; Weber et al., 2023). While this capability did not surface directly in our data, the interviewees consistently referred to agile and lean management, which in our context is included in Organizational Culture. This capability and Communication & Knowledge transfer can be understood as connected to AI project management, as described in the literature, in that it enables alignment, coordination, and exchange across teams. Effective communication and an agile culture help to conduct AI projects.

5.1.3. Environmental Dimension

Within the **environmental dimension** of the TOE framework, the literature identifies **Regulation**, **Partnerships**, and **Ethics & Moral** as relevant capabilities shaping AI adoption. These capabilities reflect the external context influencing organizations. Our empirical findings only partially align with the literature in this dimension.

First, **Regulation** (e.g. GDPR), which is widely discussed in the AI implementation literature, did not emerge as an Ordinary Capability in our interviews (Baier et al., 2019; Pumplun et al., 2019; von Hippel & Kaulartz, 2021). Interviewees rarely referred to regulatory compliance as a specific capability for general AI implementation. However, many noted the growing importance of EU sustainability reporting regulations in motivating the creation and standardization of sustainability-related data. This indicates that regulation does play an important role, but mainly as a driver to start with AI initiatives for environmental sustainability. A reason for this can be that the focus of the interviews was on environmental sustainability and the majority of interviewees worked in the sustainability area and therefore have less knowledge about AI Regulations in general, but extensive knowledge and touchpoints with sustainability regulations.

Second, both the literature and our findings identify **Partnerships** as a relevant capability. The literature views partnerships as collaborations with technology vendors, universities, and innovation ecosystems that provide access to expertise, data, and emerging technologies (D. Teece et al., 2016; Warner & Wäger, 2019). Our interviews similarly highlighted partnerships as important, however, in practice, participants described partnerships primarily as collaborations needed to obtain AI expertise, software, or computing capacity. This more pragmatic orientation differs slightly from the strategic, ecosystem-level perspective emphasized in the literature.

Third, **Ethics & Moral**, which the literature describes as an increasingly important capability to ensure fairness, transparency, and the responsible use of AI, did not emerge in our findings as a capability (Alsheibani et al., 2020; Baier et al., 2019). While interviewees acknowledged the importance of trust in AI systems, this trust was largely framed around data quality, reliability, and usefulness, rather than ethical considerations. The absence of this capability may indicate that more fundamental requirements, such as data availability and functioning AI tools, are currently of higher priority for the interviewees. These basic elements must be established before meaningfully engaging with ethics-related topics. The professional profiles of our interviewees, who were primarily involved in operational and sustainability roles rather than AI governance, may further explain why ethical considerations did not emerge prominently in the findings.

Table 5: *Overview of Literature and Interview Findings*

	Capabilities Literature		**Ordinary Capabilities Research**	
Technological	Data	Schmidt, 2020; Baier, 2019; Alsheibani, 2018; Ghosh, 2025; Weber, 2023	Data	R1, R2, R3, R4, R5, R7, R8, R9, R11, R13, R14, R15, R16
	Technology Infrastructure	Enholm et al., 2022; Wamba-Taguimdje et al., 2020; Kinkel et al., 2022; Ghosh, 2025; Weber, 2023	Technological Infrastructure	R2, R3, R4, R5
	Cybersecurity Management	Sjödin, 2021	AI-related Skills	R1, R2, R4, R5, R8, R9, R10, R12
Organizational	Culture & Organizational Readiness	Pumplun, 2019; Ghosh, 2025; Weber, 2023	Organizational Culture	R1, R2, R3, R5, R6, R7, R8, R9, R11, R12, R14, R15, R16
	Leadership & Governance	Alsheibani, 2020; Warner & Wäger, 2019; Ghosh, 2025	Leadership	R3, R4, R5, R6, R7, R8, R9, R12, R14, R16
	AI Strategy	Keding, 2021	Communication & Knowledge transfer	R2, R3, R4, R12, R15, R16
	AI Project Management	Correani et al., 2020; Weber, 2023		
Environmental	Regulation	von Hippel & Kaulartz, 2021; Pumplun, 2019; Baier, 2019	Partnerships	R2, R3, R4, R5
	Partnerships	Teece, 2016; Warner & Wäger, 2019		
	Ethics & Moral	Baier, 2019; Alsheibani, 2020		

5.2. Environmental Sustainability Capabilities

Furthermore, the most novel and insightful findings from our study relate to the identification of Environmental Sustainability Capabilities, which play a critical role in enabling organizations to implement AI specifically for environmental sustainability.
The relation and connection between the Environmental Sustainability Capabilities, Ordinary Capabilities, and the literature will be described in the following paragraphs.

First, the **Environmental Sustainability Strategy** builds on and extends the cultural and leadership capabilities identified both in the general AI adoption literature (Alsheibani et al., 2020; Ghosh, 2025; Pumplun et al., 2019; Warner & Wäger, 2019; Weber et al., 2023) and among the identified Ordinary Capabilities. It embeds sustainability considerations directly into organizational culture and strategic priorities by having a top management that promotes a holistic view in which sustainability and business value are understood as mutually reinforcing. This ensures that AI is framed not merely as a tool for achieving business value but as a vehicle for achieving environmental objectives. Furthermore, it extends the cultural and leadership capabilities by ensuring that sustainability principles are fully integrated into organizational culture, decision-making processes, and KPIs, rather than high-level strategic commitments. Thereby, it promotes the identification of AI use cases for environmental sustainability. In the sustainability literature related to AI, Kulkov et al. (2024) describe a comparable capability, Strategic Alignment and Commitment, highlighting that sustainability goals must be aligned with broader business strategies, integrated into targets, and supported by committed leadership. Whereas the Environmental Sustainability Strategy focuses specifically on the environmental aspect (E of ESG) and the integration of this dimension into the sustainability and business strategy, the Strategic Alignment and Commitment Capability focuses on the whole sustainability strategy (ESG) in alignment with the business strategy.
The Environmental Sustainability Strategy gives an overall direction and serves as a foundation for the other Environmental Sustainability Capabilities.

Second, **Environmental Sustainability Data** expands the data capability identified in the general AI adoption literature (AlSheibani et al., 2018; Baier et al., 2019; Ghosh, 2025; Schmidt et al., 2020; Weber et al., 2023) and reflected in the Ordinary Capabilities by introducing new challenges related to data availability, granularity, and cross-departmental aggregation. While Ordinary data capabilities and the literature focus on ensuring that data in general exists, is accessible, and of sufficient quality for AI applications, Environmental Sustainability Data focuses on solving specific issues to identify, collect, and integrate environmental data (e.g. CO_2 emissions, water consumption, waste). These include that especially this data did not previously exist or is scattered across systems, because of the novelty of many sustainability functions and multiple internal stakeholders. Although Kulkov et al. (2024) and Schwaeke et al. (2025) highlight the importance of data in sustainability-related AI research, they conceptualize data capabilities largely in line with general AI adoption literature and thus correspond to our Ordinary Capabilities. They do not identify the distinct and additional challenges associated with environmental sustainability data that emerged clearly in our Environmental Sustainability Capabilities.

Furthermore, the sustainability data serves as a foundation for KPIs and Collaboration by providing the necessary data-based insights to identify AI applications for environmental sustainability.

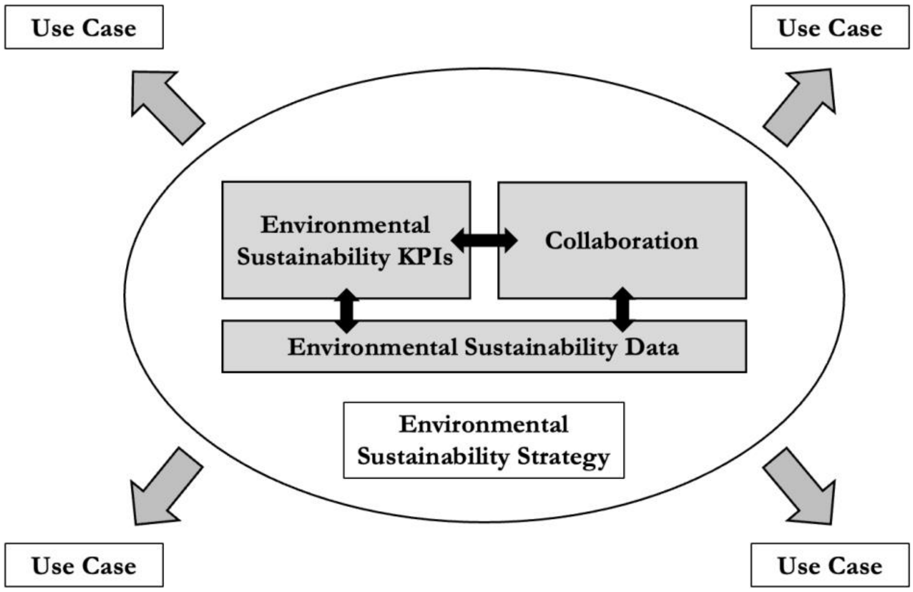
Third, **Environmental Sustainability KPIs** also extend the capabilities culture and leadership in the literature about general AI adoption (Alsheibani et al., 2020; Ghosh, 2025; Pumplun et al., 2019; Warner & Wäger, 2019; Weber et al., 2023) and within the Ordinary Capabilities by translating sustainability ambitions into measurable indicators that are embedded across the organization levels and incorporated into managerial incentive structures. By operationalizing high-level sustainability goals into specific, quantifiable KPIs, this capability ensures that AI initiatives can be evaluated against both economic and environmental performance criteria, rather than being assessed solely on operational efficiency. Moreover, by breaking down the environmental sustainability strategy into concrete metrics and targets for different departments and hierarchical levels, Environmental Sustainability KPIs enable AI to be deployed directly at the operational source, ensuring that technological solutions tangibly contribute to environmental sustainability outcomes. In the sustainability domain, these findings align with Schwaeke et al. (2025), who identify the capability Impact Measurement, which includes the integration of sustainability metrics, and Kulkov et al. (2024), who highlight the importance of sustainability metrics in their Strategic Alignment and Commitment capability.

Finally, **Collaboration** extends and deepens the cross-functional communication capabilities captured in the Ordinary Capabilities by requiring a more integrated and systematic collaboration between sustainability, operations, and IT departments. While the general AI adoption literature does not identify Collaboration as an explicit capability, it emphasizes its importance within other capability domains, particularly in the context of AI project management and coordination processes (Enholm et al., 2022; Schmidt et al., 2020). In our findings, Ordinary Capabilities highlight cooperation primarily between business units and IT. However, the Environmental Sustainability Capability Collaboration goes further by demonstrating that multi-functional collaboration is essential when applying AI for environmental sustainability. Because sustainability-relevant data, expertise, and operational insights are distributed across different parts of the organization, the sustainability function must work closely with IT and various business units to identify, develop, and implement AI-enabled sustainability initiatives.
The literature on AI for sustainability underscores the importance of engaging multiple stakeholders, though often with a broader external focus rather than only focusing on the internal organization (Kulkov et al., 2024; Schwaeke et al., 2025). To that extent, it aligns with our findings, but it does not explicitly conceptualize Collaboration as a distinct internal capability.

Furthermore, as previously indicated, the Environmental Sustainability Capabilities are **interdependent and mutually reinforcing**. As Figure 3 illustrates, the Environmental Sustainability Strategy provides the overarching direction and serves as the foundational orientation for the other capabilities by defining strategic priorities and guiding organizational focus. Environmental Sustainability Data is an additional foundational element, enabling data-driven insights and informed decision-making in line with the strategic environmental sustainability objectives. Building on both the Environmental Sustainability Strategy and the availability of relevant data, organizations are able to establish Environmental Sustainability KPIs, which translate strategic ambitions into measurable targets that drive decisions and help identify opportunities to use AI for environmental sustainability. Finally, Collaboration supports these capabilities by enhancing the collection of Environmental Sustainability Data and enabling cross-functional efforts to translate the Environmental Sustainability Strategy into practice through concrete AI initiatives.

We argue that organizations possessing this integrated system of Environmental Sustainability Capabilities exhibit a greater ability to link AI initiatives to long-term environmental sustainability objectives, rather than having environmental benefits as a by-product of efficiency-driven projects. As shown in Figure 3 our findings indicate that these organizations identify more diverse opportunities and use cases where AI can advance environmental goals. In contrast, companies lacking these capabilities tend to pursue operationally motivated applications without considering environmental sustainability aspects.

Figure 3: *Interrelation of Environmental Sustainability Capabilities*



5.2.1. Relation to RBV and Dynamic Capabilities

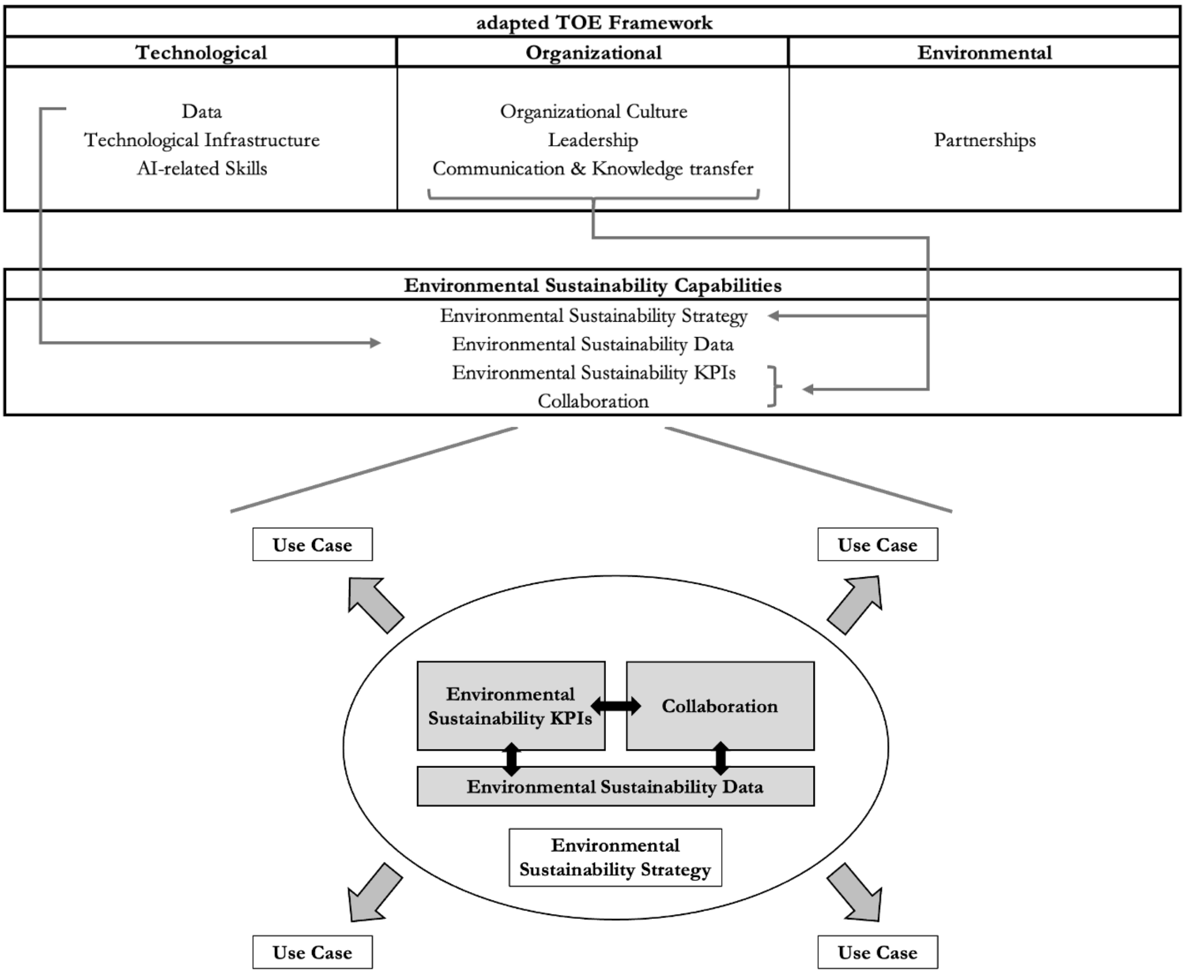
All identified capabilities (Ordinary and Environmental Sustainability Capabilities) can be seen as resources according to the RBV, as they help firms to achieve competitive advantage (Barney, 1991). Additionally, the Environmental Sustainability Capabilities specifically can be compared to Teece's (2007) Dynamic Capabilities framework, as they enable organizations to purposefully sense and seize AI opportunities related to environmental sustainability and transform their business in order to scale and implement these AI use cases. Capabilities such as Environmental Sustainability Strategy, Environmental Sustainability KPIs, and Collaboration allow organizations to identify sustainability-related challenges and opportunities, prioritize AI initiatives, allocate resources accordingly, and enable cross-functional reconfiguration of processes and knowledge structures. However, not all Environmental Sustainability Capabilities are purely dynamic. Sustainability Data, for instance, has a strong operational character, as it provides the structured information base needed for AI-enabled sustainability analyses and decisions. At the same time, by enabling organizations to detect inefficiencies, emission hotspots, or resource optimization opportunities,

Sustainability Data also contributes to the sensing dimension of dynamic capabilities. Overall, while the Environmental Sustainability Capabilities include both operational and dynamic elements, as a system, they function collectively as environmental sustainability-specific dynamic capabilities, enabling organizations to reconfigure their resources and routines to embed AI into their environmental sustainability efforts (D. J. Teece, 2007; D. J. Teece et al., 1997).
This fact also resonates with prior quantitative literature that found a positive correlation between dynamic capabilities and leveraging AI for sustainability (Feng et al., 2024).

5.3. Adapted Theoretical Framework

Having presented the analysis and discussion of the findings, an adapted version of our theoretical framework is introduced below in Figure 4. The framework positions the Ordinary Capabilities, required for general AI implementation, at the top and organizes them within the three dimensions of the TOE framework. Beneath this layer, the framework integrates the additional dimension of Environmental Sustainability Capabilities, which extend the TOE model by incorporating the specific capabilities necessary for implementing AI for environmental sustainability. The arrows between these two layers illustrate the connections and reinforcing relationships between Ordinary Capabilities and Environmental Sustainability Capabilities, highlighting how the latter build upon and modify the former. At the bottom, a zoomed-in view provides a more detailed depiction of the Environmental Sustainability Capabilities themselves, illustrating the internal relationships and interdependencies among Environmental Sustainability Data, Environmental Sustainability Strategy, Environmental Sustainability KPIs, and Collaboration.

Figure 4: *Adapted Theoretical Framework*



5.4. Theoretical and Empirical Contributions

This thesis makes several important theoretical and empirical contributions to the emerging literature on artificial intelligence and environmental sustainability. Theoretically, prior research in this domain has focused predominantly on how AI can support sustainability in general, often through AI use cases or analysis of AI's potential contributions (Kar et al., 2022; Nishant et al., 2020; Toniolo et al., 2020; Vinuesa et al., 2020). While there is substantial literature on organizational capabilities required for general AI adoption (Enholm et al., 2022; Gama & Magistretti, 2025; Ghosh, 2025; Weber et al., 2023), there is only limited research on the underlying organizational capabilities that enable firms to leverage AI for sustainability (Kulkov et al., 2024; Schwaeke et al., 2025). This limited body of research has emphasized capabilities for AI implementation for sustainability, without a specific focus on environmental sustainability (Kulkov et al., 2024; Schwaeke et al., 2025). Addressing this gap, our study identifies and conceptualizes a distinct set of Environmental Sustainability Capabilities, thereby extending the original TOE framework (Tornatzky et al., 1990) into an adapted TOE framework. This framework highlights how organizations must complement the well-established Ordinary Capabilities for AI implementation with additional environmental sustainability-oriented capabilities to effectively identify, prioritize, and implement environmentally focused AI use cases. In doing so, the thesis advances theoretical understanding of which capabilities are needed to deploy AI for environmental sustainability.

Empirically, the study contributes by providing rich, practice-based insights into how organizations across industries currently approach AI for environmental sustainability. This contribution is particularly relevant given that many organizations, even those advanced in general AI adoption, struggle to apply AI meaningfully to sustainability challenges, despite growing regulatory pressure, rising stakeholder expectations, and the urgent need to reduce environmental impact (Accenture et al., 2024). Through qualitative interviews with industry experts and consultants, the thesis highlights what capabilities support the identification and realization of environmental sustainability-oriented AI opportunities. By revealing these patterns, the thesis offers empirically grounded guidance for organizations seeking to leverage AI in addressing corporate environmental sustainability.

5.5. Practical Implications

The findings of this study indicate several important implications for how organizations can understand and approach the use of AI for environmental sustainability. The adapted TOE framework developed in this thesis suggests that general AI-related capabilities are insufficient on their own and must be complemented by distinct Environmental Sustainability Capabilities that enable systematic identification, prioritization, and realization of environmentally sustainable-oriented AI opportunities. Rather than prescribing managerial actions, these findings highlight structural conditions that shape how organizations can move from efficiency-driven AI applications with environmental sustainability benefits as a by-product toward a more integrated environmental sustainability orientation.

In the context of our findings, we suggest that managers should establish a holistic environmental sustainability strategy that embeds environmental goals into core business priorities and views environmental and economic benefits as mutually reinforcing. Building robust environmental sustainability data capabilities is essential, ensuring that environmental data is not only collected for reporting but actively used to identify and evaluate AI opportunities. These strategic ambitions must be translated into measurable environmental sustainability KPIs that are distributed across departments and guide decision-making, and which need to be tied to managers' performance measures. In addition, strong cross-functional collaboration between sustainability, IT, and operational units is necessary, as the expertise and data required for environmentally sustainable-oriented AI are distributed across the organization. This can be achieved by implementing a specific team which works at the intersection of IT and sustainability and has knowledge in both areas. Overall, AI for environmental sustainability requires a coordinated capability-building effort that integrates strategy, data, KPIs, and collaboration.

5.6. Limitations of the Study & Future Research

The transferability of this study's findings is limited by the contextual characteristics of the research setting. Most interviewees worked in organizations that were only at the beginning of implementing AI in the domain of environmental sustainability and therefore did not yet have extensive long-term experience. Nevertheless, their perspectives offer valuable insights into the capability requirements that emerge when companies apply AI for environmental sustainability. Furthermore, the sample consisted exclusively of European firms. Because European organizations operate under specific regulatory frameworks and bureaucratic structures, their approach to AI and sustainability may differ from companies in regions such as America, Asia, or Africa, where legal conditions, institutional pressures, and adoption dynamics vary considerably. Additionally, most interviewees were in low to middle-management positions, which likely shaped the focus of their responses toward operational and lower-level strategic aspects rather than high-level strategic considerations.

Future research can build on these findings in several ways. First, the capabilities identified in this study could be examined quantitatively to assess their relative importance across different industries, regulatory environments, and organizational structures. Such research may uncover patterns or relationships not visible in qualitative interviews, for example, whether specific technological or organizational capabilities consistently predict successful AI-driven environmental sustainability initiatives. Second, existing maturity models for AI or sustainability transformation could be expanded into a dedicated maturity model for AI in environmental sustainability. Using the capability framework developed in this study as a conceptual foundation, future work could define maturity stages, measurable indicators, and diagnostic tools to help organizations assess their current position and identify required capability development. Third, cross-regional comparative studies would provide important nuance by examining how variations in regulation, cultural expectations, and technological ecosystems shape the adoption of AI for sustainability outside the European context. Finally, future research could also investigate whether the capabilities needed for AI adoption in the social and governance dimensions of ESG differ from the environmental capabilities identified in this study, thereby extending understanding of how AI can support sustainability more broadly.

6. Conclusion

Many organizations are actively investing in artificial intelligence to enhance competitiveness, yet comparatively few are leveraging AI to advance environmental sustainability. As a result, companies not only struggle with AI implementation in general, but there is also a lack of empirical insight into the specific capability requirements for applying AI for environmental sustainability. To address this gap, this thesis investigated the research question:

> *What organizational capabilities are required to effectively deploy AI for corporate environmental sustainability?*

The qualitative study adopted an abductive research design and interpretivist epistemology, involving semi-structured interviews with practitioners and experts across industries. This approach enabled an iterative development of insights, allowing theoretical concepts and empirical findings to inform one another. Such an abductive process was particularly appropriate given the limited prior empirical knowledge on how organizations operationally build and integrate environmental sustainability-oriented AI capabilities.

The resulting adapted TOE framework provides a comprehensive answer to the research question. We argue that while the Ordinary Capabilities in the TOE model are necessary, they are insufficient for deploying AI to meaningfully advance environmental sustainability. These specific capabilities, which operate as an integrated system, enable companies to identify a broader range of AI initiatives that advance environmental sustainability, not merely as unintended by-products of efficiency improvements but as strategically aligned efforts aimed at achieving long-term environmental objectives. Our findings reveal that organizations that cultivate these capabilities are able to sense and identify environmental sustainability-related AI opportunities, seize and implement solutions that contribute meaningfully to environmental sustainability goals, and ultimately transform their business in line with environmental sustainability ambitions.

Within the technological, organizational, and environmental dimensions of the TOE framework, this thesis identifies seven Ordinary Capabilities that closely align with existing research. In the technological dimension, these include Data, Technological Infrastructure, and AI-related Skills. The organizational dimension entails Organizational Culture, Leadership, and Communication & Knowledge transfer. Finally, within the environmental dimension, Partnerships emerged as the key capability.

Building on these, the adapted TOE framework introduces four Environmental Sustainability Capabilities: **Environmental Sustainability Strategy, Environmental Sustainability Data**, **Environmental Sustainability KPIs**, and **Collaboration**. These are particularly critical when AI is applied to environmental sustainability. These capabilities embed environmental sustainability into the organization's strategy, generate the data foundation for environmental insights, translate environmental sustainability goals into measurable KPIs, and coordinate knowledge and expertise across functional boundaries. Together, they form an integrated capability system that enables organizations to leverage AI intentionally and effectively for environmental sustainability.

7. References

Accenture. (2024). *Only 16% of Largest Companies on Track for Net Zero Goals with Nearly Half Seeing Increased Emissions, Accenture Analysis Finds*. https://newsroom.accenture.com/news/2024/only-16-of-largest-companies-on-track-for-net-zero-goals-with-nearly-half-seeing-increased-emissions-accenture-analysis-finds

Accenture, Jamison, S., Moussavi, B., Macchi, M., & Bermudez, M. (2024). *Destination Net Zero*.

Alsheibani, S. A., Cheung, Y., Messom, D. C., & Alhosni, M. (2020). *Winning AI Strategy: Six-Steps to Create Value from Artificial Intelligence*. https://aisel.aisnet.org/amcis2020/adv_info_systems_research/adv_info_systems_research/1

AlSheibani, S., Cheung, Y., & Messom, C. (2018). *Artificial Intelligence Adoption: AI-readiness at Firm-Level*. https://aisel.aisnet.org/pacis2018/37

Baier, L., Jöhren, F., & Seebacher, S. (2019 *Challenges in the Deployment and Operation of Machine Learning in Practice*.

Baker, J. (2011). The Technology–Organization–Environment Framework. In *Information Systems Theory* (pp. 231–245). https://doi.org/10.1007/978-1-4419-6108-2_12

Bansal, P. (2005). Evolving Sustainably: A Longitudinal Study of Corporate Sustainable Development. *Strategic Management Journal (Wiley-Blackwell) - 1980 to 2009*, *26*(3), 197–218. https://doi.org/10.1002/smj.441

Bansal, P., & Song, H.-C. (2017). Similar but Not the Same: Differentiating Corporate Sustainability from Corporate Responsibility. *Academy of Management Annals*, *11*(1), 105–149. https://doi.org/10.5465/annals.2015.0095

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*(1), 99.

BCG. (2025). *From Potential to Profit: Closing the AI Impact Gap*. BCG Global. https://www.bcg.com/publications/2025/closing-the-ai-impact-gap

Bell, E. (with Bryman, A., Bryman, A., & Harley, B.). (2019). *Business research methods* (Fifth edition Emma Bell, Alan Bryman, Bill Harley). University Press.

Borges, A. F. S., Laurindo, F. J. B., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management*, *57*, 102225. https://doi.org/10.1016/j.ijinfomgt.2020.102225

Branco, M. C., & Rodrigues, L. L. (2006). Corporate Social Responsibility and Resource-Based Perspectives. *Journal of Business Ethics*, *69*(2), 111–132. https://doi.org/10.1007/s10551-006-9071-z

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Breiter, K., Crome, C., Oberländer, A. M., & Schnaak, F. (2024). Dynamic Capabilities for the Twin Transformation Climb: A Capability Maturity Model. *Information Systems Frontiers*, *26*(6), 2205–2226. https://doi.org/10.1007/s10796-024-10520-y

Brundtland, G. H. (1987). *Report of the World Commission on Environment and Development: Our Common Future*.

Charmaz, K. (2009). Shifting the Grounds: Constructivist Grounded Theory Methods. In *Developing Grounded Theory*. Routledge.

Collis, D. J. (1994). Research Note: How Valuable Are Organizational Capabilities? *Strategic Management Journal (Wiley-Blackwell) - 1980 to 2009*, *15*, 143–152. https://doi.org/10.1002/smj.4250150910

Correani, A., De Massis, A., Frattini, F., Petruzzelli, A. M., & Natalicchio, A. (2020). Implementing a Digital Strategy: Learning from the Experience of Three Digital Transformation Projects. *California Management Review*, *62*(4), 37–56. https://doi.org/10.1177/0008125620934864

Dangelico, R. M., & Pujari, D. (2010). Mainstreaming green product innovation: Why and how companies integrate environmental sustainability. *Journal of Business Ethics*, *95*(3), 471–486. https://doi.org/10.1007/s10551-010-0434-0

Demlehner, Q., & Laumer, S. (2020). Shall We Use It or Not? Explaining the Adoption of Artificial Intelligence for Car Manufacturing Purposes. *ECIS 2020 Research Papers*. https://aisel.aisnet.org/ecis2020_rp/177

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., 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

Dyllick, T., & Muff, K. (2016). Clarifying the Meaning of Sustainable Business: Introducing a Typology From Business-as-Usual to True Business Sustainability. *Organization & Environment*, *29*(2), 156–174. https://doi.org/10.1177/1086026615575176

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic Capabilities: What Are They? *Strategic Management Journal (Wiley-Blackwell) - 1980 to 2009*, *21*(10/11), 1105. https://doi.org/10.1002/1097-0266(200010/11)21:10/11%253C1105::AID-SMJ133%253E3.0.CO;2-E

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial Intelligence and Business Value: A Literature Review. *Information Systems Frontiers*, *24*(5), 1709–1734. https://doi.org/10.1007/s10796-021-10186-w

European Commission. (n.d.-a). *Corporate sustainability and responsibility*. Retrieved December 6, 2025, from https://single-market-economy.ec.europa.eu/industry/sustainability/corporate-sustainability-and-responsibility_en

European Commission. (n.d.-b). *Corporate sustainability reporting—Finance—European Commission*. Retrieved November 28, 2025, from https://finance.ec.europa.eu/capital-markets-union-and-financialmarkets/company-reporting-and-auditing/company-reporting/corporate-sustainability-reporting_en

European Commission. (2025, November 27). *AI Act | Shaping Europe's digital future*. https://digital-strategy.ec.europa.eu/en/policies/regulatory-framework-ai

Eurostat. (2025, January 23). *Usage of AI technologies increasing in EU enterprises*. https://ec.europa.eu/eurostat/web/products-eurostat-news/w/ddn-20250123-3

Feng, F., Li, J., Zhang, F., & Sun, J. (2024). The impact of artificial intelligence on green innovation efficiency: Moderating role of dynamic capability. *International Review of Economics & Finance*, *96*, 103649. https://doi.org/10.1016/j.iref.2024.103649

Flammer, C. (2013). Corporate Social Responsibility and Shareholder Reaction: The Environmental Awareness of Investors. *Academy of Management Journal*, *56*(3), 758–781. https://doi.org/10.5465/amj.2011.0744

Gama, F., & Magistretti, S. (2025). Artificial intelligence in innovation management: A review of innovation capabilities and a taxonomy of AI applications. *Journal of Product Innovation Management*, *42*(1), 76–111. https://doi.org/10.1111/jpim.12698

Ghosh, S. (2025). Developing artificial intelligence (AI) capabilities for data-driven business model innovation: Roles of organizational adaptability and leadership. *Journal of Engineering and Technology Management*, *75*, 101851. https://doi.org/10.1016/j.jengtecman.2024.101851

Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology. *Organizational Research Methods*, *16*(1), 15–31. https://doi.org/10.1177/1094428112452151

Guba, E. G., & Lincoln, Y. A. S. (1994). Competing Paradigms in Qualitative Research. *N. K. Denzin & Y. S. Lincoln (Eds.)*, *Handbook of Qualitative Research*, 105–117

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

Hansen, H. F., Lillesund, E., Mikalef, P., & Altwaijry, N. (2024). Understanding Artificial Intelligence Diffusion through an AI Capability Maturity Model. *Information Systems Frontiers*, *26*(6), 2147–2163. https://doi.org/10.1007/s10796-024-10528-4

Helfat, C. E., Kaul, A., Ketchen, D. J., Barney, J. B., Chatain, O., & Singh, H. (2023). Renewing the resource-based view: New contexts, new concepts, and new methods. *Strategic Management Journal (John Wiley & Sons, Inc.)*, *44*(6), 1357–1390. https://doi.org/10.1002/smj.3500

Helfat, C. E., & Winter, S. G. (2011). Untangling Dynamic and Operational Capabilities: Strategy for the (N)ever-Changing World. *Strategic Management Journal*, *32*(11), 1243–1250. https://doi.org/10.1002/smj.955

Kar, A. K., Choudhary, S. K., & Singh, V. K. (2022). How can artificial intelligence impact sustainability: A systematic literature review. *Journal of Cleaner Production*, *376*, 134120. https://doi.org/10.1016/j.jclepro.2022.134120

Keding, C. (2021). Understanding the interplay of artificial intelligence and strategic management: Four decades of research in review. *Management Review Quarterly*, *71*(1), 91–134. https://doi.org/10.1007/s11301-020-00181-x

Kinkel, S., Baumgartner, M., & Cherubini, E. (2022). Prerequisites for the adoption of AI technologies in manufacturing – Evidence from a worldwide sample of manufacturing companies. *Technovation*, *110*, 102375. https://doi.org/10.1016/j.technovation.2021.102375

KPMG. (n.d.). *Bridging sustainability and stakeholder trust*. KPMG. Retrieved December 2, 2025, from https://kpmg.com/sa/en/insights/esg/bridging-sustainability-and-stakeholder-trust.html

Kulkov, I., Kulkova, J., Rohrbeck, R., Menvielle, L., Kaartemo, V., & Makkonen, H. (2024). Artificial intelligence - driven sustainable development: Examining organizational, technical, and processing approaches to achieving global goals. *Sustainable Development*, *32*(3), 2253–2267. https://doi.org/10.1002/sd.2773

Leuthe, D., Meyer-Hollatz, T., Plank, T., & Senkmüller, A. (2024). Towards Sustainability of AI – Identifying Design Patterns for Sustainable Machine Learning Development. *Information Systems Frontiers*, *26*(6), 2103–2145. https://doi.org/10.1007/s10796-024-10526-6

Lichtenthaler, U. (2019). An Intelligence-Based View of Firm Performance: Profiting from Artificial Intelligence. *Journal of Innovation Management*, *7*(1), 7–20. https://doi.org/10.24840/2183-0606_007.001_0002

McKinsey. (2024a). *AI in Europe: A new opportunity for growth | McKinsey*. https://www.mckinsey.com/capabilities/quantumblack/our-insights/time-to-place-our-bets-europes-ai-opportunity

McKinsey. (2024b, September 17). *What are Scope 1, 2, and 3 emissions? | McKinsey*. https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-are-scope-1-2-and-3-emissions

McKinsey. (2025). *The state of AI in 2025: Agents, innovation, and transformation*. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai

Mishra, A. N., & Pani, A. K. (2021). Business value appropriation roadmap for artificial intelligence. *VINE Journal of Information and Knowledge Management Systems*, *51*(3), 353–368. https://doi.org/10.1108/VJIKMS-07-2019-0107

Montiel, I. (2008). Corporate Social Responsibility and Corporate Sustainability: Separate Pasts, Common Futures. *Organization & Environment*, *21*(3), 245–269. DOI:10.1177/1086026608321329

Montiel, I., & Delgado-Ceballos, J. (2014). Defining and Measuring Corporate Sustainability: Are We There Yet? *Organization & Environment*, *27*(2), 113–139. https://doi.org/10.1177/1086026614526413

Nishant, R., Kennedy, M., & Corbett, J. Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *International Journal of Information Management*, *53*, 102104. https://doi.org/10.1016/j.ijinfomgt.2020.102104

Nuruzzaman, M., & Hussain, O. K. (2018). A Survey on Chatbot Implementation in Customer Service Industry through Deep Neural Networks | Request PDF. *ResearchGate*. https://doi.org/10.1109/ICEBE.2018.00019

OECD. (n.d.). *Corporate sustainability*. OECD. Retrieved October 3, 2025, from https://www.oecd.org/en/topics/corporate-sustainability.html

OECD. (2024, June 3). *What is AI? Can you make a clear distinction between AI and non-AI systems?* https://oecd.ai/en/wonk/definition

Oliveira, T., & Martins, M. F. (2011). Literature Review of Information Technology Adoption Models at Firm Level. *Electronic Journal of Information Systems Evaluation*, *14*(1), 110–121.

Porter, M. E. (2008). The Five Competitive Forces That Shape Strategy. *Harvard Business Review*, *86*(1), 78–93. https://hbr.org/2008/01/the-five-competitive-forces-that-shape-strategy

Pumplun, L., Tauchert, C., & Heidt, M. (2019, June 1). *A New Organizational Chassis for Artificial Intelligence-Exploring Organizational Readiness Factors*. https://aisel.aisnet.org/ecis2019_rp/106/

Raisch, S., & Krakowski, S. (2021). Artificial Intelligence and Management: The Automation–Augmentation Paradox. *Academy of Management Review*, *46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

Ransbotham, S., Gerbert, P., Reeves, M., Kiron, D., & Spira, M. (2018). Artificial Intelligence in Business Gets Real. *MIT Sloan Management Review*. https://sloanreview.mit.edu/projects/artificial-intelligence-in-business-gets-real/

Russel S., & Norvig P. (2010). Artificial intelligence a modern approach, 3. ed. Pearson. https://doi.org/10.1017/S0269888900007724

Russo, M. V., & Fouts, P. A. (1997). A Resource-Based Perspective on Corporate Environmental Performance and Profitability. *Academy of Management Journal*, *40*(3), 534–559. https://doi.org/10.2307/257052

Saunders, M. (with Lewis, P., & Thornhill, A.). (2009). *Research methods for business students* (5. ed.). Financial Times Prentice Hall.

Schmidt, R., Zimmermann, A., Moehring, M. & Keller, B. (2020). *Value Creation in Connectionist Artificial Intelligence - A Research Agenda*. https://aisel.aisnet.org/amcis2020

Schreyögg, G., & Kliesch-Eberl, M. (2007). How dynamic can organizational capabilities be? Towards a dual-process model of capability dynamization. *Strategic Management Journal*, *28*(9), 913–933. https://doi.org/10.1002/smj.613

Schwaeke, J., Gerlich, C., Nguyen, H. L., Kanbach, D. K., & Gast, J. (2025). Artificial intelligence (AI) for good? Enabling organizational change towards sustainability. *Review of Managerial Science*, *19*(10), 3013–3038. https://doi.org/10.1007/s11846-025-00840-x

Sjödin, D., Parida, V., Palmié, M., & Wincent, J. (2021). How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. *Journal of Business Research*, *134*, 574–587. https://doi.org/10.1016/j.jbusres.2021.05.009

Teece, D. J. (2007). *Explicating Dynamic Capabilities: The Nature and Microfoundations of (Sustainable) Enterprise Performance*. 10.1002/smj.640

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7%253C509::AID-SMJ882%253E3.0.CO;2-Z

Teece, D., Peteraf, M., & Leih, S. (2016). Dynamic Capabilities and Organizational Agility: Risk, Uncertainty, and Strategy in the Innovation Economy. *California Management Review*, *58*(4), 13–35. https://doi.org/10.1525/cmr.2016.58.4.13

Toniolo, K., Masiero, E., Massaro, M., & Bagnoli, C. (2020). Sustainable Business Models and Artificial Intelligence: Opportunities and Challenges. In *Knowledge, People, and Digital Transformation: Approaches for a Sustainable Future*. Springer International Publishing.

Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *The Processes of Technological Innovation*. Lexington Books.

United Nations. (2015). *Transforming our world: The 2030 Agenda for Sustainable Development*. https://sdgs.un.org/goals#implementation

van Wynsberghe, A. (2021). Sustainable AI: AI for sustainability and the sustainability of AI. *AI and Ethics*, *1*(3), 213–218. https://doi.org/10.1007/s43681-021-00043-6

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S. D., Tegmark, M., & Fuso Nerini, F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. *Nature Communications*, *11*(1), 233. https://doi.org/10.1038/s41467-019-14108-y

von Hippel, E., & Kaulartz, S. (2021). Next-generation consumer innovation search: Identifying early-stage need-solution pairs on the web. *Research Policy*, *50*(8), 104056. https://doi.org/10.1016/j.respol.2020.104056

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Jean Robert, K. K., & Tchatchouang, C. E. (2020). *Influence of Artificial Intelligence (AI) on Firm Performance: The Business Value of AI-based Transformation Projects*. DOI:10.1108/BPMJ-10-2019-0411

Warner, K. S. R., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, *52*(3), 326–349. https://doi.org/10.1016/j.lrp.2018.12.001

Weber, M., Engert, M., Schaffer, N., Weking, J., & Krcmar, H. (2023). Organizational Capabilities for AI Implementation - Coping with Inscrutability and Data Dependency in AI. *Information Systems Frontiers*, *25*(4), 1549–1569. https://doi.org/10.1007/s10796-022-10297-y

Wernerfelt, B. (1984). A Resource-Based View of the Firm. *Strategic Management Journal*, *5*(2), 171–180. http://www.jstor.org/stable/2486175

Winsor, J. (2024). How to Be Systematic About Adopting AI at Your Company. *Harvard Business Review Digital Articles*, 1–6. https://hbr.org/2024/11/how-to-be-systematic-about-adopting-ai-at-your-company

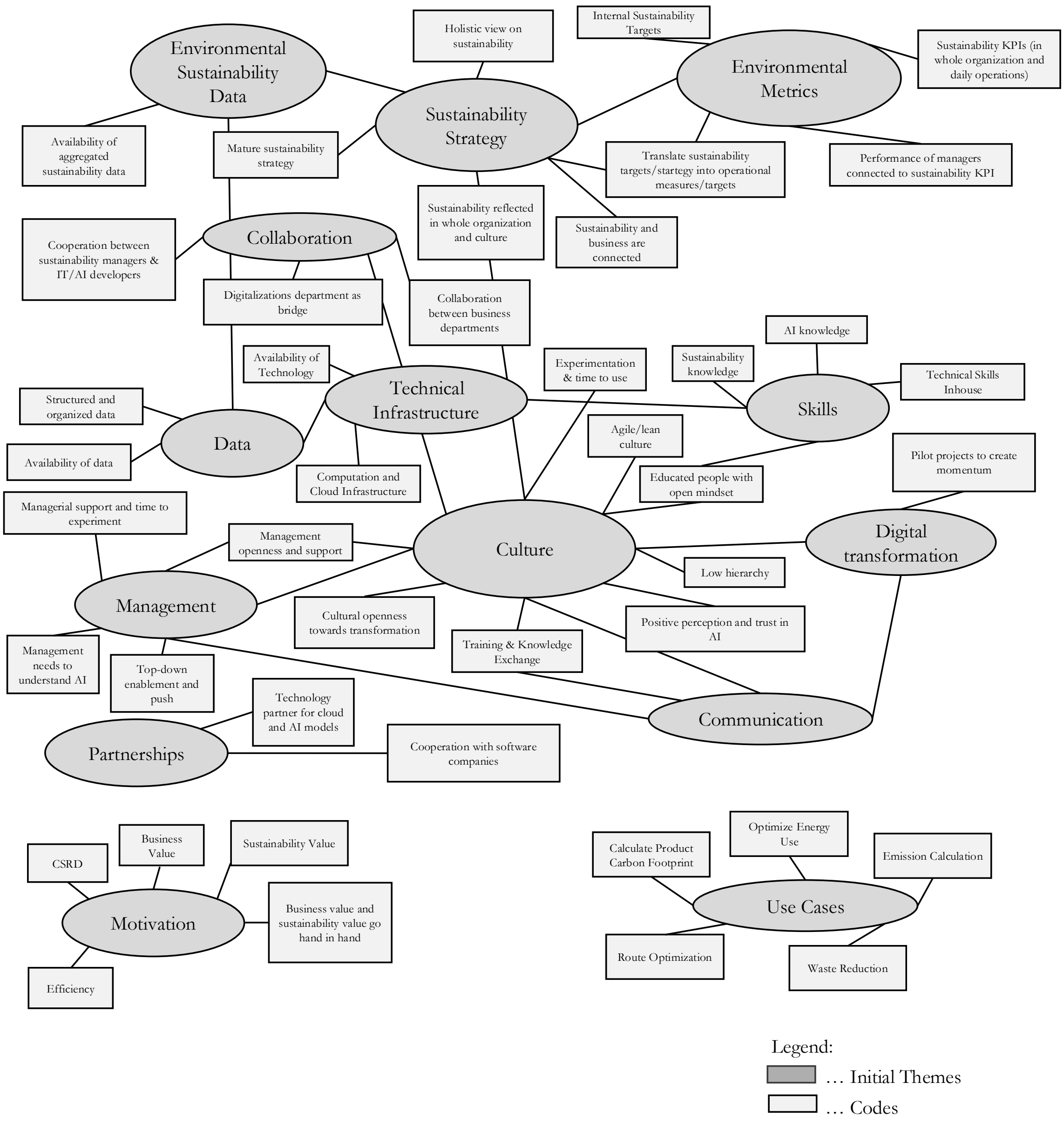
Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic Management Journal*, *24*(10), 991–995. 10.1002/smj.318

8. Appendix

8.1. Appendix A: Interview Guide

1. **Introduction and Context**
   - Can you **describe your role and for how long** have you been working in the company?
   - **Is your company already using AI for sustainability** and how/ in which initiatives?
   - Which sustainability challenges were prioritized when you started working with AI?
2. **Applications and Use Cases**
   - **Can you give concrete examples of AI applications your company has developed or is using for environmental sustainability?**
     - How do these AI solutions contribute to measurable sustainability outcomes (e.g. energy efficiency, waste reduction, emissions tracking)? How do you measure success of these solutions?
   - Do you use **AI because of Business Value** or also to improve environmental sustainability?
   - What are the **drivers to use AI** (for environmental sustainability)?
3. **Capabilities and Resources**
   - What **specific resources and capabilities did your company need to build** or strengthen to make these AI projects work? (e.g. data infrastructure, cross-functional collaboration, AI literacy)
   - Do you **require additional/different capabilities to use AI for environmental sustainability projects than for other use cases?**
   - Which existing organizational strengths made the adoption easier?
   - Did you rely on **external expertise** (consultants, universities, tech vendors), and how did that interact with internal capabilities?
   - How important have **managerial support, cultural openness**, or cross-departmental collaboration been?
4. **AI adoption Process**
   - What are **capabilities** you think might be useful to make adaption easier?
   - What governance or **decision-making structures** supported the process?
   - How were **employees trained, reskilled**, or involved? How do you handle resistance?
5. **Barriers and Challenges**
   - What were the main **obstacles** you encountered (technical, organizational, financial, regulatory)?
   - How did you overcome these barriers?
6. Is there anything left we did not ask you or do you have any more reflections?

8.2. Appendix B: Initial Thematic Map (Braun & Clarke, 2006)



8.3. Appendix C: Declaration of AI Use in this thesis

This thesis used AI tools in a limited and fully transparent manner. All conceptual development, theoretical reasoning, methodological decisions, data analysis, and conclusions presented in this thesis are the sole responsibility of the authors. AI tools were used in alignment with the *Stockholm School of Economics Guidelines regarding generative AI (Artificial Intelligence) and thesis writing* and were not used to generate arguments, interpret interview data, or develop academic contributions in order to mitigate the risks (e.g. false content creation, citing non-existent sources,…).

AI assistance was used exclusively in the following two areas in order to enhance research efficiency and understanding:

1. **Language refinement and text polishing:**
   AI-based writing support (ChatGPT, Grammarly) was used to check grammar, enhance clarity, and improve sentence structure. All content, ideas, and arguments remain authored by the thesis writers, with AI use restricted to linguistic refinement.
2. **Administrative support related to interview preparation:**
   AI tools (ChatGPT, including Agent Mode functionalities) were used to support administrative tasks during interview recruitment. This included drafting outreach messages, generating alternative formulations for communication with potential interview partners, and conducting preliminary searches to identify relevant interview contacts. ChatGPT was also used to draft the preliminary Interview Guide which was revised after the pilot interview. All outreach decisions, selections of interviewees, and communication were reviewed and approved by the authors.

Examples of prompts used in ChatGPT:

- *"You are an academic writing expert. Please correct grammar, mistakes, and eliminate redundancy. Do not add or omit any information, use only the content provided in my notes."*
- *"Act as a research assistant helping with B2B outreach. Identify 100 companies in the Nordic region (Sweden, Norway, Denmark, Finland), including a balanced mix of small, medium, and large enterprises. Prioritize companies that are currently using AI for sustainability purposes. For each company, provide the following: Company Name, a name of a person who works there in sustainability and AI. Only include companies with accessible general email addresses. Format the results as a table with three columns: Company Name; Contact Person; Contact Email. In this chat a little bit above is an excel with the contacts I already have. Please extend this list."*

No AI tool was used to generate literature reviews, analyze empirical material, create findings, or develop theoretical contributions.

The authors take full responsibility for the accuracy, originality, and integrity of the thesis.